AN ECONOMETRIC ANALYSIS OF THE FORWARD FREIGHT MARKET

by

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DECLARATION

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ABSTRACT

The success or failure of a derivatives (futures or forward) contract is determined by its ability to perform its economic functions efficiently, and therefore, to provide benefits to economic agents, over and above the benefits they derive from the spot market. These economic functions are price discovery and risk management through hedging. A considerable amount of empirical research has been directed towards examining these functions in different financial and commodity derivatives markets. The evidence however, on the over-the-counter FFA market is very limited. This thesis therefore, by investigating these issues provides new evidence in the literature for a forward market with some unique characteristics such as the trading of a service. Our empirical results can be summarised as follows. First, the FFA contracts perform their price discovery function efficiently since forward prices contribute to the discovery of new information regarding both current and expected spot prices. Furthermore, most FFA contracts contribute in the volatility of the relevant spot rate, and therefore, further support the notion of price discovery. Second, the introduction of FFA contracts has not had a detrimental effect on the volatility of the underlying spot market. On the contrary, it appears that there has been an improvement in the way that news is transmitted into prices following the onset of FFA trading. Third, FFA prices fail to reduce market risk to the extent evidenced in other markets in the literature and, hence, the FFA market does not perform its risk management function satisfactorily; this is thought to be the result of the lack of the cost-of-carry arbitrage relationship of storable assets that keeps spot and derivatives prices close together. Fourth, there seems to be a positive relationship between bid-ask spreads and expected price volatility in most FFA trading routes. Finally, in the routes where the cointegrating vector is restricted to be the lagged basis, the VECM generates more accurate forecasts than the VAR model and in the routes where the cointegrating vector is not restricted to be the lagged basis the VAR generates more accurate forecasts than the VECM model.

JEL Classification: G13, G14, C32.
Keywords: Unit Roots, Cointegration, Vector Error-Correction Models, Multivariate and Univariate GARCH Models, Price Discovery, Volatility Spillovers, Derivatives Trading and Volatility, Hedging, Time-Varying Hedge Ratios, Bid-Ask Spreads, Forecasting, Over-the-Counter Market, Forward and Futures Markets, Shipping.

LIST OF ABBREVIATIONS

ACD	Autoregressive Conditional Duration
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller Unit Root Test
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AR	Autoregressive Model
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average Model
ATBA	Agents Tanker Brokers' Association
BCa	Bias Corrected Confidence Intervals
BCI	Baltic Capesize Index
BCOI	London Brent Crude Oil Index
BFI	Baltic Freight Index
BHI	Baltic Handysize Index
BHMI	Baltic Handymax Index
BIFFEX	Baltic International Freight Futures Exchange
BITR	Baltic International Tanker Routes Index
BP	Box-Pierce Autocorrelation Test
BPI	Baltic Panamax Index
CBT	Chicago Board of Trade
CME	Chicago Mercantile Exchange
COA	Contract of Affreightment
COMEX	Commodity Exchange
CRB	Commodity Research Bureau Index
CRDW	Cointegration Regression Durbin-Watson Statistic
DF	Dickey-Fuller Unit Root Test
DGP	Data Generating Process
ECM	Error-Correction Mechanism
ECT	Error-Correction Term
EG	Engle-Granger Test for Cointegration

EMH	Efficient Market Hypothesis
FFA	Forward Freight Agreements
FFABA	Forward Freight Agreements Brokers Association
FIFC	Freight Indices and Futures Committee
FMLS	Fully-Modified Least Squares Estimation
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GIR	Generalised Impulse Responses
HE	Hedging Effectiveness
$I(d)$	Integrated of Order d
IMAREX	International Maritime Exchange
IMM	International Monetary Market
IPE	International Petroleum Exchange
ITFI	International Tanker Freight Index
JB	Jarque-Bera Normality Test
KPSS	Kwiatkowski, Phillips, Schmidt and Shin Unit Root Test
LB	Ljung-Box Autocorrelation Test
LCE	London Commodity Exchange
LCH	London Clearing House
LIBOR	London Interbank Offered Rate
LIFFE	London International Financial Futures Exchange
LL	Log-Likelihood Test
LME	London Metal Exchange
LR	Likelihood-Ratio Test
LTBP	London Tanker Brokers' Panel
MA	Moving Average Model
MLE	Maximum-Likelihood Estimation
MVHR	Minimum Variance Hedge Ratio
NOS	Norwegian Options and Futures Clearing-House
NYCE	New York Cotton Exchange
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
OTC	Over-The-Counter
PP	Phillips-Perron Unit Root Test

QMLE	Quasi Maximum-Likelihood Estimation
RMSE	Root Mean Square Error
RW	Random Walk
SBIC	Schwarz Bayessian Information Criterion
SPCI	S&P 500 Commodity Index
SPI	S&P 500 Composite Index
SURE	Seamingly Unrelated Regressions Estimation
TIFFEX	Tanker International Freight Futures Exchange
VAR	Vector Autoregression Model
VECM	Vector Error-Correction Model
VMA	Vector Moving Average
WF	Weighted Factor
WTI	West Texas Intermediate

TABLE OF SYMBOLS

I_n	nxn Identity Matrix
S_t	Spot Price at time t
F_t	Forward (FFA) Price at time t
$F_{t,t-n}$	Forward (FFA) Price at time $t-n$, for delivery at time t
Σ	2x2 Variance-Covariance Matrix
H_t	2x2 Time-Varying Variance-Covariance Matrix
$h_{S,t}$	Time-Varying Variance of Spot Returns
$h_{F,t}$	Time-Varying Variance of FFA Returns
$h_{SF,t}$	Time-Varying Covariance of Spot and FFA Returns
Ω_{t-1}	Information Set Available to Market Agents at time t-1
$E(.\|\Omega_{t-1})$	Expectation Operator Conditional on the Information Set at t-1
X'	Transpose of Matrix X
Rank(X)	Rank of Matrix X
$\sim$	Distributed as
iid	Identically and Independently Distributed
$IN(0,\sigma^2)$	Independently and Normally Distributed with Mean 0 and Variance σ^2
$\chi^2(n)$	Chi-Squared Distributed with n Degrees of Freedom
Δ	First-Difference Operator e.g. $\Delta F_t = F_t - F_{t-1}$
L	Lag Operator e.g. $LF_t = F_{t-1}$
$\forall$	For all
h	Hedge Ratio
h_t	Time-Varying Hedge Ratio at time t
ΔP_t	Change in the Hedge Portfolio from t-1 to $t = \Delta S_t - h\Delta F_t$
$\sum_{i=1}^{T}$	Summation Operator from 1 to T
ρ	Correlation Coefficient
σ^2	Variance

To my Grandmother

"Lost but not forgotten"

CHAPTER 1 - INTRODUCTION

1.1. INTRODUCTION

The aim of this thesis is to provide further evidence, which will enhance our understanding of how the Forward Freight Agreement (FFA) derivatives market, of the dry-bulk sector of the shipping industry, performs its economic functions by examining five important empirical areas: First, to investigate the price discovery function of the FFA market. The empirical analysis consists of two different testable hypotheses; the unbiasedness hypothesis, and the lead-lag relationship of spot and FFA prices in returns and volatilities. Together they constitute the level of efficiency of the FFA contract as a hedging vehicle against freight rate fluctuations. Second, to examine if FFA trading, by encouraging speculation, has impacted the volatility of the underlying spot market. Third, to examine the risk management function of the FFA contract by measuring its hedging effectiveness. Fourth, to investigate the relationship between bid-ask spreads and anticipated volatility of the FFA market. Finally, the forecasting performance of spot and FFA prices is examined in generating short-term forecasts.

This thesis is of great importance for market agents in the dry-bulk freight market, which need to cover the freight risk exposure that they face. If FFA prices are to fulfil their price discovery role, they must provide accurate forecasts of the realised spot prices, and consequently, they must provide new information in the market and in allocating economic resources. Understanding the process by which new information is incorporated into current spot and FFA prices can allow market agents to use the leading market as a price discovery vehicle, since such information may be used in decision making. Moreover, market agents whose physical operations concentrate on specific trading routes can benefit from using optimal hedge ratios that minimise their freight rate risk. Thus, a better understanding of the dynamic relation of spot and FFA prices and its relation to the basis will provide to these agents the ability to use hedging in a more efficient way. Finally market agents can benefit from having accurate short-term forecasts of the spot and FFA prices, since availability of such forecasts will enable them to design more efficient trading strategies.

The special features of this market, in comparison to the existing literature on futures and forward markets, are: (i) the non-storable nature of the underlying commodity, being that of a service. The theory of intertemporal relationships between spot and derivatives prices of continuously storable commodities is well developed (Working 1970), in contrast to that of non-storable commodities (e.g. freight services). The non-storable nature of FFA market implies that spot and FFA prices are not linked by a cost-of-carry (storage) relationship, as in financial and agricultural derivatives markets. Thus, inter-dependence between spot and FFA prices may not be as strong as for storable commodities; and (ii) the asymmetric transactions costs between spot and FFA markets. These costs are believed to be higher in the spot freight market (in relation to the FFA market) as they involve the physical asset (vessel).

In forward markets, to the best of our knowledge, there have been only few studies (with the exeption of currency forwards) investigating the economic functions of Over-The-Counter (OTC) derivatives contracts, primarily due to the unavailability of data. In contrast in futures markets there is a plethora of similar studies. The possession of daily data (bid and ask quotes) that were manually gathered and processed in an electronic format and the use of critically selected econometric techniques enable us, for the first time, to introduce empirical evidence for the price discovery, risk management, and forecasting performance of the FFA market. The uniqueness of this thesis lies in the fact that its concern is with a market that has been subject to extremely limited, if any, coverage.

The purpose of this chapter is to provide an introduction to the thesis and to familiarise the reader with the concepts and terms used in shipping finance and more specifically in the shipping freight derivatives business. It is divided in four main sections where each section considers the following issues. The first section describes the theory and practice of hedging financial risks. It presents the types of market participants, the alternative theories of hedging, it introduces the concept of basis and basis-risk and concludes with the measures of hedging effectiveness. The second section presents the use of financial derivatives in the shipping industry. It provides a historical background of their evolution in this market and focuses on hedging the freight market risk using freight derivatives.

The third section presents the characteristics and specifications of the unique FFA market with the underlying asset to be shipping trading routes from either, the Baltic Panamax Index (BPI), the Baltic Capesize Index (BCI), or the Baltic Handymax Index (BHMI) for the dry-bulk sector or from the Baltic International Tanker Routes (BITR) index for the tanker sector. It examines its use, its advantages and disadvantages and its relation with the standardised exchange-listed Baltic International Freight Futures Exchange (BIFFEX) contract, which was trading until April 2002. Finally, this chapter concludes by presenting the research areas that are investigated; the price discovery function of the FFA market, the impact of FFA trading on the volatility of the underlying spot market, the risk management function of the FFA market, the relationship between bid-ask spreads and expected FFA volatility and forecasting the spot and FFA prices.

1.2. THE THEORY OF HEDGING

The core function of the financial system is to facilitate the allocation and development of economic resources, both spatially and across time, in an uncertain environment (Merton, 1990). The economic function of financial markets can be seen in three dimensions: time, risk, and information. Borrowing and saving are the major functions of the financial systems in order to achieve an efficient intertemporal allocation of funds (Arditti, 1996). The intertemporal nature of financial decisions implies uncertainty. Risk is, therefore, an inherent characteristic of financial decisions. The capital market provides a wide range of instruments or institutional arrangements to either diversify risks (hedge), i.e. to eliminate risks for the society as a whole, or to (re)allocate the undiversifiable part of the risks among households and firms, from those who want to avoid risk to those who are willing to accept risk.

The origin of the term hedging is unclear, but it appears to derive from the use of hedges to form a protective or defensive barrier around property. In business context, the term means "*to secure oneself against a loss on an investment by investing on the other side*". The losses an investor seeks to offset (neutralise) are the direct results of adverse price level changes (fluctuations) through time of his investment (Arditti, 1996). Hedging is therefore insuring (protecting) against changes in the market so that the buyer and seller in the market will be protected against any adverse changes in prices[1]. In this way the hedgers take an equal but

[1] It should be noted that some risks cannot be hedged perfectly with derivatives instruments, such as default risk, which is the risk of one participant that the other counterparty may default, or quantity risk, which is the uncertainty about the quantity that will be sold or bought at some future date.

opposite in direction derivatives position to the position, which they are exposed to in the physical market. Before implementing a hedge, various factors should be considered: identification of risk exposure, calculation of potential risk exposure, selection of hedging instrument, calculation of the size of the hedge, and finally monitoring the hedge (Boland, 1999). Companies and individual investors can use modern risk management instruments in order to hedge their risks. These instruments are usually called derivatives instruments and can be defined simply as aggregates or *bundles* of contractually created rights and obligations, the effect of which is to create a transfer or exchange of specified cash-flows at defined future points in time (Arditti, 1996).

The quantum of these cash-flows are determined by reference to or derived from (hence the word *derivatives*) underlying spot or physical markets, i.e. foreign exchange, commodities, or from particular financial indices, such as one of the benchmark interest rates; the London Interbank Offered Rate (LIBOR). The variety and the number of derivatives instruments are enormous and the terminology used to describe them is often bewildering. However, derivatives instruments, even in their most exotic forms can, and should be, approached not as an endless series of discrete products but as examples of how basic financial building blocks can be assembled to produce an almost infinite series of products. The available methods of hedging rely upon the form of risk and the preferences of the investors. In the shipping industry, there are several factors relating to the industry, which make it an interesting environment for analysis of risk and uncertainty and the ways to minimise them. Shipping markets can be characterised as capital intensive, cyclical, volatile, and exposed to the international businesses environment.

1.2.1. Types of Market Participants

Market agents can be generally categorised, with respect to their preferences, as hedgers, speculators, or arbitrageurs.

1.2.1.1. Hedgers

Hedgers are interested in reducing a price risk that they already face by either transferring it to another hedger with an opposite position in the market, or to a party willing to accept and trade the risk. They wish to hedge their financial position against any unfavourable moves in the future. The hedger might do so to stabilise income or debt or to get a better grip on cash management, thereby managing different types of exposure in the market. By definition, they are risk-averse. Normally, a hedger will hedge an existing position in the market, referred to as *cash hedge*, such as interest payments from a loan to another party. However, the hedge might also be of *anticipatory* nature - when a cash position is expected in the future.

1.2.1.2. Speculators

Speculators wish to take a position in the market by anticipating market volatility, which will result in a profit for them, when they are correctly predicting directional changes in prices. They are less risk-averse than hedgers, betting that a price will go up or betting that it will go down, and their motivation is not to hedge any underlying physical position. They take on the risks that a hedger wants to avoid. They use their risk capital in an attempt to take advantage of favourable price fluctuations in the market by buying contracts when they believe prices will rise and selling when they believe prices will fall. If they are correct they make a profit.

Speculators are often viewed with suspicion. However, they are essential to market existence, as they are willing to take risks, thereby introducing capital to the market, ensuing its liquidity. Speculators benefit from leverage, low transaction costs, ease of opening and closing positions, narrow bid-ask spreads and the ability to *short* the market, due to their large in size positions. Without their presence, the market would tend to move violently, reaching extreme values, as there would be no one to take the opposite position and smooth the fluctuations. A hedger accepts to sustain a loss on a derivatives contract, as it probably reflects profits from the underlying asset. The speculator has no underlying asset in his portfolio and seeks profits from the derivatives contract.

1.2.1.3. Arbitrageurs

Arbitrageurs have a similar role to speculators, they seek a risk-free profit by entering simultaneously into transactions in two or more markets buying in the cheaper market and selling in the most expensive market. They take advantage of temporary discrepancies in the markets caused by time lags or temporary imbalances in demand or supply, although arbitrage opportunities occur infrequently.

Three criteria, taken from the London International Financial Futures and Options Exchange (LIFFE), should be considered as the ground rules to identify whether the trader is a hedger or a speculator:

(i) Intention: The transaction should be intended to reduce the risk exposure,

(ii) Correlation: The price of the derivatives contract and the hedged asset or liability should show a high positive correlation so that they will move in the same direction and with similar magnitude,

(iii) Certainty: There should be a reasonable expectation that the cash transaction will be fulfilled.

Working (1960) categorised the possible motives of the three different market agents:

(i) Operational hedging: Companies are buying and selling on the derivatives market as temporary substitutes for subsequent cash market transactions. This motive provides flexibility in the business operations of the firm and price risk reduction,

(ii) Arbitrage hedging (or carrying-charge hedging): A company can arbitrage the derivatives and the cash markets and earn a risk-free return from the predictable change in the price of the derivatives contract and the expected future spot price,

(iii) Anticipatory hedging: Companies are buying and selling derivatives contracts in anticipation (price expectations) of forthcoming cash market transactions.

1.2.2. Theories of Hedging

The reasons for hedging are as many as there are potential risks in the market. However, there are three views of the nature and purpose of hedging: the traditional risk minimisation view, where traders are seeking to reduce price risk; the profit maximisation view, where traders are attempting to profit from expected movements of the spot price - derivatives price spread (basis); and the portfolio approach, where traders try to reach a satisfactory risk-return trade-off by diversification (Sutcliffe, 1997). Each of these interpretations is considered next.

1.2.2.1. Risk Minimisation

Risk minimisation refers to someone who is exposed to a risk, and wishes to reduce or remove this exposure, as it is his primary goal. This is achieved by taking an additional investment whose risk cancels out or offsets the initial risk. The investments of both the initial asset and the security used to offset the risk of this asset must be of equal magnitude. The naïve hedge ratio, which is the number of derivatives contracts bought or sold, divided by the number of spot contracts whose risk is being hedged, in this case, is one-to-one (or unity). The price of the derivatives contract and the price of the spot asset to be hedged must have sufficient correlation, and therefore, losses on one position can be compensated for by gains on the other position. Thus, the traditional approach assumes that hedging will entirely eliminate price risk during the hedging period.

We must notice that, using futures or forward contracts, a small amount of risk remains unhedged (tail-risk). A perfect hedge occurs when the risk of the additional investment exactly offsets the initial risk. Unfortunately, in practice this is not a common thing. The price of the derivatives instrument and the price of its underlying spot asset cannot have a correlation of one for a great range of economic reasons, i.e. a change in the supply and demand conditions of the underlying asset in the future will influence the price of the asset.

1.2.2.2. Profit Maximisation

Working (1953) was the first to challenge the traditional risk minimisation approach, arguing that hedging is practiced not only for risk minimisation but also for other business reasons, one of them being profit maximisation. In the context of profit maximisation a hedge can be viewed as a spread between the short derivatives contract and the long underlying spot asset. Working discusses four different reasons for a market agent to initiate hedging: (i) for buying and selling decisions, where the aim is to locate a favourable price for buying and selling in relation to other current prices and not a favourable absolute level of the price; (ii) freedom for business decisions, where a market agent can purchase or sell lots of the commodity that would not otherwise be possible at a favourable price level; (iii) a reliable basis for conducting storage of commodity surpluses, where hedging allows operation on the basis by deriving that the spot price is low in relation to the derivatives price; and (iv) because hedging reduces business risks. Under these assumptions, the objective of a hedge is to make a profit (speculation) from movements in the relative prices of the derivatives contract and the spot asset, and not only to minimise risk. As a consequence, market agents must estimate *optimal* hedge ratios (Working, 1953).

1.2.2.3. Portfolio Approach

Johnson (1960) was the first to develop and present the portfolio approach of hedging, using the portfolio theory of Markowitz. A popular view of hedging is that both risk minimisation and profit maximisation are objectives of hedgers. Under this approach, a hedger is assumed to be risk-averse and can hold different positions of cash (long) and derivatives contracts (short) in his portfolio with the objective of maximising the expected value of his utility function. Therefore, the hedger will choose among the alternative portfolios on the basis of their means (expected return) and variances (expected risk). By incorporating hedges, a market agent can identify the lowest-risk portfolio for each level of return (optimal hedge).

After determining the assets of the portfolio and the desired level of risk and return of the hedged position, the hedging decision can be formulated as a Markowitz portfolio selection problem and solved with risk-aversion and expected return constraints. The efficient frontier, i.e. feasible combinations of expected profit and risk for each level, that have maximum profit, can be found by repeatedly solving this portfolio problem for a wide range of values of the risk-aversion parameter.

Ederington (1979) argues that a portfolio approach to hedging is superior to both the risk minimisation and profit maximisation approaches. An investor buys or sells derivatives contracts in the same way he buys or sells any other portfolio of assets, according to his risk-return preferences. Therefore, a portfolio with assets and/or derivatives contracts can be wholly or partially hedged, depending on the risk and return an investor wants to sustain or earn, respectively. If an investor wants more earnings, he must also be willing to take a larger risk. Portfolio strategies offer an opportunity to the hedger to select from a range of expected returns (diversify), and not just the traditional target of locking in existing returns, because this approach does not require a cash position to be fully hedged (Howard and D'Antonio, 1991).

1.2.3. Basis and Hedging

1.2.3.1. Definition of the Basis

Basis can be defined as the spot price (S_t) of the asset to be hedged minus the price of the derivatives contract used (F_t). The basis is much more predictable than the individual level of spot and derivatives prices, and can provide more information about the market conditions

(Sutcliffe, 1997)[2]. A narrowing (or strengthening) basis occurs when the basis moves toward zero and the absolute difference between spot and derivatives prices becomes smaller. On the other hand, a widening (or weakening) basis occurs when the basis moves away from zero and the absolute difference between spot and derivatives prices increases.

The outcome of hedges is influenced from the type of the derivatives position (long or short) and from market conditions (contango[3] or backwardation market[4]). If the basis is significantly positive or negative, then opportunities may exist for arbitrage or spread trading. This type of analysis is useful for arbitrage and hedge management because it is in general preferable to sell forward when they are *rich to cash* and buy forward when they are *cheap to cash.* A contango market is characterised by increasing derivatives prices as the time to delivery becomes more distant, while a backwardation market by decreasing derivatives prices as delivery becomes more distant. The terms contango and backwardation can be used to describe an entire pattern of derivatives prices, from the price of the nearest month contract to the price of the most distant month contract. A feature of the basis, which is common to both futures and forward contracts, is its tendency to narrow when the expiration of the derivatives contract approaches. This is known as *basis convergence*, where at expiration the spot and the derivatives prices are equal.

1.2.3.2. Basis Risk and Hedging

The main purpose of hedging is to eliminate or minimise the risk exposure that is caused by adverse price movements. This kind of exposure is called price risk and is provided by the uncertainty of the future price levels. Besides price risk, there is basis risk which occurs from: (i) the changes of the derivatives price in relation to the corresponding spot rates, defined in the commodity derivatives theory; and (ii) from the changes of the derivatives price in relation to the corresponding implied forward rates, defined in the financial derivatives theory. Basis risk can be better predicted and controlled when following a risk management approach, instead of

[2] A short hedger (short derivatives position) is said to be long the basis, while a long hedger (long derivatives position) is short the basis.

[3] Contango is the term used to describe the situation in which spot prices are lower than derivatives prices, and consequently the basis will be negative. Forward contracts are expensive when the basis is negative and they are cheap when the basis is positive.

[4] Backwardation is the term used to describe the situation in which spot prices are higher than derivatives prices, and consequently the basis will be positive. Thus, near forward contracts will be higher priced than distant forward contracts.

monitoring the level of prices. This is the reason that market agents use hedging and are able to accept the relatively small basis risk in order to eliminate the price risk.

In practice, the magnitude of the basis risk depends mainly on the degree of correlation between spot and derivatives prices - the higher the correlation the less the basis risk. Thus, basis risk is defined as the variance of the basis. If basis (B_t) is defined as the difference between the spot price (S_t) and the derivatives price (F_t):

$$B_t = S_t - F_t \tag{1.1}$$

Then when changes in spot and derivatives prices are not equal there will be basis risk, which is defined as the variance of the basis:

$$\sigma^2 B_t = \sigma^2[S_t - F_t] = \sigma^2 S_t + \sigma^2 F_t - 2\rho\sigma(S_t)\,\sigma(F_t) \tag{1.2}$$

where, σ^2 = variance

σ = standard deviation

ρ = correlation coefficient between the spot and the derivatives prices.

The last equation reveals that when the variances of the spot and derivatives prices are identical and the correlation coefficient between spot and derivatives prices equals one, the basis risk will be zero. Conversely, if the correlation coefficient is very low or the difference between the variances is large, then there will be some basis risk. The basis risk should be significantly less than the price risk in order for the hedge to be attractive. Since there is never a perfect correlation between spot and derivatives prices, hedgers always assume some basis risk in order to reduce their exposure to price risk[5]. The behaviour of the basis from the time a hedge is placed until the time it is lifted is of considerable importance to the hedger. The very essence of hedging involves an exchange of risk - price risk for basis risk.

[5] Hull (1997) argues that hedging with futures and forward contracts work less than perfectly in practice for the following reasons: (i) the asset whose price is to be hedged may not be exactly the same as the asset underlying the contract; (ii) the hedger may be uncertain as to the exact date when the asset will be bought or sold; and (iii) the hedge may require the contract to be closed out well before its expiration date.

1.2.4. Hedging Effectiveness

1.2.4.1. The ex ante Hedging Effectiveness

An effective hedge occurs when there is a high correlation between the spot and the derivatives prices. Thus, the hedging effectiveness can be measured by how well changes in the value of a hedge position keep pace with changes in the value of the risk-bearing position. When the anticipated basis risk is small relative to the expected price risk, the *ex ante* hedging effectiveness is high. Therefore, the measure of hedging effectiveness (HE_1) can be expressed as one minus the ratio of expected variance of the basis to the expected variance of the spot prices.

$$HE = 1 - \frac{\sigma^2(B_t)}{\sigma^2(S_t)} \tag{1.3}$$

1.2.4.2. The ex post Hedging Effectiveness

The previous measure is based on the expectation of variances and therefore, it is used only to judge how good a particular hedge is likely to be *a priori*. After a hedge is completed we can measure the *ex post* hedging effectiveness:

$$HE_2 = 1 - \frac{\text{Variance (Net Gains or Losses in Hedged Position)}}{\text{Variance (Net Gains or Losses in Unhedged Position)}} \tag{1.4}$$

The closer HE_2 is to one, the more effective the hedge.

1.3. THE USE OF DERIVATIVES IN THE SHIPPING INDUSTRY

Not even the most casual or indifferent observer of the world's capital markets can fail to have noticed the growth and evolution of financial instruments that address the needs of many different end-users in a wide range of different market environments. The pace of this growth has been explosive, being driven by an underlying demand for risk management products and financial engineering skills that reflects the fact that the overall economic environment, within which business is conducted, has grown more volatile and unstable. The last 20 years have witnessed extensive securities innovation[6]. There are numerous lists of recent financial innovations published by practitioners, and academics that show the wide range of financial innovation (see Finnerty, 1988, 1992). As already indicated, the risk associated with a financial environment, which lacks stability and is characterised by change and flux, has created a demand for financial instruments to protect against that risk. The family of the derivatives products best represents these instruments.

Derivatives can be traded on financial exchanges or on OTC markets in order to address more specific needs and to be tailored to the exact business exposures. Table 1.1 presents the differences between listed and non-listed OTC contracts. We can notice that, exchange-based and OTC derivatives can serve the same economic functions but under different contractual structures. Selection between them depends on the preferences and needs of the individual investor.

Table 1.1. Listed vs. OTC Derivatives

	LISTED	OTC
FEATURES	Standardised contracts, maturities, contract size, exercise type, delivery, payouts.	Terms are flexible and negotiable, any maturity date, varying contracts, payouts are flexible, physical or cash settlement.
TRADING	Exchange-traded, liquid.	Private placement agreements, limited liquidity.
GUARANTEE	Derivatives Clearing-House.	No organisation as guarantor.

Source: Collins, 1998.

[6] Finnerty (1988, 1992) claims that the period 1970-1990 is quite unique in financial history, in that "*no other 20-year period has witnessed such a burst of innovative activity*".

Both futures and forward derivatives contracts represent a binding obligation under which a person either sells or buys a specified asset at a specified price on the contract maturity date. The specified underlying asset of the contract is not literally bought or sold, but the market price of that contract at maturity compared to the contract price will determine whether the holder of the derivatives contract has made a profit or a loss (Duffie, 1989). Despite their similarity, each instrument is designed under different contractual and legislative terms. The contractual differences between forward and futures contracts are presented in Table 1.2.

Table 1.2. Contractual Differences between Futures and Forward Contracts

	FUTURES CONTRACT	FORWARD CONTRACT
Contract Specifications	Standardised specifications of unit, size, and price of trading.	No standardisation with individually agreed terms and prices.
Method of Trading	Open outcry auction on an exchange trading floor during specific trading hours.	OTC market between individual buyers and sellers, 24 hours per day.
Pricing	Same best price available at the time for all traders, regardless of transaction size.	The price varies with the size of the transaction, the credit risk. No guarantee that it is the best.
Daily Fluctuations Limit	There is a daily price limit for most contracts.	There are no daily price limits.
Market Liquidity	High liquidity and ease of offsetting a position due to standardisation.	Limited liquidity and offset due to variable contract terms.
Payment Schedule	Interim payments during the life of the contract (mark-to-market).	A payment is made only on the maturity date and there is no initial cash-flow.
Clearing Operation	A clearing-house deals with the daily revaluation of open positions, and cash payments.	There is no clearing-house function.
Security	A clearing-house assumes the credit risk and controls for default risk.	The trader's reputation and collateral control for default risk, and the participant bears the credit risk of the counterparty defaulting.
Delivery on Maturity	It is not the object of the transaction and only 2% of the contracts are delivered.	It is the object of the transaction and over 90% are delivered.
Delivery Procedure	Specific maturity dates per year at approved locations.	Written with specific (individual agreed) times to maturity and locations.
Publicity of Information	Information is publicly available.	Information is disclosed to the public.
Regulation	Regulated by a government agency.	Self-regulation.

Source: Hsu, 1996.

A futures market is an organised formal market in which a given underlying asset may be bought or sold in the future. In theory any commodity, financial instrument, or a service could be traded on a futures market. In practice, there are many limitations on the type of commodity, which can be traded on a futures market, and very few new contracts proved in the end to be successful (Gray, 1990). OTC derivatives are contracts not executed on regulated exchanges. The classes of underlying assets, which a derivative instrument may derive its value consist of physical commodities (i.e. agricultural products, metals, petroleum), financial instruments (i.e. debt, interest rate instruments, equity securities, foreign currencies), indices (i.e. based on interest rates or securities prices) or spreads between the value of such assets (Calvin, 1994).

As an example, of the contractual differences between futures and forward contracts, consider the financial function of providing a well-diversified portfolio of equities for individual investors. At one time, this function was best served by buying shares on a stock exchange. However, transactions and monitoring costs as well as problems of indivisibilities significantly limited the number of companies that could be held in almost any investor's portfolio. The innovation of pooling intermediaries such as unit trusts greatly reduced those costs, provided for almost perfect divisibility, and thereby allowed individual investors to achieve vastly better-diversified portfolios. Subsequently, futures contracts were created on various stock indices. These exchange-traded contracts further reduced costs, improved domestic diversification, and provided expanded opportunities for international diversification. Moreover, these contracts gave the investor greater flexibility for selecting leverage and controlling risk. Recent further innovations, that serve the diversification function, have intermediaries using equity-return forward contracts to create custom contracts with individual specification of the stock index, the investment time horizon, and even the currency mix for payments.

In the trading world there is a need to be able to plan ahead and frequently enter into commitments to buy or sell a commodity many months in advance. The problem inherent in international trading is that many products are subject to wide price fluctuations. Derivatives markets exist to provide some control of this price risk. They are also very useful mechanisms for price discovery and gauging market sentiment. Prices generated from exchange-based derivatives markets are fully transparent because they are updated second by second as trading occurs, enabling an open, equitable and competitive environment.

An example of hedging with futures (or forward) contracts can be illustrated as follows: A company which knows that is due to sell an asset at a particular time in the future can hedge by taking a short futures position (short hedge). If the price of the asset goes down, the company does not fare well on the sale of the asset but makes a gain on the short futures position. If the price of the asset goes up, the company gains from the sale of the asset but takes a loss on the futures position. Similarly, a company that knows that it is due to buy an asset in the future can hedge by taking a long futures position (long hedge).

Financial innovation has significantly expanded the investment alternatives for traders of all types. The value of derivatives can be understood by the role they can play for the traders. There are essentially four roles for derivatives (Fite and Pfleiderer, 1995): (i) to modify the risk characteristics of an investment portfolio, facilitating an efficient distribution of risks among risk bearers; (ii) to enhance the expected return of a portfolio, depending on how efficiently risks can be shared among investors; (iii) to reduce transactions cost associated with managing a portfolio; and (iv) to circumvent regulatory obstacles. Moreover, the above four roles can formulate the economic functions of derivative transactions given in Table 1.3.

Table 1.3. The Economic Functions of Derivatives Contracts

Hedging	Decreasing the risk exposure from the spot position.
Transparency of markets	Reducing transactions costs, reducing bid-ask spread, promoting liquidity.
Efficiency of markets	If traders with different risk preferences, expectations, and attitudes buy and sell the same instrument, information aggregation is stronger, and prices are more efficient in reflecting new information.
Diversification	Given that derivatives represent only a fraction of the cash investment, it is easier to diversify a given amount of capital across several assets.
Contract standardisation	Allowing quick execution of transactions.
Price discovery	Producing more information than the information that exists in the spot market.
Leverage	Requiring only a small fraction of the investment in the underlying securities, while participating from the volatility of the underlying.
Volume	Allowing traders to benefit from movements in the market as a whole.
Liquidity	Attracting new traders and new capital.
Arbitrage	Increasing liquidity and stabilising basis risk.
Financial engineering	New financial instruments can be created from the existing instruments.
Efficient risk allocation	Transferring the risk from risk-averse traders (hedgers) to risk-takers (speculators).
Complete the financial markets	A market is complete if the number of states equals the number of assets with no-redundant payoffs.
Access to asset classes	Which are not available as financial investments otherwise.

Source: Gibson and Zimmermann, 1994.

Derivatives, when used in the shipping industry, allow shipowners to minimise the negative impact of changes in interest, foreign exchange, bunker, or freight rates. Derivatives are also used to precisely tailor investment products for shipowners. The introduction of derivatives contracts in the shipping - transport industry is not a development of the last decade. Grain futures were traded a century ago in the US for protecting farmers from adverse grain price movements. Later, derivatives were used for other commodities, expanding to the financial markets using as the underlying instruments fixed-income bonds, foreign exchange, stock-indices, equities during the 1970s and 1980s. Market agents of the shipping industry were using currency swaps to provide foreign currencies for the payment of newbuildings, due to the fact that shipowners' income is in US dollars and the payments for the shipyards is mostly in Japanese Yen.

In London the commodity futures market grew mainly during the 1880s with the creation of the London Metal Exchange (LME) and during the 1980s with the creation of the International Petroleum Exchange (IPE). The IPE is a futures and options exchange that lists futures and options contracts for energy products (i.e. Brent Crude and Gas Oil). It is the second largest energy futures exchange in the world, listing futures contracts that represent the pricing benchmarks for two thirds of the world's crude oil and the majority of middle distillate traded in Europe. The contracts listed by the IPE are used by producers, refiners, traders, consumers and institutional investors across the world to either manage their inherent price risk, to speculate on outright price changes in oil and/or to balance their portfolio of risk exposure (Drewry Shipping Consultants, 1997).

The Baltic Exchange is the world's leading international shipping market. Two-thirds of all the world's open market bulk cargo movement is at some stage handled by Baltic members. In addition it is calculated that about half of the world's sale and purchase of vessels is dealt with through firms represented at the Baltic. Altogether, this international business generates around $2.5 billion a year in freight commissions, which are no less then 6 percent of the UK's total invisible earnings, and tens of billions of dollars in chartering costs go through London's banking system (Drewry Shipping Consultants, 1997).

Until April 2002, two distinct parts complemented the "*futures*" markets of freight derivatives instruments, in the dry-bulk shipping industry; the organised futures exchange of the BIFFEX contract and the OTC market of the FFA contracts. On May 1st 1985 LIFFE launched the first freight futures contract, the BIFFEX, through the Baltic Exchange for the dry-bulk industry, while in October 1991 BIFFEX Options were introduced. Also October of the same year, the OTC FFA contract was created by the shipbroking company Clarkson Securities Ltd. originally marketing it through their joint-venture company, Clarkson Wolff. Despite the early success of the BIFFEX contract, the trading volume during the last five years has been decreasing steadily, where in 2001 there were very few trades. Due to this fact, LIFFE terminated BIFFEX trading on April 2002.

Other recent developments were the creation of the Forward Freight Agreement Brokers Association (FFABA) in 1997 by members of the Baltic Exchange, and the launch of the first internet-based electronic trading platform, the FFAonline, which was introduced by Simpson Spence and Young (SSY) on April 27th 2000. Moreover, the newly formed internet venture LevelSeas launched its freight derivatives online platform during the third quarter of 2000, and the Baltic Exchange launched its own online FFA trading system for trading dry- and wet-bulk FFAs on October 2001. The Baltic FFA trading system responds to an increased demand from market users to improve price transparency and credit risk management. Finally, a web-based exchange for trading OTC freight derivatives, the International Maritime Exchange (IMAREX), started trading during November 2001. IMAREX uses the Norwegian Options and Futures clearing-house (NOS) for the clearing of standardised listed futures and other OTC derivatives. It is clear that there is considerable interest in the shipping industry for the introduction of risk management facilities and a considerable amount of time, effort and money is being channelled into the establishment of the provision of this service.

1.4. THE FORWARD FREIGHT AGREEMENT CONTRACT

1.4.1. Forward Contracts

By using hedging instruments, market agents can secure (stabilise) their future income and reduce their uncertainty and unforeseen volatility. The realisation that controlling the *price* has become the crucial factor in the global export market has turned even the most traditional and conservative players in the shipping industry to use derivatives instruments in order to react to price changes and to manage their price risk. Shipping freight derivatives have the potential to offset the risk of the dry-bulk and wet-bulk sectors of the shipping industry and its support industries. The shipowner or charterer can readily compare rates offered by the physical market (spot) as well as by the alternative forward freight market. In this way market agents can locate the *best* rates by hedging through this alternative market (Drewry Shipping Consultants, 1997).

A forward contract is not a recently created instrument. Outside the financial area, forward contracts relating to commodities have long been used to protect against price risk, *long* in this context equalling some 800 years, since historians suggest that forward contracts first appeared at medieval trade fairs in the 12th century. Furthermore, forward contracts are simple in concept: a financial forward contract is an agreement to buy or sell a given quantity of a particular asset, at a specified future date at a pre-agreed price. Forward contracts are interesting for three reasons: Firstly, new exotic financial instruments are created from a relatively small number of financial blocks. One of those building blocks is the forward contract. Secondly, much confusion still attaches to precisely what the forward price in a forward contract is indicating. Is it the market's best and most informed estimate of what the actual current spot price of a financial asset will be in the future, or is it something else. Thirdly, the principles used to price a forward contract are basic principles of widespread application that informs us much about the workings of the international capital markets in general.

The forward contract can be regarded as the most fundamental of the financial building blocks because other building blocks, the swap contract and the futures contract, for example, can be seen in essence as no more than variations of forward contracts. The forward contract is normally not traded on organised exchanges but by dealers trading, directly with one another or with their counterparties using the telephone, screens, faxes or the internet (Chance, 1998). Finally, the central insight provided by Scholes and Black in 1973 in creating the classic option pricing Black-Scholes model was that the payoff profile of an option can be created synthetically by combining a *dynamic* (continually adjusting) portfolio. This portfolio would be consisting first of forward contracts on the underlying property, which is the subject of the option and a portfolio of riskless, i.e. Treasury or Government, securities.

Forward contracts are not as liquid as futures contracts are. If they have to be reversed or unwound, then the value of a forward contract prior to maturity is taken to be the difference between the forward price at which the contract was agreed initially and the spot price that prevails in the market at the date on which the contract is unwound.

1.4.2. Forward Freight Agreements

Whenever commodities are traded, someone in the chain between the supplier (charterer) and his client, demanding the commodities, will be required to arrange for the transportation. The charterer will bear a freight risk in a volatile market. If the transportation of the cargo is to occur within a short period of time, the required freight rate can be forecasted and therefore, estimated accurately. For any longer period the ocean transportation of the cargo will be faced with financial exposure by the volatile freight rates. The longer the interval between the commodity sale and the shipment date the greater the exposure. A shipowner is faced with similar forward commitment in a volatile market.

FFA are principal-to-principal agreements, or contracts, between a seller and a buyer to settle a freight rate, for a specified quantity of cargo or type of vessel, for usually one, or a combination of, the major trade routes of the dry-bulk and wet-bulk industries. One counterparty takes the view that the price of an agreed freight route, at an agreed time, will be higher than the agreed level, and he buys FFA contracts (charterer). The other party takes the opposite position, and sells FFA contracts (shipowner). Settlement is made on the difference between the contracted price and the average price of the spot route selected in the index over the last seven working days.

FFA contracts are traded in an OTC derivatives market where two parties must agree to do business with each other. That means that each party accepts credit risk from the other party. The institutions that facilitate this market are major shipbrokers, investment banks, and other financial intermediates in the fund management industry. The primary advantage of an OTC market is that the terms and conditions are tailored to the specific needs of the two parties. It is a private market in which the general public does not know that the transaction was done. The OTC market is also an unregulated market. This gives investors more flexibility by letting them introduce their own contract specifications in order to cover their specific needs, saves money by not normally requiring initial, maintenance, and variation margins (common in the futures organised exchanges – see footnote 13), and allows the market to quickly respond to changing needs and circumstances by developing new variations of old contracts.

As with the BIFFEX contract, until November 1st 1999, the underlying asset of FFA contracts was trading routes of the Baltic Freight Index (BFI), where the two parties agreed a freight rate for a particular cargo size, i.e. 52,000 tons of HSS, on a specified trade route, i.e. US Gulf to Japan, for a designated settlement date in the future. The FFA contract (or paper trade as it has become known) was based on one or more of the 11 routes, which made up the BFI (Table 1.4). The FFA contract was settled by a cash payment (binding-fixture) from one party to the other. The cash sum was representing the difference between the agreed price of the FFA and the settlement price. The latter was determined by reference to average BFI returns of the last five days for the relevant trade route at the time of the agreed settlement date, and therefore reflected the level of the physical spot market at that time[7].

Table 1.4. Routes, Vessels and Cargoes of the Baltic Freight Index (Jan 1985)

ROUTES	VESSEL SIZE (dwt)	CARGO	ROUTE	WEIGHTING
1	55,000	Light cargo	US Gulf to North Europe	20%
2	52,000	HSS	US Gulf to South Japan	20%
3	52,000	HSS	US Pacific Coast to South Japan	15%
4	21,000	*HSS*	*US Gulf to Venezuela*	5%
5	35,000	Barley	Antwerp to Jeddah	5%
6	120,000	Coal	Hampton Roads to South Japan	5%
7	65,000 110,000	Coal Coal	Hampton Roads to ARA Hampton Roads to ARA	5%
8	130,000	Coal	Queensland to Rotterdam	5%
9	55,000	Coal	Vancouver to Rotterdam	5%
10	90,000 150,000	Iron Ore Iron Ore	Monrovia to Rotterdam Tubarao to Rotterdam	5%
11	25,000 25,000	Pig Iron Phosphate	Vitoria to China Casablanca to West Coast India	5%
12	20,000 14,000	Potash Phosphate	Hamburg to West Coast India Aqaba to West Coast India	2.5%
13	14,000	Phosphate	Aqaba to West Coast India	2.5%

Notes: **Source:** Drewry Shipping Consultants, 1997.

- HSS stands for Heavy Grain, Soya and Sorghum.
- ARA stands for Amsterdam, Rotterdam and Antwerp area.
- Skaw Passero is the strait between Denmark and Scandinavia.

[7] In terms of the BIFFEX market, there have been efforts in the past to develop a freight futures contract. In setting up a futures contract whose underlying commodity is freight rates, a fundamental problem had to be overcome. By their very definition, a futures market must trade a uniform, standardised contract, in standard quantities for delivery on specified dates in the future (complete liquidity of trading), which has good price availability (transparency of pricing), (Gray, 1987). In a service market, as the shipping market, where no standard unit exists, the only possible solution was to trade an index. It was not until January 1985 that a universal freight index the BFI was conceived in order to overcome this problem. The BIFFEX contract was ready to be launched after the introduction of the cash settlement procedure in 1985. The cash settlement corresponds for delivering the cash value of the underlying asset at expiration.

FFA contracts are a comparatively recent development and they stem from the creation of the BFI and the establishment of BIFFEX in 1985, and most recently from the introduction of the BPI in 1998 (Table 1.5), the BCI in 1999 (Table 1.6), the BHI (Baltic Handysize Index) in 1997 (Table 1.7), and the BHMI in 2000 (Table 1.8) (from October 2000 the BHMI officially replaced the BHI and consequently, FFA trades are conducted for BHMI only).

The Baltic Exchange currently publishes four dry-bulk freight indices, providing 24 individual dry-bulk routes in total; the BPI with 7 routes, the BCI with 11 routes, the BHMI with 6 routes and the Baltic Dry Index (BDI) as an overall composite index of all the above. These indices are baskets of spot freight rates designed to reflect the daily movement in rates across dry-bulk spot voyage and time-charter rates. No specific cargo or tonnage requirements are represented, but each route is given an individual *weighting* to reflect its importance in the world-wide freight market. Another development was the averaging of the settlement period. From their inception, the settlement for the FFA was based on the average of the last five trading days of a given month. On November 1st 1999 this became the last seven days, which addressed a concern by the market participants that the contracts were potentially subject to manipulation over a period as short as five days.

In the dry-bulk sector, FFA contracts are available at present to complement the capesize, panamax, and handymax routes. For those wishing to hedge long-term freight risk, a time-charter FFA is tradeable with settlement based on the difference between the contract price and the daily average of the time-charter routes from either the panamax (1A, 2A, 3A, 4)[8], capesize (8, 9, 10, 11) or handymax (1A, 1B, 3, 4A, 4B) indices. It is customary to divide the period into monthly settlements to establish cash-flow. These routes are regularly reviewed to ensure their relevance to the underlying physical market. The combination of time-charter routes can create the equivalent of a period time-charter trade (Clarkson Securities, 1999).

[8] As of April 3rd 2000 Route 9 renamed as Route 4.

Table 1.5. Baltic Panamax Index (BPI) – Route Definitions

ROUTES	WEIGHTINGS	SIZE OF VESSELS	DESTINATIONS
P1	10%	55,000	1-2 safe berths/anchorages Mississippi River not above Baton Rouge/Antwerp, Rotterdam, Amsterdam.
P1A	20%	70,000	Transatlantic (including ESCA) round of 45/60 days on the basis of delivery and redelivery Skaw-Gibraltar range.
P2	12.5%	54,000	1-2 safe berths/anchorages Mississippi River not above Baton Rouge/1 no combo port South Japan.
P2A	12,5%	70,000	Basis delivery Skaw-Gibraltar range, for a trip to the Far East, redelivery Taiwan-Japan range, duration 60/65 days.
P3	10%	54,000	1 port US North Pacific/1 no combo port South Japan.
P3A	20%	70,000	Transpacific round of 35/50 days either via Australia or Pacific (but not including short rounds such as Vostochy/ Japan), delivery and redelivery Japan/ South Korea range.
P4	15%	70,000	Delivery Japan/ South Korea range for a trip via US West Coast – British Columbia range, redelivery Skaw-Gibraltar range, duration 50/60 days.
PA1	0%	70,000	1 safe berth Richards Bay Coal Terminal/1 safe port, safe berth Belgium - Holland range.

Notes: **Source:** Baltic Exchange, 2002.

- The PA1 is the Baltic European Coal route and does not consist an underlying asset for FFA trading.

Table 1.6. Baltic Capesize Index (BCI) – Route Definitions

ROUTES	WEIGHTINGS	SIZE OF VESSELS	DESTINATIONS
C1	5%	120,000	1 port Hampton Roads excluding Baltimore /Rotterdam.
C2	10%	160,000	Tubarao/Rotterdam.
C3	10%	150,000	Turabao/Beilun and Baoshan.
C4	5%	150,000	Richards Bay/Rotterdam.
C5	15%	150,000	W. Australia/Beilun-Baoshan.
C6	10%	120,000	Newcastle/Rotterdam.
C7	5%	150,000	Bollivar/Rotterdam.
C8	10%	-	Delivery Gibraltar-Hamburg range, 5-15 days ahead of the index date, transatlantic round voyage duration 30-45 days, redelivery Gibraltar-Hamburg range.
C9	5%	-	Delivery ARA or passing Passero, 5-15 days ahead of the index date, redelivery China-Japan range, duration about 65 days.
C10	20%	-	Delivery China-Japan range, 5-15 days ahead of the index date, round voyage duration 30-40 days, redelivery China-Japan range.
C11	5%	-	Delivery China-Japan range, 5-15 days ahead of the index date, redelivery ARA or passing Passero, duration about 65 days.

Source: Baltic Exchange, 2002.

Table 1.7. Baltic Handy Index (BHI) – Route Definitions

ROUTES	WEIGHTINGS	SIZE OF VESSELS	DESTINATIONS
H1	25%	43,000	Delivery Antwerp/Skaw range trip, duration about 60/65 days, to Far East, redelivery Singapore/Japan range (including China).
H2	30%	43,000	Delivery South Korea/Japan range for 1 Australian or transpacific round voyage one laden leg redelivery South Korea/Japan range.
H3	15%	43,000	Delivery Singapore time-charter trip 65/70 days duration via Australia redelivery Gibraltar/Skaw range.
H4	30%	43,000	Delivery Skaw/Passero range 1/1 laden legs via US Atlantic, US Gulf or South Atlantic, 50/60 days duration, redelivery Skaw/Passero.
TR2	-	43,000	1SP Brazil/1SP Lisbon-Hamburg range (excluding UK/France).

Source: Baltic Exchange, 2002.

Table 1.8. Baltic Handymax Index (BHMI) – Route Definitions

ROUTES	WEIGHTINGS	SIZE OF VESSELS	DESTINATIONS
M1A	12.5%	45,500	Delivery Antwerp/Skaw range for a trip about 60/65 days redelivery Singapore/Japan range including China.
M1B	12.5%	45,500	Delivery passing Canakkale for a trip about 50/55 days redelivery Singapore/Japan range including China.
M2	25%	45,500	Delivery South Korea/Japan for 1 Australian or trans Pacific round voyage, one laden leg, redelivery South Korea/Japan range.
M3	25%	45,500	Delivery South Korea/Japan range for a trip about 60/65 days redelivery Gibraltar/Skaw range.
M4A	12.5%	45,500	Delivery Antwerp/Skaw range for a trip about 30/35 days redelivery US Gulf.
M4B	12.5%	45,500	Delivery US Gulf for a trip about 30/35 days redelivery Skaw/Passero.

Source: Baltic Exchange, 2002.

Freight rates on the individual underlying trading routes are reported on a daily basis (at 11:00 a.m. London time) by a panel of eleven independent London shipbrokers to the Baltic Exchange and the latter reports them in the market at 13:00 p.m. London time. The panel members are: Clarkson (London), Galbraiths (London), E.A. Gibson (London), Howard Houlder (London), Howe Robinson (London), Simpson Spence & Young (London), Arrow Chartering (London), J.F. Dillon (Stamford), Yamamizu (Tokyo), Banchero Costa (Genoa), Fearnleys (Oslo). The panel members are companies who (Gray, 1990):

> "*...are deemed by the Baltic Exchange to be of sufficient size, reputation and integrity to be good independent arbiters of the market*".

Each member of the panel submits, to the Baltic Exchange, its daily view of the rate on each constituent route of the Baltic indices. Each freight rate assessment is derived from actual fixtures, or in the absence of an actual fixture from the panelist's expert view of what the rate would be on that day if a fixture had been agreed. Then the Baltic Exchange, for each trade route, after excluding the highest and lowest assessments of the day, takes an arithmetic average of the remaining. The average rate of each route is then multiplied by the *Weighting Factor*[9] (WF) to return the contribution of each route to the index. Finally, by adding all the route contributions, an overall average index is created, for example the daily BPI.

There is no physical delivery under the contract and all positions are cash-settled. The market agents that use the FFA contracts are from all sectors of the shipping industry. They are shipowners, charterers, operators (fleet managers/freight traders), grain, coal and energy traders, bankers, private and professional investors. FFA contracts can be used for:

- Hedging.
- Speculation: If a market agent has an expectation of where the market is going and if the quoted price of a FFA contract is cheap compared to the expectation, he can buy the FFA contract anticipating that as the future unwinds he could make money if the expectation is correct.
- Spread play: Based on historical data, if the FFA price difference between two shipping routes is large, a market agent can buy the cheap and sell the expensive in order to take advantage of an anticipated return to normal differentials. This can be done between freights in different regions, different vessel sizes, or types of trade.
- Portfolio switching: A market agent trading a particular route where he believes that the short-term volatility is going to be low, may sell FFA contracts on the existing trade route and buy a matching volume on a different more volatile route.
- Portfolio management of existing time-charters (a market agent using FFA contracts can close any unwanted positions).
- Early access to newbuildings: When a shipowner commits to a newbuilding, there is a lead-time before the ship delivers. The shipowner can bridge this gap by using FFA contracts to cover the period before his ship delivers.

[9] The WF is a constant, unique for each route, and reflects the importance of each route to the index. For example, the WF for each BPI route is: 11.185 (route 1), 0.027 (route 1A), 7.067 (route 2), 0.015 (route 2A), 9.307 (route 3), 0.031 (route 3A), 0.023 (route 4).

- An alternative to time chartering: Buying (or selling) a FFA contract is the same as time chartering in (or out) without the operation risk of running a vessel.
- An alternative to Contracts of Affreightment (COA)[10].

Table 1.9 shows the growth in freight covered by FFA by the shipbroking company Clarkson Securities Ltd.

Table 1.9. Indications of Activity Growth in the FFA Market

Year	Number of Deals per Month	Number of Counterparties	Freight Covered by Trading FFAs ($m.)
1992	Average 2	10	0.5
1993	Average 4	18	48
1994	Average 10	25	70
1995	Average 20	35	203
1996	Average 27	52	331
1997	Average 55	86	852
1998	Average 90	118	1,114

Notes: **Source:** Clarkson Securities, 1999.

- All Indications are from Clarkson Securities Ltd. They posses a market share of around 30%.

In 1999 the total FFA volume was about 1,200 contracts at something similar to 1998, with less emphasis on the Gulf - Japan market and users focusing on other routes such as time–charter average, Pacific and coal routes. The result was increased liquidity on these trades, particularly after 1999's Panama Canal draught restrictions, which minimised the Gulf - Japan trades[11]. According to Clarkson Securities Ltd., in 2001 the total FFA volume was about 2,500 contracts:

> *"today's traders are relying more on sophisticated patterns of hedging and trading...a premium on accurate forecasting and research...should prompt further change, growth and adoption of the derivative products by the shipping industry. There are more users, more knowledge, more products to use in risk hedging and more sophistication among the users"*

[10] The COA governs a series of voyage charters in order to transport a specific quantity of cargo between areas within a certain timeframe and at specified intervals. The two major differences between this form of charter and a consecutive voyage charters are that under a COA the actual ship is not precisely designated and the voyages are not undertaken on a round-trip basis.

[11] Taken from Lloyd's List (November 2000).

Future prices in shipping are based on expectations, which are themselves highly fickle and heavily influenced by where the spot rates are. Unlike physical commodities, which are physically stored, FFA contracts, which are based on a service, have no carrying cost (no cost-of-carry arbitrage relationship). The FFA prices must reflect expectations of where the rates will be at the time of settlement.

Figures 1.1 to 1.4 present the near-month FFA prices against the spot prices in panamax routes 1 (voyage), 1A (time-charter), 2 (voyage) and 2A (time-charter), respectively. In routes 1 and 1A the estimation period is 1997:01 to 2000:07. In routes 2 and 2A the estimation period is 1997:01 to 2001:08. In every route the FFA and spot prices move together and the FFA capture closely the fluctuations of the spot prices. The correlation coefficients, of FFA prices in routes 1, 1A, 2, and 2A against the corresponding spot rates are 0.965, 0.972, 0.986, and 0.985, respectively. The correlation coefficients indicate a close relationship between FFA and spot prices, with FFA prices in routes 2 and 2A to have a stronger relationship with the corresponding spot. From the figures we notice that FFA and spot prices are not trending over time.

Figure 1.1. FFA and Spot Prices in Route 1; Daily Data (16/01/97 – 31/07/00)

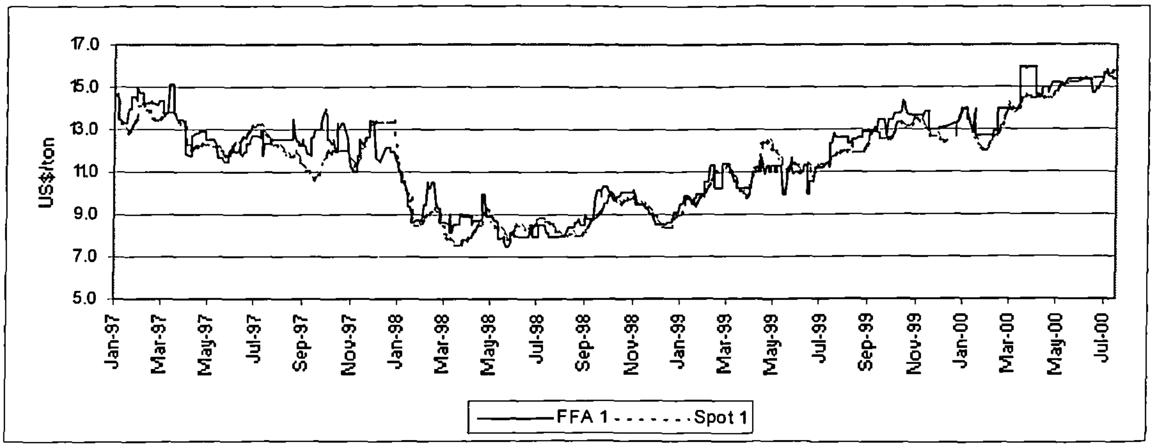


Figure 1.2. FFA and Spot Prices in Route 1A; Daily Data (16/01/97 – 31/07/00)

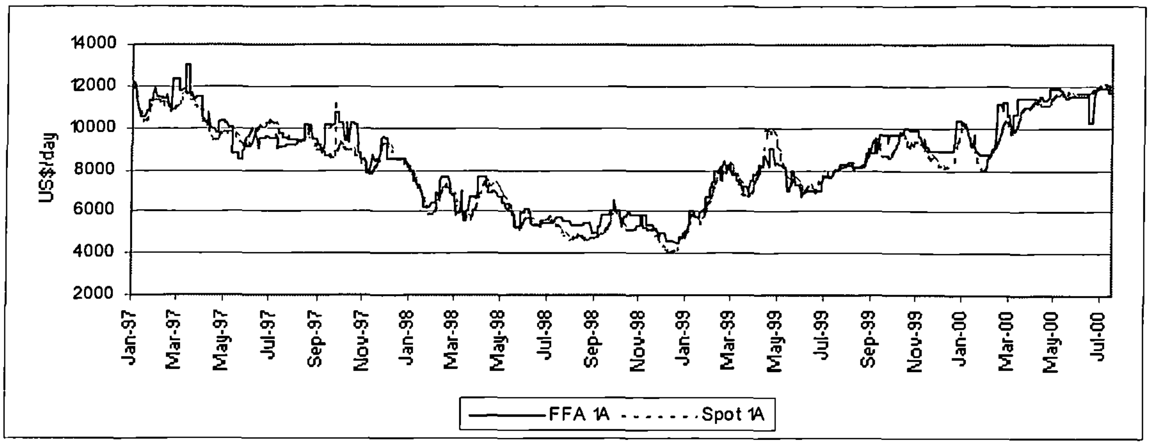


Figure 1.3. FFA and Spot Prices in Route 2; Daily Data (16/01/97 – 10/08/01)

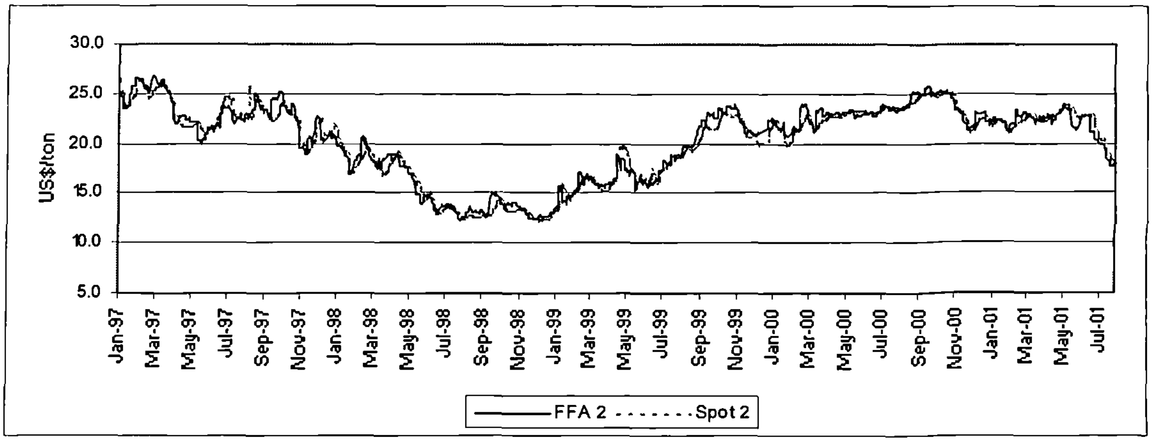
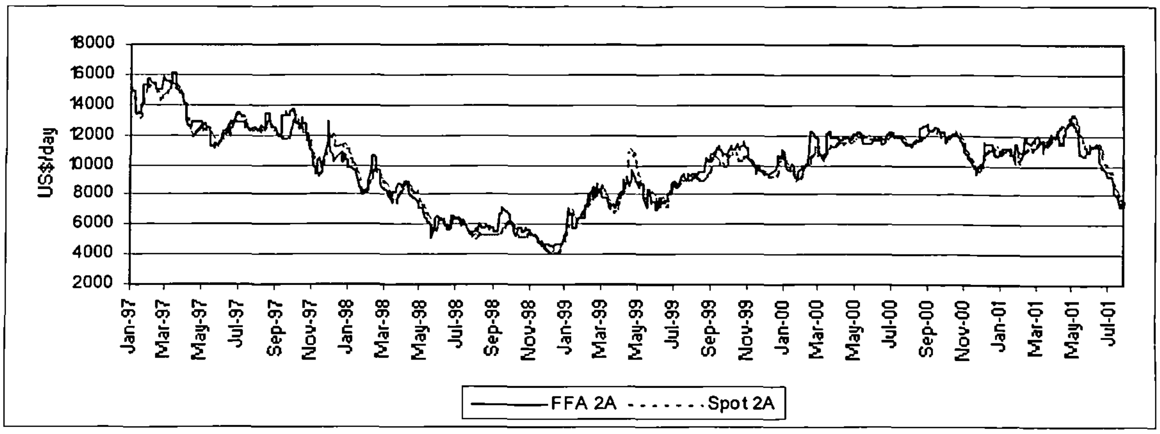


Figure 1.4. FFA and Spot Prices in Route 2A; Daily Data (16/01/97 – 10/08/01)



Figures 1.5 to 1.8 present the second near-month FFA prices against the spot prices in routes 1, 1A, 2, and 2A, respectively. The estimation periods are the same with the previous graphs for the near-month prices. The correlation coefficients of FFA prices in routes 1, 1A, 2, and 2A against the corresponding spot rates are 0.731, 0.787, 0.838, and 0.849, respectively.

Figure 1.5. FFA and Spot Prices in Route 1 (Second near-month); Daily Data

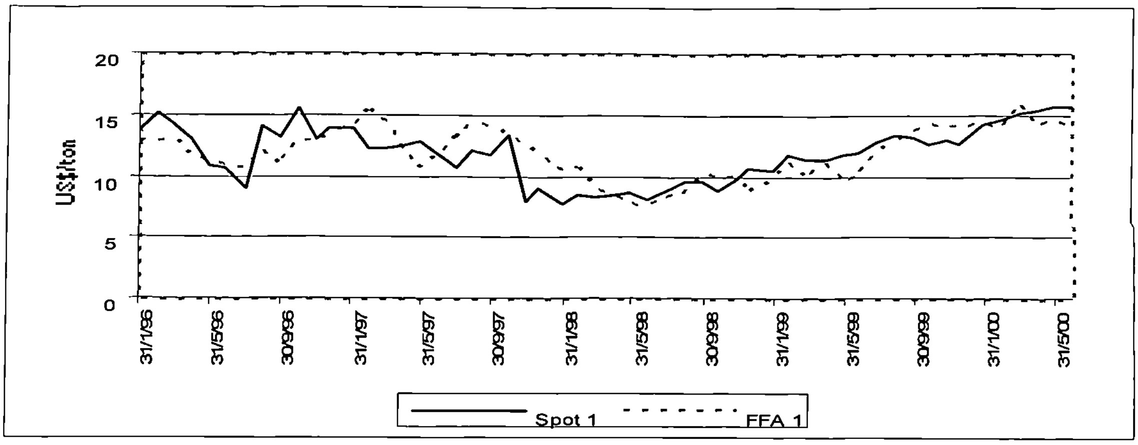


Figure 1.6. FFA and Spot Prices in Route 1A (Second near-month); Daily Data

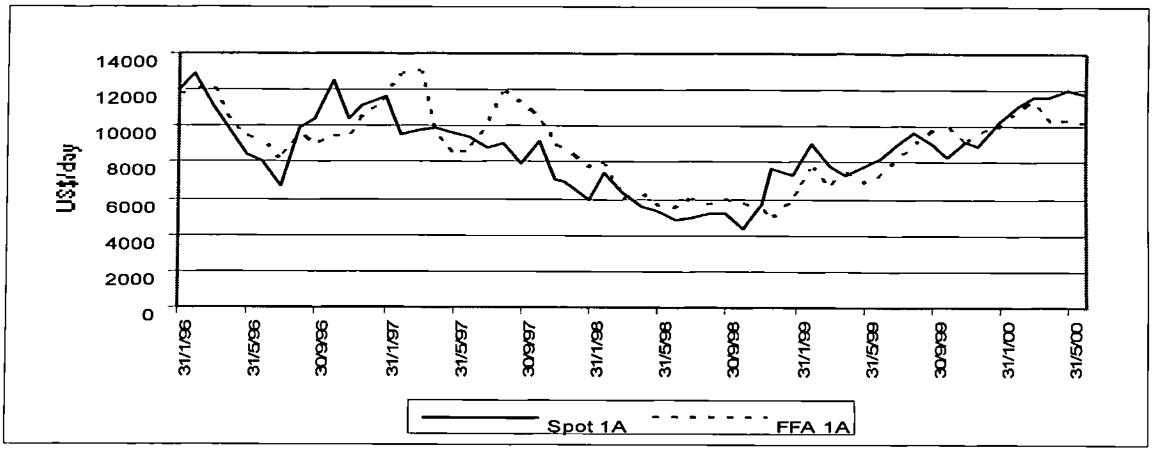


Figure 1.7. FFA and Spot Prices in Route 2 (Second near-month); Daily Data

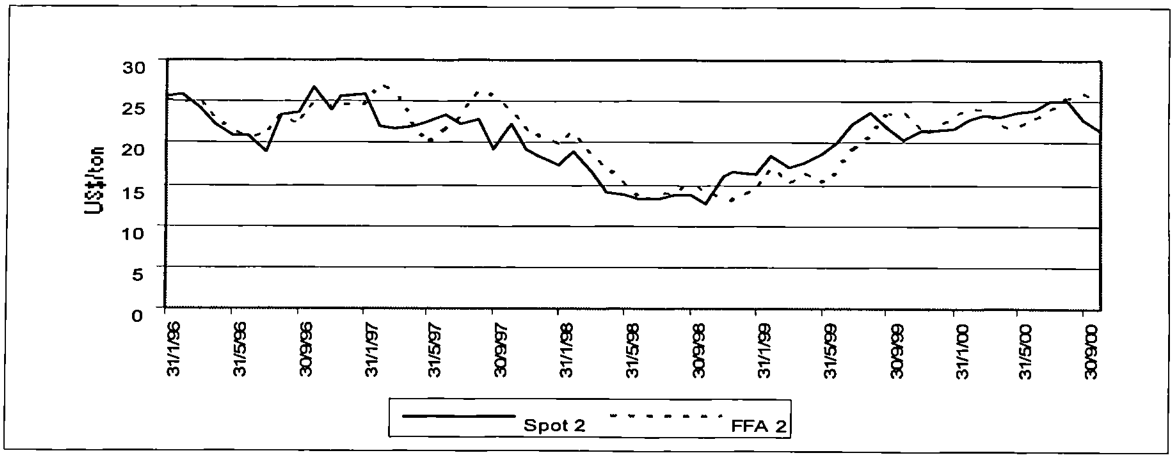
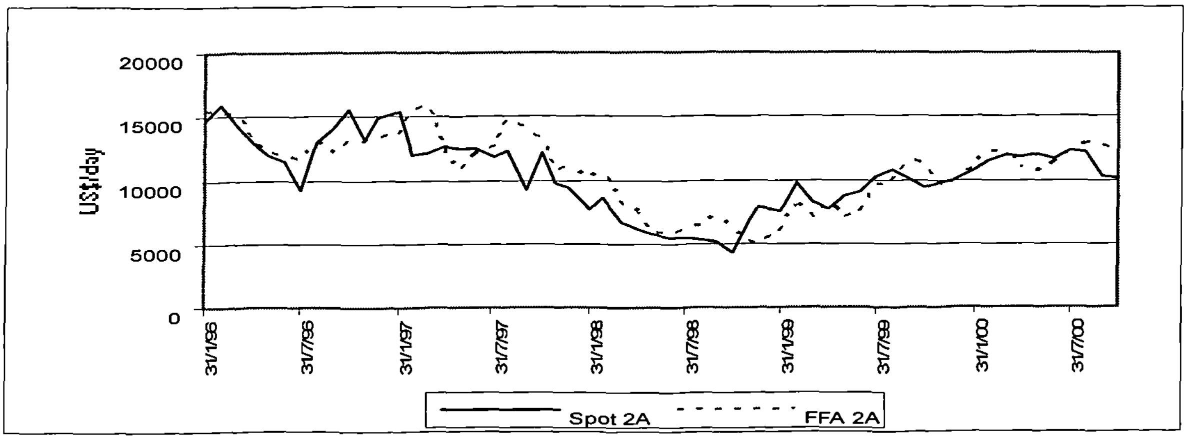


Figure 1.8. FFA and Spot Prices in Route 2A (Second near-month); Daily Data



Figures 1.9 to 1.12 present the third near-month FFA prices against the spot prices in routes 1, 1A, 2, and 2A, respectively. The estimation periods are the same with the previous graphs for the near-month prices. The correlation coefficients of FFA prices in routes 1, 1A, 2, and 2A against the corresponding spot rates are 0.583, 0.675, 0.735, and 0.775, respectively.

Figure 1.9. FFA and Spot Prices in Route 1 (Third near-month); Daily Data

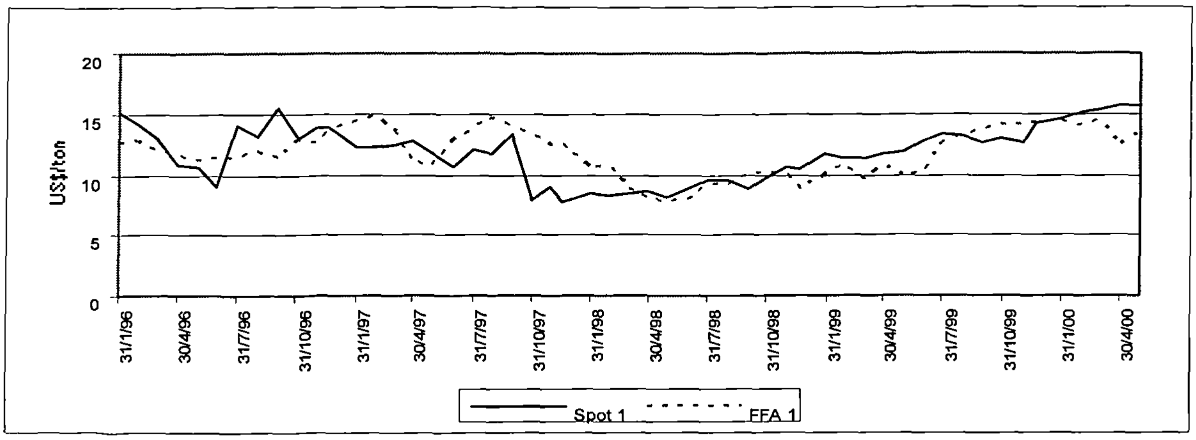


Figure 1.10. FFA and Spot Prices in Route 1A (Third near-month); Daily Data

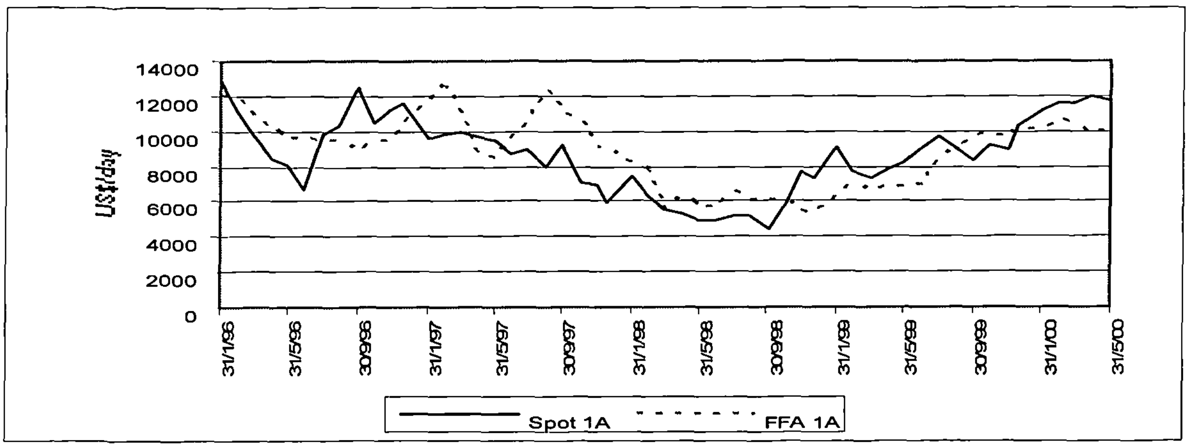


Figure 1.11. FFA and Spot Prices in Route 2 (Third near-month); Daily Data

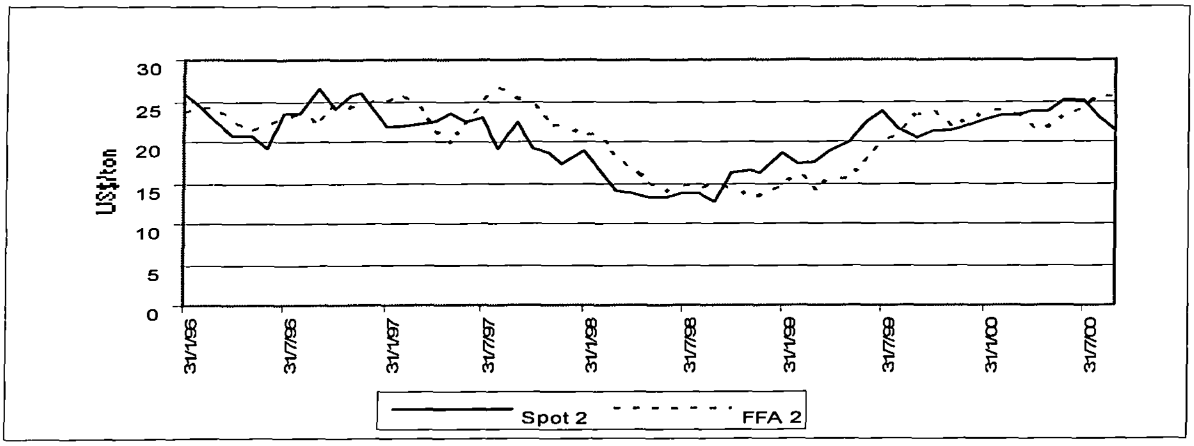
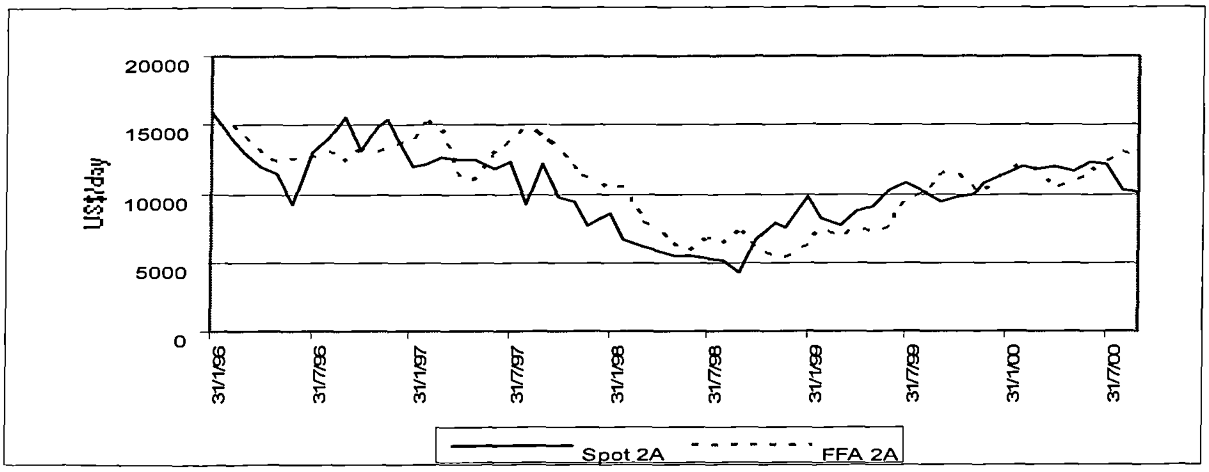


Figure 1.12. FFA and Spot Prices in Route 2A (Third near-month); Daily Data



1.4.3. The Use of FFA Contracts in Shipping Practice

Some examples of FFA contracts can illustrate the theoretical concepts already discussed:

Example A – BPI Route 2 US GULF - JAPAN

<u>Agreement</u>

- 18 May 2002
- A charterer wants to lock in Gulf/Japan (Route 2) at a forward rate with dates 26/30 July at $15.00
- A shipowner is willing to sell forward freight for similar dates at $15.00
- Shipowner: Seller of FFA
- Charterer: Buyer of FFA
- Fixed price: $15.00
- Dates: 26/30 July 2002

- Commission: Both parties to pay the broker as agreed, basis fixed price x quantity, i.e.$15.00 x 54,000
- Route: USG/Japan as per Route 2 of BPI
- Cargo size: 54,000 tons HSS

Conclusion

- 30 July 2002
- Settlement price: $18.1964 per ton
- The settlement price is higher than the fixed price, so the seller pays $3.1964 per ton to buyer, i.e. $54,000 x $3.1964 = $172,605
- $172,605 is to be paid by the shipowner to the charterer.

Example B – BCI Route 4 RICHARDS BAY - ROTTERDAM

Agreement

- 8 July 2002
- FFA Buyer. European electricity producer with large import commitments
- FFA Seller. Owner wishing to hedge against declining rates in Cape sector
- Route 4 Richards Bay/Rotterdam 150,000 mt coal. Fixed price: $5.00
- Dates: 25/31 August 2002
- Commission: Both parties to pay the broker as agreed, basis fixed price x quantity, i.e. $5.00 x 150,00 tons

Conclusion

- 31 August 2002
- Settlement price: $5.5398
- The settlement price is higher than the fixed price, so the seller pays $0.5398 per ton to buyer, i.e. $150,000 x $0.5398 = $80,970
- $80,970 is to be paid by the shipowner to the charterer.

1.4.4. Major Participants of the FFA Market

Anyone with interest in hedging, speculation or arbitrage can use FFA contracts - shipowners, charterers, freight traders, coal traders, grain traders, electricity producers, private investment funds, energy groups (oil traders), financial institutions - the prerequisite being that they are acceptable to the counterparty. Having agreed terms, the identity of the buyer and seller is revealed, and thereafter there is a short period in which either party can withdraw, i.e. if the one counterparty is not satisfied with the other's creditworthiness or if one counterparty is not fulfilling its obligations. The major FFA brokers are mostly situated in London, where the most recent trend in this market is the combination of a well-established FFA broker together with a financial derivatives broker. For example, Howe Robinson Co. Ltd. has teamed up with GNI Ltd., Fearnleys A/S with Cargill Investor Services and Clarkson with Rudolf Wolff & Co. Ltd[12].

The FFABA was formed in 1997 by members of the Baltic Exchange and Freight Indices and Futures Committee (FIFC): Clarkson Securities Ltd., Fearnleys A/S, Howe Robinson & Co Ltd., GNI Ltd., Ifchor S.A., Mallory Jones Lynch Flynn & Associates Inc, Simpson Spence & Young Ltd., Pasternak, Baum & Company Inc., Yamamizu Shipping Co. Ltd. The FFABA acts within the framework of the Baltic Exchange and seeks to:

- Promote the trading of FFA contracts.
- Promote high standards of conduct amongst market participants.
- Co-operate with the Baltic Exchange to ensure the production of high quality indices.
- Provide a forum for brokers and principals to resolve problems as they arise.
- Develop and promote the use of standard contracts.
- Develop the use of other OTC and Exchange traded derivatives products for freight risk management.
- Not only to provide tools for the freight derivatives market but also to provide credible barometers of the freight market for *physical* users.

A new type of market agent that is slowly appearing in the FFA market is the shipping-bank player. The idea that banks should want to incorporate hedges into deals has started to become more acceptable. If a shipping company has a stream of cash-flows that moves up and down with the market and it is financing a ship, the cash-flows to repay the loan will also move with the market. If the company does not hedge, it may end up with a default situation in a weaker market. The question needs to be asked whether banks should undertake deals that could potentially go wrong in the event of a weak market. Banks should be aware of the cash-flows of any owner before a loan is made. Increase of FFA trading by banks could be in the following

[12] In all the cases the first counterparty represents the FFA broker, while the other party the derivatives broker.

scenario: banks try to hedge against a time-charter. Time-charters are becoming rarer because grain houses, such as Cargill, are using FFA to manage price risk. If time-charters are not so readily available, maybe soon banks will be keen to finance ships with a hedge in place.

1.4.5. Advantages and Disadvantages of FFA Contracts

The main advantages of the FFA contracts are the following. FFA contracts can be tailored to meet specific requirements (route, size, period, type of charters, contract quantity and rate), whereas futures and options markets are designed to be liquid markets trading a standard contract. The counterparties are free to introduce their own variations (i.e. part cargoes) into the contract providing they are mutually agreed. However, greater standardisation generally leads to increased liquidity and this reinforces the active trading on a handful of routes on generally accepted terms. FFA contracts can also be traded on non-standard routes if a willing counterparty can be found. The parties would need to accept and agree a fixed differential to the most closely fitting index route, so US Gulf – China, grain, might be pro-rated to BPI route 2.

With FFA contracts (rather than time-chartering out a vessel) a shipowner retains operational control of his vessel and at the same time is taking benefit of a spot market change. Whereas, a charterer is free from any operational risks as a result from a time-chartering. FFA contracts give investors considerably more flexibility in covering their freight rate risk, with lower commissions payable to brokers; 1 percent of the principal sum (0.5 percent from the buyer and 0.5 percent from the seller) with no address commissions. The low commission structure implies that it is cheaper to trade in and out of a FFA position prior to the settlement month than trading in and out of a physical position, where the commissions are higher. In addition, the simple nature of a FFA contract makes it easier to trade in and out of a position, which in turn encourages liquidity (Drewry Shipping Consultants, 1997).

FFA contracts allow the market to respond quickly to changing needs and circumstances by developing new variations of old contracts. There is no physical delivery involved with FFA, they simply become a cash settlement upon conclusion of the agreed terms. There are not any cash deposits (initial guarantee) and margin calls like futures contracts although they can be negotiated into the agreement if the counterparties agree that this additional financial security is appropriate. Finally, the advantage of being a private market in which the general public does not know that the transaction is done, prevents other traders from interpreting the size of various trades as perhaps false signals of information.

The main disadvantage is that they are OTC instruments (principal-to-principal) and therefore are not guaranteed by a clearing-house or open exchange market. They are not mark-to-market (as futures contracts) and it is not easy to close (unwind) the open position by reversing the initial position (opposite) for the same settlement month. The opposite trade will most likely be carried out with a different counterparty and therefore the settlement obligations remain open with the two separate counterparties, so although there is no longer any risk regarding market movements, there are still counterparty risks (Collins, 1998). However, the difficulty of unwinding the open positions has been minimised with the introduction of online FFA trading systems.

Due to the fact that they are unregulated and there is no open market for OTC instruments, there is lack of liquidity (unavailability of information, absence of a standardised contract, not every type of voyage or vessel can be hedged) and lack of transparency (as fixtures and deals are undisclosed), and as a consequence, several types of risk can be created (Bank of International Settlements, 1998):

- Counterparty credit risk, which is the risk that a counterparty will fail to perform an obligation owed to the other party.
- Liquidity risk, which is the risk that a lack of counterparties will leave a firm unable to liquidate or offset a position.
- Settlement risk, which is the risk that a counterparty will not receive funds or instruments from its other party at the expected time.
- Legal risk, which is the risk that a counterparty will suffer loss as a result of contracts being unenforceable or inadequately documented.

The above types of risk must be covered by the use of collateral, close-out netting, even with the use of other instruments (credit derivatives), or controlled by a clearing-mechanism of an organised derivatives exchange (i.e. IMAREX). A number of recent high profile aberrations in performance within the dry-bulk FFA sector (25 companies defaulted from FFA inception) has led to the need of a system of financial regulation for OTC contracts. There are already moves to form a regulated body (Consultative Group) of brokers, committees and associations in order to create a structure of financial discipline, i.e. the counterparties place a deposit and adopt a marginal system similar to the futures markets.

Shipbrokers, charterers, and shipowners trading in the *paper* market have focused their attention comparing the roles and uses of the OTC traded FFA contracts. The main attraction, and possibly the potential problem for the FFA contracts, is that the parties involved only exchange cash at the end of the contract period, which can be several months ahead. On the BIFFEX market an account was set up and, once a position was held, money flew in and out of the account in control by the London Clearing-House (LCH), depending on the movement of the daily futures market[13].

1.4.6. Tanker FFA Contracts

The discussion so far about FFA contracts was primarily concentrated in hedging the market freight risk of the dry-bulk sector of the shipping industry. However, with the high amounts involved and the underlying volatility of the tanker industry, the use of tanker FFA contracts can be very promising. At present there is a slow development of a FFA market for wet-bulk trades. Tanker FFA contracts are OTC principal-to-principal cash-settled agreements, which are not subject to the financial security of a clearing-house. The tanker FFA contract is simply an agreement between two parties, whose identities are disclosed once the deal is agreed, to fix a freight rate on a predetermined tanker route, over a mutually agreed time period, at a mutually agreed price.

Settlement is made against the 10 Baltic Dirty Tanker routes of the Baltic International Tanker Routes Index (BITR) presented in Table 1.10, panel A or the 4 Baltic Clean Tanker routes of the BITR presented in the same table, panel B. Initially, the settlement was only by an

[13] Dealings on futures exchanges were conducted via a clearing-house mechanism. When a trade was transacted for the BIFFEX contract, following the confirmation of the transaction, the counterparty to every trade, whether bought or sold, was technically the LCH. This immediately released all buyers and sellers from any obligation to each other and the obligation was transferred to the LCH. The trader was required to place immediately with the LCH an initial deposit of money (Initial Margin), which was on a per contract basis and was set at a size to cover the clearing-house against any loses which the trader's new position might incurred during the day. Moreover, the exchange ensured that all participants were able to meet the claims arising from this continuous settlement process. Users of the market were required to post an amount of money (Variation Margin) in order to cover the extent to which a trading position showed a potential loss. Finally, BIFFEX contracts were mark-to-market at the end of each trading day and the resulting profit or loss was settled on that day.

assessment made in London by the London Tanker Brokers' Panel (LTBP) and in New York by the Association of Shipbrokers and Agents Tanker Brokers' Panel (ASBA) calculating worldscale rates (US$/ton equivalents for each route, which are derived assuming that a nominal tanker functions on round voyages between designated ports) for voyage assessments and daily-hire for time-charters. On February 1998 the LTBP launched its own tanker freight rate assessment system as a rival to the one launched by the Baltic Exchange. The International Tanker Freight Index (ITFI), whose main shareholders are the six members of the LTBP, plus the four brokers in the US, is only available on subscription, unlike the BITR assessment, which is free. The ITFI covers six routes, covering very large crude carriers, suezmax, aframax and panamax tankers (Table 1.11). Both systems were set up to encourage FFA trading in the tanker market, which until now, have been largely confined to the dry-bulk sector. Most market agents agree that the tanker market should be open to freight derivatives trading, and a meaningful index is the only way to do this. Although, the idea for the index was set by members of the FFABA, the Baltic Exchange had been criticised by some as not being the right vehicle for promulgating a tanker index. Its critics have said that the Baltic Exchange was perceived predominantly as a dry-cargo market, and that it is inappropriate to produce a tanker index[14].

Table 1.10. Baltic International Tanker Routes Index (BITR) – Route Definitions

ROUTES	SIZE OF VESSELS	DESTINATIONS
Panel A: Baltic Dirty Tanker Routes		
TD1	280,000	Middle East to Gulf. Ras Tanura to Loop.
TD2	260,000	Middle East Gulf to Singapore. Ras Tanura to Singapore.
TD3	250,000	Middle East Gulf to Japan. Ras Tanura to Chiba.
TD4	260,000	West Africa to US Gulf. Off Shore Bonny to Loop.
TD5	130,000	West Africa to USAC. Off Shore Bonny to Philadelphia.
TD6	130,000	Cross Mediterranean Sidi Kerrir to Lavera.
TD7	80,000	North Sea to Continent. Sullom Voe to Wilhelmshaven.
TD8	80,000	Kuwait to Singapore. Mena al Ahmadi to Singapore.
TD9	70,000	Caribbean to US Gulf. Puerto La Cruz to Corpus Christi.
TD10	75,000	Caribbean to USAC. Aruba to New York.
Panel B: Baltic Clean Tanker Routes		
TC1	50,000	Middle East Gulf to Japan. Ras Tanura to Yokohama.
TC2	50,000	Continent to USAC. Rotterdam to New York.
TC3	50,000	Caribbean to USAC. Aruba to New York.
TC4	50,000	Singapore to Chiba.

Source: Baltic Exchange, 2002.

[14] Taken from Lloyd's List (September 2000).

Table 1.11. International Tanker Freight Index (ITFI) – Route Definitions

ROUTES	SIZE OF VESSELS	DESTINATIONS
1	250,000	Persian Gulf to Japan, 20 to 30 days notice periods.
2	280,000	Persian Gulf to US Gulf, 20 to 30 days.
3	80,000	Persian Gulf to Singapore, 10 to 15 days.
4	130,000	West Africa to US Atlantic Coast, 20 to 30 days.
5	50,000	Caribbean to US Atlantic Coast, 7 to 10 days.
6	70,000	Caribbean to US Gulf, 7 to 10 days.

Source: London Tanker Brokers' Panel, 2001.

The panelists on the ITFI are: Clarkson Securities, Galbraith's, E.A. Gibson, Howard Houlder (Tankers), Jacobs and Partners, and Seascope Shipping (the six members of the LTBP), and McQuilling Brokerage Partners, Odin Marine, Poten and Partners, and Charles R. Weber Company. The panel brokers on the Baltic Exchange are: Simpson Spence & Young Ltd., Braemar, ACM Capital, Lorentzen & Stemoco, Mallory Jones Lynch Flynn & Associates, and Fearnleys. Freight derivatives brokers in London have been anxious for some time to form a credible, international basis for assessing freight rates that could be used as settlements for tanker FFA contracts.

The introduction of hedging with freight derivatives in the tanker industry is a major debate between market agents. Today, many brokers are dealing with freight derivatives on a daily basis for the dry-bulk industry. The wet-bulk industry has been ignored by that trend of the business. The only exception was an attempt to build a similar instrument, like BIFFEX, for the tanker industry, the Tanker International Freight Futures Exchange (TIFFEX) in 1986, which failed due to lack of interest shown from the industry. Explanations for this converge to the opinion that there is normally only limited interest from shipowners. Charterers, in the tanker market, see freight risk as a small part of very little interest in their total cost (about 2%) (Drewry Shipping Consultants, 1997). The only solution left was the tanker FFA contract, but it was only from mid-1997 that it appeared on the tanker industry. A forward freight market could prove beneficiary to the tanker industry because it would provide *secured* freight for long-term refinery supply and greater stability within the shipping markets.

1.4.7. OTC Derivatives and Risk

In view of the rapid growth of OTC derivatives business, numerous international groups and regulatory agencies have studied the risks arising from OTC derivatives trading (i.e. Basle Committee on Bank Supervision, Bank of International Settlements, Commodity Futures Trading Commission, Securities and Investments Board, United States General Accounting Office, amongst others). These risks include credit risk, liquidity risk, settlement risk, operations risk and legal risk (see section 1.4.5).

Such risks are not unique to OTC derivatives transactions, but are of special concern due to the volume, scope, and variety of OTC transactions, the degree of interrelatedness of participants, the opaqueness and uncertain liquidity of OTC markets, and the complexity and potential leverage of such instruments. The financial risks of such instruments must be carefully assessed, as a weakness of one market participant can have ramifications elsewhere in the system (i.e. as in the case of Enron). It is now generally acknowledged, by financial services regulators, financial services providers and corporate users alike, that a key component of a robust framework for the management of the risks attaching to OTC derivatives business is a strong structure of risk management controls within companies active in this business.

In order for market agents in the shipping industry to safeguard their positions, they may well terminate or restrict activities with market participants as to which there may be doubts as to the adequacy of their management controls. Market agents must adopt a qualitative approach and check their counterparty's business profile, geographical location, management profile, trading track record, business history, and financial flexibility. Moreover, each company should ensure that their counterparty:

- has the power to enter into a proposed transaction,
- is represented by an officer with actual or ostensible authority,
- is creditworthy, and
- has access to appropriate payment systems.

Derivatives brokers have incentives to monitor customers' use of derivatives to ensure that they use derivatives to hedge and not to speculate (Hentschel and Smith, 1997). Brokers often have access to information about counterparty characteristics that mitigates the information asymmetry concerning the motive behind the OTC derivatives. Specifically, the broker may know the *direction* of the counterparty's operating exposure to the underlying risk factor, based on which it can infer whether the OTC derivative contract is meant to be a hedge or not. Moreover, it is possible to implement the simple accept/reject decision rule based on observed counterparty credit rating (certain investment grade threshold level) that guarantees the exclusion of speculative contracts.

More recently, however, sub-investment grade counterparties have been allowed to enter into OTC derivatives contracts, largely due to two developments: (i) much of the business has moved away from small broking agencies to large ones, which have long-term relationships with OTC derivatives counterparties. Such a relationship provides the broker with better information about the nature of the underlying operating exposure and the true company quality; and (ii) the market has increasingly come to rely on non-price credit enhancement mechanisms to limit exposures, especially with counterparties of doubtful quality. The most commonly used credit enhancements are: master agreements, netting arrangements, collateralisation of transactions, credit triggers, marking-to-market, letters of credit and guarantees[15]. These techniques assures that all realised OTC derivatives transactions are undertaken for hedging purposes and default-risk ceases to be important.

While OTC derivatives serve important risk management and other economic functions, these products can present significant dangers if misused or misunderstood by market agents. A number of large, well-published financial losses over the last few years have focused the attention of the financial services industry, its regulators, and derivatives end-users, on potential problems and abuses in the OTC markets. As a consequence, risk management control mechanisms for OTC derivatives should be integrated within a company's overall risk management framework.

However, risk management control mechanisms are not a substitute for adequate capital. The control structure that should be established, and the practices that should apply, in the case of any particular institution, must be appropriate to that institution relative to the scale, the risk

[15] See Wakeman (1996) for a detailed survey of credit enhancement techniques.

profile and the complexity of its OTC derivatives activities (Basle Committee on Banking Supervision, 1994).

In the Baltic Exchange freight derivatives forum, on April 11th 2002, the main issue was the credit risk and the methods and procedures to diminish it. Several opinions were formed with the most attractive, for the market, to be a marginal system, a clearing system, an internet based clearing-house, or a credit-rating system specifically for the market agents of the shipping industry. Another strand of opinions were to revise the current FFA contract in order to include clear definitions of a default event, default procedures, and rights and remedies to net and offset against physical freight that may exist between counterparties or their affiliates. The issue of credit-risk has not been resolved at the time of writing and consists one of the major disadvantages of the OTC FFA market. From one hand, all the above procedures will force the small players out of the market due to the increased transactions costs, but from the other hand, the creditworthiness of the market will attract the big professional players.

1.5. STRUCTURE OF THE THESIS AND ITS CONTRIBUTION TO THE LITERATURE

In this section the research areas that are investigated in this thesis, along with the motivation for further research in each area and the contributions of this thesis to the existing literature are presented. These research areas are examined in chapters 3 to 8. More analytically, chapter 2 provides an introduction to the econometric procedures that are employed in this thesis. Chapter 3 examines the unbiasedness hypothesis of the FFA and expected spot prices (presented at the 2nd International Safety of Maritime Transport Conference, 7-9 June 2001, Chios, Greece and at the 12th International Association of Maritime Economists (IAME) Conference, 13-15 November 2002, Panama City, Panama). Chapter 4 examines the lead-lag relationship between spot and FFA prices in returns and volatility (presented at the City University Cass Business School, Research Workshop in Finance, 21 January 2002, London and at the 12th IAME Conference, 13-15 November 2002, Panama City, Panama). Chapter 5 investigates the impact of FFA trading on the volatility of the spot market. Chapter 6 examines the hedging effectiveness function of the FFA contracts. Chapter 7 investigates the relationship between bid-ask spreads and anticipated volatility of the FFA contracts. Chapter 8 examines the forecasting performance of spot and FFA prices. Finally, chapter 9 presents our conclusions and some suggestions for fruitful future research which, due to space constraints, are not covered in this thesis. The general structure of these chapters is similar. We introduce the approach; discuss the relevant theory and related issues; describe the methodology and the testing procedure to be used; report the empirical findings; and draw conclusions. The contributions of each research area, to the literature, are presented next.

1.5.1. The Unbiasedness Hypothesis of Forward and Expected Spot Prices in the Forward Freight Market

For many years observers sought to discover whether prices in financial markets exhibited patterns over time, and thus, discover whether these patterns made accurate predictions possible. The earliest examples of this are the works of Roberts (1959) and Samuelson (1965) which set the ground rules for what was became known as the Efficient Market Hypothesis (EMH) with the seminal paper of Fama (1970).

In efficient markets, market agents process information rationally and incorporate current and past information into asset prices (Fama, 1970). In that sense, only new information, or *news*, should cause changes in prices. Since *news* are by definition unforecastable, then price changes (or returns) should be unforecastable; no information at time t or earlier should help to improve the forecast of prices (or returns). Forecast errors should be therefore zero on average and should be uncorrelated with any information that is available at the time the forecast was made. In such efficient markets, the existence of futures/forward markets can help to discover prices which are likely to prevail in the spot market. Thus, according to the unbiasedness hypothesis, FFA contract prices must be unbiased estimators of the spot prices of the underlying asset that will be realised at the expiration date. If during the life of the FFA contract, the forward price, which is the price agreed at the initiation of the contract, continually mirrors the spot price of the underlying asset, then there is negligible credit risk associated with the forward contract and the contract can be sold at the market price[16].

[16] The credit risk associated with the FFA contract is the risk that occurs when one party is not performing, on the expiration date, the obligations relative to a change in the value of the forward contract from zero.

The motivation for the investigation of the topic can be characterised by the following arguments: First, the price discovery function provides a strong and simple theory of the determination of spot prices. The existence of biased forward prices can increase the cost of hedging, assuming that the market agents are fully informed when they set the forward price in FFA contracts[17]. Moreover, investigation of the subject is of particular interest to market agents, because if forward prices are not unbiased forecasts then they may not perform their price discovery function efficiently. However, it should be noted that this argument is not valid for markets in which the derivatives price is determined by arbitrage (e.g. stock-index futures), but is valid for markets in which arbitrage is not present (e.g. freight forwards). If forward prices are to fulfil their price discovery role, they must provide accurate forecasts of the realised spot prices, and consequently, they must provide new information in the market and in allocating economic resources (Stein, 1961).

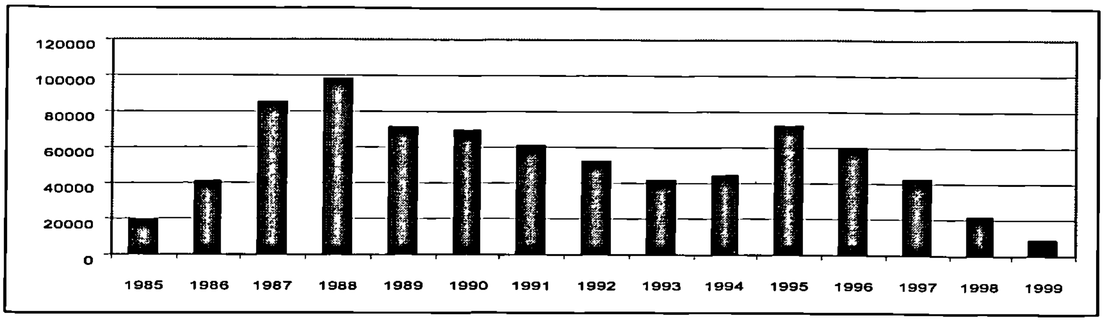
Second, the apparent lack of academic research in the FFA trades further mitigates this study and provides a fruitful way to complement the specific market and to provide a performance comparison with the BIFFEX market, investigated by Chang (1991), Chang and Chang (1996), Kavussanos and Nomikos (1999), and Haigh (2000). Kavussanos and Nomikos (1999) examine the BIFFEX contract using cointegration techniques and argue that futures prices one and two months from maturity provide unbiased forecasts of the realised spot prices. On the other hand, futures prices three months from maturity are biased estimates of the realised spot prices. They conclude that the direction of the futures price is usually correct but not necessarily a good predictor of the exact spot rates at settlement time. Moreover, the decrease in volume in futures contracts has coincided with the creation of the FFA contracts at the beginning of 1992 (Figure 1.13). Market agents attribute this decrease in BIFFEX trading to be associated with the growth in hedging activity with the FFA contracts. Empirical testing of the unbiasedness of the FFA market provides us a helpful direction towards the validity of the above inference.

Third, it can provide a yard-stick to practitioner's operations, where research output can be thought of increasing the attractiveness of the market and subsequently bringing more volume to the market. Perhaps the strongest evidence on the importance of the investigation of the price

[17] When forward prices are well above (below) the expected spot prices, long (short) hedgers are obliged to buy (sell) the forward contracts at a premium (discount) over the price they expect to prevail on expiration.

discovery function is the very large growing number of papers addressing the topic. However, different studies tend to reach different conclusions even when investigating the same set of prices over the same sample period. This study provides evidence of the price discovery function, for the first time, of a unique forward contract, specifically designed for hedging freight rates in the dry-bulk industry.

Figure 1.13. Yearly Volumes of the BIFFEX Contract (May 1985 – June 1999)



Source: LIFFE, 2000.

1.5.2. The Lead-Lag Relationship in Returns and Volatility Between Spot and Forward Prices in the Forward Freight Market

The first part of the price discovery function examines whether FFA prices form unbiased estimators of the spot prices that will prevail at the expiration date. The second part of the price discovery function of the FFA contracts examines whether FFA prices provide information regarding current spot prices. The lead-lag relationship in returns and volatility between spot and FFA prices is regarded as FFA prices are responding rapidly to new market information, and therefore, leading the changes in spot prices[18]. If this is true then market agents, who have collected and analysed the new information, would prefer to trade in the FFA market rather than in the spot market. This, in turn, could bring more volume in the FFA market, as agents would be more confident in trading a derivatives instrument that serves effectively and efficiently its price discovery function.

The interesting aspect that makes the analysis important is that besides the plethora of studies in various futures markets, the empirical investigation of the lead-lag relationship in forwards market is undermined. This is due to the secretive nature of the unregulated OTC forward

[18] Causality between FFA and spot prices can run in one (FFA to spot) or both (FFA / spot feedback) directions, depending on the specific market, but always FFA prices must contribute to the discovery of new information regarding current spot rates.

markets, where the public availability of economic data is limited. The possession of daily data for the FFA trades provides us the opportunity to examine a function of forward contracts of paramount importance for the market agents and for the market as a whole. A special feature of this market is that the underlying commodity is a service. The theory of intertemporal relationships between spot and derivatives prices of continuously storable commodities is well developed (Working 1970), in contrast to that of non-storable commodities (e.g. freight services). The non-storable nature of FFA market implies that spot and FFA prices are not linked by a cost-of-carry (storage) relationship, as in financial and agricultural derivatives markets. Thus, inter-dependence between spot and FFA prices may not be as strong as for storable commodities.

Kavussanos and Nomikos (2001) examine the lead-lag relationship in returns in the BIFFEX market and argue that spot and BIFFEX prices stand in a long-run relationship between them. Causality tests indicate that futures prices tend to discover new information more rapidly than spot prices. They conclude that BIFFEX performs its price discovery function efficiently. The current study investigates the issue further by providing empirical evidence, for the first time, on the price discovery function of the forward freight market. The special features then of this market, in comparison to the existing literature on futures markets, are: (i) the non-storable nature of the underlying commodity, being that of a service; and (ii) the asymmetric transactions costs between spot and FFA markets. These costs are believed to be higher in the spot freight market (in relation to the FFA market) as they involve the physical asset (vessel).

Although research devoted towards the relationship between derivatives and spot returns (first moment conditions) is voluminous (see for example, Stoll and Whaley, 1990; Chan *et al.*, 1991; Chan, 1992, amongst others), there is currently a growth in interest for examining higher moment dependencies (time-varying volatility) between markets; volatility spillovers or risk transmission between spot and derivatives markets in commodities and in financial markets (see for example, Ng and Pirrong, 1996; Crain and Lee, 1996; and Koutmos and Tucker, 1996, amongst others)[19]. Interest on the impact of volatility spillovers from one market to the next has primarily arisen due to the realisation of speculative price changes being interwoven with

[19] "Volatility spillover" is the impact of an innovation of market *i* on the conditional variance of market *j*.

higher moment dependencies, such as shown by Bollerslev *et al.* (1992)[20]. Cheung and Ng (1996) argue that volatility spillovers are important because changes in volatility reflect the arrival of information. Additionally, the investigation of a causal relationship in volatility provides insight into the dynamics of asset prices.

This study is of great importance for market agents in the dry-bulk freight market, which need to cover the risk exposure that they face. Understanding the process by which new information is incorporated into spot and FFA prices can allow market agents to use the leading market as a price discovery vehicle, since such information may be used in decision making. Thus, a better understanding of the dynamic relation of spot and FFA prices and its relation to the basis will provide to these agents the ability to use hedging in a more efficient way.

1.5.3. An Investigation of the Introduction of Forward Freight Trading on Spot Market Price Volatility

While derivatives (futures and forward) markets can be seen to be enhancing economic welfare by allowing for new positions and expanding the investment sets or enabling existing positions to be taken at lower costs, they have been criticised for encouraging speculation. Goss and Yamey (1978) argue that derivatives markets, by allowing individuals to undertake speculative activity without having them to become involved in the production, handling or processing of the commodity or asset, can increase speculation. Furthermore, the low cost of participating and the rapid implementation of a position in the derivatives markets make it easy for market agents to engage in speculation. Thus, there has been a considerable concern regarding the impact that derivatives markets may have on prices of the underlying spot market. This study examines whether, and to what extent, the recent introduction of trading in FFA contracts has impacted on the volatility of the underlying spot market.

In general there are two main beliefs between market agents. The first is that speculators in derivatives markets have a destabilising impact on spot prices. The second is the exact opposite, were speculators are seen to have a stabilising impact on spot market prices. This controversial interest has been the subject of considerable empirical analysis (mostly in futures and options

[20] Ross (1989) argues that the variance of price changes is related directly to the rate of flow of information. Hence, previous studies ignoring the volatility mechanism may not offer a thorough understanding of the information transmission process.

markets, where in forward markets analysis is limited) and has received the attention of policymakers. Despite that, the issue of whether derivatives trading destabilises or stabilises the spot market, is still viewed with suspicion by market agents and policymakers alike.

The classical view of the impact of speculators is that they have a useful role and assist to stabilise prices (Kaldor, 1960). The issue of the impact of speculators dates back almost to the inception of derivatives trading. The main reason for this is the fact that derivatives trading may encourage speculation. It can be argued that derivatives markets require speculators, to enable hedgers to transfer risks, which they wish to avoid. Since derivatives prices have a close relationship with spot prices, yet impose less costs on speculators than would trading in the spot market, they are very attractive to those seeking to engage in speculation.

This study contributes to the literature on the relationship between FFA trading and spot price volatility in the following four respects. First, the study not only investigates if FFA prices have an impact on spot volatility, but also attempts to question why FFA trading might has an impact on spot market price volatility. Second, the proposed methodology enables the investigation of the link between information and volatility and of the market dynamics, as reflected by a change in the asymmetric volatility response. Third, the FFA forward market is organised quite differently from a futures market. All trading is bilateral, there is no clearing-house, no open outcry, and no centralised exchange. Only at the end of the trading day, information on deals negotiated during the day, is widely disseminated. During the day, traders must rely on their contacts for information on the transactions consummated. Finally, much of the analysis in previous studies has been devoted on considering the impact of trading in market-wide instruments (i.e. index contracts). Such studies are useful in assessing market-wide impact, but any effect in the underlying spot market can be dissipated across the many constituent assets in the index, making it difficult to detect. Because FFA contracts are route-specific, since the underlying asset is freight rates of a trading route, changes in the volatility of individual routes can be examined.

This study can provide regulators and traders with important insights into the FFA trading - spot price volatility relationship. If FFA contracts cause a change in the level of volatility in the spot market (as in the arguments that speculators increase volatility) and this, in turn, is associated with greater uncertainty and unduly higher required freight rates, then there may well be a case for FFABA and FIFC to increase the regulation of these contracts. However, if FFA contracts lead to new channels of information being provided, more information due to more traders, and a reduction in uniformed investors, then FFA contracts provide a useful service and calls for their regulation are unwarranted.

1.5.4. The Hedging Performance of the Forward Freight Market

The reason for the existence of derivatives markets is to provide instruments for businesses to reduce or control the unwanted risk of price change by transferring it to others more willing to bear the risk. This function of the derivatives markets is performed through hedging the spot position by holding an equal but opposite position in the derivatives market, in order to *neutralise* the impact of adverse price level changes. Throughout the financial literature there is a plethora of research studies focusing on the hedging effectiveness of derivatives markets by estimating hedging ratios, which indicate the strength of offsetting the price risk of the spot market[21] (see for example, Lindahl, 1992; Park and Switzer, 1995; Geppert, 1995; Kavussanos and Nomikos, 2000a, 2000b, 2000c; Butterworth and Holmes, 2001, amongst others).

The hedger initially must answer two questions, which will determine the type of the contract that is the most appropriate to use and how the hedge will be constructed; what kind of derivatives instrument to use and which contract month. Answering the previous questions the hedger must decide his *continuous* hedging strategy: to hedge with a nearby derivatives contract and rolling the hedge forward; or hedge with a more distant derivatives contract, and rolling it less frequently in the future[22]. Rolling the hedge more frequently causes higher brokerage and transactions costs. On the other hand, using a more distant contract increases basis risk, as the derivatives price will be less correlated with the spot price. Researchers have concentrated on three hedge strategies: the traditional one-to-one (naïve) hedge; the beta hedge; and the conventional minimum variance hedge. The traditional naïve strategy involves hedgers adopting a derivatives position equal in magnitude but opposite in sign to the spot position, i.e. $h = -1$, i.e. an investor who is long in the spot market should sell a unit of derivatives today and buy the derivatives back when he sells the spot. Implicit in such strategy is the view that

[21] The hedge ratio, h, is defined as the number of derivatives contracts that an agent must buy or sell for each unit of the spot position on which there is price risk.
[22] Rolling a hedge forward can be accomplished by buying in the current settlement month a derivatives contract and simultaneously selling a similar contract in a later settlement month, in the hope that it can be lifted at a higher net price.

derivatives and spot prices move closely together. Indeed, if proportionate price changes in one market exactly match those in the other market, then price risk is eliminated (perfect hedge).

The beta hedge strategy is very similar, but recognises that the spot portfolio to be hedged may not match the portfolio underlying the derivatives contract. With the beta hedge strategy, h is calculated as the negative of the beta of the spot portfolio. Thus, beta is the coefficient of the independent variable in a regression of market returns on spot portfolio returns. For example, if the spot portfolio beta is 1.5, the hedge ratio will be -1.5, since the spot portfolio is expected to move by 1.5 times the movement in the derivatives contract. Where the spot portfolio is that which underlies the derivatives contract, the traditional strategy and the beta strategy yield the same value for h. In practice, price changes in the two markets do not move exactly together and, therefore, the traditional or beta hedge will not minimise risk.

The portfolio explanation of hedging, first presented by Johnson (1960), Stein (1961) and Ederington (1979) apply the Markowitz foundations of portfolio theory to show that the hedge ratio that minimises the risk of the spot position is given by the ratio of the unconditional covariance between spot and derivatives price changes over the unconditional variance of derivatives price changes. The model of hedging ratios, developed by Johnson (1960) and Ederington (1979) assumes that hedger's interests are in minimising risk, and the covariance between spot and derivatives price changes as well as the variance of spot and derivatives price changes are known with certainty or are well-specified ex ante. The derivation of this model is as follows. Market agents in derivatives markets choose a hedging strategy that reflects their individual goals and attitudes towards risk. In particular, consider a shipowner who wants to secure his freight rate income in the forward freight market. Suppose the investor has a fixed long position of one unit in the spot market and a short position of $-h$ units in the FFA market. The random return to this portfolio, ΔP_t, between t-1 and t, is equal to:

$$\Delta P_t = \Delta S_t - h\Delta F_t \tag{1.5}$$

where, $\Delta S_t = S_t - S_{t-1}$ is the logarithmic change in the spot position between t-1 and t; $\Delta F_t = F_t - F_{t-1}$ is the logarithmic change in the FFA position between t-1 and t, and h is the hedge ratio (the proportion of the portfolio held in FFA contracts)[23]. By using the portfolio theory the variance of the returns of the hedged portfolio is given by:

$$\mathrm{Var}(\Delta P_t) = \mathrm{Var}(\Delta S_t) + h^2\mathrm{Var}(\Delta F_t) - 2h\mathrm{Cov}(\Delta S_t, \Delta F_t) \tag{1.6}$$

where, $\mathrm{Var}(\Delta S_t)$, $\mathrm{Var}(\Delta F_t)$ and $\mathrm{Cov}(\Delta S_t, \Delta F_t)$ are, respectively, the unconditional variances and covariance of the spot and FFA price changes. The hedger must choose the value of h that minimises the unconditional variance of his hedged portfolio returns i.e. $\min_h [\mathrm{Var}(\Delta P_t)]$. Taking the partial derivative of Equation (1.6) with respect to h, setting it equal to zero and solving for h, yields the conventional Minimum Variance Hedge Ratio (MVHR), h^*, as follows:

$$h^* = -\frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)} \tag{1.7}$$

The conventional MVHR takes account the imperfect correlation between the two markets and identifies the hedge ratio which minimises risk (as measured by variance)[24]. The negative sign reflects that to hedge a long spot position requires selling derivatives. Using the conventional MVHR as the basis for hedging implicitly assumes investors are infinitely risk-averse, i.e. they will forgo an infinite amount of expected return in exchange for an infinitely small risk reduction. While such an assumption about the risk-return trade-off is unrealistic, the conventional MVHR provides an unambiguous benchmark against which to assess hedging performance[25]. Ederington (1979) argues that a portfolio approach to hedging is superior to both the traditional one-to-one risk minimising and Working's (1953) profit-maximising interpretations. However, Benninga *et al.* (1984) argue that unless there is an unbiased derivatives market, where the derivatives price is equal to the expected spot price, the conventional MVHR is not necessarily the optimal hedging strategy.

[23] We should notice that, the proportion of the portfolio held in the spot commodity equals 1 by assumption.
[24] It can be shown that, provided expected returns to holding derivatives contracts are zero, the conventional MVHR of Equation (1.7) is equivalent to the utility-maximising hedge ratio. A proof of this result is available in Benninga *et al.* (1984) and Kroner and Sultan (1993).
[25] While some studies have incorporated expected returns into hedging decisions and developed risk-return measures of hedging effectiveness (see, for example Howard and D'Antonio, 1991, amongst others), such models suffer from the same shortcoming in that they require a subjective assessment to be made in relation to investor preferences.

Empirically, this approach is equivalent to the slope coefficient, h^*, in the following regression:

$$\Delta S_t = h_0 + h^* \Delta F_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{iid}(0,\sigma^2) \tag{1.8}$$

where ΔS_t and ΔF_t are changes in logarithmic spot and FFA prices, respectively, ε_t is an error term, and h_0, $h^*$are regression parameters. In addition, the estimated h_0 and h^* in this specification give a best fit of the historical linear relationship between S_t and F_t, and guarantee that the sum of the squared error terms ($\Sigma\varepsilon_t^2$) will be as small as possible. The degree of variance reduction in the hedged portfolio achieved through hedging is given by the coefficient of determination (R^2) of the regression, since it represents the proportion of risk in the spot market that is eliminated through hedging; the higher the R^2 the greater the effectiveness of the minimum variance hedge.

In the freight futures (BIFFEX) market, the conventional MVHR methodology is applied by Thuong and Vischer (1990) where they estimate the degree of hedging effectiveness achieved by BIFFEX across all the BFI routes from August 1986 to December 1988. They find that the hedging effectiveness of the contract is higher for the panamax routes, compared to the capesize and the handysize routes. Overall they conclude that the conventional MVHR fails to eliminate the risk of the spot position to the extent in other commodities markets (the higher R^2 being only 32%). They argue that this is due to the heterogeneous composition of the underlying asset, the BFI, which consists of dissimilar shipping routes in terms of vessel size and transported commodities. In a similar study, Haralambides (1992) argues that a shipowner, operating on route 3 (of the BFI) can achieve greater risk reduction by using the conventional MVHR compared to a traditional (naïve) hedge.

Several points need to be mentioned regarding the performance of these hedging strategies. First, h^* and R^2 of Equation (1.8) are ex-post measures of hedging effectiveness, since they depend upon the previously explained correlation between the spot and derivatives prices and, as such, give an indication of the historical performance of the hedging strategy (*in-sample* performance). In reality, hedgers in the market use the historical hedge ratios to hedge a position in the future. Hence, a more realistic way to evaluate the effectiveness of alternative hedging strategies is in an *out-of-sample* setting.

Second, Myers and Thompson (1989) and Kroner and Sultan (1993) argue that Equation (1.8) implicitly assumes that the risk in spot and derivatives markets is constant over time. This assumption is too restrictive and contrasts sharply with the empirical evidence in different markets, which indicates that spot and derivatives prices are characterised by time-varying distributions (see for example, Choudhry, 1997; Hogan *et al.*, 1997; and Kavussanos and Nomikos, 2000a, 2000b, amongst others). This in turn, implies that MVHR should be time-varying, as variances and covariances entering the calculations are time-varying as new information arrives in the market and the information set is updated.

Third, economic analysis and intuition suggest that the prices of the spot asset and the derivatives contract are jointly (simultaneously) determined (see for example, Stein, 1961). Consequently, the estimation of Equation (1.8) is subject to simultaneity bias, i.e. the estimated hedge ratio will be upward biased and inconsistent. Furthermore, Equation (1.8) is potentially misspecified because it ignores the existence of a long-run cointegrating relationship between spot and derivatives prices (Engle and Granger, 1987) resulting in downward biased not optimal hedge ratios (see for example, Ghosh, 1993b; Chou *et al.* 1996; and Lien, 1996, amongst others). These issues raise concerns regarding the risk reduction properties of the hedge ratios generated from Equation (1.8). These problems have been addressed in several commodity and financial derivatives markets (see for example, Kroner and Sultan, 1993; Gagnon and Lypny, 1995, 1997; and Kavussanos and Nomikos, 2000a, 2000b, amongst others).

This study contributes to the existing literature in a number of ways. First, despite the growing importance of the forward freight market, no effort has been devoted to ascertaining the relative importance and feasibility of the effectiveness of constant and time-varying optimal hedge ratios. Second, different model specifications are estimated and compared so as to arrive at the most appropriate model, which takes into account the univariate properties of spot and FFA prices. Third, in-sample and out-of sample tests are employed so as to assess the effectiveness of the FFA contract in minimising the risk in the spot freight market. Market agents (shipowners and charterers) whose physical operations concentrate on specific panamax routes can benefit from using optimal hedge ratios that minimise their freight rate risk. Finally, the interesting research aspect is to analyse the hedging effectiveness of the FFA contract and to compare it with the hedging effectiveness of the BIFFEX contract, analysed by Kavussanos and Nomikos (2000a, 2000b, 2000c). The latter argue that time-varying hedge ratios outperform alternative specifications and have been found successful in reducing spot market risk in four shipping routes, but they fail to reduce the risk of the spot position to the extent found for other markets in the literature.

Due to the lack of the existence of a long-run cointegrating relationship between spot and derivatives prices in the optimal hedge ratio methodology, we model the spot and the FFA prices as a Vector Error-Correction Model (VECM) (Engle and Granger, 1987 and Johansen, 1988) with a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) error structure (Bollerslev, 1986). This framework meets the earlier criticisms of possible model misspecifications and time-varying h_t^*, since the Error-Correction Term (ECT) describes the long-run relationship between spot and FFA prices and the GARCH error structure permits the second moments of their distribution to change over time. We also include the squared lagged ECT of the cointegrated spot and FFA prices in the specification of the conditional variance, in what is termed the GARCH-X model (Lee, 1994)[26]. The time-varying hedge ratios are then calculated from the estimated covariance matrix and their in sample and out-of-sample hedging performance is compared to that of constant hedge ratios. In the above, the selection criterion (loss function) for the optimum model to use is the variance reduction of the hedged portfolio.

1.5.5. The Relationship Between Bid-Ask Spreads and Price Volatility in the Forward Freight Market

Transactions costs are usually ignored in asset pricing theories but are an important consideration in investors' investment decisions. One significant cost is the bid-ask spread (BAS). Brokers match buy and sell contracts and the price charged for this service is known as the bid-ask spread, the difference between the buying (bid) and selling (asked) price per contract. This normally is regarded as compensation to brokers for providing liquidity services in a continuously traded market. The mark-up charged by brokers in the financial markets, as in any other market, is a function of the operational efficiency of the brokers and the nature of the product. Tinic and West (1972) argue that there is a positive relationship between spreads and price volatility on the grounds that the greater the variability in price, the greater the risk

[26] A principal feature of cointegrated variables is that their time paths are influenced by the extent of deviations from their long-run equilibrium (Engle and Granger, 1987). As spot and FFA prices respond to the magnitude of disequilibrium, then, in the process of adjusting they may become more volatile. Thus, inclusion of the ECT in the conditional variance specification is appropriate and may lead to the estimation of more accurate hedge ratios.

associated with performance of the function of the brokers. Bollerslev and Melvin (1994) also argue that greater uncertainty regarding the future price of the asset, as associated with greater volatility of the price of the asset, is likely to result in a widening of the spread.

The nature and the behaviour of the BASs have been examined thoroughly in the equity (see McInish and Wood, 1992), foreign exchange (see Bollerslev and Melvin, 1994; and Bessembinder, 1994) and bond markets (see Kalimipalli and Warga, 2000). However, knowledge of derivatives spreads is limited, presumably due to the lack of information on bid-ask quotes (with the exception of the studies of Laux and Senchack, 1992; Ma *et al.*, 1992; Wang et al., 1994; Ding, 1999; and Wang and Yau, 2000, amongst others). Transactions costs related to derivatives is an important issue because: (i) the low cost of trading is often cited as one rationale for the existence of derivatives markets; (ii) high transactions costs will affect market participants' ability to trade quickly and cheaply; and (iii) regulators (FFABA and FIFC) will need to consider how their policy decisions may impact the volatility of the market, and consequently, the BASs.

The purpose of this study is to investigate what impact an anticipated increase in FFA price volatility will have on transactions costs in terms of BAS. Extant literature that provides some possible answers to the previous question includes those studies on the relationship between BASs and price volatility (see for example, Tinic and West, 1972; Benston and Hagerman, 1974; Stoll, 1978; Copeland and Galai, 1983; and McInish and Wood, 1992, amongst others). This study contributes to existing literature in a number of dimensions. First, we examine the relationship between BAS and expected price volatility in the forward freight market, which offers a unique and directly observable BAS data set. Second, we employ a two-step modeling specification in order to ensure robust inferences on the relationships between variables. In the first-step the GARCH specification is used for modeling the volatility of the FFA prices. This specification is consistent with a return distribution which is leptokurtic (speculative prices), and it also allows for a long-term memory (persistence) in the variance of the conditional return distributions. The GARCH model is known to be capable of mimicking observed statistical characteristics of many time-series of return on financial assets (see Bollerslev, 1987 and Baillie and Bollerslev, 1989). In the second-step we investigate if the expected conditional volatility (led by one-day) has a significant positive relationship with the current BAS using the General Method of Moments (GMM) approach (Hansen, 1982).

Third, volatilities in the several markets of the shipping industry are subject to sudden movements which are, at best, only partially predictable. A better understanding of the movements of FFA prices, and the consequent effect in transactions costs, may provide important information and insights for market agents about the timing of trades, the sentiment and the future direction of the FFA market. For example, a widening of the BAS may discourage risk-averse market agents from participating and trading as it may indicate a period of high volatility. More specifically, traders, speculators, hedgers, and arbitrageurs alike are interested in extracting information from these variables to know how their reaction to new information can be used in predicting future prices.

1.5.6. The Forecasting Performance of Forward and Spot Prices in the Forward Freight Market

Forecasting is of fundamental importance in all of the sciences, including financial economics. Forecast accuracy is of obvious importance to users of forecasts because forecasts are used to provide superior signals that guide future supply and demand decisions in ways that contribute to a more efficient allocation of economic resources. Comparisons of forecast accuracy are also of importance to economists, more generally, who are interested in discriminating among competing economic models. As in the case of other financial and commodity derivatives markets, market agents in the FFA market can potentially benefit through the use of more accurate forecasts.

In this study, we investigate the performance of alternative time-series models in generating short-term forecasts of the spot and FFA prices. We want to investigate if FFA prices provide more accurate short-term forecasts of the spot prices than forecasts generated by time-series models. Market agents can benefit from having accurate short-term forecasts of the spot and FFA prices, since availability of such forecasts will enable them to design more efficient trading strategies. In order to identify the model that provides the most accurate forecasts, we estimate alternative multivariate and univariate specifications and assess their forecasting performance. The statistical test of Diebold and Mariano (1995) is used to assess whether the forecasts from the competing models are equally accurate.

Cullinane (1992) was the first to propose time-series models for forecasting the BFI. Cullinane applies the Box-Jenkins (1970) methodology to identify the best Autoregressive Integrated Moving Average (ARIMA) model for the BFI. The forecasting performance of this model is then compared to forecasts generated from simple 10- and 20-days moving averages of the BFI and from Holt-Winters (Holt, 1957 and Winters, 1960) exponential smoothing model. Cullinane (1992) concludes that an AR model outperforms the other specifications for forecasts up to 7 days ahead, while for greater lead times, the Holt-Winters model provides superior forecasts.

Following Kavussanos and Nomikos (2001), we compare the forecasting performance of a VECM, to that of ARIMA, Vector Autoregressive (VAR) and Random Walk (RW) models. Kavussanos and Nomikos (2001) investigate the forecasting performance of the BFI and BIFFEX prices. They report that the VECM generates significantly the most accurate forecasts of BFI prices, for a period up to 15 days ahead, and therefore, BIFFEX prices help in improving the forecasting performance of spot prices. For the BIFFEX prices however, they report that the increase in forecasting performance, through the VECM, is insignificant across all the forecasting horizons. However, Tashman (2000) argues that non-independent forecasts can be biased (a shock in a specific forecast horizon may affect all other forecasts horizons) and can invalidate the forecasting results. Thus, in order to avoid biased forecasts, induced by serially correlated forecast errors, we estimate independent out-of-sample N-period ahead forecasts over the test period.

1.5.7. Data and Estimation Periods

Our empirical analysis is undertaken using four spot trading routes from the BPI (1, 1A, 2, and 2A) and FFA price data for the period 29 November 1989 to 26 December 2001. The dataset used in each study is different, depending on the nature of the investigated hypothesis. Price data for the panamax spot routes are from the Baltic Exchange and Datastream. FFA prices are collected in a hard copy format, from the shipbroking company Clarkson Securities Ltd, and processed in an electronic format by the author. In every trading day, we collected the bid and ask quotes for every trading route of the BPI, one-, two-, and three-months from maturity (see Table 1.12 for a daily FFA report). We also present in an Appendix (at the end of the thesis) an example of a FFA contract.

The unbiasedness hypothesis, in chapter 3, is examined using FFA prices one, two and three months from maturity and spot prices on the maturity day of the contract, for the period January 1996 to July 2000 in routes 1 and 1A and January 1996 to December 2000 in routes 2 and 2A. The choice of this dataset is dictated by the delivery periods of the FFA contract. Since there is a FFA contract maturing every month in the market, the smallest feasible frequency for such a study is monthly data. The lead-lag relationship in returns and volatility between contemporaneous spot and FFA prices, in chapter 4, is investigated using daily spot and FFA prices over the periods 16 January 1997 to 31 July 2000 in routes 1 and 1A and 16 January 1997 to 30 April 2001 in routes 2 and 2A.

The impact of the introduction of FFA contracts on spot market price volatility, in chapter 5, is examined using daily spot route data. The dataset covers the periods 29 November 1989 to 31 July 2000 in route 1, 7 August 1990 to 31 July 2000 in route 1A, 29 November 1989 to 24 August 2001 in route 2, and 12 February 1991 to 24 August 2001 in route 2A. The hedging performance of the FFA market, in chapter 6, is investigated using weekly spot route and FFA prices, for the periods 16 January 1997 to 26 July 2000 in routes 1 and 1A and 16 January 1997 to 26 December 2001 in routes 2 and 2A. A weekly hedging horizon is preferred, in line with other studies in the hedging literature, such as Kroner and Sultan (1993) and Kavussanos and Nomikos (2000a, 2000b).

The relationship between bid-ask spreads and volatility of the FFA market, in chapter 7, is examined using daily bid-ask spreads and FFA prices in panamax Atlantic routes 1 and 1A from 16 January 1997 to 31 July 2000 and daily bid-ask spreads and FFA prices in panamax Pacific routes 2 and 2A from 16 January 1997 to 10 August 2001. Finally, the forecasting performance of spot and FFA prices, in chapter 8, is examined using alternative time-series models, which are estimated from 16 January 1997 to 30 June 1998 for all routes (corresponding to one and a half year). The period from 1 July 1998 to 31 July 2000 for the Atlantic routes (1 and 1A) and the period from 1 July 1998 to 30 April 2001 for the Pacific routes (2 and 2A) are used to obtain out-of-sample N-period ahead forecasts. The choice of a daily dataset for this study is dictated by two factors. First, the proposed VECM model is based on our empirical model in chapter 4, which is estimated using daily spot and FFA prices. Second, the objective of this chapter is to propose a short-term model for forecasting spot and FFA prices; from that respect, the choice of daily data is also necessary.

Table 1.12. Clarkson Securities Ltd. FFA Report

PANAMAX *AND CAPESIZE FFA REPORT*

Day Month Year

CLARKSON
SECURITIES LIMITED

BPI	BDI	BCI	Usd/Dm	Usd/Yen	UK/Usd	180cst rdmT	380cst rdm
1,503(+7)	1,454 (+1)	1,813 (-2)	2.1944	121.12	1.4338	132.00	124.00

PANAMAX FORWARD FREIGHT AGREEMENT INDICATIONS:

	2. US Gulf/Japan		2A. TCT East	
	Bid	Offer	Bid	Offer
May	22.65	22.85	11,950	12,250
Jun	21.30	21.70	11,200	11,650
Jul	20.25	20.65	10,200	11,000
Oct	20.75	21.40		
BPI	22.907		12,554	

	3a. TP Round		4. Feast / Cont	
	Bid	Offer	Bid	Offer
May	9,800	10,100	9,350	9,900
Jun	9,500	9,800	9,000	9,600
Jul	8,700	9,500	8,500	9,300
BPI	9,459		9,256	

CAPESIZE FORWARD FREIGHT AGREEMENT INDICATIONS:

	Bolivar / Rotterdam R7		Rich Bay / Rotterdam R4	
	Bid	Offer	Bid	Offer
May	6.00	6.45	7.95	8.25
Jun	6.00	6.40	7.90	8.15
Jul	6.20	6.45	7.85	8.15
Aug	6.20	6.45	7.85	8.15
Sep	6.20	6.55	7.90	8.2
Oct	6.30	6.55	8.05	8.25
Nov	6.30	6.55	7.85	8.25
Dec	6.20	6.50	7.69	8.10
BCI	6.431		8.150	

Baltic Exchange Spot Indices:

Baltic Panamax Index (BPI)	1503 (+7)	**Baltic Capesize Index (BCI)**	1813 (-2)
1. US Gulf / Cont	15.243	1. Hampton Roads / Rotterdam	6.456
1a. TA Round Voyage	12,366	2. Tubarao / Rotterdam	6.728
2. US Gulf/Japan	22.907	3. Tubarao / Beilun + Baoshan	9.500
2a. Skaw-Gibraltar/Taiwan-Japan	12,554	4. Richards Bay/ Rotterdam	8.150
3. NoPac/Japan	15.242	5. W. Australia / Beilun + Baoshan	5.242
3a. TP Round Voyage	9,459	6. Newcastle / Rotterdam	12.689
4. Japan-S Korea/Skaw-Gibraltar	9,256	7. Bolivar / Rotterdam	6.431
		8. Trans-Atlantic Round Voyage	16,938
		9. ARA-Passero/China-Japan	17,094
		10. Trans-Pacific Round Voyage	16,483
		11. China-Japan / ARA-Passero	16,667

CHAPTER 2 - ECONOMETRIC TIME-SERIES METHODS

2.1. INTRODUCTION

The objective of this chapter is to introduce the reader to the time-series techniques and methodologies that will be applied throughout this thesis. The standard classical methods of estimation, in applied econometric work, are based on the assumption that the means and variances of the variables are well-defined constants and independent of time. However, it has been shown that these assumptions are not satisfied by a large number of macroeconomic time-series and the results of the classical econometric regressions as a result are misleading and biased (Granger and Newbold, 1974).

Variables whose means and variances change over time are known as non-stationary, *having* a unit root. Furthermore, it has been shown that using classical estimation methods, such as Ordinary Least Squares (OLS), to estimate relationships with non-stationary variables gives *spurious* inferences. This is known as the spurious regression problem[27] (see section 2.3). As a result, it became important to examine the univariate properties of the regression variables, in terms of unit roots, and a new econometric framework has emerged. This framework is presented in this chapter, where we start with some important definitions in time-series analysis and then proceed with a discussion on the underlying properties of stationary and non-stationary processes. Two of the most well known tests for unit roots, developed by Dickey and Fuller (1979, 1981) and Phillips and Perron (1988) are analysed.

[27] If the means and variances of non-stationary variables change over time, all the computed statistics in a regression model, which use these means and variances, are also time dependant and fail to converge to their true values as the sample size increases. Furthermore, conventional tests of hypothesis will be seriously biased towards rejecting the null hypothesis of no relationship between the dependant and independent variables. Phillips (1987) also shows that the Durbin-Watson (DW) statistic converges towards zero (low DW statistics indicate that the variables in a regression model are non-stationary).

The cointegration methodology, which is regarded as a technique to estimate the equilibrium or long-run parameters in a relationship with unit root variables, is presented next. If individual variables are non-stationary they may be cointegrated. If these variables are cointegrated, they cannot move *too far* away from each other. In contrast, lack of cointegration suggests that such variables have no long-run link; in principle, they can wander arbitrarily faraway from each other. Two alternative approaches for cointegration are presented; First, the Engle and Granger (1987) test, which amounts to estimating a static OLS regression in order to test for the existence of an equilibrium relationship between non-stationary variables. This can be accomplished by performing unit root test on the residuals of the OLS regression. Second, the Johansen (1988) test, which is a Maximum-Likelihood Estimation (MLE), under which the non-stationary variables are modelled as a VAR model. The Johansen (1988) test provides a test statistic with an exact limiting distribution enabling us to perform hypothesis tests.

The last section introduces the ARCH family of models, firstly introduced by Engle (1982), which are specifically designed to model the time-varying conditional variance of time-series variables. The theory of these models, the variety and purpose of the most important ARCH models, their representation, and estimation is analytically presented.

This chapter is organised as follows. In section 2.2 some important definitions of time-series econometric analysis are presented. Section 2.3 discuses the underlying properties of non-stationary and stationary variables. Sections 2.4 and 2.5 present the unit root and cointegration tests, respectively. Section 2.6 presents the characteristics and properties of the ARCH models. Finally, section 2.7 summarises this chapter.

2.2. SOME IMPORTANT DEFINITIONS

Let T be a linear (if $t_1, t_2 \in T$, then $t_1 + t_2 \in T$) index set and $\{X_t: t \in T\}$ a collection of random variables. The collection $\{X_t: t \in T\}$ is said to be a *stochastic process*. A stochastic process is *covariance stationary* (or *weakly stationary*) if the following conditions are satisfied for all values of t:

1. If its mean remains constant over time; $E[y_t] = \mu, \ \forall t$

2. If its variance remains constant over time; $Var(y_t) = E[(y_t - \mu)^2] = \sigma_y^2 = \gamma(0), \forall t$
3. If its autocovariances depend only on the distance between two observation points; $Cov(y_t, y_{t-\tau}) = E[(y_t - \mu)(y_{t-\tau} - \mu)] = \gamma(\tau), \tau = 1,2,\ldots \forall t$

Let $\{X_n: n \in N\}$ be a sequence of random variables, where $N = \{0, \pm 1, \pm 2, \ldots\}$. The stochastic process is said to be *strictly stationary* (or *stationary in the strict sense*) if and only if its properties are unaffected by changes of time origin. In other words, the joint probability distribution at any set of times, t, $t+1$, $t+2,\ldots,T$, must be the same as the joint probability distribution at times, $T+1$, $T+2,\ldots,T+t$. Note that, weak stationarity plus normality is equal to strict stationarity.

A white noise series $\{\varepsilon_t\}$, $t = -\infty \leq t \leq +\infty$, has a sequence of zero mean, finite variance, mutually uncorrelated, random variables. Often the additional requirement that the variance is unity is added to the definition of white noise. This definition is useful when dealing with covariance stationary as distinct from strictly stationary processes; when dealing with the latter, we define white noise to be a sequence of independent identically distributed (iid), zero mean, finite variance random variables.

Notice three implications of this assumption:
1. $E(\varepsilon_t) = E(\varepsilon_t / \varepsilon_{t-1}, \varepsilon_{t-2},\ldots) = E(\varepsilon_t /$ all information at t-1$) = 0$
2. $E(\varepsilon_t\, \varepsilon_{t-j}) = Cov(\varepsilon_t\, \varepsilon_{t-j}) = 0$
3. $Var(\varepsilon_t) = Var(\varepsilon_t / \varepsilon_{t-1}, \varepsilon_{t-2},\ldots) = Var(\varepsilon_t /$ all information at t-1$) = \sigma^2_{\varepsilon t}$

The first and second properties are the absence of any serial correlation or predictability. The third property is conditional homoskedasticity or a constant conditional variance.

Let ε_t be a white noise sequence, and define:

$$u = \{u_n : u_n = \sum_{s=-\infty}^{\infty} a_s \varepsilon_{n-s},\ n \in N\} \tag{2.1}$$

The sequence u is said to be a (bilateral or two-sided) Moving Average (MA) process of infinite extent, denoted by MA(∞); if $a_s = 0$, $s < 0$, it is said to be a (unilateral or one-sided) moving average of infinite extent; if $a_s = 0$, $|s| > q$ it is said to be a moving average of order q, and is denoted by MA(q).

Let ε_t be a white noise sequence, and define:

$$u = \{u_n: \varepsilon_n = \sum_{j=-\infty}^{\infty} b_j u_{n-j},\ \mathrm{n} \in N\} \tag{2.2}$$

The sequence u is said to be a (bilateral) Autoregression (AR) of infinite order and is denoted by AR(∞); if $b_j = 0, j < 0$, it is said to be a unilateral autoregression of infinite order; if $b_j = 0$ for $|i| > p$ it is said to be a finite autoregression of order p, and is denoted by AR(p).

Let ε_t be a white noise sequence, and define:

$$u = \{u_n: \sum_{j=-\infty}^{\infty} b_j u_{n-j} = \sum_{s=-\infty}^{\infty} a_s \varepsilon_{n-s},\ \mathrm{n} \in N\} \tag{2.3}$$

u is said to be a bilateral Autoregressive Moving Average (ARMA) process of infinite order, and is denoted by ARMA(∞,∞). If $b_j = 0, j < 0$ and $a_s = 0$, $s < 0$, it is said to be a unilateral process of infinite order; if $b_j = 0$ for $|i| > p$ and $a_s = 0$, $|s| > q$, it is said to be a finite autoregression moving average of order (p, q) and is denoted by ARMA(p, q).

2.3. UNIT ROOT PROCESSES

Consider the following AR(1) model:

$$y_t = \rho\, y_{t-1} + \varepsilon_t, \quad t = 1,2,3,\ldots,T \quad ; \sim IN(0,\sigma^2) \tag{2.4}$$

where $y_0 = 0$ and ε_t are normally distributed error terms with zero mean and finite variance σ^2.

The variable y_t will be:

- Stationary, if $|\rho| < 1$ (shocks are temporary and disappear with reversion of the series to long-run mean).
- Non-stationary, if $\rho = 1$ (follows a stochastic trend and shocks are permanent with no reversion to long-run mean, and with time dependant variance).
- Explosive, if $|\rho| > 1$ (tends towards $\pm\infty$).

When ρ approaches 1 the OLS estimator of ρ is biased downward. If the true process is a random walk ($\rho = 1$), then the deviation of the OLS estimate from the true value ($\hat{\rho} - 1$) must be multiplied by T rather than $\sqrt{T}$ to obtain a variable with a useful asymptotic distribution, which is not the usual Gaussian distribution but is a ratio involving a $\chi^2(1)$ variable in the numerator and a separate, non-standard distribution in the denominator.

The solution of the difference Equation (2.4) when $\rho = 1$, given some initial condition y_0, is:

$$y_t = \sum_{i=1}^{t} y_0 + \varepsilon_i \tag{2.5}$$

From Equation (2.5) we can see that the accumulated disturbances imply that a ε_i shock has a permanent effect on the conditional mean of the y_t, where y_t does not converge to its mean value since, if at some point in time $y_t = c$ then the expected time until y_t again returns to c is infinite. Furthermore, the variance and the covariance of y_t increase to become infinitely large as t increases. The correlation coefficient between y_t and y_{t-k}:

$$\rho_k = \frac{\mathrm{Cov}(y_t, y_{t-k})}{\sqrt{\mathrm{Var}(y_t)\mathrm{Var}(y_{t-k})}} = \frac{(t-k)\sigma^2}{\sqrt{t\sigma^2(t-k)\sigma^2}} = \sqrt{\frac{t-k}{t}} \tag{2.6}$$

will be approximately unity as t is large relative to k, and the Autocorrelation Function (ACF) of the series will decay very slowly.

When a series is non-stationary then it is said to follow a stochastic trend (the series drifts upwards or downwards) as a result of the cumulative effects of the disturbance terms, and does not return to its long-run mean of zero. This stochastic trend is eliminated by taking the first-difference of the price series. Taking for example the first-difference of y_t yields $\Delta y_t = \varepsilon_t$, which is a stationary process since $E(\Delta y_t) = 0$, $Var(\Delta y_t) = \sigma^2$ and $Cov(\Delta y_t, \Delta y_{t-k}) = 0$. Since the first-difference of y_t is stationary, then y_t is referred to as first-difference stationary or integrated of order 1 series, denoted as $I(1)$ (Engle and Granger, 1987). In general, if a series must be differenced d times to become stationary, then it contains d unit roots and is denoted as $I(d)$.

Using non-stationary variables in standard regression methods can lead to biased inferences because the OLS estimates are inconsistent and the t- and F-statistics do not follow standard distributions generated by stationary series. This phenomenon in econometric modelling is known as *spurious* or *nonsense regressions* whereby the regression results may falsely indicate the existence of a causal relationship between the price series (Granger and Newbold, 1974). Thus, it is important to test the order of integration of each variable in a model before further econometric analysis is undertaken. This can be done by employing unit root tests, which are presented next.

2.4. UNIT ROOT TESTS

2.4.1. Dickey and Fuller Test

A time series is stationary if its mean, variance and autocovariances are independent of time. A property of stationary variables is that the effect of a shock is not persistent, and consequently there is not a high degree of dependence between successive observations. The ACF of the series, in Equation (2.6), decays very fast. Hence, failure of the ACF to die down quickly is an indication of non-stationarity. Although visual inspection of the ACF is a useful indicator for detecting the presence of unit roots, this method is subjective since what appears as a non-stationary process to one observer may appear as a stationary process to another. This problem arises when ρ in Equation (2.4) takes values close to 1, giving a non-stationary pattern of the ACF (slowly decaying) when in fact it is not.

Dickey and Fuller (1979) consider the AR(1) process in Equation (2.4) where y_0 is a fixed initial value and ε_t is an iid sequence of random variables. By subtracting y_{t-1} from both sides of Equation (2.4) we obtain the following equivalent forms depending on whether no deterministic components or, an intercept term or, an intercept and a linear trend term appear in Equation (2.1), respectively:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{2.7}$$

$$\Delta y_t = \mu + \gamma y_{t-1} + \varepsilon_t \tag{2.8}$$

$$\Delta y_t = \mu + \delta t + \gamma y_{t-1} + \varepsilon_t \tag{2.9}$$

where $\gamma = \rho - 1$, μ is an intercept term t is a linear trend term, and whichever equation is assumed to determine y_t, we assume that ε_t is an iid process. The DF test involves estimating one of the Equations (2.7) to (2.9) using OLS, and then *testing the null hypothesis of a unit root*, H_0: $\gamma = 0$ (or equivalently $\rho = 1$), against the alternative of stationarity, H_1: $\gamma < 0$ (or $\rho < 1$). If ρ is less than one in absolute value then Equation (2.7) is a zero mean stationary AR(1) process, Equation (2.8) is a stationary AR(1) process with a mean of $\mu / (1 - \rho)$, and Equation (2.9) a stationary AR(1) process about a linear trend if δ is non zero.

If the data are generated according to Equation (2.7) with ρ equal to one then it can be said that y_t is integrated of order one and is a random walk without a drift. If the data are generated according to Equation (2.8) with ρ equal to one and μ non-zero then y_t is again integrated of order one and is a random walk with non-zero drift. Finally, if the data are generated according to Equation (2.9) with ρ equal to one and μ non-zero then y_t is a random walk about a non-linear time trend. At this point it is useful to make explicit the various alternative combinations of estimating equations and true parameter values that can be considered. We may either choose to estimate Equations (2.7), (2.8) or (2.9). On the other hand the values of μ and δ in Equation (2.9) will necessarily be in accord with one and only one of the following possibilities:

$\mu = 0$ and $\delta = 0$ (I)

$\mu = 0$ and $\delta \neq 0$ (II)

$\mu \neq 0$ and $\delta = 0$ (III)

$\mu \neq 0$ and $\delta \neq 0$ (IV)

Thus, for example, case (I) implies Equation (2.7) is correct, Equation (2.8) includes an unrequired intercept term and Equation (2.9) includes both an unrequired intercept and an unrequired time trend. Case (II) implies Equation (2.7) excludes a required time trend, Equation (2.8) includes an unrequired intercept and excludes a required time trend and Equation (2.9) includes an unrequired intercept. The standard testing procedure for this hypothesis is to construct a *t*-test and compare it to the critical values of the *t*-distribution. However, under non-stationarity, the computed statistic does not follow a standard *t*-distribution but, rather, a DF distribution. Dickey and Fuller (1979) derive a limiting distribution for the least squares *t*-statistic for the null hypothesis that $\rho = 1$ where Equations (2.7) to (2.9) are each in turn assumed to be the estimated equation, but in each case under the assumption that case (I) is correct (i.e. the Equation (2.7) generates the data).

Critical values for these tests are tabulated by Dickey and Fuller (1979, p. 373); these depend on the sample size as well as the deterministic regressors contained in the model and are denoted as, τ when Equation (2.7) is the estimated equation, τ_μ when Equation (2.8) is the estimated equation, and τ_τ when Equation (2.9) is the estimated equation. Note that, because the alternative hypothesis in each case is that $\rho < 1$, a calculated value smaller than the (negative) critical value would lead to rejection of the null hypothesis of a unit root in favor of the alternative of stationarity. The results in the last paragraph are valid in case (I). They are not necessarily true in other cases we have identified. Thus:

1. if the data are generated according to Equation (2.8) with a non-zero intercept, i.e. case (III) describes how the data are generated, then the limiting distribution of τ_μ is standard normal but the limiting distribution of τ_τ remains non-standard.
2. if the data are generated according to Equation (2.9) with a non-zero value of δ then the limiting distributions of τ_μ and τ_τ are both standard normal. This is so whether or not μ is zero, so that we are concerned with either case (II) or (IV).

The issue that arises is which model, in Equations (2.7) to (2.9), one should choose in order to test for a unit root, since each of these models implies a different alternative hypothesis for the d.g.p. of the underlying series with different critical values. Moreover, since $\tau_\tau < \tau_\mu < \tau < 0$, adding a constant and a time trend increases (in absolute value) the critical values thus making it more difficult to reject the null of a unit root when it should be rejected. Since in practice we will not know the correct values for μ and δ, it is necessary to follow a data-based sequential testing procedure in which one tests jointly for the presence of an intercept term and/or a time trend as well as for a unit root. Perron (1988) suggests such a sequential testing procedure, to decide which model to use for unit roots testing; Table 2.1 presents the procedure:

- In the first step, we start with the least restrictive of the plausible DF models - Equation (2.9). If we cannot reject the null of a unit root using the τ_τ statistic, then it is necessary to determine whether too many deterministic regressors are included in the model.
- Thus, in step 2, we test the null hypothesis H_0: $\gamma = \delta = 0$ using a non-normal F-test; critical values for this test, denoted as Φ_3, are tabulated in Dickey and Fuller (1981). If the null is rejected using the Φ_3 statistic, then the trend term is significant under the null of a unit root, which results in the τ_τ, statistic to be asymptotically normal.
- In this case, we proceed to step 2A and test the null hypothesis of a unit root, H_0: $\gamma = 0$ in Equation (2.9), using the standard-normal critical values.
- If we fail to reject the null hypothesis using the Φ_3 statistic, then we proceed to step 3 with the examination of the more restrictive Equation (2.8) and test for a unit root using the τ_μ statistic.
- If we cannot reject the null, then we proceed to step 4 and test the hypothesis $\gamma = \mu = 0$ using the non-standard F-test, Φ_1, reported in Dickey and Fuller (1981). Rejection of the null hypothesis using the Φ_1 statistic, implies that the constant term in Equation (2.8) is significant under the null hypothesis of a unit root and asymptotic normality for the τ_τ statistic follow;
- Thus, the standard-normal critical values are used to test the null hypothesis H_0: $\gamma = 0$ in Equation (2.8), as described in step 4A.
- If the null hypothesis $\gamma = \mu = 0$ cannot be rejected then, we proceed to step 5 where we estimate Equation (2.7) and test for a unit root using the τ statistic.

Table 2.1. Perron's (1988) Sequential Testing Procedure for Unit Roots

Step	Model	Null Hypothesis	Test Statistic	5% Critical Values
1	$\Delta y_t = \gamma y_{t-1} + \mu + \delta t + \varepsilon_t$	$\gamma = 0$	τ_τ	-3.45
2	$\Delta y_t = \gamma y_{t-1} + \mu + \delta t + \varepsilon_t$	$\gamma = \delta = 0$	Φ_3	6.49
2A	$\Delta y_t = \gamma y_{t-1} + \mu + \delta t + \varepsilon_t$	$\gamma = 0$	Standard Normal	-1.96
3	$\Delta y_t = \gamma y_{t-1} + \mu + \varepsilon_t$	$\gamma = 0$	τ_μ	-2.89
4	$\Delta y_t = \gamma y_{t-1} + \mu + \varepsilon_t$	$\gamma = \mu = 0$	Φ_1	4.71
4A	$\Delta y_t = \gamma y_{t-1} + \mu + \varepsilon_t$	$\gamma = 0$	Standard Normal	-1.96
5	$\Delta y_t = \gamma y_{t-1} + \varepsilon_t$	$\gamma = 0$	T	- 1.95

Notes:

- 5% critical values for the tests are based on a sample size of 100 observations.

Perron (1988) argues that the testing procedure starts with the most general model specification and the testing continues down to more restrictive alternatives. The testing stops as soon as the null hypothesis of a unit root is rejected. If it cannot be rejected at any of the stages then the series has a unit root. Steps 2A and 4A are undertaken only if the joint hypotheses in steps 2 and 4 can be rejected, respectively.

However, even when asymptotic normality holds for the τ_τ and τ_μ statistics, the DF distribution provides a better approximation than the standard normal in finite samples. Harris (1995) argues that the results obtained from steps 2A and 4A should be treated with caution and that tests based on the DF distribution should be preferable. Enders (1995) suggests that rather than applying the Perron (1988) testing strategy, the deterministic regressors in the DF tests should be determined using the information provided by the series. The plots of spot and FFA prices in chapter one, do not indicate that any of the series contains a deterministic trend, although the mean of the series is different than zero in all the cases. Therefore, only an intercept term should be included in the DF and ADF tests (see next section), as in Equation (2.8).

2.4.2. Augmented Dickey and Fuller Test

The DF test can be extended to accommodate higher order autoregressive processes. Lagged values of the dependent variable are added to compensate for the presence of autocorrelation in the residual series since the DF distribution in based on the assumption that ε_t is white noise. These tests are called Augmented Dickey Fuller tests (ADF, 1981). We have so far assumed that the disturbance term, ε_t, is an iid process. If this assumption is incorrect then the limiting distributions and critical values obtained by the DF test cannot be assumed to hold. However, Dickey and Fuller (1981) demonstrate that the limiting distributions and critical values that they obtain under the assumption that ε_t is an iid process are in fact also valid when ε_t is autoregressive if the ADF regression is run.

The null hypothesis is the existence of a unit root. Fuller (1976) reports the appropriate cumulative distribution and the critical values. Critical values for the ADF (1981) statistics, computed from sample sizes smaller than 100, are provided in Engle and Yoo (1987). The null and alternative hypotheses in the standard unit root tests can be interchanged. The appropriate regressions are:

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \varepsilon_t \tag{2.10}$$

$$\Delta y_t = \mu + \gamma y_{t-1} + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \varepsilon_t \tag{2.11}$$

$$\Delta y_t = \mu + \delta t + \gamma y_{t-1} + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \varepsilon_t \tag{2.12}$$

In performing the ADF (1981) tests it is important to select the appropriate lag-length, p; too few lags may result in over-rejecting the null hypothesis of a unit root when it is actually true, while too many lags may reduce the power of the test (i.e. the probability of rejecting a false null hypothesis). An appropriate solution for the choice of p is to use a model selection criterion such as the Akaike Information Criterion (AIC) (Akaike, 1973) or the Schawarz Bayessian Information Criterion (SBIC) (Schwarz, 1978):

$$\text{AIC} = -2(LL - K) \tag{2.13}$$

$$\text{SBIC} = -2(LL - 0.5K\,\text{In}T) \tag{2.14}$$

where LL is the maximum value of the log-likelihood function of the ADF regression, K is the number of regressors and T is the number of observations. These criteria trade off the increase in the value of the log-likelihood function against the loss of degrees of freedom when the lag-length of the model increases. The selected model is the one which receives the highest value of the AIC or SBIC. Usually, the SBIC is preferred over the AIC because it is strongly consistent, penalise for the degrees of freedom lost, and always determines the true model asymptotically, whereas for the AIC an over-parameterised model will always emerge. Dickey and Fuller (1981) argue that the ADF procedure is valid asymptotically as long as the value of p used in estimation increases at the rate $T^{1/3}$ as the sample size, T, increases. In practice it is usual to include as many terms in the lagged dependent variable as is necessary to achieve white noise residuals.

2.4.3. Phillips and Perron Test

The ADF (1981) test includes additional higher-order lagged terms to account for the fact that the underlying d.g.p. is more complicated than a simple AR(1) process. The extra terms, involving lags of the dependent variable, are used to *whiten* the error term in the regression equation used for testing, since autocorrelated errors (due to the misspecification of the dynamic structure of y_t) will invalidate the use of the DF distribution. An alternative approach is that suggested by Phillips (1987) and extended by Perron (1988) and Phillips and Perron (1988). Rather than taking account of extra terms in the d.g.p. by adding them to the regression model, a non-parametric correction to the *t*-test statistic is undertaken to account for the autocorrelation that will be present (when the underlying d.g.p. is not AR(1)). Thus, DF-type Equations (2.7) to (2.9) are estimated, in line with Perrons (1988) testing strategy, and then the *t*-test statistic (of the null hypothesis of non-stationarity) is amended to take account of any bias due to autocorrelation in the error term of the DF-type regression model.

The Phillips and Perron (1988) tests use a non-parametric adjustment to the standard Dickey-Fuller tests for non-independent and identically distributed processes in order to handle any possible serial correlation or time-dependent heteroskedasticity in the residuals, and accommodate models with a drift and a time trend so that they may be used to discriminate between unit root non-stationarity and stationarity about a deterministic trend. The tests involve computing one of three OLS regressions defined from:

$$y_t = \hat{\alpha} y_{t-1} + \hat{\varepsilon}_t \tag{2.15}$$

$$y_t = \mu^* + \alpha^* y_{t-1} + \varepsilon_t^* \tag{2.16}$$

$$y_t = \bar{\mu} + \bar{\beta}(T - t/2) + \bar{\alpha} y_{t-1} + \bar{\varepsilon}_t \tag{2.17}$$

where T denotes the sample size and the disturbance terms ($\hat{\varepsilon}_t, \varepsilon_t^*, \bar{\varepsilon}_t$) are such that their expected values are zero, but there is no requirement that the disturbance terms are serially uncorrelated or homogeneous. Instead of the Dickey-Fuller assumptions of independence and homogeneity, the Phillips-Perron (PP, 1988) tests allow the disturbances to be weakly dependent and heterogeneously distributed.

Given Equation (2.15), the null hypothesis of a unit root, i.e. H_0^1: $\hat{\alpha} = 1$, is tested against the stationary alternative by the adjusted t-statistic $Z(t_{\hat{\alpha}})$ given in Table 2.2. In the model of Equation (2.16) the null hypotheses of a unit root, with or without a drift, i.e. H_0^2: $\alpha^* = 1$ and H_0^3: $\mu^* = 0$, $\alpha^* = 1$, are tested against the stationary alternatives by means of the adjusted t- and F-statistics $Z(t_{\alpha^*})$ and $Z(\varphi_1)$, respectively given in Table 2.2. Finally, in the model of Equation (2.17), which allows for a deterministic trend, the null hypotheses H_0^4: $\overline{\alpha} = 1$, H_0^5: $\overline{\beta} = 0, \overline{\alpha} = 1$, and H_0^6: $\overline{\mu} = 0, \overline{\beta} = 0, \overline{\alpha} = 1$ can be tested by means of the test statistics $Z(t_{\overline{\alpha}})$, $Z(\varphi_3)$, and $Z(\varphi_2)$, respectively given in Table 2.2. The critical values for the PP (1988) statistics are precisely those given for the Dickey-Fuller tests.

Table 2.2. Test Statistics for a Unit Root in the Univariate Models (2.15) – (2.17)

Null Hypothesis	Test Statistics	Critical Values
$\hat{\alpha} = 1$ in (2.15)	$Z(t_{\hat{\alpha}}) = (S_0/S_{Tl})t_{\hat{\alpha}} - \frac{1}{2}(S_{Tl}^2 - S_0^2)$ $[T^{-1}S_{Tl}(\Sigma\, y_{t-1}^2)^{\frac{1}{2}}]^{-1}$	Fuller (1976, Table 8.5.2)
$\alpha^* = 1$ in (2.16)	$Z(t_{\alpha^*}) = (S_0/S_{Tl})\, t_{\alpha^*} - (\frac{1}{2}S_{Tl})\,(S_{Tl}^2 - S_0^2)$ $[T^{-2}\Sigma\,(y_{t-1} - \overline{Y}_{-1})^2]^{-\frac{1}{2}}$	Fuller (1976, Table 8.5.2)
$\mu^* = 0$, $\alpha^* = 1$ in (2.16)	$Z(\varphi_1) = (S_0^2/S_{Tl}^2)\varphi_1 - (\frac{1}{2}S_{Tl}^2)(S_{Tl}^2 - S_0^2)$ $\{T(\alpha^* - 1) - \frac{1}{4}(S_{Tl}^2 - S_0^2)\,[T^{-2}\Sigma\,(y_{t-1} - \overline{Y}_{-1})^2]^{-1}\}$	Dickey and Fuller (1981, Table IV)
$\overline{\alpha} = 1$ in (2.17)	$Z(t_{\overline{\alpha}}) = (S_0/S_{Tl})t_{\overline{\alpha}} - (S_{Tl}^2 - S_0^2)T^3$ $\{S_{Tl}4(3D_x)^{-\frac{1}{2}}\}^{-1}$	Fuller (1976, Table 8.5.2)
$\overline{\beta} = 0, \overline{\alpha} = 1$ in (2.17)	$Z(\varphi_3) = (S_0^2/S_{Tl}^2)\varphi_3 - (\frac{1}{2}S_{Tl}^2)(S_{Tl}^2 - S_0^2)$ $[T(\alpha - 1) - T^6/48D_x)\,(S_{Tl}^2 - S_0^2)]$	Dickey and Fuller (1981, Table IV)
$\overline{\mu} = 0, \overline{\beta} = 0, \overline{\alpha} = 1$ in (2.17)	$Z(\varphi_2) = (S_0^2/S_{Tl}^2)\varphi_2 - (1/3S_{Tl}^2)(S_{Tl}^2 - S_0^2)$ $[T(\overline{\alpha} - 1) - T^6/48D_x)\,(S_{Tl}^2 - S_0^2)]$	Dickey and Fuller (1981, Table IV)

Notes:

- $\varphi_1 = (2S^{*2})^{-1}\, T(S_0^2 - S^{*2})$, $\varphi_3 = (2\,\overline{S}^2)^{-1}\, T[S_0^2 - (\overline{Y} - \overline{Y}_{-1})^2 - \overline{S}^2]$, and $\varphi_2 = (3\,\overline{S}^2)^{-1}\, T(S_0^2 - \overline{S}^2)$
- $t_{\hat{\alpha}}$, t_{α^*}, and $t_{\overline{\alpha}}$ are the standard t-test statistics for $\hat{\alpha} = 1$ in (2.15), $\alpha^* = 1$ in (2.16), and $\overline{\alpha} = 1$ in Equation (2.17), respectively.
- D_x is the determinant of $(x'x)$, where x denotes the Tx3 matrix of explanatory variables in the OLS regression by Equation (2.17).
- S_0^2, S^{*2}, and $\overline{S}^2$ denote the residual variance under the appropriate null hypotheses and OLS residual variances, respectively.
- S_{Tl}^2 refers to a consistent estimator for the variance of $\Sigma\,\varepsilon_t$, under the appropriate null hypothesis, as defined by $S_{Tl}^2 = T^{-1}\sum_{t=1}^{n}\varepsilon_t^2 + 2T\sum_{\tau=1}^{l}\sum_{t=\tau+1}^{n} w_{\tau l}\,\varepsilon_t\,\varepsilon_{t-\tau}$ and the weights $w_{\tau l} = 1 - \tau/(l+1)$ ensure that the estimate of the variance S_{Tl}^2 is positive (see Newey and West, 1987).

Both the PP (1988) and the ADF (1981) approaches are based on asymptotic theory. Thus, in both cases it is important to consider how well the limiting distributions approximate the finite sample distribution of the relevant statistic. In addition it is interesting to consider whether there is evidence concerning the relative power properties of the PP (1988) statistics as compared to the ADF (1981) statistics. Monte Carlo work by Schwert (1987) suggests that the Phillips-type tests have poor size properties, with the tendency to over-reject the null when it is true, when the underlying d.g.p. has negative moving-average components.

Phillips and Perron (1988) assume that ε_t in Equation (2.8) is generated by a MA(1) process in their simulation experiments:

$$\varepsilon_t = \theta e_{t-1} + e_t \tag{2.18}$$

where e_t are iid. They find that when the disturbance term has a positive moving average component (θ is positive) the power of ADF (1981) tests is low compared to the PP (1988) statistics, so that the latter statistics is preferred. However, when θ is negative, matters are less clear since the evidence suggests that the PP (1988) statistics can have serious finite sample size distortions in this case.

An indication as to whether the PP (1988) statistics should be used in addition to (or in place of) the ADF (1981) tests might be obtained in the diagnostic statistics from the DF and ADF regressions. If normality, autocorrelation or heterogeneity statistics are significant, one might adopt the PP approach. Furthermore, power may be adversely affected by misspecifying the lag length in the ADF regression, although it is unclear how far this problem is mitigated by choosing the number of lags using data-based criteria, and the PP (1988) tests have the advantage that this choice does not have to be made. Against this, one should avoid the use of the PP (1988) tests if the presence of negative moving average components is somehow suspected in the disturbances (Bhaskara, 1994).

2.5. COINTEGRATION TESTS

2.5.1. The Cointegration Concept

The basic idea behind cointegration is that if all the components of a vector time-series process X_t, $[y_t\ z_t]'$, have a unit root there may exist linear combinations $\xi^T X_t$ without a unit root. These linear combinations may then be interpreted as long-term relations between the components of X_t, or in economic terms as static equilibrium relations. Therefore, the concept of cointegration mimics the existence of a long-run equilibrium relationship to which an economic system converges over time, and ε_t (the residuals obtained from regressing y_t on z_t) can be interpreted as the disequilibrium error, i.e. the distance that the system is away from equilibrium at time *t*. For bivariate economic *I*(1) processes, cointegration often manifests itself by more or less parallel shapes of the plots of the two series involved.

The concept of cointegration was first introduced by Granger (1981) and elaborated further by Engle and Granger (1987), Engle and Yoo (1987, 1991), Phillips and Ouliaris (1990), Stock and Watson (1988), Phillips (1991), Johansen (1988, 1991) and Bierens (1997), amongst others. Working in the context of a bivariate system with at most one cointegrating vector, Engle and Granger (1987) estimate the cointegrating vector $\xi = (1, \xi_2)^T$ by regressing the first component $x_{1,t}$ (y_t) of X_t on the second component $x_{2,t}$ (z_t), using OLS, and then testing whether the OLS residuals of this regression have a unit root, using the ADF (1981) test. However, since the ADF (1981) test is conducted on estimated residuals, the tables of the critical values of this test in Fuller (1976) do not apply anymore. The correct critical values involved can be found in Engle and Yoo (1987)[28].

Phillips and Ouliaris' (1990) tests are also based on these residuals, but instead of using the ADF (1981) test for testing the presence of a unit root they use further elaborations of the Phillips (1987) and Phillips and Perron (1988) unit root tests. Both types of tests have absence of cointegration as the null hypothesis. Their main disadvantage is that they cannot apply parameter restrictions on the cointegrating vector in order to test for hypotheses.

[28] For a further analysis of the Engle and Granger (1987) test see next section.

Park (1992) proposes a test for unit root and cointegration using the variable addition approach, by regressing the OLS residuals of the cointegrating regression on powers of time and testing whether the coefficients involved are jointly zero. The same idea has been used by Bierens and Guo (1993) to test (trend) stationarity against the unit root hypothesis. However, also Park's approach requires consistent estimation of the long-run variance of the errors of the true cointegrating regression by a Newey-West (1987) type estimator, which sacrifices a substantial amount of asymptotic power of the test, and consequently it is not recommended when the sampling period is small. Also the tests of Hansen (1992) and Park (1992) are based on a single cointegrating regression, and both tests employ variants of the instrumental variables estimation method of Phillips and Hansen (1990).

2.5.2. Engle and Granger Test

If the long-run components in two time-series are modelled as stochastic trends and if they move together, then the two time-series should be cointegrated (Granger, 1986). Engle and Granger (EG, 1987) propose the following two-step approach for testing for cointegration of two series. The first step tests whether each of the two variables of interest has a stochastic trend ($I(1)$). That is investigated by performing unit root tests on the variables. If both variables are found non-stationary then, the second step tests whether stochastic trends in these variables are related. This is investigated by estimating the residuals, ε_t, from the following regression, called the cointegrating or equilibrium regression:

$$y_t = \beta_1 + \beta_2 z_t + \varepsilon_t \tag{2.19}$$

If y_t and z_t are cointegrated, then the estimated residual series ($\hat{\varepsilon}_t$) must be stationary. The $\hat{\varepsilon}_t$ series represents the deviations of y_t and z_t from their long-run relationship. Testing the residuals for stationarity, under the Engle and Granger methodology, involves one of the following: (i) the Durbin-Watson statistic from the cointegration regression of Equation (2.19) (CRDW statistic). If the Durbin-Watson statistic is sufficiently large, is deemed stationary and the two series are cointegrated; (ii) the Dickey-Fuller (1979) type regressions to test whether the estimated time-series of the residuals from the cointegration regression has a unit root (if there is a unit root the two series are not cointegrated); or (iii) the ADF (1981) test which is similar to the previous, but additional lags of the residuals are used to be sure that the residuals are uncorrelated. The ADF (1981) test is based on the estimated residual series $\widehat{\varepsilon}_t$:

$$\Delta\widehat{\varepsilon}_t = \psi_0 \widehat{\varepsilon}_{t-1} + \sum_{i=1}^{p-1} \psi_i \Delta\widehat{\varepsilon}_{t-i} + \omega_t \quad ; \quad \omega_t \sim IN\left(0, \sigma_\omega^2\right) \tag{2.20}$$

where lagged values of $\Delta\widehat{\varepsilon}_{t-i}$ are entered into the equation so as to *whiten* the errors. The inclusion of a trend term and/or a constant in Equation (2.20) depends on whether a constant or a trend appears in the cointegrating regression since deterministic components can appear in Equation (2.19) or in Equation (2.20). If deterministic terms appear in both Equations (2.19) and (2.20) then, the cointegrating test is misspecified (Harris, 1995).

The null hypothesis of no cointegration (existence of a unit root), in the estimated residual series, H_0: $\psi_0 = 0$, is based on a *t*-test with a non-normal distribution. Since all unit root tests are concluded on estimated residuals, the tables of the critical values of the DF (1979) and ADF (1981) tests in Fuller (1976) do not apply anymore. The correct critical values for DF (1979) and ADF (1981) tests are given by Engle and Yoo (1987) and MacKinnon (1991)[29].

The Granger Representation Theorem (Engle and Granger, 1987) states that if a set of non-stationary variables are cointegrated then an Error-Correction Model (ECM) can be estimated, and conversely, if a set of non-stationary variables can be modelled as an ECM then, these variables are cointegrated. Engle and Granger (1987) following their theorem, try to identify an ECM of the joint process, using the estimates of last period's disequilibrium $\widehat{\varepsilon}_{t-1} = y_{t-1} - \beta_1 - \beta_2 z_{t-1}$ to obtain information on the speed of adjustment to equilibrium:

$$\Delta y_t = -\alpha_1 \widehat{\varepsilon}_{t-1} + \gamma_1 \Delta z_t + \sum_{j=1}^{m} \theta_j \Delta z_{t-j} + \sum_{j=1}^{k} \varphi_j \Delta y_{t-j} + v_t \quad ; \quad v_t \sim IN\left(0, \sigma_v^2\right) \tag{2.21}$$

[29] Moreover, the Box-Pierce (1970) statistic can also be employed to test for serial correlation, which has a χ^2distribution.

where α_1 is the speed of adjustment coefficient and lagged values of Δy_t and Δz_t are included in the model to capture any autocorrelation in the residuals. All the terms in Equation (2.21) are stationary and hence, statistical inference using standard *t*- and *F*-tests is applicable.

The ECM representation incorporates short-run adjustment of Δy_t to changes in the right-hand side variables, captured by current and past values of Δz_t and lagged values of Δy_t, and long-run adjustment through the ECT, $\hat{\varepsilon}_{t-1}$, which measures the distance of the system being away from equilibrium (speed of adjustment). For example, suppose that y_t starts falling more rapidly than is consistent with Equation (2.19); this results in $\hat{\varepsilon}_{t-1} \langle 0$. Since the α_1 coefficient in Equation (2.21) has a negative sign, the net result is an increase in Δy_t, thereby forcing y_t back towards its long-run path.

A problem with this approach is that it requires the researcher to choose one of the jointly endogenous variables to put on the left-hand side. While the test is asymptotically invariant to this so-called direction normalisation rule (order of the variables in the cointegrating regression), the test results may be very sensitive to it in finite samples. Indeed, practical experience indicates that the result of the test depends qualitatively on which variable is chosen to be on the left-hand side (Bhaskara, 1994). Another disadvantage of this procedure is that it is not possible to perform hypothesis tests on the estimated coefficients, β_1 and β_2, in the cointegrating regression Equation (2.19). Durlauf and Philips (1988) derive the asymptotic distributions of the OLS estimators, β_1 and β_2, and their associated standard errors in Equation (2.19) and show these to be highly non-normal thus invalidating standard inference. Although the coefficient estimator can be shown to be consistent, the estimated standard errors may be misleading for hypothesis testing (Stock, 1987)[30].

The ECM of Equation (2.21) imposes the restriction that z_t is *weakly exogenous* to y_t (i.e. the current value of z_t is not affected by the current value of y_t) and, as a result, the z_t series appears only on the right-hand side of Equation (2.21). This does not take into account all the information that the variables have to offer. The Engle and Granger approach is bivariate in design. Johansen (1992) points out that, in general, there are efficiency losses from single-

[30] Stock (1987) suggests a way to correct the estimated standard errors. The statistical test is, however, very sensitive to the nuisance parameters of the underlying series.

equation estimation in cointegrated systems. In addition, Phillips (1991) points out that the use of single-estimation techniques in cointegrated systems imparts second-order asymptotic bias and nuisance parameter dependencies. A multivariate extension was provided by Engle and Yoo (1987).

2.5.3. Johansen Test

Johansen (1988, 1991) and Johansen and Juselius (1990) provide a statistical procedure for testing parameter restrictions in cointegrated systems using the full MLE method, where it allows to formally conducting likelihood ratio tests of the parameters of the equilibrium relationship between non-stationary variables. The procedure is based on a VAR model that allows for possible interactions (short- and long-run dynamics) in the determination of the variables of interest. Furthermore, this procedure does not make any assumptions regarding the exogeneity of the variables, since all variables in the system are endogenous, and uses the information provided by both series so as to generate the cointegration tests[31].

The Johansen (1988) approach is based on the multivariate technique of canonical correlations. The canonical correlation analysis is trying to find a linear combination of a set of variables, such that the correlation among the variables is maximised. Johansen (1988) shows that the hypothesis of cointegration can be formulated as the hypothesis of reduced rank of a regression coefficient matrix, which can be estimated consistently from two vector regression equations. Thus, the likelihood ratio test for cointegration involves deriving the squared canonical correlations between the regression residuals, which require calculation of eigenvalues.

In short, the cointegrating VAR analysis involves a number of steps: (i) ensuring that the jointly determined variables of the model are $I(1)$; (ii) deciding the order of the VAR model; (iii) identifying the nature of the deterministic variables such as intercepts and trends in the underlying VAR; (iv) resolving the identification problem of the long-run relations that arises when the number of the cointegrating relations is larger than unity; and (v) testing over-identifying restriction on the long-run relations. The above steps are presented in the next sections.

[31] Since the Johansen (1988) procedure takes into account the error structure of the underlying d.g.p., the procedure can provide more precise parameter estimates than the Engle and Granger (1987) procedure.

2.5.3.1. VAR and VECM Models

To illustrate the Johansen (1988) cointegration test consider a set of two $I(1)$ variables, (y_t, z_t), which are generated by the following bivariate system.

$$y_t = \sum_{i=1}^{p} A_{11}(i) y_{t-i} + \sum_{i=1}^{p} A_{12}(i) z_{t-i} + \varepsilon_{y,t} \qquad (2.22a)$$

$$z_t = \sum_{i=1}^{p} A_{21}(i) y_{t-i} + \sum_{i=1}^{p} A_{22}(i) z_{t-i} + \varepsilon_{z,t} \qquad (2.22b)$$

where $A_{kj}(i)$ ($k,j = 1, 2$, $i=1, 2, ..., p$) are coefficients and $\varepsilon_{y,t}$ and $\varepsilon_{z,t}$ are uncorrelated white noise disturbances. In matrix form this system (VAR model of order p) can be written as:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + \ldots + A_p X_{t-p} + \varepsilon_t \quad ; \quad \varepsilon_t \sim IN(0,\Sigma) \qquad (2.23)$$

where X_t is the 2x1 vector of variables $(y_t, z_t)'$, ε_t is the 2x1 vector of residuals $(\varepsilon_{y,t}, \varepsilon_{z,t})'$ which are normally distributed with mean zero and variance / covariance matrix Σ and A_i, ($i = 1, 2, ..., p$) are 2x2 matrices of coefficients:

$$A_i = \begin{bmatrix} A_{11}(i) & A_{12}(i) \\ A_{21}(i) & A_{22}(i) \end{bmatrix}$$

By subtracting X_{t-1} from each side of (2.23) we obtain:

$$\Delta X_t = (A_1 - I_2) X_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + \ldots + A_p X_{t-p} + \varepsilon_t$$

where I_2 is a 2x2 identity matrix. Next we add and subtract $(A_1 - I_2)X_{t-2}$ from the right-hand side to obtain:

$$\Delta X_t = (A_1 - I_2) \Delta X_{t-1} + (A_2 + A_1 - I_2) X_{t-2} + A_3 X_{t-3} + \ldots + A_p X_{t-p} + \varepsilon_t$$

Next we add and subtract $(A_2 + A_1 - I_2)X_{t-3}$ from the right-hand side to obtain:

$$\Delta X_t = (A_1 - I_2)\Delta X_{t-1} + (A_2 + A_1 - I_2)\Delta X_{t-2} + (A_3 + A_2 + A_1 - I_2)X_{t-3} + \ldots + A_p X_{t-p} + \varepsilon_t$$

Continuing in this stepwise fashion we obtain:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \qquad (2.24)$$

where $\Pi = -\left(I_2 - \sum_{i=1}^{p} A_i\right)$ and $\Gamma_i = -\left(I_2 - \sum_{j=1}^{i} A_j\right)$. Equation (2.24) is called a VECM. The VECM specification contains information on both the short- and long-run adjustment to changes in X_t, via the estimates of Γ_i and Π, respectively. Johansen and Juselius (1990) show that the coefficient matrix Π contains the essential information about the relationship between y_t and z_t. In order to examine for cointegration relationships between the two variables of interest y_t and z_t we examine the rank of matrix Π[32]. If rank(Π) = 0, then Π is the 2x2 zero matrix implying that there are no any cointegrating relationships between y_t and z_t; in this case Equation (2.24) is reduced to a VAR model in first differences. If rank(Π) = 2 (full rank), then all the variables in X_{t-1} are stationary and the a VAR model in levels as in Equation (2.23) is estimated. If rank(Π) = 1 (reduced rank), *then there is a single cointegration relationship* between y_t and z_t, which is given by any row of matrix Π and the expression ΠX_{t-1} is the ECT.

The rank of Π is equal to the number of its characteristic roots (or eigenvalues) which are different from zero. Thus, the number of distinct cointegrating vectors can be obtained by estimating how many of these eigenvalues are significantly different from zero[33]. The above VECM is based on the Engle and Granger (1987) error-correction representation theorem for cointegrated systems, and the asymptotic inference is related to the work of Sims *et al.* (1990). A cointegrating relationship in the system $(y_t, z_t)'$ implies that there are 2xr (where r is the number of cointegrating relationship(s)) such that $\Pi = \alpha\beta'$ and rank(Π)= r = 1. The matrix β

[32] The rank of a square n x n matrix is the number of its linearly independent rows, or columns.
[33] The characteristic roots (or eigenvalues) of a square nxn matrix Π, are the values of λ that satisfy the following equation $|\Pi - \lambda I_n| = 0$, where I_n is an nxn identity matrix.

represents the cointegrating vector(s) and matrix a represents the speed of adjustment parameters (weights).

By step-wise concentrating all the parameter matrices in the likelihood function out, except the matrix β, Johansen (1988) shows that the MLE of β can be derived as the solution of a generalised eigenvalue problem. Likelihood ratio tests of hypotheses about the number of cointegrating vectors can then be based on these eigenvalues. Johansen (1988) proposes the following two statistics to test for the significance of the estimated eigenvalues.

$$\lambda_{\text{trace}}(r) = -T\sum_{i=r+1}^{n} 1\text{n}\left(1-\hat{\lambda}_i\right) \tag{2.25}$$

$$\lambda_{\max}(r, r+1) = -T1\text{n}\left(1-\hat{\lambda}_{r+i}\right) \tag{2.26}$$

where $\hat{\lambda}_i$ are the eigenvalues obtained from the estimate of the Π matrix and T is the number of usable observations. The λ_{trace} tests the null that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r and the $\lambda_{\max}$ tests the null that the number of cointegrating vectors is r, against the alternative of r + 1. Critical values for the λ_{trace} and $\lambda_{\max}$ statistics are provided by Osterwald-Lenum (1992). The distribution of these statistics depends upon the number or non-stationary relationships under the null and on the deterministic terms that are included in the VECM.

Consider the model in Equation (2.24), which can be expressed in terms of specific equations for each ΔX_t sequence as follows:

$$\begin{pmatrix} \Delta y_t \\ \Delta z_t \end{pmatrix} = \sum_{i-1}^{p-1}\Gamma_i\begin{pmatrix} \Delta y_{t-i} \\ \Delta z_{t-i} \end{pmatrix} + \begin{pmatrix} \pi_{11}\pi_{12} \\ \pi_{21}\pi_{22} \end{pmatrix}\begin{pmatrix} y_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{z,t} \end{pmatrix} \tag{2.27}$$

Since rank(Π) = 1, the rows of Π are linear multiples of each other and differ by a scalar, s_2:

$$\begin{pmatrix} \Delta y_t \\ \Delta z_t \end{pmatrix} = \sum_{i=1}^{p-1} \Gamma_i \begin{pmatrix} \Delta y_{t-i} \\ \Delta z_{t-i} \end{pmatrix} + \begin{pmatrix} \pi_{11} & \pi_{12} \\ s_2\pi_{11} & s_2\pi_{12} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{z,t} \end{pmatrix} \tag{2.28}$$

where s_2 is a scalar such as $s_2 \pi_{11} = \pi_{21}$ and $s_2 \pi_{12} = \pi_{22}$. Now if we define $\alpha_i = s_i \pi_{11}$, where $s_1 = 1$, and $\beta_j = \pi_{1j} / \pi_{11}$ we can transform each equation as:

$$\begin{pmatrix} \Delta y_t \\ \Delta z_t \end{pmatrix} = \sum_{i=1}^{p-1} \Gamma_i \begin{pmatrix} \Delta y_{t-i} \\ \Delta z_{t-i} \end{pmatrix} + \begin{pmatrix} \alpha_1 & \alpha_1\beta_2 \\ \alpha_2 & \alpha_2\beta_2 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{z,t} \end{pmatrix} =$$

$$= \sum_{i=1}^{p-1} \Gamma_i \begin{pmatrix} \Delta y_{t-i} \\ \Delta z_{t-i} \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \begin{pmatrix} \beta_1 & \beta_2 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{z,t} \end{pmatrix} \tag{2.29}$$

where $\alpha_1 = \pi_{11}$, $\alpha_2 = s_2 \pi_{11}$, $\beta_1 = \pi_{11} / \pi_{11} = 1$, $\beta_2 = \pi_{12} / \pi_{11}$. Therefore, the general form of the VECM becomes:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha\beta' X_{t-1} + \varepsilon_t \tag{2.30}$$

where $\beta' = (1 \ \beta_2)$ is the cointegrating vector, normalised with respect to the coefficient of y_{t-1} and the speed of adjustment coefficients are given by $\alpha = (\alpha_1 \ \alpha_2)'$; these show how fast Δy_t and Δz_t respond to disequilibrium changes from the cointegrating vector. For instance, the larger α_1 is, the greater is the response of Δy_t to the previous period's deviation from long-run equilibrium. At the opposite extreme, very small values of α_1 imply that Δy_t is unresponsive to the previous period's error. For y_t and z_t to be cointegrated then at least one of the α_1 and α_2 coefficients must be significantly different from zero.

Once the number of the cointegrating relations and the estimates of the cointegrating vectors have been identified, estimation of the short-run and the error-correction coefficients of Equation (2.30) is carried out by estimating each equation separately using OLS. If some of the short-run coefficients in the VECM are insignificant, then they may be excluded from the model specification so as to arrive at the most parsimonious model. In this case, the two models in Equation (2.30) contain different sets of regressors (either different variables or different lag structures for each variable) and the VECM should be estimated as a system of Seemingly Unrelated Regressions Estimation (SURE) (Zellner, 1962). This method yields more efficient estimates than OLS when the equations in the system contain different regressors.

We should notice that, the determination of cointegration rank is difficult for a number of reasons, including the following: deterministic terms (such as constants and trends) play a crucial role in limiting distributions; the system may not be formulated to ensure the asymptotic similarity of key test statistics to nuisance parameters; alternative choices of test statistics may deliver apparently conflicting inferences; finite-sample critical values may differ substantially from their asymptotic equivalents; the asymptotic distributions themselves are usually approximations, obtained by simulation and possibly summarised by response surfaces; dummy variables can alter critical values; and the lag length selected may not remove all residual serial correlation, or it may be too long (Doornik and Nielsen, 1999).

2.5.3.2. Model Specification

Initially, Johansen (1988) considers the case where X_t is absent. Later on, Johansen (1991) extends his approach to the case where X_t contains an intercept and seasonal dummy variables, and in Johansen (1995) also a time trend in X_t (but no seasonal dummy variables) is allowed. These three cases lead to different null distributions of the likelihood ratio tests of the number of cointegrating vectors. Moreover, also possible restrictions on the vector of intercepts or the vector of trend coefficients may lead to different null distributions. Finally, the lag length, p, of the VECM must be determined. For example, we estimate the unrestricted VAR model of Equation (2.23), using the longest lag length deemed reasonable for the data set, and then use a model selection criterion, such as the AIC (1973) or the SBIC (1978) of Equations (2.13) and (2.14), respectively to arrive at the most parsimonious model[34]. Thus, application of Johansen's tests actually requires some *a priori* knowledge about the true parameters of the VECM.

[34] For instance, 4, 12 and 21 lags can be chosen for quarterly, monthly and daily data, respectively.

Johansen and Juselius (1990) and Ostarwald-Lenum (1992) modify the VECM to contain an intercept, a linear trend or both, arriving at five different model specifications where the short-run and the long-run parts of the VECM refer to the lagged values of ΔX_{t-i} and to the cointegrating relationship, $\alpha\beta' X_{t-1}$, respectively.

Model A: Linear trend and intercept in the short-run model:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha\beta' X_{t-1} + \mu + \delta t + \varepsilon_t \tag{2.31}$$

This is the most unrestricted form of the VECM. It indicates the existence of linear trends in the differenced series, ΔX_t, and hence, the existence of quadratic trends in the levels series, X_t. However, the existence of quadratic trends in the levels series implies an ever-increasing (or decreasing) rate of growth for these series, which, is difficult to be justified on economic grounds (Harris, 1995).

Model B: Trend term in the long-run model and intercept term in the short-run model:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \begin{pmatrix} \beta \\ \delta \end{pmatrix}' \left(X'_{t-1} \ \ t \right)' + \mu + \varepsilon_t \tag{2.32}$$

This model allows for the presence of a trend term in the cointegrating vector so as to account for the any exogenous growth in the long-run relationship.

Model C: Intercept term in the short-run model:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha\beta' X_{t-1} + \mu + \varepsilon_t \tag{2.33}$$

This model specification allows for the existence of a linear trend in the levels of the data.

Model D: Intercept term in the long-run model:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \begin{pmatrix} \beta \\ \mu \end{pmatrix}' \left(X'_{t-1} \ \ 1 \right)' + \varepsilon_t \tag{2.34}$$

This model implies that there are no linear trends in the levels of the data and the intercept is restricted in the cointegration space to account for the units of measurement of the variables.

Model E: No deterministic components in the short-run model or in the cointegrating relations:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \beta' X_{t-1} + \varepsilon_t \tag{2.35}$$

This is the most restricted model and implies that the mean of the series, in X_t, is zero.

After excluding the unwanted models, following arguments from the economic theory, that are relevant to the investigated market, we arrive at two competing models. To determine which model should be used the Johansen's (1991) test is employed with the null hypothesis to be the acceptance of the first model (out of the two) and the alternative to be the acceptance of the second model:

$$-T\left[\ln\left(1-\hat{\lambda}_2^*\right) - \ln\left(1-\hat{\lambda}_2\right)\right] \sim \chi^2(1) \tag{2.36}$$

where $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ represent the smallest eigenvalues of the first and the second chosen model, respectively. For the null hypothesis to be true, the values of $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ should be equivalent. Johansen (1991) argues that if the test statistic is large, it is possible to reject the null hypothesis and accept the model of the alternative hypothesis.

2.5.3.3. Parameter Restrictions Tests

Linear parameter restriction tests on the matrix β are attained by forming likelihood ratio statistics from restricted and unrestricted model estimations, by comparing the number of cointegrating relationships under the null and alternative hypotheses. This is useful when the researcher must apply a hypothesis test in order to identify whether the variables follow a particular long-run relationship, which is dictated by economic theory. For instance, the unbiasedness hypothesis suggests that forward prices before maturity must be equal to the realised spot prices, so that the cointegrating relationship between the series is (1, -1) (S_t $F_{t,t-n}$)'. Johansen and Juselius (1990) argue that since the number of cointegrating relationships depends on the number of the largest eigenvalues of the Π matrix, in Equation (2.24) that are significantly different form zero, the test compares the largest eigenvalues of the restricted and the unrestricted models:

$$-T\left[\mathrm{In}\left(1-\hat{\lambda}_1^*\right)-\mathrm{In}\left(1-\hat{\lambda}_1\right)\right] \sim \chi^2(\mathrm{n}) \tag{2.37}$$

where $\hat{\lambda}_1$ is the largest eigenvalue of the unrestricted model and $\hat{\lambda}_1^*$ is the largest eigenvalue of the model with the imposed restrictions on the cointegrating vector. The *asymptotic distribution* of the likelihood ratio test statistic is χ^2 with degrees of freedom equal to the number of assumed parameter restrictions (n) placed on β'. Small values of $\hat{\lambda}_1^*$ relative to $\hat{\lambda}_1$ indicate a reduced number of cointegrating vectors and a larger value for the likelihood ratio statistic. Hence, the restriction embedded in the null hypothesis is rejected if the calculated value of the test statistic exceeds that in a χ^2 table.

The Johansen test should be preferred to the Engle and Granger test since it is robust to various departures from normality, it does not suffer from problems associated with normalisation, and more is known about its asymptotic behaviour[35]. Johansen (1995), shows that his test provides more efficient estimates of the cointegrating relationship that the EG test. Cheung and Lai (1993) argue that the Johansen's test is fairly robust to the presence of non-normality.

[35] See Hall and Taylor (1989) for a discussion of the relative merits of the Johansen test.

2.6. THEORY OF ARCH AND GARCH MODELS

Despite the popularity of ARMA models, they have a significant limitation, namely, they assume constant volatility. In financial economics, where correct specification of volatility is of the utmost importance, this can be a severe limitation. Investigating and modelling the behaviour of the second moment (variance) of time-series, which is considered as a measure of volatility, is proved to be of great importance. Mandelbort (1963) argues that large (small) changes tend to be followed by large (small) changes, a phenomenon he defines as *volatility clustering*. The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility many periods in the future. Mandelbort's study inspired a series of studies in modeling the behaviour of variance. ARCH models, proposed by Engle (1982), were specifically designed to model and forecast conditional variances. The variance of the dependent variable is conditioned on the square of lagged shocks in the series in an autoregressive form.

Since then, numerous studies in the literature are devoted in developing and finding the best functional form for this class of models. For example, Bollerslev (1986) proposes the Generalised ARCH (GARCH) model; Engle *et al.* (1987) introduces ARCH in Mean (ARCH-M) model; Bollerslev *et al.* (1988) develops the Multivariate GARCH (MGARCH) model; Nelson (1991) extends ARCH models to allow for asymmetric effects of shocks on volatility (Exponential ARCH or EARCH), amongst others. These models are widely used in various branches of econometrics, especially in financial time-series analysis in different areas as for example, asset pricing, exchange rates, and interest rates. Bollerslev *et al.* (1992), Bera and Higgins (1993), Engle (1993), and Bollerslev *et al.* (1994) are among the recent surveys of the extensions of ARCH class of models and cite a large number of papers in different directions of specification, estimation and applications of these models.

One of the assumptions of the classical linear regression, for the parameter estimates to be Best Linear Unbiased Estimators (BLUE), is that the residuals must be homoskedastic (the variance of the residuals, σ^2, must be constant). However, if σ^2 is time dependent (residuals show time-varying heteroskedasticity), then the OLS estimators are not BLUE. In a seminal paper, Engle (1982) proposes a test to detect such variations in the variance and then uses these variations to measure and model the volatility of the dependent variable(s). Engle's (1982) test is based on an auxiliary regression of squared residuals (from the original regression) on lagged squared residuals and an error term, which is iid with zero mean and constant variance. The joint significance of parameters of lagged squared residuals can be tested using Lagrange Multiplier (LM) or F-tests and indicates if the lagged squared residuals can explain the current squared residuals.

In the linear GARCH(p, q) model with Gaussian shocks ε_t, the conditional variance is postulated to be a linear function of the past q squared innovations (the ARCH term) and of the past p conditional variances (the GARCH term):

$$y_t = \varphi_0 + \sum_{i=1}^{k} \varphi_i x_t + \varepsilon_t \quad ; \quad \varepsilon_t | \Omega_{t-1} \sim \mathrm{iid}(0, h_t) \qquad (2.38a)$$

$$h_t = a_0 + \sum_{i=1}^{p} a_i h_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \qquad (2.38b)$$

Equation (2.38a) is the mean equation and is written as a function of exogenous variables with an error term. Since h_t is the one-period ahead forecast variance based on past information, Equation (2.38b) is called the conditional variance. The conditional variance is a function of three terms: the mean a_0, news about volatility from the past periods, measured as the lag of the squared residual from the mean Equation (2.38a), ε_{t-j}^2, and past forecast variances, h_{t-i}. This process is described by q coefficients $\beta_j, j = 0,\ldots, q$; p+1 coefficients a_i, $i = 1,\ldots, p$; mean φ_0; k linear regression coefficients φ_i, $i = 1,\ldots, k$; endogenous and exogenous variables y_t and x_t, respectively; shocks ε_t; and the set of all information up to time t-1, Ω_{t-1}.

For this model to be well defined and the conditional variance to be positive, almost surely the parameters must satisfy $a_0 > 0$, $a_i > 0$, and $\beta_j > 0$. The process is stationary with a finite variance if and only if $0 < \sum_{i=1}^{p} a_i + \sum_{j=1}^{q} \beta_j < 1$. For $p = 0$ a GARCH(p, q) model is called the ARCH(q) model of Engle (1982). The number of the lagged error terms and lagged variances in the variance equation is called the order of ARCH or GARCH model, denoted ARCH(p) or

GARCH(p, q), respectively. However, the most common type of GARCH(p, q) model used in the literature to model economic variables is the GARCH(1,1) model.

Significance of lagged variance parameters, a_i, in Equation (2.38b) indicates the dependence of the current value of the conditional variance on its lagged values. On the other hand, if the parameters of lagged squared errors and variance are not statistically significant, then the variance of the regression is constant (no GARCH effects). GARCH(p, q) processes, where the mean is constant (both conditional and unconditional), the unconditional variance is constant, but the conditional variance is non-constant, are uncorrelated but not independent. The dependence of the conditional variance on the past is the reason that the process is not independent. The independence of the conditional mean on the past is the reason that the process is uncorrelated.

In many applications with high frequency data the estimate for $\sum_{i=1}^{p} a_i + \sum_{j=1}^{q} \beta_j$ turns out to be very close to unity. This provides an empirical motivation for the so-called Integrated GARCH(p, q) or IGARCH(p, q) model, introduced by Engle and Bollerslev (1986). In the IGARCH class of models a shock to the conditional variance is persistent in the sense that it remains important for future forecasts of all horizons. IGARCH processes are either non-stationary or have an infinite variance (heavy-tailed distribution).

2.6.1. Multivariate Specifications

The specification of Equation (2.38b) is a univariate GARCH(p, q) model. However, multivariate GARCH(p, q) models can also be used to model the means and variances of two or more variables simultaneously. These types of models have been suggested by Bollerslev *et al.* (1988) in asset pricing specifications.

If two or more time-series are cointegrated then it is suggested that there is a long-run relationship between the variables. If such a relationship exists, one can expect the short-run adjustment to the long-run equilibrium to influence both the mean and the variance of the variables (Lee, 1994). Such a model is known as the multivariate GARCH-X, where the lagged ECT is used in the conditional mean equation to impose the long-run equilibrium relationship, and the conditional volatility equation is augmented with the lagged squared ECT (z_{t-1}^2). As an example the variance and covariance equations of a bivariate GARCH(1,1)-X model can be expressed as follows:

$$h_{11t} = a_{0,1} + b_{11}h_{11,t-1} + c_{11}\varepsilon_{1,t-1}^2 + e_{11}z_{t-1}^2 \tag{2.39a}$$

$$h_{12t} = a_{0,12} + b_{12}h_{12,t-1} + c_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + e_{12}z_{t-1}^2 \tag{2.39b}$$

$$h_{22t} = a_{0,2} + b_{22}h_{22,t-1} + c_{22}\varepsilon_{2,t-1}^2 + e_{22}z_{t-1}^2 \tag{2.39c}$$

The actual implementation of a multivariate GARCH model necessarily requires some assumptions regarding the format of the temporal dependencies in the conditional covariance matrix sequence [$E_{t-1}(\varepsilon_t\varepsilon_t')$]. For a *parameterisation of* $E_{t-1}(\varepsilon_t\varepsilon_t')$ *several key issues must* be considered: First, all useful specifications must necessarily restrict the dimensionality of the parameter space. Second, whether such restrictions impose the required positive definiteness of the conditional covariance matrix estimators. Third, it is important to recognise whether Granger causality in variance, as in Granger *et al.* (1986), is allowed (does the past information on one variable predict the conditional variance of another). Fourth, whether there are linear combinations of the variables with less persistence than individual series.

Let vech(.) denote the vector-half operator of an (NxN) matrix. Since the conditional covariance matrix is symmetric, vech(H_t) contains all the unique elements in H_t. Following Kraft and Engle (1982) and Bollerslev *et al.* (1988), a natural multivariate extension of the univariate GARCH(p, q) model is then:

$$\text{vech}(H_t) = A_0 + \sum_{i=1}^{p} B_i \text{vech}(H_{t-i}) + \sum_{j=1}^{q} C_j \text{vech}(\varepsilon_{t-j}\varepsilon_{t-j}') \tag{2.40}$$

where A_0 is an [N(N + 1)/2] x 1 vector, and the B_i and C_j matrices are of dimension [N(N + 1)/2] x [N(N + 1)/2]. This formulation is the so-called VECH representation, introduced by Engle and Kroner (1995). It allows each of the elements in H_t to depend on all of the most recent q past cross products of the ε_t's and all of the most recent p lagged conditional variances and covariances, resulting in a total of $[N(N + 1)/2][(1 + p + q)\ N(N + 1)/2]$ parameters. However, even for low dimensions of N and small values of q and p, the number of parameters is very large. In practice, some simplifying assumptions will therefore, have to be imposed. In the diagonal GARCH(p, q) model, originally suggested by Bollerslev *et al.* (1988), the B_i and C_j matrices are all taken to be diagonal. This restriction reduces the number of parameters to $[N(N + 1)/2](1 + p + q)$. However, this model clearly does not allow for causality in variance, co-persistence in variance, or asymmetries.

Bollerslev (1990) introduced another attractive way to simplify H_t. Bollerslev assumed that the conditional correlation between the residuals of the mean equations ($\varepsilon_{Y,t}$ and $\varepsilon_{X,t}$) is constant over-time and expressed H_t as:

$$H_t = \begin{bmatrix} h^2_{YY,t} & h^2_{YX,t} \\ h^2_{XY,t} & h^2_{XX,t} \end{bmatrix} = \begin{bmatrix} h_{Y,t} & 0 \\ 0 & h_{X,t} \end{bmatrix} \begin{bmatrix} 1 & \rho_{YX} \\ \rho_{YX} & 1 \end{bmatrix} \begin{bmatrix} h_{Y,t} & 0 \\ 0 & h_{X,t} \end{bmatrix} \tag{2.41}$$

where ρ_{YX} (< 1) is the time-invariant correlation coefficient, and the individual variances $h^2_{Y,t}$ and $h^2_{X,t}$ are assumed to be a standard univariate GARCH process. It is clear that the *constant correlation* representation involves 7 parameters. Also, positive definiteness of the specification is assured if $h_{Y,t} > 0$ and $h_{X,t} > 0$. However, constancy of correlation is a very strong assumption and validity of Equation (2.41) remains an empirical question.

In the alternative representation of the multivariate GARCH(p, q) model termed by Engle and Kroner (1995) the Baba, Engle, Kraft and Kroner, (henceforth, BEKK), representation, the conditional covariance matrix is parameterised as[36]:

$$y_t = \Pi' x_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{dist}(0, H_t) \tag{2.42a}$$

$$H_t = A'A + \sum_{i=1}^{p} B_i' H_{t-i} B_i + \sum_{j=1}^{q} C_j' \varepsilon_{t-j} \varepsilon_{t-j}' C_j + E' s_t s_t' E \tag{2.42b}$$

[36] The BEKK model originally proposed by Baba, Engle, Kraft and Kroner (1987) where it takes its name.

where y_t is an (Nx1) vector of dependent variables, x_t is a (kxk) vector of independent variables, s_t is (px1) vector of exogenous variables, ε_t is an (Nx1) vector of regression residuals, and Π is an (Nxk) matrix of parameters in the mean Equation (2.42a). In the variance Equation (2.42b) H_t is a symmetric variance-covariance matrix, A is a (NxN) lower triangular matrix of constant parameters, and B_j $j = 1,\ldots, q$, and C_j $j = 1,\ldots, p$ are (NxN) matrices of parameters for the lagged variance and squared residual terms, respectively, and E is an (Nxp) matrix of parameters for exogenous variables.

This formulation has the advantage over the general specification in Equation (2.40) that H_t is guaranteed to be positive definite for al t. Because the second and third terms on the right-hand side of Equation (2.42b) are expressed in quadratic forms, the positive definiteness of the conditional covariance matrix of asset returns is guaranteed, provided that A is positive definite. The model in Equations (2.42a) and (2.42b) involves a total of $[1 + (p + q)K]N^2$ parameters. However, in empirical applications, the structure of the B_i and C_j matrices must be further simplified as this model is also overparameterised, which results in loss of degrees of freedom. A way to overcome this problem is to restrict some or all of the off-diagonal elements in B_i and C_j matrices as follows:

$$A = \begin{pmatrix} a_{11} & 0 & \ldots & 0 \\ a_{21} & a_{22} & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ a_{n1} & a_{2n} & \cdots & a_{nn} \end{pmatrix}, \quad B_i = \begin{pmatrix} b_{11} & 0 & \ldots & 0 \\ 0 & b_{22} & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & b_{nn} \end{pmatrix}, \quad C_j = \begin{pmatrix} c_{11} & 0 & \ldots & 0 \\ 0 & c_{22} & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & c_{nn} \end{pmatrix}, \quad H_t = \begin{pmatrix} h_{11,t} & 0 & \ldots & 0 \\ h_{21,t} & h_{22,t} & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ h_{n1,t} & h_{2n,t} & \cdots & h_{nn,t} \end{pmatrix}$$

However, such off-diagonal terms measure the spillover effects between volatilities and restricting them might involve some misspecification costs, if such effects exist between time-varying conditional variances. In order to measure volatility spillover effects in X_t, say $X_t = [y_{1t}, y_{2t}]$ in a simultaneous framework, we construct an additional matrix containing specific parameters measuring such effects. The VECM of Equation (2.24) then becomes the following bivariate BEKK VECM-GARCH model:

$$\Delta X_t = \mu_0 + \mu_1 t + \sum_{i=1}^{k} \Gamma_i \Delta X_{t-i} + \alpha\beta' z_{t-k} + \Psi D_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{dist}(0, H_t) \tag{2.43a}$$

$$H_t = A'A + B'H_{t-1} B + C'\varepsilon_{t-1}\varepsilon_{t-1}'C + S1'u_{1,t-1}u_{1,t-1}'S1 + S2'u_{2,t-1}u_{2,t-1}'S2 \tag{2.43b}$$

where

$$\Delta X_t = \begin{pmatrix} \Delta y_{1,t} \\ \Delta y_{2,t} \end{pmatrix}, \quad \mu_0 = \begin{pmatrix} \mu_{10} \\ \mu_{20} \end{pmatrix}, \quad \mu_1 = \begin{pmatrix} \mu_{11} \\ \mu_{21} \end{pmatrix}, \quad D_t = \begin{pmatrix} d_{1,t} \\ \vdots \\ d_{s,t} \end{pmatrix}, \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}, \quad \Gamma_i = \begin{pmatrix} \gamma_{1,11} & \gamma_{1,12} \\ \gamma_{1,21} & \gamma_{1,22} \end{pmatrix},$$

$$\Gamma_k = \begin{pmatrix} \gamma_{k,11} & \gamma_{k,12} \\ \gamma_{k,21} & \gamma_{k,22} \end{pmatrix}, \quad a = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, \quad \beta' = \begin{pmatrix} \delta_{10} & \delta_{11} & \beta_{11} & \beta_{12} \\ \delta_{20} & \delta_{21} & \beta_{21} & \beta_{22} \end{pmatrix}, \quad z_t = \begin{pmatrix} c \\ t \\ y_{1,t-1} \\ y_{2,t-1} \end{pmatrix},$$

$$\Psi = \begin{pmatrix} \phi_{1,1} & \cdots & \phi_{1,11} \\ \phi_{2,1} & \cdots & \phi_{2,11} \end{pmatrix}, \quad H_t = \begin{pmatrix} h_{1,t} & h_{12,t} \\ h_{21,t} & h_{2,t} \end{pmatrix}, \quad A = \begin{pmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{pmatrix}, \quad B_j = \begin{pmatrix} b_{11} & 0 \\ 0 & b_{22} \end{pmatrix}, \quad C_j = \begin{pmatrix} c_{11} & 0 \\ 0 & c_{22} \end{pmatrix}$$

$$S1 = \begin{pmatrix} 0 & 0 \\ 0 & s1_{21} \end{pmatrix}, \quad S2 = \begin{pmatrix} s2_{12} & 0 \\ 0 & 0 \end{pmatrix}, \quad u_{1,t} = \begin{pmatrix} 0 & 0 \\ 0 & \varepsilon_{1,t} \end{pmatrix}, \quad u_{2,t} = \begin{pmatrix} \varepsilon_{2,t} & 0 \\ 0 & 0 \end{pmatrix}$$

Expanding the matrices of coefficients and variables explaining the mean model the following model results:

$$\Delta y_{1,t} = \mu_{10} + \mu_{11} t + \sum_{i=1}^{p-1} a_{1,i}\Delta y_{1,t-i} + \sum_{i=1}^{p-1} a_{2,i}\Delta y_{2,t-i} + a_{11}\beta z_{t-1} + \sum_{i=1}^{11} \varphi_{1,i} d_t + \varepsilon_{1,t} \tag{2.44a}$$

$$\Delta y_{2,t} = \mu_{20} + \mu_{21} t + \sum_{i=1}^{p-1} b_{1,i}\Delta y_{1,t-i} + \sum_{i=1}^{p-1} b_{2,i}\Delta y_{2,t-i} + a_{21}\beta z_{t-1} + \sum_{i=1}^{11} \varphi_{2,i} d_t + \varepsilon_{2,t} \tag{2.44b}$$

where β represents the cointegrating vector (the long-run relationship between the two variables in X_t). Similarly, explaining the variance specification to show elements in matrices of coefficients the following model results:

$$h_{1,t} = a_{11}^2 + b_{11}^2 h_{1,t-1} + c_{11}^2 \varepsilon_{1,t-1}^2 + s2_{11}^2 \varepsilon_{2,t-1}^2 \tag{2.45a}$$

$$h_{2,t} = a_{21}^2 + a_{22}^2 + b_{22}^2 h_{2,t-1} + c_{22}^2 \varepsilon_{2,t-1}^2 + s1_{22}^2 \varepsilon_{1,t-1}^2 \tag{2.45b}$$

$$h_{12,t} = a_{11} a_{21} + b_{11} b_{22} h_{12,t-1} + c_{11} c_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} \tag{2.45c}$$

where s_{ij} (i and j = 1, 2, $i \neq j$) coefficients are used to measure volatility spillovers between two variables.

We should notice that, in the financial literature shocks (news) might have different impact on the behaviour of the volatilities of time-series. The impact of a positive shock on the volatility can be different from the impact of the negative shock of the same magnitude. Statistically, this effect occurs when an unexpected decrease in price (bad news) increases predictable volatility more than an unexpected increase in price (good news) of similar magnitude. This leverage effect is important when modelling the second-order moments because univariate or multivariate GARCH models can be misspecified and lead to biased estimates of volatilities as well as inaccurate forecast intervals[37].

Engle and Ng (1993) develop a set of tests to detect any form of misspecification in GARCH models due to the asymmetric behaviour of volatility to shocks. Engle and Ng (1993) suggest that the Ljung-Box test may not have much power in detecting misspecifications related to the asymmetric effects. These tests are based on regressing the squared standardised residual, ($u_t^2 = \hat{\varepsilon}_t^2 / h_t$), on a series of dummies which are constructed using the sign and relative size of shocks in the mean equation: (i) the sign bias test considers the variable Y_{t-1}^-, a dummy variable that takes a value of one when ε_{t-1} is negative and zero otherwise. This test examines the impact of positive and negative return shocks on volatility not predicted by the model; (ii) the negative

[37] If a negative return shock causes more volatility than a positive return shock of the same size, the GARCH model underpredicts the amount of volatility following bad news and overpredicts the amount of volatility following good news. Furthermore, if large return shocks cause more volatility than a quadratic function allows, then the standard GARCH model underpredicts volatility after a large return shock and overpredicts volatility after a small return shock (Engle and Ng, 1993).

size bias test utilizes the variable $Y^{-}_{t-1}\varepsilon_{t-1}$. It focuses on the different effects that large and small negative return shocks have on volatility which is not predicted by the volatility model; (iii) the positive size bias test utilises the variable $Y^{+}_{t-1}\varepsilon_{t-1}$, where $Y^{+}_{t-1} = 1 - Y^{-}_{t-1}$. It focuses on the different impacts that large and small positive return shocks may have on volatility, which are not explained by the volatility model; (iv) a joint test of all the previous tests.

The suggested tests are the following:

$$u^2_t = a_0 + bY^{-}_{t-1} + \beta' z_{0t} + \omega_t \tag{2.46}$$

$$u^2_t = a_0 + bY^{-}_{t-1}\varepsilon_{t-1} + \beta' z_{0t} + \omega_t \tag{2.47}$$

$$u^2_t = a_0 + bY^{+}_{t-1}\varepsilon_{t-1} + \beta' z_{0t} + \omega_t \tag{2.48}$$

$$u^2_t = a_0 + b_1Y^{-}_{t-1} + b_2Y^{-}_{t-1}\varepsilon_{t-1} + b_3Y^{+}_{t-1}\varepsilon_{t-1} + \beta' z_{0t} + \omega_t \tag{2.49}$$

where β' is a constant parameter vector $\beta = (\beta_{01}, \beta_{02})'$ and z_{0t} is a vector of parameters that explain the variance under the null hypothesis; in the case of a GARCH(1,1) model, $z_{0t} = (h_t, \varepsilon^2_{t-1})$. In Equation (2.46), significance of the term b, implies that negative shocks (bad news) have a relatively greater impact on volatility than positive shocks (good news). Significance of the b coefficients in Equations (2.47) and (2.48) implies that the shocks with different magnitudes have different relative impact on the volatility; that is negative and positive size biases, respectively. Equation (2.49) performs a joint LM or F-test, in which the null is H_0: $b_1 = b_2 = b_3 = 0$, in order to detect any sign and size biases in the impact of the shocks on the conditional variance.

Furthermore, in analysing a GARCH model the persistence factor of volatility should also be estimated. Persistence of volatility can be defined as the degree of convergence of the conditional volatility to the unconditional volatility after a shock. For example, if the conditional volatility is defined as a GARCH(1,1) process, $h_t = a_0 + b_1h_{t-1} + c_1\varepsilon^2_{t-1}$, then the unconditional volatility would be $a_0/(1 - b_1 - c_1)$. Therefore, the degree of persistence of the conditional volatility can be defined as $(b_1 + c_1)$. The conditional volatility converges to its unconditional volatility value, if and only if $(b_1 + c_1) < 1$. Also, note that in the BEKK specification persistence is calculated as $(b_1^2 + c_1^2)$.

2.6.2. Estimation Methods of ARCH and GARCH Models

The actual implementation of the maximum likelihood procedure requires an explicit assumption regarding the conditional density of the process. Assuming the conditional joint distribution of the returns of the two markets is normal, the log-likelihood for the GARCH models can be written as:

$$L(\Theta) = -T\log(2\pi) - (0.5)\sum_{t=1}^{T}(\log|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t) \qquad (2.50)$$

where H_t is the 2x2 time-varying conditional covariance matrix, $\varepsilon_t = (\varepsilon_{Y,t}, \varepsilon_{X,t})'$ is the 2x1 vector of innovations at time t, T is the sample size, and Θ is the parameter vector to be estimated. The log-likelihood function is highly non-linear and, therefore, numerical maximisation techniques have to be used. The Broyden, Fletcher, Goldfarb, and Shanno (henceforth, BFGS) iterative optimisation algorithm, which utilises derivatives to maximise the log-likelihood or alternatively the Berndt, Hall, Hall, and Hausman (1974) (henceforth, BHHH) iterative optimisation algorithm can be used.

The GARCH(p, q) model with conditional normal errors results in a leptokurtic unconditional distribution. However, the degree of leptokurtosis induced by the time-varying conditional variance often does not capture all of the leptokurtosis present in high frequency speculative prices. To circumvent this problem Bollerslev (1987) suggests using a standardised Student t-distribution:

$$L(H_t, \varepsilon_t, \theta) = \frac{\Gamma[(2+v)/2]}{\Gamma(v/2)[\pi(v-2)]}|H(\theta)_t|^{-1/2}\left[1 + \frac{1}{v-2}\varepsilon(\theta)_t' H(\theta)_t^{-1}\varepsilon(\theta)_t\right]^{-[(2+v)/2]} \qquad (2.51)$$

$$, \text{for } v > 2$$

where $\Gamma(.)$ denotes the gamma function, and v denotes the degrees of freedom. The *t*-distribution is symmetric around zero, and converges to the normal distribution for $n \rightarrow \infty$. However, for $v < 4$ the Student-*t* distribution has an undefined or infinite degree of kurtosis [the theoretical kurtosis is computed as $3(v-2)(v-4)^{-1}$]. In such cases the Quasi-Maximum Likelihood Estimation (QMLE), which estimates robust standard errors, and thus, yields an asymptotically consistent normal covariance matrix, is preferred (Bollerslev and Wooldridge, 1992). Under appropriate regularity conditions this is sufficient to establish consistency and asymptotic normality (Wooldridge, 1994). For symmetric departures from conditional normality, the QMLE is generally close to the exact MLE.

2.7. CONCLUSION

In this chapter, the econometric framework of analysing non-stationary price series was presented. We discussed the properties of stationary and non-stationary processes and presented the Dickey and Fuller (1979, 1981) and Phillips and Perron (1988) unit root tests. We also presented and described the Engle and Granger (1987) and Johansen (1988) testing procedures. The latter procedure is more powerful than the Engle and Granger (1987) procedure and provides a test statistic which has an exact limiting distribution and enables us to perform hypothesis tests for restricted versions of the cointegrating relationships. Finally, the ARCH family of models, designed to model time-varying conditional variances, was also discussed. These techniques are employed in this thesis in order to investigate the economic functions and uses of the forward freight market.

CHAPTER 3 - THE UNBIASEDNESS HYPOTHESIS OF FORWARD AND EXPECTED SPOT PRICES IN THE FORWARD FREIGHT MARKET

3.1. INTRODUCTION

According to Fama (1970), a market is efficient if prices always *fully reflect* all available information, and in turn, provide accurate signals for resource allocation. Excess or abnormal market profits (or returns) from trading follow a *fair game* process, with respect to the information set available at the time when expectations of future prices are formed, or in other words excess profits should be zero[38]. Thus, agents process information efficiently and immediately incorporate this information into asset prices.

If current and past information is immediately incorporated into current prices then only new information or *news* should cause changes in prices. Since *news* is by definition unforecastable, then price changes (or returns) should be unforecastable: no information at time t or earlier should help to improve the forecast of prices (or returns). This independence of forecast errors from previous information is known as the orthogonality property; information available today should be of no use in forecasting tomorrow's price. Forecast errors should be therefore zero on average and should be uncorrelated with any information that was available at the time the forecast was made. The latter is often referred to as the rational expectations element of the Efficient Market Hypothesis (EMH).

In such efficient markets, the existence of futures/forward markets can help to discover prices which are likely to prevail in the spot market. In efficient markets, according to the unbiasedness hypothesis, forward contract prices must be unbiased estimators of the spot prices of the underlying asset that will be realised at the expiration date.

[38] The expected net return to speculators engaging in intertemporal speculation on assets should be zero.

Investigation of the unbiasedness hypothesis for the forward freight market is interesting for the following reasons: First, the underlying asset is a service, which is a unique feature. Second, the price discovery function provides a strong and simple theory of the determination of spot prices that may prevail in the future. Third, if forward prices are to fulfil their price discovery role, they must provide accurate forecasts of the realised spot prices, and consequently provide new information in the market and in allocating economic resources (Stein, 1981). The existence of inefficiency of forward prices in marking spot prices can increase the cost of hedging, assuming that the market agents are fully informed when they set the forward price in FFA contracts[39]. Finally, the apparent lack of research in the forward freight trades further motivates this investigation as the findings can serve as a performance comparison with the BIFFEX futures market, investigated by Kavussanos and Nomikos (1999), amongst others.

Kavussanos and Nomikos (1999) examine the BIFFEX contract using cointegration techniques and find that futures prices one- and two-months from maturity provide unbiased forecasts of the realised spot prices. On the other hand, futures prices three-months from maturity seem to be biased estimates of the realised spot prices. The decrease in volume in BIFFEX contracts has coincided with the creation of FFA market at the beginning of 1992. Market agents attribute this decrease in BIFFEX futures trading to the growth in hedging activity with the FFA contracts (Haigh, 2000). Empirical examination of the efficiency of the FFA market would provide a helpful direction towards the validity of the above inference.

The remainder of this chapter is organised as follows. Section 3.2 presents the unbiasedness hypothesis. Section 3.3 discusses the alternative methodologies for testing the unbiasedness hypothesis, which can be categorised as traditional-regression and modern-cointegration methods. A selective literature review of the unbiasedness hypothesis, using forward contracts in several markets, is presented in section 3.4. Section 3.5 takes a preliminary look of the data and tests their statistical properties. Section 3.6 applies cointegration methods to the FFA market and tests the unbiasedness hypothesis. Finally, section 3.7 summarises this chapter.

[39] When forward prices are well above (below) the expected spot prices, long (short) hedgers are obliged to buy (sell) the forward contracts at a premium (discount) over the price they expect to prevail on expiration.

3.2. FORWARD RATES AS OPTIMAL PREDICTORS OF FUTURE SPOT RATES

The hypothesis that forward prices are the best-unbiased forecasts of future spot prices is often presented in the economic and financial analysis of forward and futures markets[40]. In economic analysis, the hypothesis often appears under the guise of rational expectations, while in the financial literature the term *market efficiency* is more generally employed. The joint assumptions of risk neutrality (or no risk-premium) and rationality (so that speculators cannot expect to make excess returns) are so central in many finance models that their importance cannot be understated. Together, these two assumptions have been called by some: *simple efficiency* (Hansen and Hodrick, 1980), *speculative efficiency* (Bilson, 1981), *unbiasedness hypothesis* (Hodrick and Srivastava, 1984), and *market efficiency* (Hakkio and Rush, 1989). Across the literature it is argued that forward prices can deviate from future spot prices because of transactions costs, information costs, and risk aversion that produce a risk-premium.

The unbiasedness hypothesis is formulated under the proposition that the expected excess rate of net return to speculation in the forward (futures) market, conditioned on available information, is zero. Any discussion of the efficiency of a market requires a specification of the preferences and information sets of economic agents, the technology available for production, and the costs inherent in transactions. If economic agents are risk neutral, information is used rationally, and the market is competitive, then the FFA market will be efficient in the sense that the expected rate of return to speculation from the FFA contracts will be zero.

If a risk-premium is not observed in the forward price for holding long or short forward contracts, then speculators are not rewarded for taking on risk. On average the forward price today $F_{t,t-n}$ should mirror the expected price of the forward price at expiration, $E_{t-n}(F_t/\Omega_{t-n})$; given that the information set Ω_{t-n} available to the market participants at time *t-n* is assumed to contain all past and current values of forward and spot prices, and the exact stochastic process by which prices are determined. Because the expected forward price at expiration should equal the expected spot price at expiration, $E_{t-n}(S_t/\Omega_{t-n})$, we obtain the following result[41]:

[40] Early studies that test the unbiasedness hypothesis are from Hickman and Braddock (1942), and Culbertson (1975).

[41] In the FFA market the forward prices are derived by the expectations of market participants, at time (*t-n*), regarding the future spot prices at the expiration (*t*) of the contract.

$$F_{t,t-n} = E_{t-n}(S_t/\Omega_{t-n}) \tag{3.1}$$

where $F_{t,t-n}$ is the FFA price at time $t-n$ expiring at time t, S_t is the spot price at expiration, Ω_{t-n} is the information set available to the market participants at time $t-n$, and E_{t-n} is the expectations operator[42]. This statement implies that the forward price today is the market's expectation of the future spot price given the information set available. Forward prices will then be unbiased estimators of future spot prices. Moreover, let $u_{t,t-n}$ be the realised return of the forward contract[43]:

$$u_{t,t-n} = [F_{t,t-n} - S_t] / F_{t,t-n} \tag{3.2}$$

The null hypothesis of a zero risk-premium implies that $E_{t-n}(u_{t,t-n}/\Omega_{t-n}) = 0$. Hence, the unconditional mean of $u_{t,t-n}$ is zero, and that $u_{t,t-n}$ is uncorrelated with any variable included in the information set Ω_{t-n}. The assumption that agents are risk neutral, so that the risk-premium is zero, and that agents use all available information rationally, so that the expected returns to speculators are zero, are properties imposed in theoretical macroeconomic models and are summarised by saying that markets in which they hold are unbiased. If both parts of the hypothesis hold, then the current forward rate is an unbiased predictor of the future spot rate.

3.3. TESTING THE UNBIASEDNESS HYPOTHESIS

The unbiasedness hypothesis posits parameter restrictions on the relationship between realised spot and forward prices. Because most macroeconomic (time-series) variables are found to be non-stationary, use of OLS standard regression-based techniques are inappropriate for statistical inference and the tests using them are non-informative in the sense that they are incapable of correctly testing the hypothesis[44]. Specifically, many of these tests are based on regressions that

[42] All time-series are expressed in logarithmic form.
[43] This expression can be thought of as the difference between holding yields from the spot contracts and the forward contracts.
[44] Geweke and Faige (1979) state: "*To be informative, an econometric procedure should be powerful enough to reject the efficient markets hypothesis, and it should provide some indication of why the hypothesis is not true in the market being studied*".

suffer from simultaneity bias, resulting in biased and inconsistent estimators. The cointegration framework, developed by Engle and Granger (1987) and Johansen (1988, 1991) can be used to resolve the problem and reliably test for unbiasedness[45]. Therefore, we must test for the existence of a cointegrating relationship between the forward price and the realised spot price at expiration. If the two price series are not cointegrated, one might not reject the unbiasedness hypothesis, whereas if series are found to be cointegrated, it is possible to predict one on the basis of another.

3.3.1. Traditional Methods for Testing the Unbiasedness Hypothesis

There are two general traditional methods commonly used to empirically investigate unbiasedness[46]. In the first, through a *levels* specification, two suppositions form the unbiased expectations hypothesis, where researchers regress the logarithm of the expected future spot rate at the delivery date, $E(S_t)$, on the logarithm of the forward rate observed today $t\text{-}n$ for the delivery date t, $F_{t,t-n}$, and the expectation of the spot price is formed rationally ($E(S_t) = S_t - u_t$). Therefore, conditional on the assumption of rational expectations, the realised spot price as time t, will differ from its conditional expectation at time $t\text{-}n$ by a white noise error process[47]. It should be noted that the test of unbiasedness is not a simple one, but relates the degree of bias to the level of the forward price. The first supposition suggests the following parameter restrictions $\beta_1 = 0$ and $\beta_2 = 1$ [$(\beta_1, \beta_2) = (0, 1)$] in:

$$S_t = \beta_1 + \beta_2 F_{t,t-n} + u_t \quad ; \quad u_t \sim iid(0,\sigma^2) \tag{3.3}$$

where u_t is a white noise error process.

[45] If a stochastic process must be differenced once in order to become stationary, then the series contains one unit root and is said to be integrated of order one [$I(1)$]. If S_t and $F_{t,t-n}$ are $I(1)$ series, any linear combination among these two series will also be $I(1)$. However, there may be a number of b such that $S_t - bF_{t,t-n} = \varepsilon_t$ is stationary. In this special case the two price series, S_t and $F_{t,t-n}$, are said to be cointegrated of order $CI(1,1)$, implying that they cannot drift apart, but return to the long-run equilibrium level.

[46] References include Fama (1976), Tryon (1979), Levich (1979), Bilson (1981), Longworth (1981), Hsien (1984), Huang (1984), Gregory and McCurdy (1984), and Hodrick and Srivastava (1984).

[47] Unless we have some independent estimates of $E_{t-n}(S_t/\Omega_{t-n})$, there is no way to separate the unbiasedness hypothesis into its two components: the rational expectations and the no risk-premium hypotheses. Only with the availability of survey data, these two components can be tested separately (Froot and Frankel, 1989, and Liu and Maddala, 1992).

This method is used by Frenkel (1977, 1980) and others to test for unbiasedness. Most tests reject the null hypothesis, finding β_2 positive but significantly less than one (and α equal to zero). This consists indirect evidence in favour of the unbiasedness hypothesis, but forecasts embedded in forward rates tend to be systematically biased upward because of the existence of a term-premium. Often the estimate of β_2 is close to zero or negative. In the special case of $\beta_2 = 0$, the spot rate follows a random walk (no predictive power in the test). A test of the unbiasedness hypothesis is of both theoretical and practical significance. The condition of a non-zero expected premium (i.e. normal backwardation $\beta_1 < 0$, or contango, $\beta_1 > 0$) increases the cost of hedging, to compensate speculators for the risk of net long or net short positions when hedgers are net short or net long, respectively[48].

This technique cannot be applied to a forward market where the observation period and the forward contract maturity do not coincide. We avoid using higher-frequency data, which are available[49], otherwise, a moving-average effect would be produced. The overlapping contract periods would result in serially correlated errors on the regressions and this would result in inefficient and biased hypothesis tests (Gilbert, 1986).

The second *percent change* method regresses the percent change in the realised spot rate relative to the current spot rate $[S_t - S_{t-n}]$ against the forward premium or the difference between the forward and spot rates $[F_{t,t-n} - S_{t-n}]$:

$$(S_t - S_{t-n}) = \beta_1 + \beta_2(F_{t,t-n} - S_{t-n}) + u_t \quad ; \quad u_t \sim iid(0,\sigma^2) \tag{3.4}$$

where u_t is an innovation process in the price and satisfies $E_{t-n}(u_t/\Omega_{t-n}) = 0$. In this case, efficiency without a risk-premium again requires that the constant term be 0 and the slope be 1 (see for example, Bilson, 1981; Geweke and Feige, 1979; Hansen and Hodrick, 1980; and Huang, 1984, amongst others). The second method is often preferred because non-stationary spot and forward rates make the first regression suspect (Johansen, 1988). Unfortunately, the second method generally yields weak results: one often cannot reject the hypothesis ($\beta_1 = 0$ and

48 When FFA prices are above the expected spot prices, long hedgers buy FFA contracts at a premium over the price they expect to prevail on maturity.

49 However, a semi-parametric technique enables us to both estimate and make inferences even in the case of *overlapping observations* (Phillips and Hansen, 1990).

$\beta_2 = 1$), but simultaneously one also often cannot reject that the constant is 0 and the slope is −1 (Moore, 1994).

Moore (1994) shows that meaningful inferences cannot be made from Equation (3.4) because it is, in general, misspecified. The basic source of the specification error is the fact that many asset prices are typically non-stationary. Furthermore, Liu and Maddala (1992) argue that this second regression method has some interesting aspects if S_t and $F_{t,t-n}$ are non-stationary. The left-hand side of Equation (3.4) is stationary. But there is no guarantee that the variable on the right-hand side ($F_{t,t-n} - S_{t-n}$) is stationary. In fact, it will only be stationary if the unbiasedness hypothesis is true. If ($F_{t,t-n} - S_{t-n}$) is non-stationary, since ($S_t - S_{t-n}$) is stationary we have a regression of a stationary variable on a non-stationary one. Thus, the unbiasedness hypothesis will almost surely be rejected. On the other hand, if ($F_{t,t-n} - S_{t-n}$) is stationary the unbiasedness hypothesis is true, in which case there is no point in testing it using Equation (3.4). In order to see if this is a problem, we must also regress ($F_{t,t-n} - S_{t-n}$) on ($S_t - S_{t-n}$) in order to compare the results.

Fama (1976) conjectures that the weakness of the forecast power of the above regressions, stems from model misspecification or measurement error. Using standard regression methods in the presence of non-stationary price series results in inconsistent coefficient estimates and *t*- and *F*-statistics which do not follow the standard distributions generated by stationary series. The regressions can be characterised as *spurious regressions* or *nonsense regressions* (Granger and Newbold, 1974).

3.3.2. Cointegration Methods for Testing the Unbiasedness Hypothesis

Developments in the theory of cointegration by Engle and Granger (1987), Johansen (1988, 1991), Phillips and Ouliaris (1990) and Phillips (1991) provide new methods of testing unbiasedness. Cointegration is a property possessed by some non-stationary time series data[50]. In general terms, two variables are said to be cointegrated when a linear combination of the two is stationary, even though each variable is non-stationary.

[50] A non-stationary time-series exhibits infinite variance, which violates the central limit theorem making standard methods for statistical inference inappropriate.

The unbiasedness hypothesis implies that the current forward rate and the future spot rate are *close together*. Therefore, even if the spot and forward rates are non-stationary, they should never drift apart so that they will be cointegrated. Engle and Granger (1987) demonstrate that if two non-stationary variables are cointegrated, the variables follow a well-specified ECM, where the coefficient estimates, as well as the standard errors for the coefficients are consistent[51].

The cointegration tests, like the standard regression tests, examine the joint hypothesis of no risk-premium and rational use of information, under the parameter restrictions $(\beta_1, \beta_2) = (0, 1)$. More precisely, if two non-stationary variables, S_t and $F_{t,t-n}$ are cointegrated of order $CI(1,1)$[52], the equilibrium regression can be expressed as follows[53]:

$$S_t = \beta_1 + \beta_2 F_{t,t-n} + u_t \quad ; \quad u_t \sim I(0) \text{ and } u_t \sim \text{iid}(0,\sigma^2) \tag{3.5}$$

where S_t and $F_{t,t-n}$ are the series being tested for cointegration. If the restrictions hold, with a cointegrating vector of one, then S_t and $F_{t,t-n}$ cannot drift too far apart because their difference, u_t, is stationary[54]. Thus, if $F_{t,t-n}$, contains all the information that is relevant in forecasting the next period's spot price, S_t, then $F_{t,t-n}$ should be an unbiased estimator of the future spot price. On the other hand, if the two variables are not cointegrated then with probability one they will drift infinitely far apart, in which case forward prices cannot be unbiased estimators of the future spot prices. The following VECM framework, proposed by Johansen (1998), is used to test for unbiasedness:

$$\Delta X_t = \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t \sim IN(0,\Sigma) \tag{3.6}$$

[51] If two variables are cointegrated, the results in West (1986) and Stock and Watson (1988) also can be used to demonstrate that the ECM is well-specified.
[52] The first term of the order of cointegration pertains to the number of times it is necessary to difference the individual data series to attain stationarity; the second term is the reduction in the number of times it is necessary to difference the linear combination to achieve stationarity.
[53] When testing for cointegration, there is no *a priori* choice of which variable should be the dependent variable. Hence, we conduct each test twice, once with the future spot rate as the dependent variable and the FFA rate as independent variable, and another with the designations reversed.
[54] While cointegration is necessary for unbiasedness, it is not sufficient for two reasons. First, the cointegration vector must also equal 1 and second, unbiasedness requires the error-term in Equation (3.5) to be white noise, while cointegration only requires the error-term to be stationary.

where X_t is the 2x1 vector $(S_t, F_{t,t-n})'$, μ is a 2x1 vector of deterministic components which may include a linear trend term, an intercept term, or both, Δ denotes the first difference operator, ε_t is a 2x1 vector of residuals $(u_{S,t}, u_{F,t})'$ and Σ the variance/covariance matrix of the latter. The VECM specification contains information on both the short- and long-run adjustment to changes in X_t, via the estimates of Γ_i and Π, respectively.

Johansen and Juselius (1990) show that the coefficient matrix Π contains the essential information about cointegration between S_t and $F_{t,t-n}$. If rank(Π) = 0, then Π is 2x2 zero matrix implying that there is no cointegrating relationship between S_t and $F_{t,t-n}$. In this case the VECM reduces to a VAR model in first differences. If Π has a full rank, that is rank(Π) = 2, then all variables in X_t are $I(0)$ and the appropriate modelling strategy is to estimate a VAR model in levels. If Π has a reduced rank, that is rank(Π) = 1, then there is a single cointegration relationship between S_t and $F_{t,t-n}$, which is given by any row of matrix Π and the expression ΠX_{t-1} is the ECT. In this case, Π can be factored into two separate matrices α and β, both of dimensions 2x1, where 1 represents the rank of Π, such as $\Pi = \alpha\beta'$, where β' represents the vector of cointegrating parameters and α is the vector of error-correction coefficients, measuring the speed of convergence to the long-run steady state.

Since rank(Π) equals the number of characteristic roots (or eigenvalues) which are different from zero, the number of distinct cointegration vectors can be obtained by estimating the number of these eigenvalues, which are significantly different from zero. The characteristic roots of the qxq matrix Π, are the values of λ which satisfy the following equation $|\Pi - \lambda I_q| = 0$, where I_q is a qxq identity matrix[55].

[55] Johansen (1988), proposes the following two statistics to test for the rank of Π: the $\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i)$ and the $\lambda_{max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+i})$, where $\hat{\lambda}_i$ and $\hat{\lambda}_{r+i}$ are the estimated eigenvalues obtained from the estimated Π matrix, and T is the number of usable observations. The λ_{trace} tests the null that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r and the λ_{max} tests the null that the number of cointegrating vectors is r, against the alternative of $r + 1$. Critical values for the λ_{trace} and λ_{max} statistics are provided by Osterwald-Lenum (1992).

The choice of the deterministic components that should be included in the VECM is important since the asymptotic distributions of the cointegration test statistics are dependent upon the presence of trends and/or constants in the VECM and is a task that must be supported by some economic argument[56]. Unbiasedness is tested by the following restrictions $\beta_1 = 0$ and $\beta_2 = -1$ on the cointegrating vector. The following statistic proposed by Johansen and Juselius (1990) may be used for that:

$$-T\left[\ln\left(1-\hat{\lambda}_1^*\right)-\ln\left(1-\hat{\lambda}_1\right)\right] \sim \chi^2(2) \tag{3.7}$$

where $\hat{\lambda}_1$ is the largest eigenvalue of the unrestricted model and $\hat{\lambda}_1^*$ is the largest eigenvalue of the model with the imposed restrictions on the cointegrating vector. The asymptotic distribution of the likelihood ratio test statistic is χ^2 with degrees of freedom equal to the number of assumed parameter restrictions (r) placed on β'.

The Fully Modified-Least Squares (FMLS) cointegration test, proposed by Phillips and Hansen (1990), and the Bierens (1997) non-parametric test can also be used to test for unbiasedness. Their use is motivated by the overlapping observations problem, present in the two- and three-months maturity periods, which may affect the Johansen (1988) test (Hansen and Hodrick, 1980). With overlapping contract periods, if the observation frequency of the sample data is, say h, where $h < n$ (n is the maturity of the contract) in Equation (3.5), a moving average process of order $n / h - 1$ in the residuals may be generated.

The Phillips and Hansen (1990) method applies a non-parametric correction to the OLS coefficient estimates and to their associated t-statistics to take into account the impact of autocorrelation on the residual term when the right hand side variables of Equation (3.5) are not weakly exogenous. This method leads to fully modified estimates of both parameters and standard errors, which are asymptotically equivalent to maximum likelihood estimates. The method of Phillips and Hansen (1990) does not suffer from the overlapping observations problem, since it only involves an adjustment to the OLS estimates of the cointegration vector

[56] The following test proposed by Johansen (1991) is employed to test the most appropriate specification: $-T\left[\ln\left(1-\hat{\lambda}_2^*\right)-\ln\left(1-\hat{\lambda}_2\right)\right]$ distributed as $\chi^2(1)$, where $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ represent the smallest eigenvalues of the model that includes an intercept term in the cointegration vector and an intercept term in the short-run model, respectively.

without any reliance on the parameters governing the short-run dynamics (the estimate of the long-run covariance is positive definite in every case).

Bierens (1997) proposes a multivariate non-parametric method of estimation of Equation (3.3), which is in the same spirit as Johansen's method in that the test statistics are obtained from the solutions of a generalised eigenvalue problem and the hypotheses to be tested are the same. Their main important difference is that the Bierens method estimates two random matrices, in the generalised eigenvalue problem, constructed independently of the d.g.p. These matrices consist of weighted means of the system variables in levels and first differences and are constructed such that their generalised eigenvalues share similar properties to those in the Johansen method. In contrast, the Johansen's (1988) method constructs the qxq Π matrix to be dependent on the d.g.p. in a parametric way.

3.4. LITERATURE REVIEW

Several studies in the past have examined the unbiasedness hypothesis in various forward markets. In the foreign exchange market the existence of time-varying risk-premia are documented in the literature, amongst others, by, Frenkel (1977, 1980), Hansen and Hodrick (1980), Hodrick and Srivastava (1984), all interpreting the bias not only as evidence of a non-zero risk-premium, but also as evidence that the variance of the risk-premium is greater than the variance of expected depreciation[57, 58]. Tests of the unbiasedness hypothesis on commodity markets are fewer in number. This partly reflects the lower level of interest in these markets and partly the fact that the predominant form of trading in commodities is the futures market rather than the forward market (Engel, 1996)[59].

[57] Bilson (1981) expresses the extreme form of this view, which he calls the new *empirical paradigm*: expected depreciation is always zero, and changes in the forward discount reflect changes in the risk-premium.
[58] For a survey of the literature of the risk-premium anomaly in the currency markets see Hodrick (1987) and Engel (1996).
[59] Futures contracts differ from forward contracts in a number of respects, but the most important in relation to the unbiasedness hypothesis is that futures contracts denominate a month of delivery whilst forward contracts state a day of delivery. For this and other reasons, the implications of the unbiasedness hypothesis for futures are less clear than for forward trading.

Most of the studies that test for unbiasedness reject it and generally agree on the direction of bias. They tend to disagree, however, about whether the bias is evidence of a risk-premium or a violation of rational expectations. Some studies assume that investors are risk neutral, so that the systematic component of the rate changes in excess of the forward discount is interpreted as evidence of a failure of rational expectations. On the other hand, others attribute the same systematic component to a time-varying risk-premium that separates the forward discount from expected depreciation. Since the list of studies, on several forward markets, is almost endless we present some indicative studies using cointegration techniques.

In the forward exchange rate market, Baillie and Bollerslev (1989) examine the logarithms of daily exchange rates between seven currencies, and argue that exchange rates may be cointegrated using the Engle and Granger (1987) *two-step* cointegration test and the Johansen (1988) test. They conclude that currency markets may not be characterised by the joint hypothesis of the efficient use of information and rationality. Hakkio and Rush (1989) reject the joint hypotheses of no predictable risk-premium and unbiased expectations for the one-month forward German mark and one-month forward British pound. Sephton and Larsen (1991), investigate market efficiency with respect to the US dollar exchange rates for Canadian, Japanese, and West German currencies using the Johansen (1988) methodology. They demonstrate that the fragile nature of the test indications suggests that cointegration methodologies cannot be relied upon to provide reliable evidence on market efficiency[60]. Moreover, the Johansen (1988) test should be preferred to the Engle and Granger (1987) test since it is robust to various departures from normality, it does not suffer from problems associated with normalisation, and that more is known about its asymptotic behaviour.

Lai and Lai (1991) examine the one-month forward British pound, German mark, Swiss franc, Canadian dollar and Japanese yen exchange rates and report evidence against the unbiasedness hypothesis. Barnhart and Szakmary (1991) find that both spot and one-month forward exchange rates for the UK, Germany, Japan, and Canada are cointegrated, although they reject the parameter restrictions for unbiasedness for all currencies. Norbin and Reffett (1996) examine the three-months forward exchange rates for Germany, Canada, Japan, UK and Switzerland and

[60] The *temporal instability* in the Johansen test renders findings inconclusive. Test results depend critically on the period used to estimate the error-correction model on which the Johansen (1988) test statistic is based. Different sample periods lead to different conclusions regarding unbiasedness.

report evidence in favour of the unbiasedness hypothesis. Luintel and Paudyal (1998) examine the one-month forward exchange rates for Germany, Canada, France, Japan and US vis-à-vis the UK forward exchange rate and show that unbiasedness could not be sustained, with the exception of the Canadian currency. Barnhart *et al.* (1999) report results in favour of unbiasedness, using end of month data for one-month forward exchange rates for the British, Canadian, German, French, Swiss, Japanese and Italian currencies.

In the forward commodity market, MacDonald and Taylor (1988) examine whether any of the spot rates in the tin, lead, and zinc markets of the LMH are pair-wise cointegrated. They find that no such cointegration relationship exists, which is consistent with efficiency. Chowdhury (1991) tests for cointegration between spot prices of different metals and cointegration between forward and realised spot prices using data from the LMH during the period 1971-1988. Chowdhury uses averaged data (like the studies of Goss, 1981, 1983, 1986), which are subject to the criticisms of Gilbert (1986). Ironically, Chowdhury employs very small samples to avoid the problem of overlapping data even though this leads to very similar problems to those that arise with averaged data[61]. He reports rejection of unbiasedness in the markets of the four metals which he discusses.

Krehbiel and Adkins (1993) find that the three- and four-months forward contract prices and realised spot prices are cointegrated in the silver, copper, gold and platinum market of the Commodity Exchange (COMEX), but with the unbiasedness hypothesis to hold only for the platinum market. Moore and Cullen (1995) examine the aluminium, copper, lead, nickel, tin and zinc metal markets of the LME and conclude that unbiasedness cannot be rejected for four of these – aluminium, copper, lead, and zinc. Overall, the empirical evidence, based on cointegration techniques, is mixed. Thus, rejection or not of unbiasedness depends on the type of contract, the maturity of the contract, the market, and the time-period under investigation.

[61] For a discussion of *overlapping observations* refer to Moore (1994) and for *averaged data* to Gilbert (1986).

3.5. DESCRIPTION OF DATA AND PRELIMINARY STATISTICS

From the creation of the FFA market on February 1st 1992 until November 1st 1999, the eleven panamax and capesize voyage and time-charter routes of the BFI served as the underlying assets of the FFA trades, in the dry-bulk sector of the shipping industry. After the latter date, with the exclusion of the capesize routes and with the renamed index as BPI, the underlying assets of the FFA contracts are panamax routes. Data for FFA rates on four panamax routes, namely route 1, 1A, 2, and 2A, and three contract maturities – one-, two-, and three-months, are obtained from Clarkson Securities Ltd. for the period January 1996 to December 2000[62]. The reason for using only four routes out of seven, and January 1996 as a starting date (instead of 1992), is due to the lack of quotes of FFA brokers for the remaining routes (3, 3A, and 4) and for the years 1992-1995. The FFA price series are the average (mid-point) of bid and ask quotes (Moore and Cullen, 1995; Evans and Lewis, 1995; Luintel and Paudyal, 1998). Data for spot freight rates for the same routes are obtained from Datastream for the period January 1996 to December 2000.

For the analysis, FFA prices are matched with realised spot prices at the contract maturity (or prompt) date. The prompt date is normally the last trading day of each month, except for the December contract, which is the 20th of the month. If the prompt date falls on a non-business day, i.e. a Sunday or a holiday, it is relocated to the next available business day. The corresponding settlement price for FFA contracts is calculated as the average of the spot rates over the last five trading days or over the last five trading days prior to 20 December for the December contract, until November 1999. After November 1999 the settlement price is sampled as the average of the spot rates over the last seven trading days[63]. All price series are transformed in natural logarithms for analysis.

[62] For voyage routes 1 and 2 the prices are quoted in $/ton, and for time-charter routes 1A and 2A the prices are quoted in $/day.

[63] Using the freight rate of each route on the maturity day for our analysis, rather than the average of the last five/seven trading days, did not change our results qualitatively.

The transition from one forward contract to the next is made upon each contract's termination date (the 25th of each termination month). The delivery period is retained in the analysis because of the belief that the spot-forward price relationship continues up to the nearby contract's termination date (Bessler and Kling, 1990). To account for possible systematic relationships in the data associated with the retention of the last week of a contract (to account for the statistical effect of including the delivery period in the data set) we introduce a 0,1 dummy variable set equal to 1 at the first day of a new contract. All test statistics and estimated relationships show little sensitivity to that specification. In particular, unit root tests and cointegration tests are not qualitatively affected, and consequently, the ensuing analysis does not include any of these dummy variables specifications.

We consider three different sampling intervals. The first interval consists of closing prices of the FFA contract one-month before maturity, $F_{t,t-1}$, and the corresponding spot settlement prices at maturity, S_t, for routes 1, 1A, 2, and 2A. Thus, our estimation period for routes 1 and 1A is from the FFA contract that expires on 31 January 1996 until the FFA contract that expires on 31 July 2000, giving 54 observations. For routes 2, 2A the estimation period is from the FFA contract that expires on 31 January 1996 until the FFA contract that expires on 30 November 2000, giving 58 observations. FFA prices are sampled at the last trading day of the month preceding the delivery month.

The second interval consists of closing prices of the FFA contract two-months from maturity, $F_{t,t-2}$, and the corresponding settlement prices at maturity, for the four panamax routes. Our estimation period for routes 1, 1A is from January 1996 to June 2000, giving us 53 observations for every route. For routes 2, 2A the estimation period is from January 1996 to October 2000, giving us 57 observations for every route.

The third interval consists of closing prices of the FFA contract three-months from maturity, $F_{t,t-3}$, and the corresponding settlement prices at maturity, for the four panamax routes. Our estimation period for routes 1, 1A is from January 1996 to May 2000, giving us 52 observations for every route. For routes 2, 2A the estimation period is from January 1996 to September 2000, giving us 56 observations for every route. From the graphs of FFA and spot prices for panamax routes 1, 1A, 2, and 2A presented in chapter 1 (see Figures 1.1 to 1.4, respectively) we observe that FFA prices closely track the fluctuations of the spot prices for every route.

Summary statistics of the logarithmic first-differences of spot and FFA prices for the four panamax routes are presented in Tables 3.1 to 3.4. The unconditional means of the spot and FFA returns series are statistically zero in all cases. Coefficients of skewness and kurtosis indicate mixed evidence for both spot and FFA return series. More specifically, the results denote the existence of: (i) excess skewness in route 1 in one- and two-months spot price series, and in route 2A three-months spot price series; (ii) excess kurtosis in routes 1 and 2A spot price series and in route 1A three-months FFA price series; (iii) Jarque-Bera (1980) tests indicate that, with the exception of routes 1 and 2A spot prices and route 1A three-months FFA prices, the return series follow normal distributions.

The ADF (1981) and the PP (1988) tests have non-stationarity as the null hypothesis. However, the way the null hypotheses for the ADF and PP tests are tested is not very informative regarding the presence of a unit root. That is the ADF and PP tests are not very powerful against relevant alternative hypotheses (Lee *et al.*, 2000). Thus, the ADF and PP tests often are complemented by another test that has series stationarity as the null hypothesis. This lack of power in rejecting the null hypothesis of a unit root is addressed by conducting the KPSS test of Kwiatkowski *et al.* (1992), which is specifically designed to test the null hypothesis of stationarity.

The KPSS (1992) test statistic is calculated as:

$$\mathrm{n}_t = T^{-2} \sum_{t=1}^{T} \mathrm{K}_t^2/\mathrm{K}^2(L) \tag{3.8}$$

where L is the lag parameter, K_t is the cumulative sum of the residuals (e_t) from a regression of the series on a constant and a linear trend and

$$\mathrm{K}^2(L) = T^{-1} \sum_{t=1}^{T} \mathrm{e}_t^2 + 2T^{-1} \sum_{K=1}^{L} [1 - \mathrm{K}/(\mathrm{L} + 1)] \sum_{t=K+1}^{T} \mathrm{e}_t\, \mathrm{e}_{t-K} \tag{3.9}$$

Table 3.1. Descriptive Statistics on the Logarithmic Differences of 1-Month, 2-Months, and 3-Months Route 1 Spot and FFA Prices (1996:01-2000:07)

Panel A: 1-Month Route 1 Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	0.0052 (0.017)	-0.727 [0.034]	6.704 [0.000]	85.23 [0.00]	-0.743 (1)	-2.346	-9.586 (0)	-10.885	0.913
FFA	0.0033 (0.014)	-0.343 [0.317]	0.789 [0.268]	1.834 [0.40]	-1.514 (0)	-1.886	-7.069 (0)	-8.399	0.777

Panel B: 2-Months Route 1 Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	0.0024 (0.017)	-0.712 [0.039]	6.953 [0.000]	89.19 [0.00]	-0.772 (1)	-2.356	-9.700 (0)	-10.742	0.921
FFA	0.0021 (0.013)	0.041 [0.907]	-0.601 [0.403]	0.967 [0.616]	-1.505 (0)	-1.883	-6.001 (0)	-7.316	0.734

Panel C: 3-Months Route 1 Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) in 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	0.0007 (0.017)	-0.682 [0.051]	6.928 [0.000]	86.17 [0.00]	-0.542 (1)	-2.537	-9.546 (0)	-10.607	0.901
FFA	0.0014 (0.013)	-0.314 [0.369]	0.281 [0.699]	0.851 [0.65]	-1.765 (0)	-1.942	-6.154 (0)	-7.163	0.643

Notes:

- All series are measured in logarithmic first-differences.
- N is the number of observations, Mean is the sample mean. Standard errors of the sample mean are in parentheses (.).
- Skew and Kurt are the estimated centralised third and fourth moments of the data, denoted $\hat{\alpha}_3$ and ($\hat{\alpha}_4 - 3$), respectively; their asymptotic distributions under the null are $\sqrt{T}\ \hat{\alpha}_3 \sim N(0,6)$ and $\sqrt{T}\ (\hat{\alpha}_4 - 3) \sim N(0,24)$.
- J-B is the Jarque-Bera (1980) test for normality, distributed as $\chi^2(2)$. Exact significance levels are in square brackets [.].
- ADF is the Augmented Dickey Fuller (1981) test. The ADF regressions include an intercept term; the lag-length of the ADF test (in parentheses) is determined by minimising the SBIC (1978). PP is the Phillips and Perron (1988) test; the truncation lag for the test is in parentheses. The 5% critical value for the ADF and PP tests is –2.89.
- KPSS is the Kwiatkowski *et al.* (1992) test. The critical values for the KPSS test are 0.146 and 0.119 at the 5% and 10% levels, respectively. The null hypothesis of stationary is rejected if the test statistic exceeds them.
- Lev and 1st Diffs correspond to price series in log-levels and log first-differences, respectively.

Table 3.2. Descriptive Statistics on the Logarithmic Differences of 1-Month, 2-Months, and 3-Months Route 1A Spot and FFA Prices (1996:01-2000:07)

Panel A: 1-Month Route 1A Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	0.003 (0.017)	0.202 [0.556]	-0.346 [0.627]	2.597 [0.27]	-1.385 (0)	-1.817	-7.541 (0)	-8.485	0.578
FFA	-0.001 (0.016)	-0.239 [0.486]	-0.043 [0.952]	0.302 [0.860]	-1.437 (0)	-1.898	-6.860 (0)	-7.649	0.854

Panel B: 2-Months Route 1A Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	-0.001 (0.019)	0.601 [0.083]	0.433 [0.547]	3.190 [0.203]	-1.471 (0)	-1.998	-7.596 (0)	-8.393	0.913
FFA	-0.003 (0.016)	-0.302 [0.383]	0.434 [0.547]	1.577 [0.455]	-1.589 (0)	-1.962	-5.756 (0)	-6.496	0.798

Panel C: 3-Months Route 1A Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	-0.002 (0.019)	0.628 [0.073]	0.429 [0.555]	3.386 [0.184]	-1.133 (0)	-2.187	-7.271 (0)	-8.332	0.905
FFA	-0.003 (0.014)	-0.593 [0.090]	1.583 [0.029]	6.661 [0.036]	-1.585 (0)	-1.927	-5.736 (0)	-6.272	0.767

See Notes in Table 3.1

Table 3.3. Descriptive Statistics on the Logarithmic Differences of 1-Month, 2-Months, and 3-Months Route 2 Spot and FFA Prices (1996:01-2000:11)

Panel A: 1-Month Route 2 Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	-0.002 (0.011)	0.218 [0.510]	0.591 [0.387]	0.901 [0.637]	-1.686 (0)	-1.939	-7.455 (0)	-8.629	1.025
FFA	-0.002 (0.011)	-0.129 [0.696]	-0.698 [0.308]	1.478 [0.478]	-1.386 (0)	-1.833	-5.509 (0)	-6.571	0.948

Panel B: 2-Months Route 2 Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	-0.003 (0.011)	0.239 [0.472]	0.563 [0.415]	0.918 [0.632]	-1.743 (0)	-1.966	-7.660 (0)	-8.565	1.010
FFA	0.000 (0.011)	-0.041 [0.902]	-0.704 [0.308]	1.342 [0.511]	-1.708 (1)	-1.692	-5.039 (0)	-5.847	0.930

Panel C: 3-Months Route 2 Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs	KPSS
Spot	-0.003 (0.012)	0.247 [0.463]	0.507 [0.467]	0.838 [0.658]	-1.371 (0)	-2.076	-7.311 (0)	-8.492	1.011
FFA	0.001 (0.009)	-0.124 [0.713]	-0.593 [0.395]	1.111 [0.574]	-1.115 (0)	-1.578	-5.057 (0)	-5.966	0.889

See Notes in Table 3.1

Table 3.4. Descriptive Statistics on the Logarithmic Differences of 1-Month, 2-Months, and 3-Months Route 2A Spot and FFA Prices (1996:01-2000:11)

Panel A: 1-Month Route 2A Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1^{st} Diffs	PP(12) 1^{st} Diffs	KPSS
Spot	-0.005	0.611	1.591	7.86	-1.931 (0)	-1.918	-8.450 (0)	-9.189	0.998
	(0.018)	[0.064]	[0.020]	[0.02]					
FFA	-0.007	-0.093	0.169	0.086	-1.563 (0)	-1.897	-5.936 (0)	-6.759	0.971
	(0.015)	[0.778]	[0.805]	[0.958]					

Panel B: 2-Months Route 2A Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1^{st} Diffs	PP(12) 1^{st} Diffs	KPSS
Spot	-0.006	0.634	1.571	7.836	-2.056 (0)	-1.981	-8.563 (0)	-9.031	0.998
	(0.018)	[0.057]	[0.023]	[0.020]					
FFA	-0.004	-0.084	0.077	0.067	-1.531 (0)	-1.852	-5.971 (0)	-6.627	0.955
	(0.016)	[0.800]	[0.912]	[0.967]					

Panel C: 3-Months Route 2A Spot and FFA Price Series

	Mean	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1^{st} Diffs	PP(12) 1^{st} Diffs	KPSS
Spot	-0.008	0.666	1.589	8.138	-1.649 (0)	-2.161	-8.257 (0)	-9.029	0.992
	(0.019)	[0.048]	[0.023]	[0.017]					
FFA	-0.004	-0.181	0.474	0.539	-1.367 (0)	-1.807	-5.439 (0)	-6.046	0.930
	(0.014)	[0.591]	[0.497]	[0.764]					

See Notes in Table 3.1

The null hypothesis of stationarity is rejected in favour of the unit root alternative if the calculated test statistic exceeds the critical values estimated in Kwiatkowski *et al.* (1992, Table 1, p. 166). Results from the KPSS (1992) test in Tables 3.1 to 3.4 indicate that all spot and FFA price series in all routes have a unit root in their log-levels representation, as the null hypothesis of stationarity is not accepted. The results from Table 3.5 indicate that the means of the forecast errors are statistically zero for all maturities in all routes and that the variance of the forecast errors increases as the forecast horizon increases from one- to three-months in all routes. Financial theory indicates that the closer to maturity the contract is, the more information about prices exists, and consequently, there is less volatility and uncertainty regarding the outcome of the expected final spot prices, compared with longer days to delivery (Fama, 1970, 1991).

Table 3.5. Statistics on Forecast Errors

Panel A: Route 1 Forecast Errors

	N	Mean	Variance (S^2)	Test for Equal Variances	
1-Month	55	-0.065 (-0.308)	2.481	$F=S_2^2/S_1^2 \sim F(53,54)$	1.052 [0.426]
2-Months	54	-0.022 (-0.101)	2.611	$F=S_3^2/S_1^2 \sim F(52,54)$	1.551 [0.056]
3-Months	53	-0.009 (-0.034)	3.848	$F=S_3^2/S_2^2 \sim F(52,53)$	1.474 [0.081]

Panel B: Route 1A Forecast Errors

	N	Mean	Variance (S^2)	Test for Equal Variances	
1-Month	55	-102.2 (-0.609)	1,549,932	$F=S_2^2/S_1^2 \sim F(53,54)$	1.305 [0.167]
2-Months	54	-117.9 (-0.609)	2,021,205	$F=S_3^2/S_1^2 \sim F(52,54)$	1.878 [0.012]
3-Months	53	-193.7 (-0.826)	2,910,738	$F=S_3^2/S_2^2 \sim F(52,53)$	1.440 [0.095]

Panel C: Route 2 Forecast Errors

		Mean	Variance (S^2)	Test for Equal Variances	
1-Month	59	-0.166 (-0.689)	3.406	$F=S_2^2/S_1^2 \sim F(57,58)$	1.505 [0.062]
2-Months	58	-0.232 (-0.781)	5.125	$F=S_3^2/S_1^2 \sim F(56,58)$	2.325 [0.001]
3-Months	57	-0.285 (-0.765)	7.919	$F=S_3^2/S_2^2 \sim F(56,57)$	1.545 [0.050]

Panel D: Route 2A Forecast Errors

		Mean	Variance (S^2)	Test for Equal Variances	
1-Month	59	-263.3 (-1.459)	1,921,919	$F=S_2^2/S_1^2 \sim F(57,58)$	1.338 [0.136]
2-Months	58	-321.8 (-1.529)	2,570,709	$F=S_3^2/S_1^2 \sim F(56,58)$	1.955 [0.006]
3-Months	57	-415.4 (-1.618)	3,757,209	$F=S_3^2/S_2^2 \sim F(56,57)$	1.462 [0.078]

Notes:

- Exact significance levels are in square brackets [.].
- Mean and Variance are the sample mean and variance of the series, respectively.
- The *t*-statistic for the null hypothesis that the mean is zero are in parentheses (.).
- The *F*-test is the variance ratio test for the null hypothesis of the equality of variances with degrees of freedom ($n_1 - 1$) for the numerator and ($n_2 - 1$) for the denominator.

Applying an ordinary *F*-variance ratio test to examine the above inference with the null hypothesis to be equality of variances, we report that only the variances of the three-months forecast errors are significantly higher than the variances of the one-month forecasts in all routes, except in route 1 which is slightly insignificant. Also the variance of the three-months forecast errors is slightly higher than the variance of the two-months forecasts in route 2.

These findings may be due to the small size bias of our sampling intervals, which influence the degrees of freedom of the test or may be attributed to the non-normality of all forecast errors of all routes (applying a Jarque-Bera test). In order to interpret the above we employ the bootstrap technique with 10,000 iterations. Bootstrap resamples 10,000 new samples each of the same size, as the observed data are drawn with replacement from the observed data. The statistic of interest (variance ratio) is first calculated using the observed data and then recalculated using each of the new samples, yielding a bootstrap distribution. The resulting replicates are used to calculate the bootstrap estimates of the bias, the mean and standard error for the variance ratios.

Bias Corrected (BCa) confidence intervals are derived from the empirical confidence intervals, when the distributions are not normal, which transform the specified probabilities values to determine which percentiles of the empirical distribution most accurately estimate the percentiles of interest. The percentiles of the empirical distribution are then returned. Following the bootstrap procedure we notice that the variances of the three-months forecast errors are significantly higher than the variances of the one- and two-months forecast errors in all routes, except in route 2A where the variance of the three-months forecast error is statistically insignificant from the variance of the two-months forecast error (Table 3.6).

The results of the Box-Pierce (1970) and Ljung-Box (1978) autocorrelation tests applied to the forecast errors in all routes and for all sampling intervals, for the first 12 lags of the sample autocorrelation function, indicate mixed evidence (Table 3.7) about the power of past forecast errors predicting future forecast errors. In an efficient market, with rational market agents, past information should be already incorporated in current prices and therefore, there should be no autocorrelation of forecast errors.

Table 3.6. Bootstrap Results of Forecast Errors Variance Ratio Tests for 10,000 Replications

Panel A: Route 1

	Summary Statistics				Empirical Percentiles				BCa Percentiles			
	Obs	Mean	SE	*t*-stat	2.5%	5%	95%	97.5%	2.5%	5%	95%	97.5%
V(FE1M2)/ V(FE1M1)	1.052	1.106	0.329	336.2	0.651	0.702	1.621	1.788	0.646	0.700	1.614	1.768
V(FE1M3)/ V(FE1M1)	1.551	1.622	0.515	315.1	0.999	1.062	2.273	2.481	0.957	1.032	2.197	2.355
V(FE1M3)/ V(FE1M2)	1.474	1.529	0.447	342.1	0.931	0.997	2.170	2.362	0.950	1.018	2.217	2.405

Panel B: Route 1A

	Summary Statistics				Empirical Percentiles				BCa Percentiles			
	Obs	Mean	SE	*t*-stat	2.5%	5%	95%	97.5%	2.5%	5%	95%	97.5%
V(FE1AM2)/ V(FE1AM1)	1.304	1.369	0.420	325.6	0.789	0.855	2.030	2.191	0.734	0.818	1.950	2.087
V(FE1AM3)/ V(FE1AM1)	1.878	1.974	0.580	340.3	1.289	1.361	2.742	2.946	1.234	1.321	2.650	2.806
V(FE1AM3)/ V(FE1AM2)	1.440	1.498	0.411	364.3	0.952	1.021	2.102	2.246	0.934	1.002	2.066	2.200

Panel C: Route 2

	Summary Statistics				Empirical Percentiles				BCa Percentiles			
	Obs	Mean	SE	*t*-stat	2.5%	5%	95%	97.5%	2.5%	5%	95%	97.5%
V(FE2M2)/ V(FE2M1)	1.504	1.572	0.457	343.9	0.863	0.939	2.306	2.537	0.790	0.875	2.191	2.342
V(FE2M3)/ V(FE2M1)	2.325	2.437	0.681	357.9	1.588	1.687	3.296	3.536	1.519	1.623	3.170	3.372
V(FE2M3)/ V(FE2M2)	1.545	1.599	0.393	406.7	1.091	1.159	2.178	2.296	1.051	1.129	2.125	2.236

Panel D: Route 2A

	Summary Statistics				Empirical Percentiles				BCa Percentiles			
	Obs	Mean	SE	*t*-stat	2.5%	5%	95%	97.5%	2.5%	5%	95%	97.5%
V(FE1AM2)/ V(FE1AM1)	1.338	1.389	0.400	346.9	0.770	0.838	2.072	2.275	0.720	0.801	1.992	2.139
V(FE1AM3)/ V(FE1AM1)	1.955	2.046	0.571	358.3	1.287	1.378	2.757	2.957	1.218	1.320	2.649	2.811
V(FE1AM3)/ V(FE1AM2)	1.462	1.516	0.396	382.4	0.937	1.004	2.145	2.301	0.911	0.982	2.099	2.243

Notes:

- Obs, Mean, SE, and *t*-stat are the observed value of the variance ratio test, the sample mean with its standard error and the *t*-statistic, before the replications, respectively.
- FE1, FE1A, FE2, and FE2A correspond to Forecast Errors for routes 1, 1A, 2, and 2A, respectively.
- M1, M2, and M3 correspond to 1-Month, 2-Months, and 3-Months, respectively.

In all routes in the one-month forecast errors sampling interval the Q(12) statistics reveal that there is no autocorrelation. In two-months and three-months sampling intervals autocorrelation exists in all routes. We conclude, that overall the one-month forecast errors are free of autocorrelation and for higher sampling intervals (two-months and three-months) market agents can predict future forecast errors from reviewing the past.

Table 3.7. Autocorrelation Tests on Forecast Errors

Panel A: Autocorrelation Tests on Route 1 Forecast Errors (12 Lags)

	Autocorrelation Coefficient	Standard Error	Box-Pierce Statistic Q(12)	Ljung-Box Statistic Q(12)
FE1M1 (Sample 1-55)	0.068	0.172	17.691 [0.125]	20.235 [0.063]
FE1M2 (Sample 1-54)	-0.093	0.183	22.509 [0.032]	24.329 [0.018]
FE1M3 (Sample 1-53)	-0.064	0.202	30.825 [0.002]	33.295 [0.001]

Panel B: Autocorrelation Tests on Route 1A Forecast Errors (12 Lags)

	Autocorrelation Coefficient	Standard Error	Box-Pierce Statistic Q(12)	Ljung-Box Statistic Q(12)
FE1AM1 (Sample 1-55)	0.072	0.178	20.633 [0.056]	21.012 [0.051]
FE1AM2 (Sample 1-54)	-0.120	0.189	25.684 [0.012]	27.946 [0.006]
FE1AM3 (Sample 1-53)	-0.125	0.209	35.983 [0.000]	39.131 [0.000]

Panel C: Autocorrelation Tests on Route 2 Forecast Errors (12 Lags)

	Autocorrelation Coefficient	Standard Error	Box-Pierce Statistic Q(12)	Ljung-Box Statistic Q(12)
FE2M1 (Sample 1-59)	0.078	0.164	17.874 [0.120]	19.861 [0.070]
FE2M2 (Sample 1-58)	0.029	0.186	29.297 [0.004]	31.875 [0.001]
FE2M3 (Sample 1-57)	-0.116	0.209	43.671 [0.000]	47.411 [0.000]

Panel D: Autocorrelation Tests on Route 2A Forecast Errors (12 Lags)

	Autocorrelation Coefficient	Standard Error	Box-Pierce Statistic Q(12)	Ljung-Box Statistic Q(12)
FE2AM1 (Sample 1-59)	0.827	0.160	15.494 [0.216]	17.952 [0.117]
FE2AM2 (Sample 1-58)	-0.001	0.177	23.965 [0.021]	26.564 [0.009]
FE2AM3 (Sample 1-57)	-0.082	0.196	34.243 [0.001]	37.364 [0.000]

Notes:

- Q(12) are the Box-Pierce (1970) and Ljung-Box (1978) Q statistics distributed as $\chi^2(12)$; 5% critical value of 21.03.
- Exact significance levels are in square brackets [.].

3.6. EMPIRICAL RESULTS

Having identified that spot and FFA prices are $I(1)$ variables we test for cointegration of the spot and FFA series. The FMLS test, proposed by Phillips and Hansen (1990), is applied on the OLS regression of the realised spot price on the FFA price of Equation (3.5). The test consists of a non-parametric correction to the OLS estimates to take account of the impact on the residual term of autocorrelation and possible endogeneity if the right-hand-side variables in the cointegrating equation are not weakly exogenous. The critical values of the ADF (1981) and PP (1988) cointegration tests of the estimated residuals, in Table 3.8, do not have the standard Dickey-Fuller (1981) critical values. MacKinnon (1991) has linked the critical values for particular tests to a set of parameters of an equation of the response surfaces. Using the table of MacKinnon (1991) we can derive the critical values for the ADF (1981) and PP (1988) cointegration tests on the estimated residuals by the following equation:

$$C(p) = \Phi + \Phi_1 T^{-1} + \Phi_2 T^{-2} \tag{3.10}$$

where $C(p)$ is the p per cent critical value (5% in our test) and T is the number of observations. The residual-based ADF (1981) and PP (1988) tests for cointegration assume that the variables in the FMLS equation are all $I(1)$, such that the test for cointegration is whether $u_t \sim I(1)$ (no cointegration relationship) against the alternative that $u_t \sim I(0)$ (cointegration relationship).

Results in Table 3.8 indicate that for one- and two-months maturities the residuals are stationary in all routes. Thus, FFA and realised spot prices are cointegrated, with the parameter restrictions of unbiasedness to hold in routes 1, 1A, and 2A. In route 2 unbiasedness is rejected for both one- and two-months maturities. For the three-months maturity none of the FFA price series and the realised spot rates are cointegrated, and thus, unbiasedness is rejected in all routes.

Next the Johansen (1988) procedure is employed in order to test for cointegration. The first step is to decide on the specification of the VECM with the appropriate deterministic components and a robust lag structure, so as to capture any residual autocorrelation. SBIC (1978) and AIC (1973), used to determine the lag length in the VECM, select 1, 2, and 1 lags for the one- two- and three-months maturities, respectively[64]. Due to the convergence of forward and spot prices at the expiration date of the FFA contracts, we do not expect the presence of linear trend term in the cointegrating vector (exclude model 2.32); Moreover, from the graphs of spot and forward prices, in chapter 1, we cannot observe the presence of a quadratic trend in the series (exclude model 2.31); Finally, the existence of an intercept term, either restricted in the long-run cointegrating space or unrestricted in the short-run model is needed to account for the units of measurement of the variables (exclude model 2.35). For our analysis we are left with two different model specifications; model 2.33 – intercept in the short-run model and model 2.34 – intercept in the long-run model (for a description of the five models see section 2.5.3.2). Use of the Johansen (1991) LR test select a restricted intercept in the cointegration vector in all cases (model 2.34).

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[64] The lag length corresponds to an unrestricted VAR in levels: $X_t = \sum_{i=1}^{p} A_i X_{t-i} + \varepsilon_t$. A VAR with p lags of the dependent variable can be reparameterised in a VECM with p-1 lags of first-differences of the dependent variable plus the levels terms.

Table 3.8. Unbiasedness Hypothesis Tests using the Phillips-Hansen (1990) Fully Modified-Least Squares Estimator

Panel A: 1-Month Sampling Interval

	Cointegration Tests		Coefficient Estimates		Hypothesis Tests		
	τ (lags) (a)	Z (lags) (b)	β_1	β_2	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 1$	$H_0: \beta_1 = 0, \beta_2 = 1$
Route 1	-5.851 (0)	-6.173 (10)	0.351 (0.240)	0.85492 (0.0975)	2.135 [0.144]	2.215 [0.137]	2.297 [0.317]
Route 1A	-5.421 (0)	-5.361 (10)	0.511 (0.763)	0.94196 (0.0843)	0.448 [0.503]	0.474 [0.491]	0.922 [0.630]
Route 2	-5.919 (0)	-6.233 (10)	0.530 (0.158)	0.82271 (0.0524)	11.233 [0.001]	11.433 [0.001]	11.513 [0.003]
Route 2A	-6.0301 (0)	-6.117 (10)	0.825 (0.559)	0.90818 (0.0606)	2.177 [0.140]	2.296 [0.130]	3.624 [0.163]

Panel B: 2-Months Sampling Interval

	Cointegration Tests		Coefficient Estimates		Hypothesis Tests		
	τ (lags) (a)	Z (lags) (b)	β_1	β_2	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 1$	$H_0: \beta_1 = 0, \beta_2 = 1$
Route 1	-3.909 (0)	-3.996 (10)	0.424 (0.315)	0.820 (0.128)	1.889 [0.169]	1.963 [0.161]	2.056 [0.358]
Route 1A	-3.562 (0)	-3.493 (10)	1.019 (0.986)	0.885 (0.108)	1.068 [0.301]	1.108 [0.292]	1.556 [0.459]
Route 2	-3.536 (0)	-3.556 (10)	0.620 (0.236)	0.791 (0.078)	6.864 [0.009]	7.087 [0.008]	7.341 [0.025]
Route 2A	-3.932 (0)	-3.826 (10)	0.972 (0.814)	0.891 (0.088)	1.428 [0.232]	1.515 [0.218]	2.676 [0.262]

Panel C: 3-Months Sampling Interval

	Cointegration Tests		Coefficient Estimates		Hypothesis Tests		
	τ (lags) (a)	Z (lags) (b)	β_1	β_2	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 1$	$H_0: \beta_1 = 0, \beta_2 = 1$
Route 1	-3.435 (0)	-3.447 (10)	-	-	-	-	-
Route 1A	-2.983 (0)	-3.022 (10)	-	-	-	-	-
Route 2	-3.050 (0)	-3.171 (10)	-	-	-	-	-
Route 2A	-3.440 (0)	-3.433 (10)	-	-	-	-	-

Notes:

- Exact significance levels are in square brackets [.].
- The estimation method is the Phillips and Hansen (1990) Fully-Modified OLS. Estimation is carried out using Parzen weights; the truncation lag is set equal to 1, 2, and 1 for the one-, two- and three-months maturities, respectively, minimising the SBIC (1978).
- (a) τ is the Dickey and Fuller (1981) residual-based test for cointegration; the lag length, in parentheses (.), is determined by minimising the SBIC (1978).
- (b) Z is the Phillips and Perron (1988) test for cointegration; the truncation lag, in parentheses (.), is computed using the formula suggested by Schwert (1987), i.e. $\text{int}[12(N/100)^{0.25}]$.
- The critical values for the τ and Z tests for the null hypothesis of no cointegration ($I(1)$) are: for the one-month -3.451, -3.451, -3.443, and -3.443 for routes 1, 1A, 2, and 2A, respectively. For the two-months -3.453, -3.453, -3.445, and -3.445 for routes 1, 1A, 2, and 2A, respectively. For the three-months -3.455, -3.455, -3.447, and -3.447 for routes 1, 1A, 2, and 2A, respectively (MacKinnon, 1991).
- The asymptotic standard errors of the coefficient estimates are in parentheses (.). Hypotheses tests on the coefficient estimates are carried out using a Wald test distributed as χ^2 with degrees of freedom equal to the number of restrictions.

The Johansen's (1988) trace (λ_{trace}) and maximal (λ_{max}) statistics, in Table 3.9, indicate that FFA and realised spot prices are cointegrated for all maturities and in all routes, except in route 1A for the three-months maturity. Due to our relatively small sample (maximum of 58 observations in routes 2 and 2A in the one-month interval) it is appropriate to adjust the λ_{max} and λ_{trace} cointegrating rank test statistics by a small-sample correction proposed by Reimers (1992). The Reimers (1992) small sample correction on Johansen's λ_{trace} and λ_{max} test statistics (denoted as λ^{*}_{trace} and λ^{*}_{max}) confirms cointegration of all variables except in routes 1 and 1A for the three-months maturity[65].

The unbiasedness hypothesis is examined next by testing the restrictions $\beta_1 = 0$ and $\beta_2 = -1$ in the cointegration relationship $\beta' X_{t-1} = (1\ \beta_1\ \beta_2)(S_{t-1}\ C\ F_{t-1;\ t-n-1})'$. If these restrictions hold, then the price of the FFA contract is an unbiased predictor of the realised spot price. The estimated coefficients of the cointegrating vectors, the hypothesis tests on β' using Equation (3.6), along with the residual diagnostics of the models, are presented in Tables 3.10 to 3.12 for the one- two- and three-months maturities, respectively. The results indicate that for the one- and two-months FFA prices in all routes, and for the three-months FFA prices in routes 2 and 2A, unbiasedness cannot be rejected at conventional levels of significance. However, unbiasedness is rejected for the three-months FFA prices in routes 1 and 1A, as FFA and spot prices are not cointegrated (see Table 3.9, Panel C)[66].

The unbiasedness hypothesis is not rejected, in all routes and maturities, where the realised spot prices and the FFA prices are cointegrated. The unbiasedness hypothesis is rejected in routes 1 and 1A, in the three-months maturity, where the spot and FFA prices are not cointegrated (based on the λ^{*}_{max} and λ^{*}_{trace} statistics). Therefore, there is no need to adjust the LR statistics of Equation (2.37) by the Psaradakis (1994) small-sample correction[67].

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[65] Reimers (1992) small sample correction consists of using the factor $(T - kp)$ instead of T in the calculation of the λ_{max} and λ_{trace}, where T is the number of observations, k is the number of regressors, and p is the lag length of the VECM.

[66] The discrepancy in our results from the Johansen (1988) test may be attributed to the low power of residual-based cointegration tests compared to the Johansen (1988) test. Another reason is the small-sample correction of Reimers (1992) in the Johansen (1988) test.

[67] Psaradakis (1994), suggests correcting the LR test of Equation (2.37) by a factor of $(T - m/k)/T$, where m is the number of estimated parameters in the VECM subject to the reduced rank restriction $\Pi = \alpha\beta'$.

Table 3.9. Johansen (1988) Tests for the Number of Cointegrating Vectors Between FFA and Spot Prices

Panel A: 1-Month Sampling Interval (Lag Length of VECM is 1)

	Hypothesis (Maximal)		Test Statistic		Hypothesis (Trace)		Test Statistic		95% Critical Values	
	H_0	H_1	λ_{max}	λ^*_{max}	H_0	H_1	λ_{trace}	λ^*_{trace}	λ_{max}	λ_{trace}
Route 1	$r=0$	$r=1$	33.17	31.94	$r=0$	$r>=1$	34.51	33.24	15.67	19.96
	$r<=1$	$r=2$	1.35	1.30	$r<=1$	$r=2$	1.35	1.30	9.24	9.24
Route 1A	$r=0$	$r=1$	29.19	28.11	$r=0$	$r>=1$	30.51	29.38	15.67	19.96
	$r<=1$	$r=2$	1.32	1.27	$r<=1$	$r=2$	1.32	1.27	9.24	9.24
Route 2	$r=0$	$r=1$	37.21	35.93	$r=0$	$r>=1$	39.41	38.05	15.67	19.96
	$r<=1$	$r=2$	2.19	2.12	$r<=1$	$r=2$	2.19	2.12	9.24	9.24
Route 2A	$r=0$	$r=1$	40.93	39.52	$r=0$	$r>=1$	43.40	41.90	15.67	19.96
	$r<=1$	$r=2$	2.47	2.39	$r<=1$	$r=2$	2.47	2.39	9.24	9.24

Panel B: 2-Months Sampling Interval (Lag Length of VECM is 2)

	Hypothesis (Maximal)		Test Statistic		Hypothesis (Trace)		Test Statistic		95% Critical Values	
	H_0	H_1	λ_{max}	λ^*_{max}	H_0	H_1	λ_{trace}	λ^*_{trace}	λ_{max}	λ_{trace}
Route 1	$r=0$	$r=1$	20.73	19.16	$r=0$	$r>=1$	23.33	21.57	15.67	19.96
	$r<=1$	$r=2$	2.60	2.41	$r<=1$	$r=2$	2.60	2.41	9.24	9.24
Route 1A	$r=0$	$r=1$	27.89	25.79	$r=0$	$r>=1$	31.47	29.09	15.67	19.96
	$r<=1$	$r=2$	3.57	3.30	$r<=1$	$r=2$	3.57	3.30	9.24	9.24
Route 2	$r=0$	$r=1$	38.61	35.90	$r=0$	$r>=1$	42.69	39.69	15.67	19.96
	$r<=1$	$r=2$	4.08	3.80	$r<=1$	$r=2$	4.08	3.80	9.24	9.24
Route 2A	$r=0$	$r=1$	42.95	39.94	$r=0$	$r>=1$	46.78	43.49	15.67	19.96
	$r<=1$	$r=2$	3.82	3.56	$r<=1$	$r=2$	3.82	3.56	9.24	9.24

Panel C: 3-Months Sampling Interval (Lag Length of VECM is 1)

	Hypothesis (Maximal)		Test Statistic		Hypothesis (Trace)		Test Statistic		95% Critical Values	
	H_0	H_1	λ_{max}	λ^*_{max}	H_0	H_1	λ_{trace}	λ^*_{trace}	λ_{max}	λ_{trace}
Route 1	$r=0$	$r=1$	16.16	15.54	$r=0$	$r>=1$	19.03	18.30	15.67	19.96
	$r<=1$	$r=2$	2.87	2.76	$r<=1$	$r=2$	2.87	2.76	9.24	9.24
Route 1A	$r=0$	$r=1$	15.80	15.20	$r=0$	$r>=1$	19.03	18.30	15.67	19.96
	$r<=1$	$r=2$	3.23	3.11	$r<=1$	$r=2$	3.23	3.11	9.24	9.24
Route 2	$r=0$	$r=1$	27.19	26.22	$r=0$	$r>=1$	31.22	30.10	15.67	19.96
	$r<=1$	$r=2$	4.03	3.88	$r<=1$	$r=2$	4.03	3.88	9.24	9.24
Route 2A	$r=0$	$r=1$	23.50	22.65	$r=0$	$r>=1$	27.19	26.22	15.67	19.96
	$r<=1$	$r=2$	3.70	3.57	$r<=1$	$r=2$	3.70	3.57	9.24	9.24

Notes:

- r represents the number of cointegrating vectors,
- $\lambda_{max}(r,r+1) = -T\ln(1-\hat{\lambda}_{r+1})$ and $\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\hat{\lambda}_i)$ where $\hat{\lambda}_i$ are the estimated eigenvalues of the Π matrix in Equation (2.24).
- $\lambda^*_{max} = (T-kp)/T\,\lambda_{max}$ and $\lambda^*_{trace} = (T-kp)/T\,\lambda_{trace}$, are small-sample adjusted cointegrating rank tests, where k is the number of regressors in the VECM (Reimers, 1992).
- Critical values are from Osterwald-Lenum (1992), Table 1*.

Table 3.10. Likelihood Ratio Tests of Parameter Restrictions on the Normalised Cointegrating Vector of One-Month FFA and Spot Prices

Panel A: Model Specification

$$\begin{pmatrix} \Delta S_t \\ \Delta F_{t,t-1} \end{pmatrix} = \Gamma_1 \begin{pmatrix} \Delta S_{t-1} \\ \Delta F_{t-1,t-2} \end{pmatrix} + \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} \begin{pmatrix} 1 & \beta_1 & \beta_2 \end{pmatrix} \begin{pmatrix} S_{t-1} \\ 1 \\ F_{t-1,t-2} \end{pmatrix} + \begin{pmatrix} u_{S,t} \\ u_{F,t} \end{pmatrix} \; ; \; \begin{pmatrix} u_{S,t} \\ u_{F,t} \end{pmatrix} \sim IN(0,\Sigma) \quad (3.6)$$

	Coefficient Estimates					Hypothesis Tests on β'		
	α_1	α_2	$\beta' = (1\ \beta_1\ \beta_2)$			H_0: $\beta_1 = 0$	H_0: $\beta_2 = -1$	H_0: $\beta_1 = 0$ and $\beta_2 = -1$
Route 1	-0.385 (-3.392)	0.440 (5.544)	1	-0.049	-0.976	0.031 [0.860]	0.043 [0.835]	0.249 [0.883]
Route 1A	-0.326 (-2.834)	0.420 (4.938)	1	0.4278	-1.045	0.216 [0.642]	0.201 [0.654]	0.561 [0.755]
Route 2	-0.099 (-1.807)	0.026 (0.463)	1	-0.3517	-0.882	3.457 [0.063]	3.493 [0.062]	3.504 [0.173]
Route 2A	-0.268 (-2.180)	0.528 (6.547)	1	-0.1550	-0.981	0.736 [0.786]	0.0891 [0.765]	0.790 [0.674]

Notes:

- α_1 and α_2 are the coefficient estimates of the error-correction model implied by the normalised cointegrating parameters, t-statistics for the null hypothesis ($\alpha_i = 0$) are in parentheses (.).
- Estimates of the coefficients in the cointegrating vector are normalised with respect to the coefficient of the spot rate, S_t.
- The statistic for the unbiasedness hypothesis tests on the coefficients of the cointegrating vector is $-T\,[\ln(1 - \hat{\lambda}^*_1) - \ln(1 - \hat{\lambda}_1)]$ where $\hat{\lambda}^*_1$ and $\hat{\lambda}_1$ denote the largest eigenvalues of the restricted and the unrestricted models respectively. The statistic is distributed as χ^2 with degrees of freedom equal to the total number of restrictions minus the number of the just identifying restrictions, which equals the number of restrictions placed on the cointegrating vector. Exact significance levels are in square brackets [.].

Panel B: Residual Diagnostics

	Residuals	LM(1)	Q(12)	ARCH(4)	J-B
Route 1	$u_{S,t}$	0.013 [0.908]	8.788 [0.721]	0.609 [0.962]	85.56 [0.000]
	$u_{F,t}$	3.792 [0.051]	20.92 [0.052]	4.021 [0.400]	0.853 [0.653]
Route 1A	$u_{S,t}$	1.822 [0.177]	5.632 [0.933]	9.095 [0.059]	1.087 [0.581]
	$u_{F,t}$	2.689 [0.101]	22.16 [0.036]	1.788 [0.775]	1.433 [0.488]
Route 2	$u_{S,t}$	0.898 [0.343]	7.430 [0.828]	1.199 [0.878]	0.031 [0.985]
	$u_{F,t}$	0.772 [0.380]	12.39 [0.414]	5.841 [0.211]	1.373 [0.503]
Route 2A	$u_{S,t}$	0.130 [0.718]	7.911 [0.792]	3.131 [0.536]	3.826 [0.148]
	$u_{F,t}$	7.729 [0.005]	50.06 [0.000]	5.014 [0.286]	0.721 [0.697]
	5% c. v.	3.84	21.03	9.49	5.99

Notes:

- $u_{S,t}$ and $u_{F,t}$ are the estimated residuals from the spot and the FFA equation in the VECM, respectively.
- LM(1) is the Godfrey (1978) Lagrange Multiplier test for serial correlation of order 1 and is asymptotically distributed as $\chi^2(1)$. Exact significance levels are in square brackets [.].
- Q(12) is the Ljung-Box (1978) Q statistic of the sample autocorrelation function on the first 12 lags and is distributed as $\chi^2(12)$. Exact significance levels are in square brackets [.].
- ARCH(4) is the Engle (1982) test for ARCH effects and is distributed as $\chi^2(4)$. Exact significance levels are in square brackets [.].
- J-B is the Jarque-Bera (1980) test for normality and is distributed as $\chi^2(2)$. Exact significance levels are in square brackets [.].

Table 3.11. Likelihood Ratio Tests of Parameter Restrictions on the Normalised Cointegrating Vector of Two-Months FFA and Spot Prices

Panel A: Model Specification

$$\begin{pmatrix} \Delta S_t \\ \Delta F_{t,t-2} \end{pmatrix} = \sum_{i}^{2} \Gamma_i \begin{pmatrix} \Delta S_{t-i} \\ \Delta F_{t-i,t-2-i} \end{pmatrix} + \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} \begin{pmatrix} 1 & \beta_1 & \beta_2 \end{pmatrix} \begin{pmatrix} S_{t-1} \\ 1 \\ F_{t-1,t-3} \end{pmatrix} + \begin{pmatrix} u_{S,t} \\ u_{F,t} \end{pmatrix} \; ; \; \begin{pmatrix} u_{S,t} \\ u_{F,t} \end{pmatrix} \sim IN(0,\Sigma) \quad (3.6)$$

	Coefficient Estimates					Hypothesis Tests on β'		
	α_1	α_2	$\beta' = (1\ \beta_1\ \beta_2)$			H_0: $\beta_1 = 0$	H_0: $\beta_2 = -1$	H_0: $\beta_1 = 0$ and $\beta_2 = -1$
Route 1	-0.359 (-0.271)	0.417 (4.601)	1	0.178	-1.067	0.204 [0.652]	0.172 [0.678]	0.506 [0.776]
Route 1A	-0.009 (-0.066)	0.517 (5.377)	1	0.896	-1.097	0.845 [0.358]	0.809 [0.368]	2.434 [0.488]
Route 2	0.213 (1.701)	0.642 (7.209)	1	-0.099	-0.965	0.242 [0.623]	0.264 [0.607]	0.394 [0.821]
Route 2A	0.057 (0.423)	0.631 (7.482)	1	0.591	-1.062	0.988 [0.320]	0.924 [0.336]	2.129 [0.345]

See Notes in Table 3.10, Panel A.

Panel B: Residual Diagnostics

	Residuals	LM(1)	Q(12)	ARCH(4)	J-B
Route 1	$u_{S,t}$	3.127 [0.077]	7.662 [0.811]	0.1882 [0.996]	57.946 [0.000]
	$u_{F,t}$	2.157 [0.142]	36.767 [0.000]	2.577 [0.631]	1.357 [0.507]
Route 1A	$u_{S,t}$	2.695 [0.101]	4.157 [0.980]	2.808 [0.590]	3.482 [0.175]
	$u_{F,t}$	2.383 [0.123]	44.042 [0.000]	7.135 [0.129]	1.861 [0.394]
Route 2	$u_{S,t}$	0.027 [0.869]	6.654 [0.880]	1.096 [0.895]	1.149 [0.563]
	$u_{F,t}$	4.521 [0.033]	33.335 [0.001]	3.577 [0.466]	0.535 [0.765]
Route 2A	$u_{S,t}$	0.2059 [0.650]	5.363 [0.945]	6.225 [0.183]	4.781 [0.092]
	$u_{F,t}$	4.206 [0.040]	45.022 [0.000]	4.425 [0.351]	0.481 [0.786]
	5% c. v.	3.84	21.03	9.49	5.99

See Notes in Table 3.10, Panel B.

Table 3.12. Likelihood Ratio Tests of Parameter Restrictions on the Normalised Cointegrating Vector of Three-Months FFA and Spot Prices

Panel A: Model Specification

$$\begin{pmatrix} \Delta S_t \\ \Delta F_{t,t-3} \end{pmatrix} = \Gamma_1 \begin{pmatrix} \Delta S_{t-1} \\ \Delta F_{t-1,t-4} \end{pmatrix} + \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} (1\,\beta_1\,\beta_2) \begin{pmatrix} S_{t-1} \\ 1 \\ F_{t-1,t-4} \end{pmatrix} + \begin{pmatrix} u_{S,t} \\ u_{F,t} \end{pmatrix} \quad ; \quad \begin{pmatrix} u_{S,t} \\ u_{F,t} \end{pmatrix} \sim IN(0,\Sigma) \qquad (3.6)$$

	Coefficient Estimates					Hypothesis Tests on β'		
	α_1	α_2	$\beta' = (1\ \beta_1\ \beta_2)$			H_0: $\beta_1 = 0$	H_0: $\beta_2 = -1$	H_0: $\beta_1 = 0$ and $\beta_2 = -1$
Route 1	-	-	-	-	-	-	-	-
Route 1A	-	-	-	-	-	-	-	-
Route 2	0.005 (0.068)	0.314 (5.724)	1	-0.399	-0.863	1.016 [0.313]	1.079 [0.299]	1.346 [0.510]
Route 2A	-0.088 (-0.978)	0.287 (5.287)	1	-0.004	-0.997	0.001 [0.998]	0.001 [0.982]	0.455 [0.796]

See Notes in Table 3.10, Panel A.

Panel B: Residual Diagnostics

	Residuals	LM(1)	Q(12)	ARCH(4)	J-B
Route 1	$u_{S,t}$	-	-	-	-
	$u_{F,t}$	-	-	-	-
Route 1A	$u_{S,t}$	-	-	-	-
	$u_{F,t}$	-	-	-	-
Route 2	$u_{S,t}$	2.448 [0.118]	7.705 [0.808]	0.449 [0.978]	0.906 [0.636]
	$u_{F,t}$	0.947 [0.330]	24.136 [0.019]	2.761 [0.599]	1.948 [0.377]
Route 2A	$u_{S,t}$	1.630 [0.202]	7.930 [0.791]	1.945 [0.746]	3.444 [0.179]
	$u_{F,t}$	1.252 [0.263]	38.834 [0.000]	9.290 [0.054]	0.556 [0.757]
	5% c. v.	3.84	21.03	9.49	5.99

See Notes in Table 3.10, Panel B.

After applying the Bieren's (1997) λ_{min} and $g_m(r_0)$ cointegration statistics to determine the cointegration rank, using Equation (3.5), results in Table 3.13 indicate that the FFA prices one- two- and three-months prior to maturity are cointegrated with the realised spot prices in all routes, with the exception of route 1A three-months FFA prices. To test for linear restrictions (unbiasedness) on the cointegrating vectors, we apply the trace statistic proposed by Bierens (1997). The results indicate that in those routes and maturities for which cointegration was found, unbiasedness cannot be rejected. The results of the Bierens (1997) test are in line with the Johansen (1988) test results. Their only difference lies after the small sample correction of Reimers (1992), which indicates that FFA prices three-months prior to maturity in route 1 are not cointegrated and are thus, biased predictors of the realised spot prices.

Table 3.13. Unbiasedness Hypothesis Tests using the Bierens (1997) Test

Panel A: 1-Month Sampling Interval

	Hypothesis λ_{min}	Critical Values	Hypothesis $g_m(r_0)$	Coef. Estimates	Hypothesis Test
	$r = 0 / r = 1$ $r = 1 / r = 2$	5% Significance Level	$r_0 = 0, 1, 2$	(Spot, FFA)	H_0: β' (1 –1)
Route 1	0.0009 1.3587	(0.017) (0.054)	12.99e+003 **12.16e-002** 65.44e+001	(1, -0.844)	1.41*
Route 1A	0.0001 0.8892	(0.017) (0.054)	13.54e+004 **27.23e-003** 62.80e+000	(1, -0.612)	2.08*
Route 2	0.0005 1.3097	(0.017) (0.054)	12.37e+006 **15.85e-005** 91.48e-002	(1, -0.952)	1.10*
Route 2A	0.0002 1.5895	(0.017) (0.054)	18.31e+004 **72.70e-004** 61.79e+000	(1, -0.868)	1.37*

Panel B: 2-Months Sampling Interval

	Hypothesis λ_{min}	Critical Values	Hypothesis $g_m(r_0)$	Coef. Estimates	Hypothesis Test
	$r = 0 / r = 1$ $r = 1 / r = 2$	5% Significance Level	$r_0 = 0, 1, 2$	(Spot, FFA)	H_0: β' (1 –1)
Route 1	0.0000 1.4003	(0.017) (0.054)	12.21e+007 **11.73e-006** 64.61e-003	(1, -0.791)	1.26*
Route 1A	0.0014 0.8839	(0.017) (0.054)	10.14e+002 **35.45e-001** 77.79e+002	(1, -0.612)	3.77*
Route 2	0.0023 1.4766	(0.017) (0.054)	16.91e+002 **88.17e-002** 62.43e+002	(1, -0.774)	1.62*
Route 2A	0.0020 1.9603	(0.017) (0.054)	29.23e+001 **28.93e-001** 36.12e+003	(1, -0.712)	1.85*

Panel C: 3-Months Sampling Interval

	Hypothesis λ_{min}	Critical Values	Hypothesis $g_m(r_0)$	Coef. Estimates	Hypothesis Test
	$r = 0 / r = 1$ $r = 1 / r = 2$	5% Significance Level	$r_0 = 0, 1, 2$	(Spot, FFA)	H_0: β' (1 –1)
Route 1	0.0000 1.5101	(0.017) (0.054)	59.33e+005 **19.99e-005** 12.32e-001	(1, -0.996)	1.41*
Route 1A	0.0184 1.1467	(0.017) (0.054)	**47.67e+000** 43.14e+000 15.34e+004	-	-
Route 2	0.0103 1.6007	(0.017) (0.054)	30.55e+001 **40.06e-001** 32.19e+003	(1, -0.621)	2.15*
Route 2A	0.0081 2.1553	(0.017) (0.054)	57.77e+000 **11.69e+000** 17.02e+004	(1, -0.560)	2.90*

Notes:

- λ_{min} is the Lambda-min test statistic, the parameter m is chosen from optimal values tabulated in Bierens (1997). Critical values, in parentheses (.), for the 5% significance level are from Bierens (1997). $g_m(r_0)$ estimates the number of the cointegration rank, r, consistently (0, 1, 2) using $\hat{r} = \text{argmin}_{r_0} \leq 2\ g_m(r_0)$, m = 2. Bold indicates minimum value of statistic.
- The estimated cointegrating vector is normalised with respect to realised spot prices.
- The hypothesis test on the cointegrating vector is the Bieren's Trace test for linear restrictions, m = 2n with n the dimension of the system.
- * denotes significance at the 5% level.

In order to investigate the short-run properties of the spot and FFA prices, we examine the estimated error-correction coefficients of the spot prices, α_1, and of the FFA prices, α_2, for the investigated routes (Tables 3.10 to 3.12). The results indicate that for the one-month maturity the error-correction coefficients of both spot and FFA prices are statistically significant but have opposite signs. The negative spot price coefficients and the positive FFA price coefficients are in accordance with convergence towards a long-run equilibrium. Thus, in response to a positive forecast error both the FFA and the spot price series will increase and decrease in value, respectively in order to restore the long-run equilibrium. For the two-months maturity we observe that the coefficients on the spot prices are negative and statistically insignificant for routes 1 and 1A and positive and statistically insignificant for routes 2 and 2A. On the other hand, the coefficients on the FFA prices are positive and statistically significant for all routes. The sign and the significance of the coefficients indicate that only FFA prices respond to correct the previous period's deviations and restore the long-run relationship. For the remaining three-months maturity the coefficients on the spot prices are statistically insignificant in both investigated routes, with a positive sign on route 2 and a negative sign on route 2A. Again only FFA prices correct the disequilibrium that is created from previous period's deviations.

The signs and the significance of the error-correction coefficients for all routes and maturities are consistent with the empirical findings regarding the lack of a bias. Any disequilibrium from the previous period is not carried forward to the current period, as would be expected if there was a bias in FFA prices. More specifically, both spot and FFA prices respond to restore the long-run equilibrium in the one-month maturity, while in the two- and three-months maturities only FFA prices respond to the previous period's deviations from the long-run equilibrium relationship and do all the correction to eliminate this disequilibrium. This finding is consistent with the hypothesis that past forecast errors affect the current forecasts of the realised spot prices, i.e. FFA prices, but not the spot prices themselves. The differences in signs and significance levels between routes in each maturity period may lie in the different economic circumstances and trading fluctuations of each route, responding to different shocks in the system.

The results of the analysis indicate that FFA prices in routes 1 and 1A three-months prior to maturity do not follow a long-run relationship with spot prices. The finding of no cointegration between spot and forward prices may be due to the following reasons: First, lack of cointegration is normally interpreted to imply either market inefficiency or that the markets do not represent the same asset (Engel, 1996). Second, many FFA brokers suggest that for a creditworthy agent to initiate a FFA contract with another, less creditworthy, agent, the former may require a security against a potential default of the latter in the form of a default-premium. Thus, the FFA price in Equation (3.5) may be substantially different than the spot price, by the existence of such a premium, creating lack of cointegration between them.

Third, another reason for finding lack of cointegration may be that spot and forward prices differ in their ability to incorporate information (Crain and Lee, 1996). The international dry-bulk spot freight market provides an immediate fixture of a vessel, and suppliers and buyers on the spot market may not have time to respond to new market information. Due to the forward nature of the FFA market, there may be more time for information to be incorporated in prices (see also Chapter 4, section 4.5.2). Thus, FFA prices, as they can aggregate more information, may be set at a different level than spot prices, creating lack of cointegration between them. Yang and Leatham (1999) argue that this difference between commodity spot and forward prices may be more significant for commodities traded largely in international markets.

Thin trading (low volume) may provide an explanation for finding lack of cointegration in some routes three-months prior to maturity (1 and 1A) and not in others (2 and 2A). FFA brokers provide only actively trading dry-bulk routes as the underlying assets of the FFA contracts. From August 2000 FFA brokers stopped trading FFA contracts for routes 1 and 1A as their volumes decreased steadily, making FFA bid and ask prices in these routes to be almost unchanged for several months (especially prices for FFA contracts three-months prior to maturity). Consequently, FFA prices may have not followed closely the relevant underlying spot prices, creating a deviation in their long-run relationship. Moreover, finding FFA prices for Atlantic routes (routes 1 and 1A) not cointegrated with the spot prices and FFA prices for Pacific routes (routes 2 and 2A) cointegrated with the spot prices three-months prior to maturity, may be due to the different sampling periods, which may be liable to different economic circumstances (Engel, 1996)[68].

[68] Routes 1 and 1A are sampled from January 1996 to July 2000, while routes 2 and 2A are sampled from January 1996 to November 2000.

Finally, another explanation may be the specific characteristics of the Atlantic and the Pacific trades. Demand for shipping services in each trade route depends on the economics of the commodities transported, world economic activity and the related macroeconomic variables of major economies involved (Stopford, 1997 p. 238). As a policy action FFA brokers should reassess the way they submit their long-term (three-months) FFA estimates, as in OTC forward markets there is no guarantee that the current forward price is also the best available estimate in the market (as opposed in futures markets). Kavussanos and Nomikos (1999) examine the futures BIFFEX contract and conclude that BIFFEX prices are cointegrated with spot prices one-, two-, and three-months prior to maturity, but finding unbiasedness only in the first two maturities.

The implications of the analysis can be stated as follows. First, shipowners and charterers can receive accurate signals from FFA prices, one- and two-months prior to maturity in all investigated routes, and from FFA prices three-months prior to maturity in routes 2 and 2A, regarding the future course of spot prices. Consequently, market agents can use the information generated by FFA prices so as to guide their decisions in the physical market and secure their cash-flow (transportation costs). Freight rates may deviate from the expected level quite considerably, and eliminate expected operating profits (Kavussanos, 1996). Thus, FFA contracts may provide a valuable tool for a market agent operating in the dry-bulk sector to protect himself against adverse freight rate movements, by using unbiased FFA prices to better predict the spot market.

Second, given the fact that FFA prices are found biased in routes 1 and 1A three-months prior to maturity (which may be due to the low trading volume), speculation and arbitrage opportunities may create possibilities for excess profits to be made. This however, could well provide an extra incentive for speculators to enter the market and consequently, attract the much-needed volume. Third, routes 1 and 1A three-months prior to maturity, where FFA prices are found biased, risk-averse agents, with the choice of employing information from the FFA market to construct rolling-hedges, should avoid using these FFA contracts. It appears that the specific time of the expiration of the contracts is not a time when the markets are efficient and hence, it is not the time when the hedges should be rolled over. FFA brokers must have realised the aforementioned bias and as a policy action they have withdrawn FFA trading in these routes. The results of a clear absence of any cointegration relationship between spot and FFA prices three-months prior to maturity for routes 1 and 1A, confirm prior work of Leuthold (1979) and Naik and Leuthold (1988), which suggest the greater the distance over time the greater the degree of independence between spot and forward prices. However, to what extent FFA contracts can offset effectively the freight rate risk (hedging) and increase market agents wealth (speculation) are matters of further research.

3.7. CONCLUSION

This chapter investigates the unbiasedness hypothesis of FFA prices. Voyage routes 1 and 2 and time-charter routes 1A and 2A of the BPI index, from January 1996 to December 2000, have been examined. Parameter restriction tests on the cointegrating relationship between spot and FFA prices indicate that FFA prices one- and two-months prior to maturity are unbiased predictors of the realised spot prices in all investigated routes. However, the efficiency of the FFA prices three-months prior to maturity gives mixed evidence, with routes 2 and 2A being unbiased estimators and with routes 1 and 1A being biased estimators of the realised spot prices.

The results in this study are in line with the studies by Moore and Cullen (1995) and Barnhart *et al.* (1999), which find unbiasedness for the one- and two-months commodity and foreign exchange forward prices, respectively. However, rejection of unbiasedness for the three-months FFA prices, for routes 1 and 1A, is not in line with the study of Norrbin and Reffett (1996) which provides evidence in favour of unbiasedness in the three-month foreign exchange forward prices, but is in line with the study of Krehbiel and Adkins (1993) which find three-months commodity forward prices biased estimators of the realised spot prices. Thus, it seems that unbiasedness depends on the market and type of contract under investigation. For the investigated routes and maturities for which unbiasedness holds, market agents can use the FFA prices as indicators of the future course of spot prices, in order to guide their physical market decisions. Furthermore, speculation and spread/arbitrage opportunities, due to the fact that FFA prices three-months prior to maturity for routes 1 and 1A are found to be biased, may provide the possibility for excess profits to be made, while it may increase the much-needed volume of this derivatives market.

CHAPTER 4 – THE LEAD-LAG RELATIONSHIP IN RETURNS AND VOLATILITY BETWEEN SPOT AND FORWARD PRICES IN THE FORWARD FREIGHT MARKET

4.1. INTRODUCTION

Following Working (1970), price discovery refers to the use of one price series (e.g. derivatives returns) for determining (predicting) another price series (e.g. spot returns). The lead-lag relationship between the price movements of derivatives returns and the underlying spot market returns illustrates how fast one market reflects new information relative to the other, and how well the two markets are linked. In a perfectly frictionless world, price movements of the two markets would be contemporaneously perfectly correlated and non cross-autocorrelated. Thus, in perfectly efficient derivatives and spot markets, informed investors are indifferent between trading in either market, and new information is reflected in both simultaneously. However, if one market reacts faster to information, and the other market is slow to react, due to market frictions such as transactions costs or market microstructure effects, a lead-lag relation in returns is observed. In particular, volatility spillovers from one market to the next arises primarily due to the realisation that speculative price changes are being interwoven with higher moment dependencies, such as shown by Bollerslev *et al.* (1992)[69].

Thus, the lead-lag relationship in returns and volatilities between spot and derivatives markets is of interest to academics, practitioners, and regulators for a variety of reasons. Firstly, the issue is linked to market efficiency (as explained earlier) and arbitrage[70]. Secondly, it is

[69] Ross (1989) uses a no-arbitrage model to show that the variance of price changes is related directly to the rate of flow of information. Engle *et al.* (1990) provide an alternative interpretation that relates information processing time to variance movements. This development suggests price volatility has significant implications concerning information linkages between markets. Hence, previous studies ignoring the volatility mechanism may not offer a thorough understanding of the information transmission process.

[70] If new information disseminating into the marketplace is immediately reflected in spot and derivatives prices by triggering trading activity in one or both markets simultaneously, there should be no systematic lagged responses long enough, or large enough to economically exploit, considering transactions costs. Significant causal relationships would, however, be incompatible with market efficiency because they would imply that forecast accuracy of the spot (derivatives) market's subsequent performance can be improved upon by using past information from the derivatives (spot) market. To avoid contradicting the unbiasedness hypothesis paradigm, the joint co-movement of price changes in the two markets should be predominantly contemporaneous (Chan *et al.* 1991).

believed that derivatives markets potentially provide an important function of price discovery. If so, then derivatives prices should contain useful information about subsequent spot prices, beyond that already embedded in the current spot price. Thirdly, if volatility spillovers exist from one market to the other, then the volatility transmitting market may be used by market agents, which need to cover the risk exposure that they face, as a vehicle of price discovery. For example, the instantaneous impact and lagged effects of shocks between spot and derivatives prices is of interest, since such information may be used in decision making regarding hedging activities and budget planning (Wahab and Lashgari, 1993). Thus, a better understanding of the dynamic relation of spot and futures prices and its relation to the basis provides to these "agents" the ability to use hedging in a more efficient way. Furthermore, if a return analysis is inconclusive, volatility spillovers provide an alternative measure of information transmission (Chan *et al.* 1991).

For all these reasons research devoted towards the relationship between futures and spot returns (first moments) has been voluminous (see Chan *et al.*, 1991; Chan, 1992, amongst others), with this interest expanding to examining higher moment dependencies (time-varying volatility spillovers[71]) between markets (see Ng and Pirrong, 1996; and Koutmos and Tucker, 1996, amongst others).

In forward markets, to the best of our knowledge, there have not been any studies investigating the lead-lag relationship in returns and volatilities between spot and forward prices (with the exeption of currency forwards), primarily due to the unavailability of data. This study investigates the lead-lag relationship between derivatives and spot markets, both in terms of returns and volatility utilising the FFA market of the dry-bulk sector of the shipping industry. A special feature of this market is that the underlying commodity is a service. The theory of intertemporal relationships between spot and derivatives prices of continuously storable commodities is well developed (Working 1970), in contrast to that of non-storable commodities (e.g. freight services). The non-storable nature of FFA market implies that spot and FFA prices are not linked by a cost-of-carry (storage) relationship, as in financial and agricultural derivatives markets, Thus, inter-dependence between spot and FFA prices may not be as strong as for storable commodities.

[71] "Volatility spillover" is the impact of an innovation in market *i* on the conditional variance of market *j*.

Kavussanos and Nomikos (2001) have investigated the latter relationship by examining the BIFFEX market[72]. They find a bi-directional causal relationship between the BIFFEX futures contract and spot prices, with the relationship being stronger from BIFFEX to spot prices. The latter is thought to be a consequence of higher transactions costs that prevail in the spot market in comparison to those in the freight futures market. The current study investigates the issue further by providing empirical evidence, for the first time, on the price discovery function of the forward freight market. The special features then of this market, in comparison to the existing literature on futures markets, are: (i) the non-storable nature of the underlying commodity, being that of a service; and (ii) the asymmetric transactions costs between spot and FFA markets. These costs are believed to be higher in the spot freight market (in relation to the FFA market) as they involve the physical asset (vessel).

During the last years participants in the shipping markets have been switching gradually from using BIFFEX to FFA contracts for risk management purposes. The reasons for this have been documented in Kavussanos and Nomikos (2000), and relate mainly to the low hedging effectiveness that BIFFEX contracts offer to agents. In addition, FFA contracts are perceived to be more easily understood by agents in the industry and do not involve mark-to-market costs[73].

The lead-lag relationship between spot and FFA returns is investigated through a multivariate Vector Error-Correction (VECM)-Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model. Variances and covariances of price series are allowed to vary over time, which allows for and mimics volatility spillovers between the spot and derivatives markets. The procedure ensures efficient econometric specification and improves market analysis and forecasts.

[72] The BIFFEX freight futures contract was listed in LIFFE between May 1985 and April 2002. Its underlying asset was the index basket of the seven routes of the BPI, (see Table 1.5 in chapter 1). It has been used as a hedging instrument for the freight markets of the shipping industry.
[73] In futures markets, the trader is required to place with the clearing-house an initial margin, which is an amount of money on a per contract basis and is set at a size to cover the clearing-house against any loses which the trader's new position might incur during the day. Moreover, futures contracts are mark-to-market at the end of each trading day. That is, the resulting profit or loss is settled on that day. Traders are required to post a variation margin in order to cover the extent to which their trading positions show losses. FFA transactions costs are 1% of the contract price, shared equally between the buyer and the seller.

The remainder of this chapter is organised as follows. Section 4.2 presents the literature review on the lead-lag relationship in returns and volatility between several derivatives and spot markets. Section 4.3 describes the methodology and presents some theoretical considerations. Section 4.4 presents the properties of the data. The empirical results of the lead-lag relationship in returns and volatility between the spot and FFA markets are presented in section 4.5. Finally, section 4.6 summarises this chapter.

4.2. LITERATURE REVIEW

The empirical work whether the derivatives market leads the underlying spot market is voluminous and the review in this section is not exhaustive. Rather it seeks to identify the most influential work in this area. Previous studies that examine lead-lag relationships between commodity or financial derivatives and spot markets, indicate that derivatives prices respond to new market information in the same way as the underlying spot prices and lead the changes in these prices (Chan, 1992; Tse and Booth, 1996). In the commodity market, Garbade and Silber (1983) argue that, in general, wheat, and corn futures of the Chicago Board of Trade (CBT) market, and orange juice futures of the New York Cotton Exchange (NYCE) market lead price changes in the relevant spot markets. Silver futures of the Commodity Exchange (Comex), oats futures of the CBT and copper futures of the Comex have a bi-directional relationship with their relevant spot markets. Schroeder and Goodwin (1991) examine the same economic function for the Chicago Mercantile Exchange's (CME) live hog futures and Omaha's spot market prices. They argue that price discovery originates in the futures market with the Omaha spot market lagging the CME live hog futures contract.

In the stock index futures market, Kawaller *et al.* (1990) put forward the general principle that spot prices are affected by their past history, current and past futures prices, and other market information. Likewise, derivatives prices are affected by their past history, current and past spot prices, and other market information. Thus, causality is likely to be bi-directional. They further argue that potential lead-lag patterns are subject to change as new information arrives. Ghosh (1993a) examines the intra-day S&P 500 index futures and spot market data and concludes that there are more information flows from the futures to the spot. In the forward exchange market, Wang and Wang (2001) examine the spot and forward exchange rates of the British, German, French and Canadian currencies against the US dollar and conclude that there is price discovery in both markets, implying a feedback effect between each pair of markets. These studies found mixed evidence for cointegration for storable commodities but no cointegration for non-storable commodities.

In recent years, there has been an increasing interest in investigating the volatility interaction between spot and derivatives markets. Ross (1989) suggests that it is the volatility of an asset's price, and not the asset's price change, that is related to the rate of flow of information to the market. If information arrives first in the derivatives (spot) market, then there will be volatility spillovers to the spot (derivatives) market. In the stock index futures market, Kawaleer *et al.* (1990) argue that there is no systematic pattern of lead-lag relationship in volatilities, contrary to the observed lead and lag relationship in price changes between the futures and the spot market. Arshanapali and Doukas (1994) also examine whether the S&P 500 index futures and the underlying spot index have the same volatility process. They report evidence against interdependence of volatilities in futures and spot markets. Koutmos and Tucker (1996) examine the S&P 500 spot index and stock index futures and report that volatility of both markets are an asymmetric function of past innovations and that the spot volatility is influenced by the news that originates from the futures market in an asymmetric way.

In the currency futures market, Chatrath and Song (1998) examine for volatility spillover relationships the spot and futures markets for Japanese Yen and argue that the futures volatility influence the spot due to faster incorporation of new market related information, such as macroeconomic announcements in the United States. Most of the volatility spillover studies argue that although the lead-lag relationship in returns is almost unidirectional or asymmetric (derivatives leading spot), for volatility this relationship is bi-directional or symmetric (see for example, Chan, *et al.*, 1991; Chan and Chung, 1993, amongst others).

Most of the studies on the time-varying volatility in various markets have considered the spot rates or the spot and derivatives rates separately (see for example, McCurdy and Morgan, 1988; Hsieh, 1989; Baillie and Bollerslev, 1990). A limited number of studies on multivariate volatility measures includes Diebold and Nerlove (1989), Lee (1994), Koutmos and Tucker (1996), Chatrath and Song (1998), Wang and Wang (2001), and Bhar (2001). Another strand of research on volatility spillovers is in the same market but between different geographical domains (see for example, Koutmos and Booth, 1995; Karolyi, 1995; and Lin and Tamvakis, 2001, amongst others).

The econometric methodology employed by most of the above research for testing volatility dependencies between markets has primarily focused upon accounting for the presence of conditional heteroskedasticity within time-series. The reason being that most financial data usually exhibit volatility clustering, perhaps due to increased uncertainty from new information arrival and the time delays for traders to adjust to it. Engle (1982) accounted for this by modeling asset returns via an ARCH process, where it has further extended by Bollerslev (1986) to a GARCH process. GARCH models allow variances to be a conditional function of past variances and squared error residuals. Thus, data which have leptokurtic distributions can be more readily accommodated, as conditional heteroskedastic modelling generates a degree of unconditional excess kurtosis.

4.3. METHODOLOGY AND THEORETICAL CONSIDERATIONS

Given the time-series nature of the data, the first step in the analysis is to determine the order of integration of each price series using ADF (1981) and PP (1988) unit root tests. Given a set of two $I(1)$ series[74], Johansen (1988, 1991) tests are used to determine whether the series stand in a long-run relationship between them; that is that they are cointegrated. The following VECM (Johansen, 1988) is estimated:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t \mid \Omega_{t-1} \sim \text{dist}(0, H_t) \tag{4.1}$$

where X_t is the 2x1 vector $(S_t, F_t)'$ of log-spot and log-FFA prices, respectively, Δ denotes the first difference operator, ε_t is a 2x1 vector of residuals $(\varepsilon_{S,t}, \varepsilon_{F,t})'$ that follow an as-yet-unspecified conditional distribution with mean zero and time-varying covariance matrix, H_t. The VECM specification contains information on both the short- and long-run adjustment to changes in X_t, via the estimated parameters Γ_i and Π, respectively. The Johansen (1988)

[74] $I(1)$ stands for a price series which is integrated of order 1; that it is needed to be differenced once to become stationary.

procedure is preferred because it provides more efficient estimates of the cointegration vector than the Engle and Granger (1987) two-step approach (see Gonzalo, 1994). Toda and Phillips (1993) argue that causality tests based on OLS estimators of unrestricted VAR models in levels are not very useful in general because of uncertainties regarding the relevant asymptotic theory and potential nuisance parameters in the limit. However, maximum likelihood estimators based on Johansen's (1988, 1991) ML method (for large samples of more than 100 observations) are asymptotically median unbiased, have mixed normal limit distributions and they take into account the information on the presence of unit roots in the system. Therefore, they are much better suited to perform inference.

Johansen and Juselius (1990) show that the coefficient matrix Π contains the essential information about the relationship between S_t and F_t. Specifically, if rank(Π) = 0, then Π is 2x2 zero matrix implying that there is no cointegration relationship between S_t and $F_{t,t-n}$. In this case the VECM reduces to a VAR model in first differences. If Π has a full rank, that is rank(Π) = 2, then all variables in X_t are $I(0)$ and the appropriate modelling strategy is to estimate a VAR model in levels. If Π has a reduced rank, that is rank(Π) = 1, then there is a single cointegrating relationship between S_t and F_t, which is given by any row of matrix Π and the expression ΠX_{t-1} is the ECT. In this case, Π can be factored into two separate matrices α and β, both of dimensions 2x1, where 1 represents the rank of Π, such as $\Pi = \alpha\beta'$, where β' represents the vector of cointegrating parameters and α is the vector of error-correction coefficients measuring the speed of convergence to the long-run steady state.

Since rank(Π) equals the number of characteristic roots (or eigenvalues) which are different from zero, the number of distinct cointegrating vectors can be obtained by estimating the number of these eigenvalues, which are significantly different from zero. The characteristic roots of the nxn matrix Π, are the values of λ which satisfy the following equation $|\Pi - \lambda I_n| = 0$, where I_n is a nxn identity matrix. Johansen (1988), proposes the following two statistics to test for the rank of Π:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right) \tag{4.2}$$

$$\lambda_{max}(r, r+1) = -T\ln\left(1-\hat{\lambda}_{r+i}\right) \tag{4.3}$$

where $\hat{\lambda}_i$ are the eigenvalues obtained from the estimate of the Π matrix and T is the number of usable observations. The λ_{trace} tests the null that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r and the λ_{max} tests the null that the number of cointegrating vectors is r, against the alternative of $r + 1$. Critical values for the λ_{trace} and λ_{max} statistics are provided by Osterwald-Lenum (1992).

If spot and FFA prices are cointegrated then causality must exist in at least one direction (Granger, 1988). Granger causality can identify whether two variables move one after the other or contemporaneously. When they move contemporaneously, one provides no information for characterising the other. If "X causes Y", then changes in X should precede changes in Y. In particular, to say that "X causes Y", two conditions should be met. First, X should help to predict Y; i.e., in a regression of Y against past values of Y, the addition of past values of X as independent variables should contribute significantly to the explanatory power of the regression. Second, Y should not help to predict X. Consider the VECM specification of Equation (4.1), which can be written as follows:

$$\Delta S_t = \sum_{i=1}^{p-1} a_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i}\Delta F_{t-i} + a_S z_{t-1} + \varepsilon_{S,t} \tag{4.4a}$$

$$\varepsilon_{j,t} \mid \Omega_{t-1} \sim \text{distr}(0, H_t)$$

$$\Delta F_t = \sum_{i=1}^{p-1} a_{F,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i}\Delta F_{t-i} + a_F z_{t-1} + \varepsilon_{F,t} \tag{4.4b}$$

where $a_{S,i}$, $b_{S,i}$, $a_{F,i}$, $b_{F,i}$ are the short-run coefficients, $z_{t-1} = \beta' X_{t-1}$ is the ECT, and $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$ are residuals (as explained earlier).

Unidirectional causality from FFA-to-spot (F_t Granger causes S_t) requires: (i) that some of the $b_{S,i}$ coefficients, $i = 1, 2, \ldots, p$-1, are non zero and/or (ii) a_S, the error-correction coefficient in Equation (4.4a), is significant at conventional levels. Similarly, undirectional causality from spot-to-FFA (S_t Granger causes F_t) requires: (i) that some of the $a_{F,i}$ coefficients, $i = 1, 2, \ldots, p$-1, are non zero and/or (ii) a_F is significant at conventional levels. If both variables Granger cause each other, then it is said that there is a two-way feedback relationship between S_t and F_t (Granger, 1988). These hypotheses can be tested by applying Wald tests on the joint significance of the lagged estimated coefficients of ΔS_{t-i} and ΔF_{t-i}. When the residuals of the error-correction equations exhibit heteroskedasticity, the *t*-statistics are adjusted by White (1980) heteroskedasticity correction. The significance level of the error-correction coefficients, a_S and a_F, can be tested by adjusted *t*-tests applied to the VECM of spot and FFA, respectively[75].

In order to examine for higher moment dependencies (volatility spillovers), the conditional second moments of spot and FFA prices are measured using the family of ARCH models. For this purpose, the following VECM-GARCH-X model with the Baba *et al.* (1987) augmented positive definite parameterisation is used (see for example, Kavussanos and Nomikos, 2000a, 2000b)[76]:

$$H_t = A'A + B'H_{t-1}B + C'\varepsilon_{t-1}\varepsilon_{t-1}'C + S1'u_{1,t-1}u_{1,t-1}'S1 + S2'u_{2,t-1}u_{2,t-1}'S2 + E'(z_{t-1})^2E \qquad (4.5)$$

where A is a 2x2 lower triangular matrix of coefficients, B and C are 2x2 diagonal coefficient matrices, with $\beta^2_{kk} + \gamma^2_{kk} < 1$, k = 1,2 for stationarity, S1 and S2 are matrices, which contain parameters of spillover effects, $u_{1,t-1}$ and $u_{2,t-1}$ are matrices whose elements are lagged square error terms ($u_{1,t-1}$ represents the volatility spillover effect from the spot to the derivatives market and $u_{2,t-1}$ represents the volatility spillover effect from the derivatives to the spot market), $(z_{t-1})^2$ is the lagged squared basis, and E is a 1x2 vector of coefficients of the lagged squared basis[77]. The B and C matrices are restricted to be diagonal because this results in a more parsimonious representation of the conditional variance (Bollerslev *et al.*, 1994). In this diagonal representation, the conditional variances are a function of their own lagged values (old news), their own lagged error terms (new news), volatility spillover parameters, and a lagged

[75] The error-correction coefficients serve two purposes: (i) to identify the direction of causality between the two variables and (ii) to measure the speed of adjustment to the long-run equilibrium (Granger, 1988).
[76] Several other specifications are also used, such as a bivariate VECM-EGARGH, allowing for volatility spillovers, but yield inferior results judged by the evaluation of the log-likelihood and in terms of residual specification tests (not reported).
[77] The use of the lagged square basis specification, instead of the lagged level or the lagged absolute value specifications, is justified in the empirical work because it provides uniformly superior results.

squared basis parameter, while the conditional covariance is a function of lagged covariances and lagged cross products of the ε_t's.

The model incorporates the lagged squared basis as an ECT in order to examine the relation between the two markets, as a factor that influences the variances of the two variables[78]. Engle and Yoo (1987) show that the ECT, which is the short-run adjustment from the long-run cointegrating relationship, has important predictive power for the conditional variances of cointegrated series. This may imply that if the series deviate further from each other they are harder to predict. The main virtue of this model lies in its capability of pointing to a particular feature of cointegrated series, which is the potential relationship between disequilibrium (measured by the ECT) and uncertainty (measured by the conditional variance), (Lee, 1994).

In this setting, spillover effects between spot and FFA volatilities can be tested through the coefficients of S1 and S2. For example, the element of S1, $s1_{21}$, measures the spillovers of the volatility of the spot equation to the volatility of the FFA equation. Similarly, the element of S2, $s2_{12}$, measures the spillovers of the volatility of the FFA equation to the volatility of the spot equation. Moreover, this specification guarantees H_t to be positive-definite almost surely for all t and allows the conditional covariance of cash and FFA returns to be time-varying[79]. Finally, the most parsimonious specification for each model is estimated by excluding insignificant variables. Following Bollerslev (1987), the conditional Student-t distribution is used as the density function of the error term, ε_t, and the degrees of freedom, v, is treated as another parameter to be estimated. The general form of the likelihood function becomes:

$$L(H_t, \varepsilon_t, \theta) = \frac{\Gamma[(2+v)/2]}{\Gamma(v/2)[\pi(v-2)]}|H(\theta)_t|^{-1/2} [1 + \frac{1}{v-2} \varepsilon(\theta)_t', H(\theta)_t^{-1} \varepsilon(\theta)_t]^{-[(2+v)/2]} \qquad (4.6)$$

$$, \text{for } v > 2$$

[78] Booth and Tse (1997), in a study for US and Eurodollar interest rates, report that interest rate volatilities are time-varying and that the dynamic of this risk is, to some extent, predictable by the spread between these two interest rates. Ng and Pirrong (1994, 1996) suggest that an alternative way to study the relation of economic factors that influence volatility could be through the relation of basis and volatility. In another study for the spot and futures market for Australia, Hong Kong, and Japan, Choudhry (1997) argues that both the short-run deviation of spot and futures returns, and shocks to the spot and futures markets should affect volatility.

[79] For a formal discussion of the properties of this model and alternative multivariate representations of the conditional covariance matrix see Bollerslev *et al.* (1994) and Engle and Kroner (1995).

where $\Gamma(.)$ is the gamma function, and v denotes the degrees of freedom. This distribution converges to the multivariate normal as $v \rightarrow \infty$, although in empirical applications the two likelihood functions give similar results for values of v above 20. Baillie and Bollerslev (1995) show that for $v < 4$, the Student-*t* distribution has an undefined or infinite degree of kurtosis [the theoretical kurtosis is computed as $3(v-2)(v-4)^{-1}$]. In such cases the QMLE, which estimates robust standard errors, and thus, yields an asymptotically consistent normal covariance matrix, is preferred (Bollerslev and Wooldridge, 1992). Preliminary evidence on our data set with the Student-*t* distribution reveals that the parameter of the degrees of freedom, v, is lower than 4 in all cases (v = 2.012 in route 1, v = 2.001 in route 1A, v = 2.217 in route 2, and v = 2.003 in route 2A). Thus, the QMLE should be used in the estimation of the VECM-GARCH-X models in all routes. Assuming the conditional joint distribution of the returns of the two markets is normal, the log-likelihood for the VECM-GARCH-X models can be written as:

$$L(H_t, \varepsilon_t, \theta) = - \log(2\pi) - (0.5)\sum_{t=1}^{T} (\log|H(\theta)_t| + \varepsilon(\theta)_t' H(\theta)_t^{-1}\varepsilon(\theta)_t) \tag{4.7}$$

where H_t is the 2x2 time-varying conditional covariance matrix, $\varepsilon_t = (\varepsilon_{S,t}, \varepsilon_{F,t})'$ is the 2x1 vector of innovations at time *t*, and θ is the parameter vector to be estimated[80]. For symmetric departures from conditional normality, the QMLE is generally close to the exact MLE. The log-likelihood function is highly non-linear and, therefore, numerical maximisation techniques have to be used. The BFGS algorithm, which utilises derivatives to maximize the log-likelihood, is used.

[80] Using standard MLE, the variance-covariance matrix of the estimated coefficients is given by $var(\hat{\theta}) = J^{-1}$, where J is the information matrix, i.e. $J = -E(\partial^2 L/\partial\theta\partial\theta')$. Under QMLE, $var(\hat{\theta}) = J^{-1}KJ^{-1}$, where K is the outer product of the first-order derivatives, $K = \sum_{t=1}^{T} (\partial L/\partial\theta)(\partial L/\partial\theta)'$.

4.4. DESCRIPTION OF DATA AND PRELIMINARY STATISTICS

The data set used consists of daily spot and FFA prices in panamax routes 1 and 1A from 16 January 1997 to 31 July 2000 and daily spot and FFA prices in panamax routes 2 and 2A from 16 January 1997 to 30 April 2001[81]. The difference in the sample periods between the Atlantic and the Pacific routes is because the Atlantic routes are characterised by modest FFA trading and FFA brokers have stopped publishing FFA quotes for those routes. In contrast, the Pacific routes concentrate most of the FFA trading, and therefore, are the most liquid BPI routes. Spot price data are from the Baltic Exchange. FFA price data for the four panamax routes are from Clarkson Securities Limited. All price series are transformed into natural logarithms.

FFA prices are always those of the nearby contract because it is highly liquid and is the most active contract. However, to avoid thin markets and expiration effects (when futures and forward contracts approach their settlement day, the trading volume decreases sharply) we rollover to the next nearest contract one week before the nearby contract expires.[82] There is sufficient liquidity in the nearby contract up to a few days before its maturity date to justify such a rollover policy. Using daily data (instead of monthly) enables us to utilise as much as possible information embedded in the daily data. The use of a monthly frequency, for the purposes of this chapter, for a data set consisting of one-month forward and spot prices it would result in information loss (Baillie and Bollerslev, 1989).

Combining information from FFA contracts with different times to maturity may create structural breaks in the series at the date of the forward rollover since FFA returns for that day are calculated between the price of the expiring contract and the price of the next nearest contract. Such structural breaks in the series may possibly lead to biased results. To account for possible systematic relationships in the data associated with the retention of the last week of a contract (to account for the statistical effect of including the delivery period in the data set) a *perpetual* FFA contract could be calculated as a weighted average of near and distant FFA contracts, weighted according to their respective number of days from maturity. This procedure

[81] Hakkio and Rush (1991) argue and empirically show that switching to high frequency data from low frequency adds little power to detect cointegration relationships among variables because basically cointegration is a long-run property of data. Consequently, we assume that with daily data we can reasonably detect any cointegration relationship, if it exists.

[82] This procedure prevents the possibility of squeezes in the delivery period from distorting prices (inducing serial correlation in the price series). This price series is assured to have come from a highly liquid market.

could generate constant maturity price series that avoids the problem of price-jumps caused by the rollover of the contracts (Pelletier, 1983). Herbst *et al.* (1989) suggest a *perpetual* contract 22-days horizon, which corresponds to the average number of trading days in a month, by taking a weighted average of the rates of contracts that expire before and after the 22-day period. Let S and P denote the days to expiry of the spot and prompt month FFA contracts, with $S \leq 22 \leq P$. The price of a 22-days *perpetual* contract is calculated as follows:

$$\mathrm{FFA}_{22} = \mathrm{FFA}_S\,[(P-22)/(P-S)] + \mathrm{FFA}_P\,[(22-S)/(P-S)] \tag{4.8}$$

where FFA_S and FFA_P denote the prices of the spot and prompt month FFA contracts, respectively[83]. However, in the OTC FFA market, such a trading strategy cannot be formulated for the following reasons. First, this procedure assumes high market liquidity. Second, this procedure assumes that market agents must take long positions in the spot and prompt FFA contracts and rebalance these positions on a daily basis as the time to expiry of a FFA contract changes. However, due to the nature of the shipping business it is not in the interest of market agents to hedge their spot positions on a daily basis. Third, this procedure can generate excessive brokerage and transactions costs in the current investigated market than a single FFA contract position. Consequently, our results in the following sections are based on the price of a single FFA contract.

Summary statistics of logarithmic first-differences of daily spot and FFA prices for the four panamax routes are presented in Table 4.1. The results indicate excess skewness and kurtosis in all price series, with the exception of the skewness statistic in routes 1, 1A and 2A FFA price series. In turn, Jarque-Bera (1980) tests indicate departures from normality for spot and FFA prices in all routes. The Ljung-Box Q(36) and $Q^2(36)$ statistics (Ljung and Box, 1978) on the first 36 lags of the sample autocorrelation function of the raw series and of the squared series indicate significant serial correlation and existence of heteroskedasticity, respectively. The existence of serial correlation in spot prices may be attributed in the way shipbroking companies calculate freight rates. These rates are based either on actual fixtures, or in the

[83] As an example, on 13 March 2000 the prices of the spot (March 00) and prompt (April 00) FFA contracts for route 2A were 11,750 (15) and 11,875 (33), respectively (days to maturity in parentheses). The price of the 22-days *perpetual* FFA contract on route 2A of that day was 11,799 applying Equation (4.8). The following day, 14 March 2000, the prices of the spot (March 00) and prompt (April 00) FFA contracts for route 2A were 11,225 (14) and 11,625 (32), respectively. The price of the *perpetual* FFA contract of that day was 11,403.

absence of an actual fixture, on the shipbroker's view of what the rate would be if there was a fixture. In the latter case, shipbrokers submit an assessment, which may be a mark-up over the previous day's rate which, in turn, induces autocorrelation in the route prices. After applying the ADF (1981) and PP (1988) unit root tests on the log-levels and log first-differences of the daily spot and FFA price series, the results indicate that all variables are log first-difference stationary, all having a unit root on the log-levels representation.

Table 4.1. Descriptive Statistics of Logarithmic First-Differences of Spot and FFA Prices

Panel A: Route 1 Spot and FFA Price Series (16/01/97 to 31/07/00)

	Skew	Kurt	Q(36)	$Q^2(36)$	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs
Spot	-0.168	13.347	216.43	264.77	6,609.8	-1.534 (3)	-1.315	-9.169 (2)	-15.751
FFA	-0.151	5.429	304.47	283.47	1,096.7	-1.646 (0)	-1.570	-31.722 (0)	-32.070

Panel B: Route 1A Spot and FFA Price Series (16/01/97 to 31/07/00)

	Skew	Kurt	Q(36)	$Q^2(36)$	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs
Spot	1.811	30.788	186.29	290.45	35,637.3	-1.890 (2)	-1.665	-10.343 (1)	-14.051
FFA	-0.037	4.708	258.59	221.35	822.28	-1.607 (0)	-1.775	-29.547 (0)	-29.714

Panel A: Route 2 Spot and FFA Price Series (16/01/97 to 30/04/01)

	Skew	Kurt	Q(36)	$Q^2(36)$	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs
Spot	0.626	522.25	507.73	215.81	12,271,081	-1.847 (3)	-1.827	-13.995 (1)	-32.768
FFA	0.286	5.049	285.55	276.36	1,158.85	-1.519 (0)	-1.628	-30.421 (0)	-30.457

Panel B: Route 2A Spot and FFA Price Series (16/01/97 to 30/04/01)

	Skew	Kurt	Q(36)	$Q^2(36)$	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs
Spot	-1.281	31.348	157.80	246.01	44,392.5	-2.121 (2)	-1.885	-12.481 (1)	-15.215
FFA	0.096	6.237	292.49	404.80	1,747.4	-1.891 (1)	-1.952	-30.009 (0)	-30.029

Notes:

- All series are measured in logarithmic first-differences.
- Skew and Kurt are the estimated centralised third and fourth moments of the data; their asymptotic distributions under the null are $\sqrt{T}\,\hat{\alpha}_3 \sim N(0,6)$ and $\sqrt{T}\,(\hat{\alpha}_4 - 3) \sim N(0,24)$, respectively.
- Q(36) and $Q^2(36)$ are the Ljung-Box (1978) Q statistics on the first 36 lags of the sample autocorrelation function of the raw series and of the squared series; these tests are distributed as $\chi^2(36)$. The critical values are 58.11 and 51.48 for the 1% and 5% levels, respectively.
- J-B is the Jarque-Bera (1980) test for normality, distributed as $\chi^2(2)$.
- ADF is the Augmented Dickey Fuller (1981) test. The ADF regressions include an intercept term; the lag-length of the ADF test (in parentheses) is determined by minimising the SBIC (1978).
- PP is the Phillips and Perron (1988) test; the truncation lag for the test is in parentheses.
- Lev and 1st Diffs correspond to price series in log-levels and log first-differences, respectively.
- The 5% critical value for the ADF (1981) and PP (1988) tests is –2.89.

4.5. EMPIRICAL RESULTS

4.5.1. Cointegration in the Markets

After identifying that spot and FFA price series are non-stationary in all investigated routes, cointegration techniques are used next to examine the existence of a long-run relationship between these series (Table 4.2). SBIC (1978), used to determine the lag length in the VECM, indicate 3 lags in routes 1A, 2 and 2A, and 4 lags in route 1. The Johansen's (1991) LR test, of Equation (2.36) indicates that an intercept term should be restricted in the cointegrating vector (not reported). The estimated λ_{max} and λ_{trace} statistics show that the spot and FFA prices in all routes are cointegrated, and thus, stand in a long-run relationship between them. The normalised coefficient estimates of the cointegrating vector in Equation (4.1) for each route are also presented in Table 4.2. In order to examine whether the exact lagged basis should be included as an ECT in the VECM model, the following cointegrating vector, $z_t = \beta' X_t = (S_t\ \beta_1\ F_t)'$ is examined, with $\beta' = (1, 0, -1)$, implying that the equilibrium regression is the lagged basis, $z_{t-1} = S_{t-1} - F_{t-1}$ (see for example, Viswanath, 1993; Zapata and Rambaldi, 1997; Kavussanos and Nomikos, 2000a). The results in Table 4.2 indicate that in route 1 the restrictions on the cointegrating vector to represent the exact lagged basis hold. In routes 1A, 2, and 2A the restrictions are not accepted. This discrepancy in the results may arise from the different economic and trading conditions that prevail in each trading route.

Table 4.2. Johansen (1988) Tests for the Number of Cointegrating Vectors Between Spot and FFA Prices

	Lags	Hypothesis (Maximal)		Test Statistic	Hypothesis (Trace)		Test Statistic	Cointegrating Vector	Hypothesis Test
		H_0	H_1	λ_{max}	H_0	H_1	λ_{trace}	$\beta' = (1, \beta_1, \beta_2)$	$\beta' = (1, 0, -1)$
Route 1	4	$r = 0$	$r = 1$	34.55	$r = 0$	$r >= 1$	36.81	(1, 0.017, -1.00)	3.76 [0.153]
		$r <= 1$	$r = 2$	2.25	$r <= 1$	$r = 2$	2.25		
Route 1A	3	$r = 0$	$r = 1$	47.70	$r = 0$	$r >= 1$	51.20	(1, 0.509, -1.054)	10.17 [0.006]
		$r <= 1$	$r = 2$	3.498	$r <= 1$	$r = 2$	3.49		
Route 2	3	$r = 0$	$r = 1$	75.09	$r = 0$	$r >= 1$	78.03	(1, -0.204, -0.933)	16.47 [0.000]
		$r <= 1$	$r = 2$	2.94	$r <= 1$	$r = 2$	2.94		
Route 2A	3	$r = 0$	$r = 1$	78.67	$r = 0$	$r >= 1$	82.76	(1, 0.172, -1.017)	8.16 [0.017]
		$r <= 1$	$r = 2$	4.09	$r <= 1$	$r = 2$	4.09		

Notes:

- Lags is the lag length of an VAR model; the lag length is determined using the SBIC (1978).
- Figures in square brackets [.] indicate exact significance levels.
- r represents the number of cointegrating vectors.
- $\lambda_{max}(r,r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$ and $\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$ where $\hat{\lambda}_i$ are the estimated eigenvalues of the Π matrix in Equation (4.1).
- Estimates of the coefficients in the cointegrating vector are normalised with respect to the coefficient of the spot rate, S_t.

- The statistic for the parameter restrictions on the coefficients of the cointegrating vector is $-T$ [$\ln(1 - \hat{\lambda}^*_1) - \ln(1 - \hat{\lambda}_1)$] where $\hat{\lambda}^*_1$ and $\hat{\lambda}_1$ denote the largest eigenvalues of the restricted and the unrestricted models, respectively. The statistic is distributed as χ^2 with degrees of freedom equal to the total number of restrictions minus the number of the just identifying restrictions, which equals the number of restrictions placed on the cointegrating vector.
- In route 1 the cointegrating vector is restricted to be $z_t = \beta' X_t = (1, 0, -1)$, while in routes 1A, 2, and 2A the cointegrating vector is $z_t = \beta' X_t = (1\ \beta_1\ F_t)'$.

4.5.2. The Lead-Lag Relationships between Spot and FFA Returns

The results from estimating the short-run parameters of the VECM, for the FFA market, using SURE, are reported in Table 4.3, Panel A. The SURE method (Zellner, 1962) is used because the system is reduced to a partial VECM, as insignificant variables are dropped to arrive at the most parsimonious model. This ensures efficient and consistent parameter estimates. Given the results from Table 4.2, in route 1 we apply the restrictions $\beta' = (1, 0, -1)$ on the cointegrating vector (i.e. the lagged basis), while in routes 1A, 2, and 2A the cointegrating vector is not restricted to be the lagged basis. The residual diagnostic tests, presented in the same table, Panel B, indicate existence of heteroskedasticity, in some routes. Thus, we adjust the *t*-statistics, as well as the Wald test statistics in the same table, Panel A, which are employed to test for Granger causality, by the White (1980) heteroskedasticity correction.

The coefficients (a_S and a_F) of the ECTs, provide some insight into the adjustment process of spot and FFA prices towards equilibrium in all investigated routes. The coefficients of the ECTs in the FFA equations (a_F) are statistically significant and positive, while the coefficients of the ECTs in the spot equations (a_S) are statistically significant and negative. This implies that both FFA and spot prices respond to correct a shock in the system in order to reach the long-run equilibrium. For example, in response to a positive deviation from their equilibrium relationship at period *t*-1, FFA prices in the next period increase in value and spot prices decrease in value, thus, eliminating any disequilibrium.

The estimated coefficients of the lagged own-returns ($a_{S,i}$ and $b_{F,i}$) and lagged cross-market returns ($b_{S,i}$ and $a_{F,i}$) in all routes indicate that between one and three lags of changes in spot and FFA's are significant in the spot and FFA equations. Adjusted Wald tests on the joint significance of the lags in the spot and FFA equations (performed on the unrestricted VECM) indicate the existence of a two-way feedback causal relationship between the two markets.

The results in all routes indicate that the FFA markets, equally with the spot markets, serve as a focal point of information assimilation for large numbers of buyers and sellers. Market agents may depend on price changes in the FFA market when making their own trading decisions. These findings are in accordance with previous studies in futures markets. Chan *et al.* (1991), Chan (1992), and Wahab and Lashgari (1993), amongst others, suggest that there is a bi-directional relationship between derivatives and spot returns. However, the coefficients of the spot lags on the FFA equations are broadly larger in magnitude than the coefficients of the FFA lags on the spot equations in all trading routes. Thus, it seems that FFA prices play a leading role in incorporating new information.

Overall, possible explanations for finding FFA markets informationally more efficient than their corresponding spot markets may be the following. First, FFA trades are cash-settled deals, which require no chartering of a ship or movement of a cargo, and therefore, are due to lower transactions costs than the spot market. Second, an investor can have a FFA contract on one or more of the trading routes for several time intervals, providing him ease of shorting (it is not common to establish a short position in a spot market, which trades a service, by hiring in vessels). If new information indicates that freight rates are likely to rise, a speculator has the choice of either buying a FFA or fixing a spot deal. Although the FFA transaction can be implemented immediately with no up-front cash, spot fixtures require a greater initial outlay, a constraint of resources (vessels) and may take longer to be completed. Third, FFA markets provide more flexibility to investors in the sense that they enable investors to speculate on the price movements of the underlying asset without the financial burden of owning the asset itself; this point is important given the highly capital intensive nature of the shipping industry. Therefore, market agents may react to the new information by indulging in FFA rather than spot transactions. Spot prices will react with a lag because spot transactions cannot be executed so quickly.

Table 4.3. Estimates of the SURE-VECM and Granger Causality for Spot and FFA prices in Routes 1, 1A (16/01/97 - 31/07/00) and 2, 2A (16/01/97 – 30/04/01)

Panel A: SURE-VECM Model Estimates and Wald Tests for Granger Causality

$$\Delta S_t = \sum_{i=1}^{p-1} a_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i}\Delta F_{t-i} + a_S Z_{t-1} + \varepsilon_{S,t} \qquad (4.4a)$$

$$\Delta F_t = \sum_{i=1}^{p-1} a_{F,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i}\Delta F_{t-i} + a_F Z_{t-1} + \varepsilon_{F,t} \quad ; \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \mid \Omega_{t-1} \sim IN(0, \Sigma) \qquad (4.4b)$$

	Route 1		Route 1A		Route 2		Route 2A	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
Z_{t-1}	-0.016* (-3.657)	0.061* (4.084)	-0.025* (-4.279)	0.083* (5.026)	-0.060* (-7.794)	0.034** (1.879)	-0.043* (-6.074)	0.081* (4.511)
ΔS_{t-1}	0.439* (13.572)	0.465* (5.282)	0.520* (15.697)	0.345* (3.708)	0.549* (23.166)	0.573* (8.890)	0.481* (16.493)	0.295* (5.001)
ΔS_{t-2}	0.093* (2.686)	-	0.171* (5.278)	0.182** (1.958)	-	-	0.094* (3.353)	-
ΔS_{t-3}	0.141* (4.495)	-	-	-	-	-0.290* (-5.209)	-	-
ΔF_{t-1}	0.059* (5.810)	-0.068* (-1.981)	0.035* (2.908)	-	0.068* (5.268)	-	0.099* (7.489)	0.094* (2.818)
ΔF_{t-2}	-	-	-	-0.100* (-2.983)	-	-0.111* (-3.627)	-	-
ΔF_{t-3}	-	-	-	-	-	-	0.032* (2.547)	-
Wald Tests	38.181 [0.000]	26.920 [0.000]	9.623 [0.002]	42.372 [0.000]	29.097 [0.000]	58.797 [0.000]	57.313 [0.000]	25.198 [0.000]

Panel B: Residual Diagnostics

	Route 1		Route 1A		Route 2		Route 2A	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
$\bar{R}^2$	0.437	0.046	0.473	0.073	0.477	0.057	0.501	0.041
Q(12)	7.325 [0.835]	17.914 [0.118]	19.453 [0.078]	5.921 [0.921]	14.119 [0.293]	13.575 [0.329]	7.325 [0.835]	17.914 [0.118]
$Q^2(12)$	26.068 [0.010]	5.492 [0.940]	63.556 [0.000]	20.619 [0.055]	136.61 [0.000]	19.948 [0.068]	26.068 [0.010]	5.492 [0.940]

Notes:

- * and ** denote significance at the 5% and 10% levels, respectively.
- Figures in parentheses (.) and in squared brackets [.] indicate t-statistics and exact significance levels, respectively.
- t-statistics and Wald tests (performed on the unrestricted VECM) are adjusted using the White (1980) heteroskedasticity consistent variance-covariance matrix, in the cases of heteroskedasticity in the residuals (see Panel B).
- The cointegrating vector $z_{t-1} = \beta' X_{t-1}$ is restricted to be the lagged basis $(S_{t-1} - F_{t-1})$ in route 1. In the remaining routes the ECT is the following spread: ECT = $S_{t-1} - 1.054*F_{t-1} + 0.5093$ in route 1A; ECT = $S_{t-1} - 0.9327*F_{t-1} - 0.204$ in route 2; and ECT = $S_{t-1} - 1.017*F_{t-1} + 0.172$ in route 2A.
- Q(12) and $Q^2(12)$ are the Ljung-Box (1978) tests for 12th order serial correlation and heteroskedasticity in the residuals and in the squared residuals, respectively; the test statistics are $\chi^2(12)$ distributed.

Newberry's (1992 p. 210) postulation that derivatives markets provide opportunities for market manipulation, suggests another argument for the hypothesis. According to this argument, derivatives markets may be manipulated either by the better informed at the expense of the less informed or by the larger at the expense of the smaller. For example, big chartering houses may find it profitable to intervene in the FFA market to influence the production decisions (i.e. of grain or coal) of their competitors in the spot market. Again, the implied causality runs from FFA to spot prices. Fleming *et al.* (1996) introduce what they call the *trading cost hypothesis*, which predicts that the market with the lowest overall trading costs will react most quickly to new information and thus, exhibit price leadership. They suggest that the lead-lag relationship should change when it becomes more costly or less costly for traders to exploit the information in the spot market.

4.5.3. Impulse Response Analysis

A more detailed insight on the causal relationship between spot and FFA prices is obtained by analysing the impulse response function of the SURE-VECM. This measures the reaction of spot and FFA prices in response to one standard error shocks in the equations of the VECM. Following Sims (1980), impulse responses can be computed by *orthogonalising* the underlying shocks to the model using a Cholesky decomposition of the covariance matrix in Equation (4.1). However, this approach leads to impulses, which are not unique and depend on the ordering of the variables in the system (Lutkepohl, 1991). A solution to these problems is proposed by Pesaran and Shin (1997) who suggest the use of Generalised Impulse Responses (GIR). Consider the following VAR model in standard form $X_t = \sum_{i=1}^{p} A_i X_{t-i} + \varepsilon_t$; this has the following infinite order Vector Moving Average (VMA) representation (Sims, 1980): $X_t = \sum_{i=1}^{\infty} \Phi_i \varepsilon_{t-i}$ where the 2x2 matrices Φ_i are computed using the recursive relations $\Phi_i = A_1\Phi_{i-1} + A_2\Phi_{i-2} + \ldots + A_p\Phi_{i-p}$, $i = 1,2\ldots$ with $\Phi_0 = I_2$, and $\Phi_i = 0$ for $i < 0$. Pesaran and Shin (1997) define the GIR function of the FFA price at time $t+N$, following a standard error shock (σ_{v1}) in the equation of the spot price at time t as: $GI_{Spot,FFA,t+N} = \frac{e_2' \Phi_N \Sigma e1}{\sigma_{v1}}$, where e2 = (0 1)', Σ is the variance-covariance matrix of the system and Φ_N is computed from the recursive equation described above. In the case of a VAR model in levels, $\lim\Phi_i = 0$. However, for a VECM $\lim\Phi_i = C(1)$ which is a non-zero 2x2 matrix with rank 1, derived from the VMA representation of the underlying VECM (see Pesaran and Shin, 1997). This implies that when the underlying variables in the VAR are $I(0)$ in levels, the effect of the shocks in the variables eventually vanishes while in the case of a VECM, where the variables are first-difference stationary, this effect will be persistent and the variables will adjust to a new long-run level once shocked.

The time profiles of the GIR responses of spot and FFA prices to innovations in the spot returns are presented in Figures 4.1, 4.3, 4.5, and 4.7 for routes 1, 1A, 2, and 2A, respectively. In every case, an overshooting is observed in the spot market, while FFA prices adjust gradually to equilibrium. The adjustment period is more or less the same, only the time path is different. The impact of a shock in the spot market is much more direct in spot rates. The time to adjustment varies between routes, taking approximately 25-30 days in route 1, and 15-20 days for the rest of the routes (1A, 2, and 2A). Route 2 is slightly different compared to the rest in that FFA rates jump to the new equilibrium in 1-2 periods. Also adjustment in 2A for FFA rates is in half the period than spot rates take to adjust - 10 to 20 days. These differences may be explained by the different economic conditions and liquidity in each trading route. Figures 4.2, 4.4, 4.6, and 4.8 for routes 1, 1A, 2, and 2A, respectively show the reaction of spot and FFA prices to one standard error shock in FFA returns. With the exception of route 1 (for which there is very low volume of trade) FFA prices adjust almost immediately - 1-3 days - to the new long-run equilibrium. In contrast, spot prices adjust gradually and seem to take 15 days to reach the new equilibrium.

These results are in accordance with the earlier results of the causality tests, based on a SURE-VECM model, and confirm the bi-directional findings of the Wald tests. In addition, they indicate that FFA prices respond to new information and reach the long-run equilibrium level more rapidly than their corresponding spot prices, with the result being more emphatic when the shock is in the FFA market. In a world with non-differential transactions costs across markets and no restrictions on borrowing or short selling, we would expect the spot and FFA markets to be equally accessible to all traders. Investors who have collected and analysed new information would tend to be indifferent about transacting in one market or the other and thus, new information would tend to be revealed simultaneously in the prices of both markets. However, if conditions tend to favour transactions in a particular market, then new information may be processed more rapidly in that market. This is the case here, where transactions costs are much higher in the spot compared to the FFA market.

Figure 4.1. GIR to One S.E. Shock in the Equation for Spot in Route 1

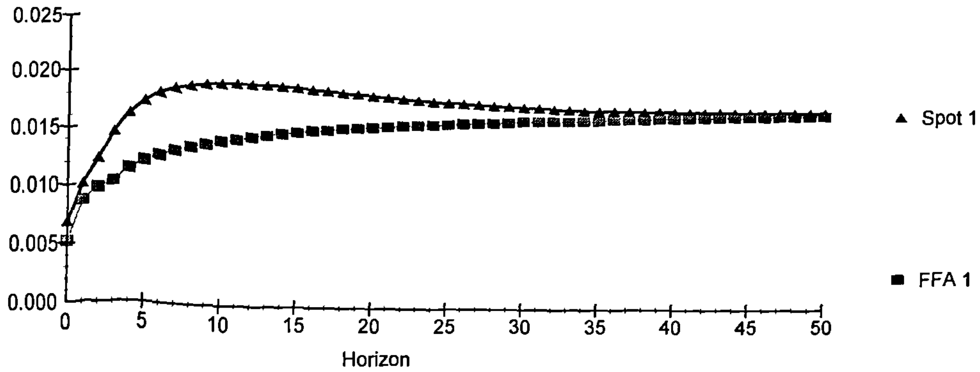


Figure 4.2. GIR to One S.E. Shock in the Equation for FFA in Route 1

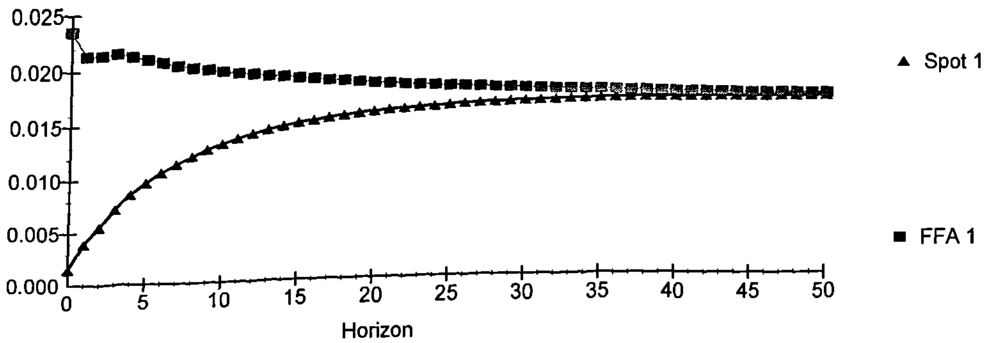


Figure 4.3. GIR to One S.E. Shock in the Equation for Spot in Route 1A

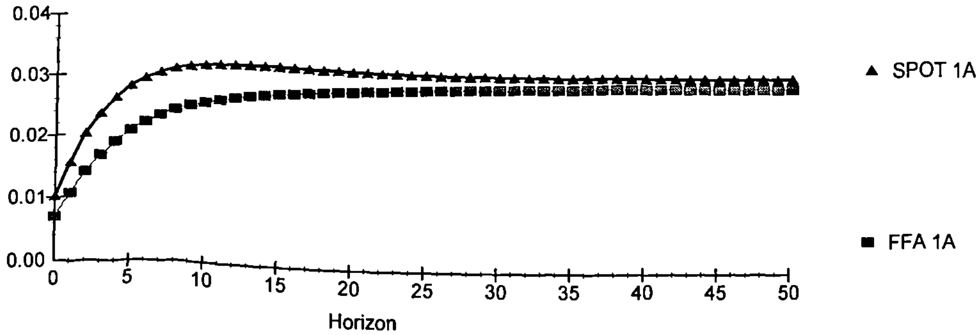


Figure 4.4. GIR to One S.E. Shock in the Equation for FFA in Route 1A

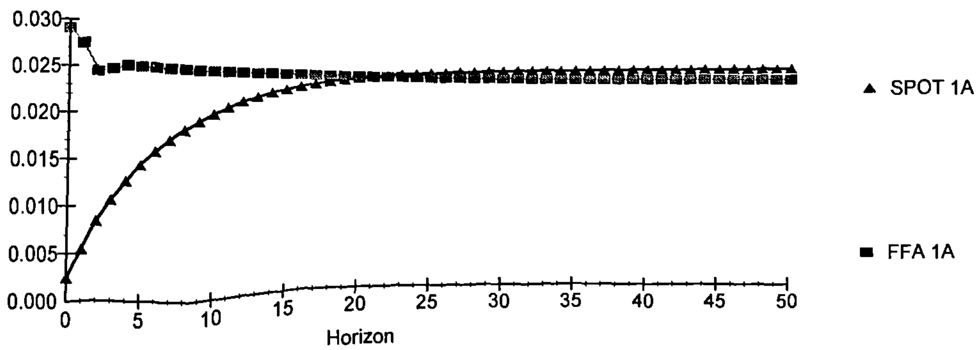


Figure 4.5. GIR to One S.E. Shock in the Equation for Spot in Route 2

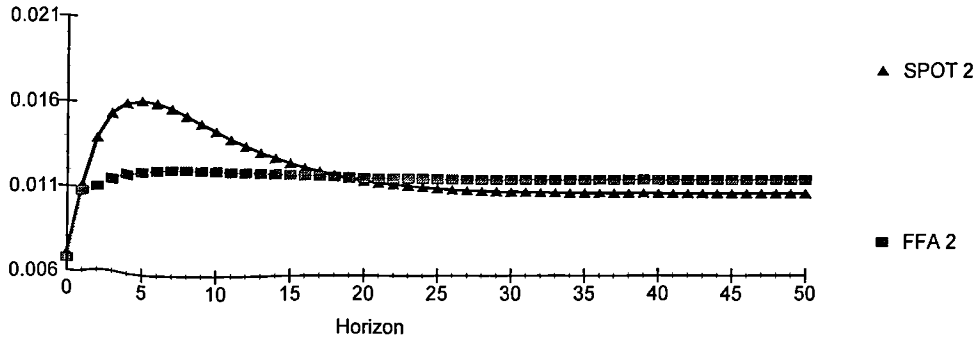


Figure 4.6. GIR to One S.E. Shock in the Equation for FFA in Route 2

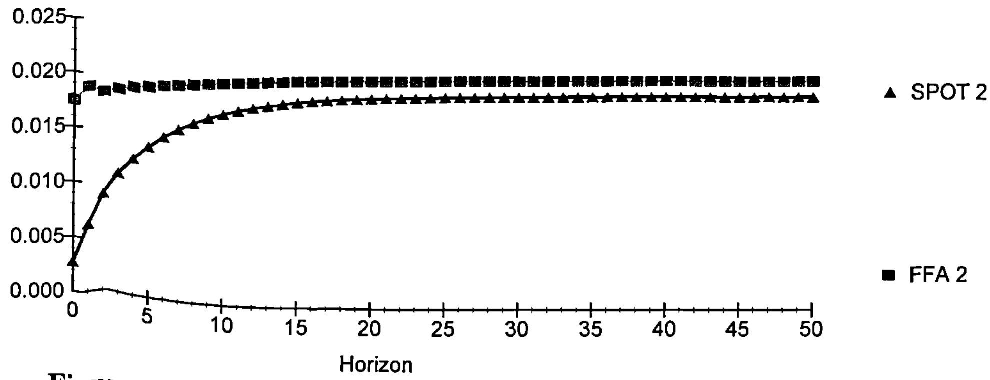


Figure 4.7. GIR to One S.E. Shock in the Equation for Spot in Route 2A

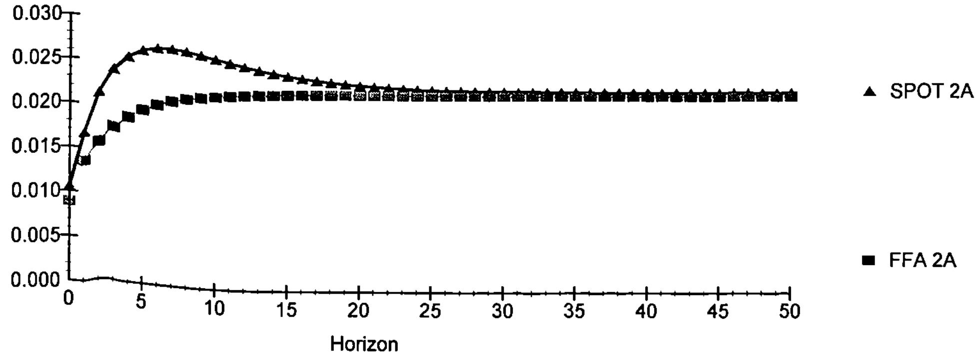
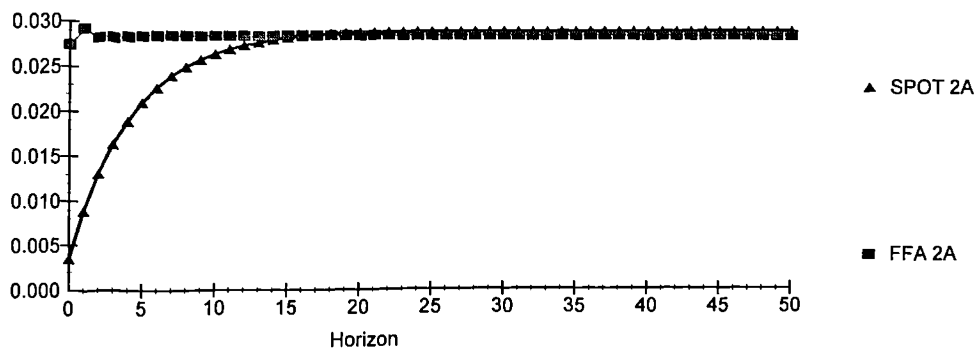


Figure 4.8. GIR to One S.E. Shock in the Equation for FFA in Route 2A



4.5.4. The Lead-Lag Relationships between Spot and FFA Volatilities

Having examined the lead-lag relationship between spot and FFA markets in the mean we turn now to the examination of the relationship in the variance. The QMLE estimates of the VECM-GARCH-X model for route 1 and the VECM-GARCH models for routes 1A, 2, and 2A are shown in Table 4.4. These have been selected on the basis of LR tests, Schwartz (1978) information criteria, and on the basis of diagnostic tests. The estimates of the coefficients of the mean equation and the variance equation, including the volatility spillover parameters are presented in panels A and B, respectively. Any insignificant variables are excluded from the model to reach a more parsimonious specification. In most cases the VECM-GARCH(1,1) specification provides a good description of the joint distribution of spot and FFA price returns, with the exception of route 1, where a VECM-GARCH(1,4)-X model is found superior (see footnote 84).

Table 4.5 reports diagnostic tests based on the standardised residuals ($\varepsilon_t / \sqrt{H_t}$). Ljung-Box (1978) statistics for 12th-order serial correlation in the level and squared standardised residuals, as well as the test statistics for asymmetry (sign bias, negative size bias, positive size bias, joint sign and size bias test) developed by Engle and Ng (1993) – see Table 4.5 notes – indicate that models are well-specified. The exception is for the spot variance equation in routes 1 and 2A, which indicates that standardised residuals exhibit ARCH effects and for the FFA variance equation in route 2, which indicates a sign bias asymmetry[84]. The estimated implied kurtosis indicates the presence of excess kurtosis in the residuals in all investigated routes. As a result, the Jarque-Bera (1980) test rejects normality in all routes.

[84] Different specifications of VECM-GARCH(p, q)-X are used to capture excess ARCH effects in the residuals for the spot equation in routes 1 and 2A. However, the ARCH effects could not be removed completely. Therefore, estimation results of the VECM-GARCH models with the least ARCH effects in the standardised residuals for the spot equation in routes 1 [VECM-GARCH(1,4)-X] and 2A [VECM-GARCH(1,1)] are presented. We have to note, that the SBIC (1978) in the case of route 1 selects a VECM-GARCH(1,1) specification. However, in terms of residual diagnostics the model exhibited severe asymmetries. Using an asymmetric VECM-EGARCH(1,1) model in route 2, to remove the sign asymmetry in the FFA variance equation, yield inferior results judged by the evaluation of the log-likelihood and in terms of the SBIC (1978).

Table 4.4. Estimates of VECM-GARCH Models for the Spot and FFA Prices (Routes 1 and 1A: 1997:01-2000:07, Routes 2 and 2A:1997:01-2001:04)

$$\Delta S_t = \sum_{i=1}^{p-1} a_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i}\Delta F_{t-i} + a_S z_{t-1} + \varepsilon_{S,t} \quad (4.4.a)$$

$$\Delta F_t = \sum_{i=1}^{p-1} a_{F,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i}\Delta F_{t-i} + a_F z_{t-1} + \varepsilon_{F,t} \;;\quad \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \mid \Omega_{t-1} \sim IN(0, H_t) \quad (4.4.b)$$

$$H_t = A'A + B'H_{t-1}B + C'\varepsilon_{t-1}\varepsilon_{t-1}'C + S1'u_{1,t-1}u_{1,t-1}'S1 + S2'u_{2,t-1}u_{2,t-1}'S2 + E'(z_{t-1})^2E \quad (4.5)$$

Coefficients	Spot 1	FFA 1	Spot 1A	FFA 1A	Spot 2	FFA 2	Spot 2A	FFA 2A
Panel A: Conditional Mean Parameters								
a_j, j = 1, 2	-0.017* (-3.259)	0.063* (4.504)	-0.013* (-2.329)	0.083* (4.248)	-0.045* (-6.925)	0.039* (2.547)	-0.036* (-5.428)	0.083* (5.362)
$a_{j,1}$, j = S, F	0.494* (11.034)	0.563* (7.046)	0.654* (9.727)	0.419* (2.902)	0.599* (19.470)	0.665* (6.917)	0.567* (9.203)	0.510* (5.824)
$a_{j,2}$, j = S, F	0.139* (3.582)	-	0.134* (2.846)	0.165* (1.422)	-	-0.161** (-1.714)	0.102* (1.984)	-
$a_{j,3}$, j = S, F	0.072* (2.212)	-	-	-	-	-0.237* (-2.759)	-	-
$a_{j,4}$, j = S, F	-	-0.205* (-2.223)	-	-	-	-	-	-
$b_{j,1}$, j = S, F	0.043* (3.975)	-0.080* (-2.369)	0.028* (2.495)	-	0.079* (3.829)	-	0.054* (3.634)	0.082* (2.910)
$b_{j,2}$, j = S, F	-	-	-	-0.095* (-3.055)	-	-0.095* (-3.742)	0.031* (2.604)	-
$b_{j,3}$, j = S, F	-	-	-	-	0.029* (2.152)	-	-	-
Panel B: Conditional Variance Parameters								
a_{11}	0.0047* (7.991)		0.0026 (1.349)		0.0024* (3.055)		0.0007 (1.637)	
a_{21}	0.0010* (2.757)		0.0049* (6.801)		0.0047* (7.507)		0.0019* (2.992)	
a_{22}	0.0178* (2.359)		0.0093** (1.839)		0.0093* (4.285)		0.0056** (1.748)	
b_{kk}, k = 1, 2	-0.030 (-0.252)	0.614 (1.464)	-0.599* (-6.625)	0.897* (11.028)	-0.365* (-2.412)	0.755* (9.603)	-0.848* (-20.276)	0.925* (19.447)
$c_{1,kk}$, k = 1, 2	0.379* (3.406)	0.014 (0.391)	0.619* (5.149)	0.173* (3.236)	0.549* (6.472)	0.061 (1.621)	0.476* (5.287)	0.017 (0.590)
$c_{2,kk}$, k = 1, 2	0.246** (1.768)	0.059 (0.669)	-	-	-	-	-	-
$c_{3,kk}$, k = 1, 2	0.202* (3.193)	-0.067 (-0.511)	-	-	-	-	-	-
$c_{4,kk}$, k = 1, 2	0.276* (3.059)	0.036 (0.532)	-	-	-	-	-	-
e_{kk}, k = 1, 2	0.030* (2.114)	0.082 (1.558)	-	-	-	-	-	-
$S1_{21}$ (Spot →)	-	-0.00006 [0.999]	-	0.546 [0.191]	-	0.790* [0.000]	-	0.894* [0.003]
$S2_{12}$ (FFA →)	0.117* [0.002]	-	7.42E-07 [0.999]	-	0.099* [0.041]	-	0.091* [0.002]	-

Notes:

- All variables are transformed in natural logarithms.
- * and ** indicate significance at the 5% and the 10% levels, respectively.
- Figures in parentheses (.) and in squared brackets [.] indicate *t*-statistics and exact significance levels, respectively.
- The GARCH-X process is estimated with the QMLE. The BFGS algorithm is used to maximise the QMLE.

- z_{t-1} represents the lagged ECT. The ECT is restricted to be the lagged basis in route 1 only. In routes 1A, 2, and 2A the ECT is the unrestricted basis (see notes in Table 4.3).
- Volatility spillovers are measured by the coefficients of the S1 and S2 matrices. They indicate volatility spillovers from the market shown in the row to the market shown in the column [see the ($\rightarrow$) symbol].

Focusing next on the parameters describing the conditional variance of the VECM-GARCH models in each market, it can be seen that in the spot variance equation in route 1, the coefficient of the lagged variance (b_{11} = -0.030) is insignificant, while the coefficients of the lagged error terms ($c_{1,11}$ to $c_{4,11}$) are significant, which indicate that there is only ARCH in the spot rates. Insignificant coefficients of lagged variance (b_{22} = 0.614) and lagged error terms ($c_{1,22}$ to $c_{4,22}$), in the FFA variance equation in route 1, indicate that volatility of FFA rates is not time-varying. The results in routes 1A and 2 and 2A indicate time-varying variances in both spot and FFA equations. Overall, the coefficients of the lagged error-terms in the spot variance equation are higher than those in the FFA variance equation in all routes, implying that past shocks (new news) have a greater impact on the spot rather on the FFA volatility. On the other hand, the coefficient of the lagged variance in the spot variance equation is lower than that in the FFA variance equation in all routes, implying that informed agents use past volatility (old news) more in the FFA market. The results of the coefficients of the lagged squared basis (e_{kk}) in the variance equations indicate that the basis is significant and affects positively the volatility of the spot market in route 1 only. Therefore, variation in the lagged squared basis for the spot market results in increased volatility in the spot market. In routes 1A, 2, and 2A the lagged squared unrestricted basis is found insignificant in the spot and FFA variance equations. This in turn implies that the unrestricted basis does not assist in explaining the relationship between disequilibrium and conditional volatility.

The coefficients of volatility spillover effects, $s1_{21}$ and $s2_{12}$, pick up the effect of lagged squared forecast errors (residuals) of the spot equation in explaining the volatility of FFA rates, and of the FFA equation in explaining the volatility of spot rates, respectively. In general, a volatility spillover from one market to another means that any piece of information that is released by the volatility transmitting market has a superior information role and therefore, has an effect on the market that receives the volatility spillover.

Table 4.5. Diagnostic Tests on Standardised Residuals of VECM-GARCH Models

	Spot 1	FFA 1	Spot 1A	FFA 1A	Spot 2	FFA 2	Spot 2A	FFA 2A
System *LL*	6,925.822		6,431.812		7,140.977		6,465.179	
Skewness	0.384 [0.000]	-0.043 [0.604]	0.549 [0.000]	0.264 [0.001]	0.018 [0.823]	0.774 [0.000]	0.639 [0.000]	1.274 [0.000]
Kurtosis	7.979 [0.000]	10.688 [0.000]	14.281 [0.000]	8.429 [0.000]	8.878 [0.000]	9.608 [0.000]	4.748 [0.000]	13.579 [0.000]
J-B Normality Test	2,377.39 [0.000]	4,221.99 [0.000]	7,599.68 [0.000]	2,642.29 [0.000]	2,916.60 [0.000]	3,503.87 [0.000]	895.45 [0.000]	7,078.38 [0.000]
Q(12)	8.449 [0.673]	13.907 [0.238]	12.411 [0.334]	6.145 [0.864]	7.166 [0.786]	12.110 [0.355]	9.572 [0.569]	5.526 [0.903]
$Q^2(12)$	38.991 [0.000]	4.255 [0.962]	2.937 [0.992]	15.371 [0.166]	2.373 [0.997]	7.746 [0.736]	24.306 [0.012]	2.474 [0.996]
ARCH(12)	3.288 [0.000]	0.335 [0.983]	0.245 [0.996]	0.983 [0.463]	0.226 [0.997]	1.268 [0.232]	1.855 [0.036]	0.212 [0.998]
Persistence ($b^2_{kk} + c^2_{kk}$)	0.322	-	0.742	0.835	0.435	0.574	0.946	0.856
H-L	1.61	-	3.32	4.83	1.65	2.25	13.41	5.46
AIC	-13,799.644		-12,829.624		-14,245.953		-12,896.359	
SBIC	-13,675.277		-12,748.307		-14,159.853		-12,815.042	
LR (E = 0)	$7.556 \sim \chi^2(2)$		$10.154 \sim \chi^2(2)$		$7.584 \sim \chi^2(2)$		$1.070 \sim \chi^2(2)$	
Sign and Size Bias Tests								
Sign Bias	0.197 [0.844]	1.119 [0.264]	-0.814 [0.416]	0.632 [0.528]	-0.264 [0.792]	2.191 [0.029]	-0.230 [0.818]	-0.121 [0.903]
Negative Size Bias	-0.225 [0.822]	0.095 [0.925]	-0.059 [0.953]	0.276 [0.783]	-0.095 [0.924]	-0.095 [0.924]	0.150 [0.881]	0.425 [0.671]
Positive Size Bias	-0.238 [0.812]	-0.102 [0.919]	0.293 [0.770]	-0.106 [0.916]	0.309 [0.757]	-1.784 [0.075]	0.908 [0.364]	-0.603 [0.547]
Joint Test for 3 Effects	0.027 [0.994]	0.582 [0.627]	0.356 [0.785]	0.276 [0.843]	0.063 [0.979]	2.303 [0.076]	0.311 [0.818]	0.241 [0.868]

Notes:

- Figures in squared brackets [.] indicate exact significance levels.
- System *LL* is the System Log-Likelihood.
- J-B Normality is the Jarque-Bera (1980) normality test, with probability values in square brackets.
- Q(12) and $Q^2(12)$ are the Ljung-Box (1978) tests for 12th order serial correlation and heteroskedasticity in the standardised residuals and in the standardised squared residuals, respectively.
- ARCH(12) is the Engle's (1982) *F* test for Autoregressive Conditional Heteroskedasticity.
- The persistence coefficient is calculated as $b^2_{kk} + c^2_{kk}$ (see footnote 85).
- H-L is the Half-Life test, which measures the number of days that it takes for volatility to reduce its size to half its original size after a shock. It is measured as $1 - [\log(2) / \log(b^2_{kk} + c^2_{kk})]$, k = 1, 2.
- AIC and SBIC are the Akaike Information Criterion (1973) and Schwartz Bayesian Information Criterion (1978), respectively.
- LR(E = 0) is the likelihood ratio statistics for the restriction E = 0. Let LLU and LLR be the maximised value of the log-likelihood functions of the unrestricted and the restricted models, respectively. Then the following statistic 2(LLU – LLR) is χ^2 distributed with degrees of freedom equal to the number of restrictions placed in the model.
- The test statistics for the Engle and Ng (1993) tests are the *t*-ratio of *b* in the regressions: $u_t^2 = a_0 + bY^-_{t-1} + \omega_t$ (sign bias test); $u_t^2 = a_0 + bY^-_{t-1}\varepsilon_{t-1} + \omega_t$ (negative size bias test); $u_t^2 = a_0 + bY^+_{t-1}\varepsilon_{t-1} + \omega_t$ (positive size bias test), where u_t^2 are the squared standardised residuals (ε_t^2 / h_t). Y^-_{t-1} is a dummy variable taking the value of one when ε_{t-1} is negative and zero otherwise, and $Y^+_{t-1} = 1 - Y^-_{t-1}$. The joint test is based on the regression $u_t^2 = a_0 + b_1Y^-_{t-1} + b_2Y^-_{t-1}\varepsilon_{t-1} + b_3Y^+_{t-1}\varepsilon_{t-1} + \omega_t$. The joint test H_0: $b_1 = b_2 = b_3 = 0$, is an *F*-test with 95% critical value of 2.60.

In route 1, the coefficient of the volatility spillover from spot to FFA is insignificant (-0.00006), while the coefficient of the volatility spillover from FFA to spot is significant (0.117), which implies that there is a unidirectional volatility spillover from the FFA to the spot market. The finding, that only FFA volatility affects spot volatility, is consistent with the empirical work of Koutmos and Tucker (1996), Chatrath and Song (1998), amongst others. In route 1A, the coefficients of volatility spillovers for both markets are highly insignificant, indicating that there is no volatility spillover from any market to the other. The finding of no volatility spillovers is consistent with Kawaleer *et al.* (1990) and Arshanapali and Doukas (1994), amongst others.

In route 2, the coefficients of the volatility spillovers from spot to FFA (0.790) and from FFA to spot (0.099) are significant at the 5% level. Thus, there is a bi-directional relationship in volatility spillovers, but it seems to be stronger from the spot to the FFA market, which is in accordance with earlier results that the FFA market informationally leads the spot market. Finally, in route 2A, the coefficients of volatility spillovers, for both markets, are highly significant at the 5% level, which imply that there is a bi-directional relationship in volatility spillovers between the two markets. However, the magnitude of the $s1_{21}$ coefficient (0.894) is higher than the magnitude of the $s2_{12}$ coefficient (0.091), implying that the effect of the shock in the spot market on the FFA market volatility is larger than that on the spot market volatility induced by the shock in the FFA market, which again is consistent with earlier results. In routes 2 and 2A the finding that there is a bi-directional relationship in volatility spillovers is in accordance with the empirical work of Chan *et al.* (1991), Chan and Chung (1993), and Wang and Wang (2001), amongst others.

Overall, in route 1 the results of the mean equation indicate that there is a bi-directional relationship between FFA and spot prices, and that FFA prices play a leading role in incorporating new information. However, the results of the variance equation indicate that there are unidirectional volatility spillovers from the FFA to the spot market, and thus, the FFA market seems to lead the spot market in terms of volatilities. In route 1A the results of the mean equation indicate that there is a bi-directional relationship between FFA and spot prices, while there are no volatility spillovers in any direction. The discrepancy in the results between returns and volatilities, in routes 1 and 1A may be justified by the thin-trading in terms of FFA contracts, and thus, the information assimilation may change between periods of high and low trading and in terms of different economic conditions. In contrast, in routes 2 and 2A there is a bi-directional relationship in terms of both returns and volatilities, and the direction of information flow seems to be stronger from FFA to spot. These results may be attributed to the high trading activity of routes 2 and 2A, which results in information being incorporated faster in the FFA market, in comparison to the spot market.

The persistence of volatility of the spot and FFA market, following a shock in the respective market, measured by $b_{kk}^2 + c_{kk}^2$, where k = 1,2[85], show that the unconditional variances are stationary (persistence factors less than one). In routes 1A and 2, FFA price shocks seem to have a greater effect on FFA volatility, than spot price shocks on spot volatility. This is also seen through the Half-Life (H-L) measure, estimated as $1 - [\log(2)/\log(b_{kk}^2 + c_{kk}^2)]$, which indicates the time period required for the shocks to reduce to one-half of their original size[86]. According to the results, the shocks reduce to half their original size in approximately 3 days for the spot market and 5 days for the FFA market in route 1A, and 1 day for the spot market and 2 days for the FFA market in route 2. In contrast, in route 2A, spot price shocks seem to have a greater effect on spot volatility, than FFA price shocks on FFA volatility. The H-L measure indicates that shocks reduce to half their original size approximately 14 days for the spot market and 6 days for the FFA market in route 2A. Finally, in route 1, the volatility of the FFA prices is not time-varying (as the coefficients of the lagged variance and lagged error terms are statistically insignificant), and thus, there is no persistence in FFA volatility. On the other hand, spot price shocks seem to have an effect on spot volatility, with a H-L measure of 2 days.

[85] The volatility persistence factor is defined as the degree of convergence of the conditional volatility to the unconditional volatility after a shock. For example, if the conditional volatility is defined as a GARCH(1,1) process, $\sigma_t^2 = a_0 + b_1\sigma_{t-1}^2 + c_1\varepsilon_{t-1}^2$, then the unconditional volatility would be $a_0/(1-b_1-c_1)$. Therefore, the degree of persistence of the conditional volatility can be defined as $(b_1 + c_1)$. The conditional volatility converges to its unconditional value, if and only if $(b_1 + c_1) < 1$. In the BEKK specification persistence is calculated as $(b_1^2 + c_1^2)$.

[86] The closer to unity is the value of the persistence measure, the slower is the decay rate and the longer is the Half-Life measure.

4.6. CONCLUSION

This chapter investigates the lead-lag relationship in daily returns and volatility between spot and FFA price series in the panamax voyage routes 1 and 2 and time-charter routes 1A and 2A. The study contributes to the general literature by examining an OTC forward market, extending the concepts associated with intertemporal spot and forward prices to non-storable commodities (e.g. services), with no explicit storage relationship linking spot and forward prices. In addition, a feature of this market is higher transactions costs in spot compared to the FFA market.

The major findings of this chapter can be summarised as follows. First, spot and FFA prices are cointegrated (stand in a long-run relationship between them) in all routes but restrictions on the cointegrating vector, to represent the lagged basis, hold in route 1 only. This may indicate that prices do not move closely enough in the rest of the trading routes. Second, after using a SURE-VECM model and GIR analysis, the results indicate that there is a bi-directional causal relationship in all routes, implying that FFA prices can be equally important as sources of information as spot prices are in commodity markets. However, FFA prices tend to discover new information more rapidly than spot prices in all routes. This pattern is thought to reflect the fundamentals of the underlying asset since, due to the limitations of short-selling and higher transactions costs of the underlying spot rate, investors who have collected and analysed new information would prefer to trade in the FFA rather than in the spot market.

In order to investigate for volatility spillovers between the spot and FFA markets, this study utilises an extended bivariate VECM-GARCH-X model. The cointegrating lagged residual is found to be a significant determinant of the conditional mean returns but have poor explanatory power on the conditional volatilities. The results indicate that the FFA market volatility spills information to the spot market volatility in route 1. In route 1A the results indicate no volatility spillovers in either market. In routes 2 and 2A there is a bi-directional relationship as each market transmits volatility in the other. However, in routes 2, and 2A the FFA market plays a leading role in incorporating new information.

The results of the lead-lag relationship in returns are in accordance with the results in most futures markets, including futures markets in shipping freight contracts (see Chan *et al.*, 1991; Chan, 1992; and Kavussanos and Nomikos, 2001, amongst others). Results then, in terms of returns, indicate that informed agents are not indifferent between trading in the FFA and the spot market, as new market information disseminates faster in the FFA market than the spot. Thus, it seems that FFA prices in all routes contain useful information about subsequent spot prices, and therefore, can be used as price discovery vehicles, since such information may be used in decision making. Furthermore, the FFA contracts in routes 1, 2, and 2A contribute in the volatility of the relevant spot rate, and therefore, further support the notion of price discovery. The findings of this study suggest that equilibrium models that rely exclusively on first moments may be misspecified, as second moments seem to contribute to the discovery of information in most of the investigated routes. Practitioners, by explicitly modelling conditional variance dynamics, can have a clearer understanding of the price interactions in the spot and FFA markets. This can lead to a better assessment of risk management, ship-chartering and budget planning decisions.

CHAPTER 5 – AN INVESTIGATION OF THE INTRODUCTION OF FORWARD FREIGHT TRADING ON SPOT MARKET PRICE VOLATILITY

5.1. INTRODUCTION

While derivatives markets can be seen to be enhancing economic welfare by allowing for new positions and expanding the investment sets or enabling existing positions to be taken at lower costs, they have been criticised for attracting uniformed traders because of the high degree of leverage (Figlewksi, 1981), and for encouraging speculation (Cox, 1976). Figlewski (1981) and Stein (1987) argue that the lower level of information of derivatives traders, compared with that of spot market participants, results in increased spot market price volatility. Goss and Yamey (1978) argue that derivatives markets, by allowing individuals to undertake speculative activity without them having to become involved in the production, handling or processing of the commodity or asset, can increase speculation. Furthermore, the low cost of participating and the rapid implementation of a position in the derivatives markets make it easy for market agents to engage in speculation. Thus, there has been a considerable concern regarding the impact that derivatives markets may have on price volatility of the underlying spot market. This chapter examines whether, and to what extent, the recent introduction of trading in FFA contracts has impacted on the price volatility of the underlying spot market[87]. If the sole interest of a large number of market agents is not hedging themselves, against adverse freight rate movements, but to speculate using the FFA market, their actions may induce excess volatility, and therefore, destabilise the spot market.

This chapter extends the empirical literature on the relationship between derivatives (futures and forward) trading and spot market price volatility in the following ways. First, most of the studies view the question about the impact of derivatives trading on spot price volatility from a stabilising or destabilising view-point by comparing spot price volatility during the pre- and post-derivatives trading areas. While a number of methodologies have been adopted to examine

[87] FFA contracts were introduced in London in October 1991 by the shipbroking company Clarkson Securities Ltd., originally marketing them through their joint-venture company, Clarkson Wolff.

this issue the investigation of the link between information and volatility in earlier studies is neglected, (with the exemption of Chatrath *et al.*, 1996; Antoniou *et al.*, 1998; and McKenzie *et al.*, 2001).

Second, the conditional variance from Glosten, Jagannathan, and Runkle (1993) GJR-GARCH model is found to be the appropriate process of volatility of the spot freight rates, enabling the investigation of the link between information and conditional volatility and of the market dynamics, as reflected by a change in the asymmetric volatility response. Antoniou *et al.* (1998) argue that derivatives markets may change the role of market dynamics in terms of the way in which volatility is transmitted and, therefore, how information is incorporated into prices. Merton (1995) argues that the introduction of derivatives markets can improve efficiency by reducing asymmetric responses to information. The prior literature has generally restricted itself to testing changes in spot price volatility and has not considered whether reduced asymmetry (linked to news arrival) has resulted from derivatives trading. Such a restricted testing framework may lead to inappropriate policy responses.

Third, if a stabilising/destabilising impact is found, we investigate whether the introduction of FFA trading is the only cause for a change in the spot market volatility. The hypothesis that other factors may have affected market volatility is tested. For this purpose several other economic indicators are included as proxies for market factors in the variance model.

Fourth, the FFA market is organised quite differently from a futures market. All trading is bilateral, there is no clearing-house, no open outcry, and no centralised exchange. Only at the end of the trading day, information on deals negotiated during the day, is disseminated[88]. During the day, traders must rely on their contacts for information on the transactions consummated.

Finally, much of the analysis in previous studies has been devoted on considering the impact of trading in market-wide instruments (i.e. stock index contracts). Such studies are useful in assessing the market-wide impact, but any effect in the underlying spot market can be dissipated across the many constituent assets in the index, making it difficult to detect. Because

[88] Shipbrokers in London report to their clients daily the FFA quotes around 17:00 UK time.

FFA are route-specific contracts (the underlying asset is freight rates of a trading route) this study contributes in the general literature by examining changes in the volatility of individual routes (assets). In addition there are some special features in these contracts, which do not appear in other markets. These include (i) the investigation of the issue on a forward rather than a futures market. We have not seen any studies before on OTC markets, primarily due to the lack of available data. Yet differences in the results between forward and futures markets may arise; (ii) the underlying commodity is a service and the usual cost-of-carry relationship between spot and forward does not exist here; and (iii) transactions costs are thought to be lower in the FFA market in comparison to spot and also in FFA compared to futures (Kavussanos and Nomikos, 2001).

This chapter can provide regulators and practitioners with important insights into the FFA trading - spot market price volatility relationship. If the FFA market cause a change in the level of volatility in the spot market (as in the arguments that speculators increase volatility) and this, in turn, is associated with greater uncertainty and unduly higher required freight rates, then there may well be a case for the FFABA and the FIFC to increase the regulation of this market. However, if this market leads to new channels of information being provided, more information due to more traders, and a reduction in uniformed investors, then the FFA market provides a useful service and calls for its regulation are unwarranted.

The remainder of this chapter is organised as follows. Section 5.2 presents the literature review. Section 5.3 discusses the theoretical issues relating to the relationship between information and volatility and presents the research methodology. Section 5.4 describes the data and provides some preliminary statistics. The empirical results are presented in section 5.5. Finally, section 5.6 summarises this chapter.

5.2. LITERATURE REVIEW

The empirical work whether derivatives (futures and forward) trading stabilises or destabilises the spot market is voluminous and the review in this section is not exhaustive. Rather it seeks to identify the most influential work in this area. Questions pertaining to the impact of derivatives trading activity on spot market volatility have been empirically addressed in two ways. First, researchers have attempted to establish the impact of speculative trading on spot markets by comparing spot price volatility during the pre- and post-derivatives trading areas (see for example, Antoniou *et al.*, 1998; and Mckenzie *et al.* 2001, amongst others). Second, researchers have examined the relationship between speculative trading activity and spot markets by directly evaluating the impact of derivatives trading activity (generally proxied by trading volume) on the behavior of spot markets (see for example, Bessembinder and Seguin, 1992; and Chatrath *et al.*, 1996, amongst others)[89].

In general there are two main beliefs among market agents. The first is that speculators in derivatives markets have a destabilising impact on spot prices (see for example, Harris, 1989; Damodaran, 1990; and Antoniou and Holmes, 1995, amongst others). Several studies suggest that the participation of speculative traders in systems that allow high degrees of leverage could lower the quality of information and could increase uncertainty in the market, which in turn, could raise the required rate of return of investors in the market, and consequently, could increase the volatility of spot prices (see Stein, 1961; and Figlewski, 1981, amongst others). Cox (1976), argues that uniformed traders could play a destabilising role in spot markets. Furthermore, an increase in volatility on expiration days is expected as investors attempt to close out their positions, settle contracts, and trade on potential arbitrage opportunities.

The second is the exact opposite, were speculators are seen to have a useful and stabilising role in spot markets (see for example, Kaldor, 1960; Moriarty and Tosini, 1985; Edwards, 1988a; Robinson, 1994; and Choi and Subrahmanyam, 1994, amongst others)[90]. It can be argued that derivatives markets require speculators, to enable hedgers to transfer risks which they wish to avoid. It has been suggested that derivatives markets have become an important vehicle of price discovery in spot markets, as they may bring more (private) information to the market and allow for quicker dissemination of information (Schwarz and Laatsch, 1991). Several authors have argued that trading in these markets improves the overall market's depth (market's completeness) and informativeness (Powers, 1970), increases market liquidity (Kwast, 1986),

[89] In this chapter only the first approach is followed, as volume figures for the FFA market are not publicly available.

[90] Kaldor (1960) argues that: "*speculators are people of better than average foresight who step in as buyers whenever there is a temporary excess of supply over demand, and thereby moderate the price fall; they step in as sellers, whenever there is a temporary deficiency of supply, and thereby moderate the price fall...The idea that speculative activity might increase price fluctuations was not considered in traditional theory since this would require that speculative activity resulted in losses; selling when prices are low and buying when high*".

compresses spot market volatility (Kyle, 1985), enhances market efficiency (Stoll and Whaley, 1988), and thereby improves investment choices for investors (Arditti and John, 1980).

This controversial issue of the impact of speculators, which dates back almost to the inception of derivatives trading, has been the subject of considerable empirical analysis and has received the attention of policymakers. Despite that, the issue of whether derivatives trading destabilises or stabilises the spot market, is still viewed with suspicion by market agents and policymakers alike. For example, in financial futures markets such suspicion has led to suggestions that futures trading should be further regulated, including higher margins (see Bessembinder and Seguin, 1992)[91]. However, further regulation may have a negative impact on the working of financial and commodity markets and hence on economic welfare. Thus, the uncertainty of the existent theoretical literature implies that the issue of whether and how derivatives markets affect the underlying spot markets remains mainly an empirical one.

In currency markets, Eldridge (1984) examines the impact of the futures positions taken by European traders at the end of their business day on the volatility of currency futures traded on the International Monetary Market (IMM). Eldridge suggests that price volatility (measured by standard deviation) in Deutsche Mark futures contracts, temporarily rises at the close of the European business day. Clifton (1985) explicitly examines the relationship between currency futures and exchange rate volatility. The author examines the impact of currency futures trading on the interbank currency market during the early 1980s. A strong positive correlation between futures trading volume and intraday exchange volatility (measured for the spread between intraday high and low rates) is documented. However, the study is not able to provide conclusive evidence on the causality between exchange rate fluctuations and futures trading volume.

McCarthy and Najand (1993) employ a state-space model to provide mixed evidence on the stabilising influence of futures trading on daily futures currency prices. While the lagged levels of trading volume on the British Pound, Swiss Franc, and Deutsche Mark futures are found to

[91] The Brady Commission (1988) suggests that low futures margins may allow investors to control large positions with low initial investments, and thus, in order to protect the marketplace, margins on stock index futures should be consistent with margins for professional market participants in the stock market.

have a negative (stabilising) impact on the volatility of the respective futures price, the lagged trading volume levels on the Canadian Dollar futures are found to have a positive (destabilising) impact (see also Grammatikos and Saunders, 1986). Chatrath *et al.* (1996) using a GARCH model, as a proxy of volatility of the exchange rates, suggest that currency futures trading has a significant positive impact on the volatility in the exchange rate changes, with a weaker feedback from exchange rate volatility to futures trading.

In stock markets, Edwards (1988a and 1988b) analyses the impact of stock index futures trading on stock price volatility of the S&P 500 and Value Line indices by examining the volatility of the stock market before and after the inception of futures trading. Edwards (1988a) uses the variance of close-to-close percentage daily price changes to measure volatility. The results indicate that volatility has decreased post-futures for the S&P 500 index and that volatility was not significantly different post-futures for the Value Line index. Thus, there is no evidence that futures trading has had a long-run destabilising effect on the stock market. Aggarwal (1988) uses a regression model where returns on the stock index are regressed on the returns on an OTC composite index and dummy variables relating to *early* and *mature* futures periods. The regressions are also repeated using return squared deviations in place of returns. The results indicate that while the post-futures period is more volatile, this holds for all markets, and hence, stock index futures may not be the primary cause of this increase.

Harris (1989) uses cross-sectional analysis of covariance methods to examine for changes in stock index volatility since the onset of stock index futures trading. Harris suggests that, despite the fact that spot market volatility has increased with the trading in futures markets, there are other index related phenomena (i.e. growth in index funds) that could account for the results. Becketti and Roberts (1990) use a statistical model to highlight potential outliers in order to determine whether stock index futures have led to an increase in the frequency of jumps in daily stock returns. They conclude that there is little or no relationship between stock market volatility and either the existence of, or the level of activity in, the stock index futures market.

Baldauf and Santoni (1991) use an ARCH model to examine for increased volatility in the stock index following the introduction of futures trading. The squared difference in the log of daily price changes is modelled as an ARCH process for periods before and after the onset of futures trading. Testing for changes in the parameters of the model did not yield any significant evidence, suggesting that the inception of futures trading had no significant effect on volatility. Brorsen (1991) argues that the autocorrelation of stock prices should be reduced by the introduction of futures trading, since such trading reduces market friction leading to prices adjusting more rapidly to new information. Furthermore, Brorsen argues that reducing market frictions, the variance of short-run price changes increases. Tests of the homogeneity of variance for time periods before and after futures trading indicate that while the variances of daily price changes are significantly different, there is no significant difference in the variances of five and twenty day price changes.

Darrat and Rahaman (1995) conclude that S&P 500 futures volume did not affect spot market volatility. Board *et al.* (1997) report that contemporaneous futures market trading had no effect on spot market volatility. Bologna (1999) and Bologna and Cavallo (2002) argue that the introduction of stock index futures trading in the Italian stock exchange has led to diminished volatility. McKenzie *et al.* (2001) examine whether the introduction of trading in share futures contracts on individual stocks (i.e. individual share futures) has impacted on the systematic risk and volatility of the underlying shares. They report a general reduction in systematic risk on individual stocks after the listing of futures, a decline in unconditional volatility, and mixed evidence concerning the impact on conditional volatility.

5.3. METHODOLOGY AND THEORETICAL CONSIDERATIONS

The debate about the impact of derivatives trading on spot price volatility can be more successfully examined within the context of the EMH. The EMH states that prices in a market depend upon the information, which is currently available in that market. When new information becomes available in an efficient market, prices will adjust rapidly to reflect that new information. Thus, price movements, and hence price volatility, are directly related to information arrival in an efficient market. Cox (1976) argues that there are two reasons why derivatives trading can alter the amount of available information. First, derivatives trading attracts an additional group of traders to a market (speculators), who might otherwise not participate in the market. It is assumed that speculators, in pursuing their own interest, are bringing good quality information to the market (well-informed). Second, since derivatives trading incurs less transactions costs than does trading in the spot market, when new information does become available it may be transmitted to the derivatives market more quickly (price discovery role of derivatives markets).

From the point of view of market efficiency it is reasonable to argue that if derivatives trading does increase the amount of information available, then spot price volatility may increase. The assumption that must be made, however, is that speculators must be well-informed in order for a direct link between information and volatility to be established[92]. The arguments of Cox (1976) that derivatives trading might increase available information does not necessarily imply that information becomes available which would not otherwise. Rather, it may simply be that information becomes available earlier. Thus, the rate of information flow increases, as does the rate at which the information is impounded into prices. Hence, volatility of prices may increase.

Ross (1989) presents a formal theoretical connection between information (timing of the release) and volatility. Ross uses the no arbitrage methodology developed by Ross (1976) and Cox and Ross (1976) to state that in an arbitrage-free economy, the volatility of prices is directly related to the rate of information flow arriving in the market. This argument implies that if price volatility is not equal to the rate at which information arrives then arbitrage is possible. In the context of the impact of derivatives markets on spot market volatility, if derivatives trading does increase the rate of flow of information, then spot prices may exhibit increased volatility.

Although the theorem of Ross (1989) may hold, the irrational behaviour of noise/positive feedback traders may induce asymmetries in the increased volatility. Santana and Wadhwani (1992) provide an explanation of the asymmetric response of volatility to news. In particular, with a model of feedback traders who have access to less information than their informed counterparts, responses to bad news (price falls) lead to greater volatility than do responses to good news. If noise traders are attracted away from the spot market to the derivatives market, then asymmetries that are observed in the spot market prior to the inception of derivatives

[92] However, not all investors act in a rational manner when making their buy and sell decisions, and their actions may lead to asymmetries. Black (1986) terms such investors *noise traders* – they trade not on information but on noise. Black claims that such investors react to information in a way that would not be present in a fully rational model and they must be a significant proportion of total market trading. Furthermore, Shiller (1984) claims that *positive feedback traders* chase trends based upon popular models that can be related to fundamentals, but there is an element of overreaction to news.

trading will not be evident in the spot market after derivatives trading, although they may, nonetheless, be present in the derivatives market.

Thus, in examining spot price volatility pre- and post-FFA, it is important to use a model to take into account the link between information and volatility and of possible asymmetric responses to news. By examining this issue it can be seen whether the introduction of FFA trading has increased or decreased spot price volatility and to investigate the extent to which the introduction of FFA contracts also affected the nature of volatility in the underlying spot market. Even if it is found that spot market volatility has increased post-derivatives, this is not necessarily an undesirable consequence of derivatives trading, because there may, simultaneously, be a change in the spot market dynamics that removes asymmetries and improves the transmission mechanism for news.

Board and Sutcliffe (1990) have shown that studies based on historical estimates of volatility are sensitive to the measures of volatility used. However, recent studies indicate that most of the financial price series exhibit non-linear price dependencies. For example, it is possible for spot prices to be linearly unrelated and yet be non-linearly dependent. The general evidence suggests that dependencies work through the conditional variance (and other even-ordered moments), rather than being a result of certain misspecified first-order dynamics (Engle and Rothschild, 1992). Under these conditions, the applicability of traditional volatility measures would provide inconsistent estimates in the current study.

The ARCH model of Engle (1982) and the GARCH model of Bollerslev (1986) can capture such time variation in return distributions. In the ARCH model, the conditional error distribution is normal, but the conditional variance is a linear function of past squared errors. The GARCH process allows for a more flexible lag structure, as the conditional variance is a linear function of past squared errors and past variances. There is a great deal of evidence in various financial markets that the conditional variance from ARCH class of models provides a superior estimate of spot price variability (see Bollerslev *et al.*, 1992 for a review). ARCH processes allow the examination of the structure and the characteristics of volatility, explicitly address the issue of time dependence in the variance, and therefore, overcome problems associated with heteroskedasticity in the data.

More recent studies in this area have extended their scope to consider the impact of the introduction of derivatives contracts on how the market responds to news. FFA trading may potentially impact on these market dynamics. According to Antoniou *et al.* (1998), market dynamics related to the transmission of news may be responsible for asymmetries in the volatility response mechanism[93]. Thus, to test the impact of the introduction of FFA contracts, a GARCH model is modified along the lines of the GJR-GARCH model of Glosten *et al.* (1993)[94]. The impact of the onset of FFA trading is captured by the introduction of a dummy variable in the variance equation of the process, representing the time period before and after FFA trading[95].

Following Pagan and Schwert (1990) and Engle and Ng (1993), before any empirical analysis can be undertaken it is necessary to generate a news component of returns, in order to remove from the time series any predictability associated with lagged returns or day-of-the-week effects. Let r_t be the return on a FFA from time t-1 to t and Ω_{t-1} be the information set containing all relevant information up to time, t-1. Given that Ω_{t-1} is known, conditional expected returns are the values of r_t conditional on Ω_{t-1} $\{\rho_t = E(r_t/\Omega_{t-1})\}$ and conditional volatilities are the values of the variance of r_t conditional on Ω_{t-1} $[h_t = var(r_t/\Omega_{t-1})]$. News can be defined as the unexpected component of returns, u_t ($u_t = r_t - \rho_t$) where a positive u_t is treated as good news and a negative u_t as bad news. This unexpected component should be a mean-zero white noise process. Because this chapter is interested in the effect of news on conditional volatility, the returns are regressed on a constant and day-of-the-week effects, and subsequently, ensure that the residuals from this model are serially uncorrelated[96]. When such residuals are

[93] It has been suggested that the traditional explanation of the leverage effect for asymmetry (see Nelson, 1990a, 1990b) cannot fully account for observed asymmetry in the market (Bekaert and Wu, 2000).

[94] Engle and Ng (1993) suggest that the GJR-GARCH model captures asymmetries more accurately than the E-GARCH model in terms of the log-likelihood function and that the former should be preferred. In order to determine the best GARCH specification several other specifications are used, such as the symmetric GARCH (Bollerslev, 1986), and the asymmetric E-GARCH (Nelson, 1991), but yield inferior results judged by the evaluation of the log-likelihood, in terms of residual specification tests, and in terms of a LR test which is χ^2 distributed with degrees of freedom equal to the number of restrictions imposed (not reported).

[95] Besides FFA trading, other factors, such as, industrial production, grain exports and international trade are likely to impact spot price volatility. Rather than attempting to identify the whole spectrum of factors that may impact spot price volatility, the study focuses on the internal dynamics of daily spot price volatility and only considers some indicative proxy variables (see section 5.5.2), which represent major world economic conditions. Furthermore, most macroeconomic series are available on a monthly or quarterly basis, while the interest of this chapter is on a day-to-day basis of the spot freight market. This prevents their use in the ensuing analysis.

[96] In order to test for day-of-the-week effects we introduced dummy variables for Tuesday through Friday. However, the results indicate that they are insignificant at conventional levels of significance, and therefore, they are excluded in the ensuing analysis.

serially correlated an autoregressive model of the returns is formed and any linear temporal predictability is subsequently removed. Thus, the mean equation of the GJR-GARCH process can be defined as follows:

$$\Delta S_t = \varphi_0 + \sum_{i=1}^{p-1} \varphi_i \Delta S_{t-i} + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{iid}(0, h_t) \tag{5.1}$$

where S_t is the natural logarithm of the daily spot price, Δ is the first-difference operator and ε_t are the residuals that follow a normal conditional distribution with mean zero and time-varying covariance, h_t. The conditional variance of the process can be specified as follows:

$$h_t = a_0 + a_1 h_{t-1} + a_2 D_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \beta_2 D_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1}^- + \gamma_2 D_1 \tag{5.2}$$

where D_1 is a dummy variable that takes on a value of unity after the introduction of FFA contracts and D_{t-1}^- is a dummy variable that takes on a value of unity if the error is negative and zero otherwise. The specification of the conditional variance in Equation (5.2) allows the examination of the impact of FFA trading to the unconditional volatility of the spot market through the γ_2 coefficient. A significant positive γ_2 coefficient indicates increased spot price unconditional volatility in the post-FFA period, whereas a significant negative γ_2 coefficient indicates decreased spot price unconditional volatility in the post-FFA period.

Furthermore, the model allows a number of tests of the impact of FFA trading on conditional spot price volatility[97]. We may individually test the ARCH term or the GARCH term. However, in the context of the GARCH framework, it is more appropriate to test the joint null hypothesis of no impact on the conditional variance specification ($a_2 = \beta_2 = 0$) against the alternative of at least one coefficient being non-zero. Furthermore, we may test the joint hypothesis that the FFA introduction has had no impact on volatility per se ($a_2 = \beta_2 = \gamma_2 = 0$) against the alternative of at least one coefficient being non-zero. In this case, the test examines both unconditional and conditional volatility effects.

[97] For a formal discussion of dummy variables see Gujarati (1970). He argues that the Chow test might reject the hypothesis of stability but cannot tell us which particular coefficients are unstable, whereas the dummy variable method gives this information.

Finally, the specification of Equation (5.2) allows the investigation of whether FFA trading has changed the role of market dynamics in terms of the way in which volatility is transmitted, and therefore, inferences can be made on how information is incorporated into prices. When the coefficient on D_{t-1}^{-} is equal to zero, the model of Equation (5.2) is the symmetric GARCH model. A negative shock ($D_{t-1}^{-} = 1$) can generate an asymmetric response. Where $\gamma_1 > 0$ ($\gamma_1 < 0$), the model produces a larger (smaller) response for a negative shock compared to a positive shock of equal magnitude.

However, to address the issue of the relationship between information and volatility, and not simply investigate whether FFA trading has led to an increase or decrease in volatility in the spot market, the period under investigation is partitioned into two sub-periods relating to before and after FFA trading began. GJR-GARCH models of Equation (5.2) are estimated for both sub-periods, without the D_1 dummy variable for the existence of FFA trading:

$$h_t = a_0 + a_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1}^{-} \tag{5.3}$$

where $D_{t-1}^{-} = 1$ if $\varepsilon_{t-1} < 0$, $D_{t-1}^{-} = 0$ otherwise. Comparisons can then be made on the estimated coefficients, in order to examine the impact of FFA trading on the nature of spot volatility and to assess if FFA trading has led to changes in the asymmetric response of volatility. Accordingly, the impact of the FFA trading on this asymmetry feature can be assessed through a comparison of the γ_1 coefficient in pre- and post-FFA periods.

With a sample of four spot routes for which FFA contracts have been introduced, it is possible that factors, other than the introduction of forward contracts, may affect the variables considered in each of the hypotheses tests. For example, market-wide changes may have occurred around the time of the FFA introduction date that altered the dynamics of the market. Tests may erroneously attribute such a change, if it occurred, to the introduction of FFA contracts. To this end a control procedure is implemented under which we augment the conditional variances of the spot freight routes by incorporating the conditional variances of other economic indicators. Thus, the model is recursively estimated in two-steps. First, we estimate the conditional variance of every selected economic variable [S&P 500 Composite

Index (SPI), S&P 500 Commodity Index[98] (SPCI), London Brent Crude Oil Index (BCOI) and West Texas Intermediate (WTI) crude oil] computed by the most parsimonious GARCH model (in terms of the log-likelihood and residual diagnostic tests). The selected economic variables are commonly used as control variables in the literature. In the next step, the model of Equation (5.2) is augmented by incorporating the conditional variance of the economic variables from the previous step. Thus, the augmented variance model is the following:

$$h_t = a_0 + a_1 h_{t-1} + a_2 D_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \beta_2 D_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1}^- + \gamma_2 D_1 + \delta_1 G_t \quad (5.4)$$

where G_t is the conditional variance, from a GARCH model, of an economic variable. A significant δ_1 coefficient indicates that the conditional variance of the economic variable affects the conditional variance of the spot freight rates. Thus, if its inclusion in the model does not alter the significance level and sign of the γ_2 coefficient, then the unconditional volatility of the spot freight market has not increased/decreased due to this variable and the conclusions drawn with respect to the impact of the introduction of the FFA contracts are strengthened.

Bollerslev and Wooldridge (1992) argue that excess kurtosis in the estimated standardised residuals ($\varepsilon_t / \sqrt{h_t}$), even after accounting for second moment dependencies, can invalidate traditional inference procedures. Therefore, the GJR-GARCH processes are estimated with the QMLE, which estimates robust standard errors, and thus, yields an asymptotically consistent normal covariance matrix (Bollerslev and Wooldridge, 1992). The GJR-GARCH models are also estimating by using the Student-*t* distribution of Bollerslev (1987). The results, of the coefficient of the degrees of freedom, v, indicate that the QMLE should be used, as in all routes v was lower than 4, which implies an undefined or infinite degree of kurtosis (Bollerslev and Wooldridge, 1992). For symmetric departures from conditional normality, the QMLE is generally close to the exact MLE. The Berndt-Hall-Hall-Hausman (1974) (henceforth, BHHH) optimisation algorithm is employed to obtain maximum-likelihood estimates of each of the coefficients in the mean and variance equations.

[98] The SPCI covers a broad cross section of commodities traded in the US, providing a broad, accurate picture of the commodity market. It tracks 17 commodities in 6 Sectors (Grains, Meat and Livestock, Metals, Softs, Fibres and Energy).

5.4. DESCRIPTION OF DATA AND PRELIMINARY STATISTICS

The impact of FFA trading, on the volatility of the underlying spot freight market in panamax Atlantic (1 and 1A) and Pacific (2 and 2A) routes, is investigated by estimating a model for a period which covers the time before and after the introduction of FFA contracts. Due to the specific nature of the FFA market it was not until late 1990s when this market started to attract a respectful number of market agents. From Table 1.9 in chapter 1 it is clear that until 1996 the market was very thin (with only 27 deals, on average, per month in 1996), so it was unlikely that the existence of speculators (if any) could impact the spot market volatility. Thus, in the ensuing analysis, January 1997 will be the threshold point that separates pre- and post-FFA trading in order for robust inferences to be made[99]. The data set comprises daily observations of the spot freight rates for each of the aforementioned panamax routes. It covers the periods 29 November 1989 to 31 July 2000 in route 1, 7 August 1990 to 31 July 2000 in route 1A, 29 November 1989 to 24 August 2001 in route 2, and 12 February 1991 to 24 August 2001 in route 2A. Spot prices in all routes are from the Baltic Exchange. SPI, SPCI, BCOI and WTI prices are from Datastream. All prices are transformed to natural logarithms.

The descriptive statistics of logarithmic first-differences of the daily spot prices in the four routes are reported in Table 5.1, which is divided into three periods. The first period (panel A) corresponds to the whole period of the analysis. The second (panel B) and third (panel C) periods correspond to the pre- and post-FFA periods, respectively. The results indicate excess skewness and kurtosis in all price series. In turn, Jarque-Bera (1980) tests indicate departures from normality for spot prices in all routes. Applying the ADF (1981) and PP (1988) unit root tests on the log-levels and log first-differences of the daily spot price series, the results indicate that all variables are log first-difference stationary, all having a unit root on their log-levels representation[100].

[99] Several other threshold point dates were also used, which yield qualitatively the same results.

[100] The ADF (1981) and PP (1988) test statistics were undertaken allowing for the presence of an intercept only. Allowing for the presence of a time trend did not affected the results qualitatively.

Of greatest interest in Table 5.1 are the figures obtained for the standard deviation estimates, providing an initial view of volatility for each route in the sample. In the pre-FFA period spot prices in routes 2 and 2A provide the lowest standard deviations. In the post-FFA period, routes 1 and 2 provide the lowest standard deviations, where route 2 shows considerable reduction in the standard deviation from the pre-FFA period. By comparing the two periods, it seems that the volatility of the voyage routes (time-charter routes) has decreased (increased) over time.

One possible reason for this, in route 2, is the increase in inbound cargoes to the US (primarily coal following the US energy crisis), which has meant a substantial increase in tonnage coming open in the US Gulf region. This ensures that there is a constant supply of tonnage for the US Gulf market, which in turn, has guaranteed that demand is regularly met. In contrast, historically the US Gulf market was a ballasters market, i.e. shippers needed to pay owners to come to the Gulf for cargoes, adding substantially to the volatility of the freight rates. The result of the recent change in the import status of the US is that freight rates now seem to move in a narrower bound for voyage trips and volatility has been reduced. On the other hand, time-charters in this region (route 2A) are not generic in terms of specifications and every shipper introduces his preferences. This in turn can generate increased volatility in time-charter freight rates.

Similarly to the authors of earlier studies in this area, we initially conduct equality of variance tests (see Chatrath, *et al.*, 1996). The results, in Table 5.2 panel A, reveal significant differences between the pre- and post-FFA variances in all trading routes. In panel B, of the same table, we compare the pre- and post-FFA variances of various economic indicators. The results indicate that, with the exception of the *F*-test and the Levene test statistics for the WTI crude oil, the level of the variances has changed between the two periods. This may indicate that besides the introduction of FFA contracts, there might be several other economic events (i.e. Asian crisis) that contributed to this change of variances. However, we must note that all investigated market indicators have a derivatives market (either exchange-based or OTC) which may contribute as well to the above result. The results suggest that some change has taken place over the relevant period, and thus, motivates further investigation.

Table 5.1. Descriptive Statistics of Logarithmic First-Differences of Spot Freight Prices

Panel A: Spot Freight Prices; Whole Period

	SD	Skew	Kurt	J-B	ADF (lags) Lev	PP(8) Lev	ADF (lags) 1st Diffs	PP(8) 1st Diffs
Route 1	0.01255	1.196	26.327	80,742.2	-2.418 (1)	-2.799	-17.432 (3)	-36.669
Route 1A	0.01263	1.065	5.899	4,251.9	-2.704 (3)	-2.043	-15.569 (2)	-27.744
Route 2	0.01067	0.592	14.549	26,974.6	-2.825 (2)	-2.527	-24.111 (1)	-32.093
Route 2A	0.01323	2.682	32.745	124,824	-2.113 (2)	-1.758	-20.501 (1)	-28.700

Panel B: Spot Freight Prices; Pre-FFA Period

	SD	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs
Route 1	0.01394	1.397	24.881	48,294.1	-2.748 (2)	-2.610	-14.557 (3)	-30.864
Route 1A	0.01263	1.065	5.899	4,251.9	-2.704 (3)	-2.043	-15.569 (2)	-27.741
Route 2	0.01123	0.553	15.375	18,306.7	-2.763 (2)	-2.521	-19.708 (1)	-27.006
Route 2A	0.01185	3.664	53.984	189,458.4	-2.413 (3)	-1.908	-13.508 (2)	-24.372

Panel C: Spot Freight Prices; Post-FFA Period

	SD	Skew	Kurt	J-B	ADF (lags) Lev	PP(12) Lev	ADF (lags) 1st Diffs	PP(12) 1st Diffs
Route 1	0.00912	-0.650	7.475	2,213.9	-1.835 (3)	-1.427	-9.650 (2)	-16.012
Route 1A	0.01387	1.193	5.192	1,255.5	-2.017 (2)	-1.659	-10.726 (1)	-14.282
Route 2	0.00973	0.655	11.154	6,242.9	-2.085 (1)	-1.916	-16.285 (0)	-16.426
Route 2A	0.01483	1.980	19.073	18,782.8	-2.302 (2)	-1.974	-12.948 (1)	-16.694

Notes:

- All series are measured in logarithmic first-differences.
- Figures in parentheses (.) indicate *t*-statistics.
- SD is the standard deviation.
- Skew and Kurt are the estimated centralised third and fourth moments of the data; their asymptotic distributions under the null are $\sqrt{T}\,\hat{\alpha}_3 \sim N(0,6)$ and $\sqrt{T}\,(\hat{\alpha}_4 - 3) \sim N(0,24)$, respectively.
- J-B is the Jarque-Bera (1980) test for normality, distributed as $\chi^2(2)$.
- ADF is the Augmented Dickey Fuller (1981) test. The ADF regressions include an intercept term; the lag-length of the ADF test (in parentheses) is determined by minimising the SBIC.
- PP is the Phillips and Perron (1988) test; the truncation lag for the test is in parentheses.
- Lev and 1st Diffs correspond to price series in log-levels and log first-differences, respectively.
- The 5% critical value for the ADF (1981) and PP (1988) tests is –2.89.

Table 5.2. Equality of Variance Tests for Pre- and Post-FFA Trading

Panel A: Spot Freight Routes

	F-test	Bartlett	Levene	Brown-Forsythe
Route 1	3.443 [0.000]	331.74 [0.000]	20.282 [0.000]	20.132 [0.000]
Route 1A	1.289 [0.000]	14.894 [0.000]	15.704 [0.000]	15.868 [0.000]
Route 2	1.489 [0.000]	46.647 [0.000]	3.346 [0.006]	3.269 [0.007]
Route 2A	1.578[0.000]	61.136 [0.000]	54.945 [0.000]	56.458 [0.000]

Panel B: Economic Indicators

	F-test	Bartlett	Levene	Brown-Forsythe
SPI	3.105 [0.000]	477.99 [0.000]	288.85 [0.000]	287.52 [0.000]
SPCI	1.831 [0.000]	135.98 [0.000]	88.74 [0.000]	88.154 [0.000]
BCOI	1.200 [0.000]	11.849 [0.000]	7.895 [0.000]	7.922 [0.000]
WTI	1.003 [0.956]	0.004 [0.953]	20.714 [0.000]	20.797 [0.000]

Notes:

- The *F*-test is given by $F = s_L^2/s_S^2$, where s_L^2 and s_S^2 are the larger and smaller variances, respectively. The *F*-test has a *F*-distribution with $n_L - 1$ numerator degrees of freedom and $n_S - 1$ denominator degrees of freedom.
- The Bartlett test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. It is distributed as $\chi^2(1)$ degrees of freedom and is reported adjusted for departures from normality.
- The Levene test is based on an Analysis of Variance (ANOVA) of the absolute difference from the mean. The Levene test has a *F*-distribution with 1 numerator degrees of freedom and $n_L + n_S - 2$ denominator degrees of freedom.
- The Brown-Forsythe test is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference.
- SPI is the S&P 500 Composite Index; SPCI is the S&P 500 Commodity Index; BCOI is the London Brent Crude Oil Index; and WTI is the West Texas Intermediate crude oil.

Table 5.3 panels A to C, report the Ljung-Box (1976) portmanteau statistics for the first and twelfth autocorrelation of the residuals series, Q(*L*), and squared residual series, $Q^2(L)$, of the regressions of the first-difference return series on a constant, adjusted for serial correlation by the Newey-West (1987) correction. Panel A corresponds to the whole period of the analysis, while panel B and C correspond to the pre- and post-FFA periods, respectively. The results indicate significant linear and non-linear temporal dependencies in the adjusted residual series and squared adjusted residual series (with the exception in the pre-FFA period in route 2A), respectively. It is clear that these series cannot be treated as news as there is evidence of serial-correlation.

Table 5.3. Ljung-Box Statistics for Linear and Non-Linear Temporal Dependences in Regression Models

Panel A: Whole Period

	Route 1	Route 1A	Route 2	Route 2A
Q(1)	481.01 [0.000]	919.22 [0.000]	830.31 [0.000]	893.79 [0.000]
Q(12)	1,331.4 [0.000]	2,904.2 [0.000]	1,558.9 [0.000]	2,068.3 [0.000]
$Q^2(1)$	8.889 [0.003]	310.11 [0.000]	41.24 [0.000]	29.434 [0.000]
$Q^2(12)$	80.38 [0.000]	450.69 [0.000]	110.25 [0.000]	53.238 [0.000]

Panel B: Pre-FFA

	Route 1	Route 1A	Route 2	Route 2A
Q(1)	265.87 [0.000]	919.34 [0.000]	406.36 [0.000]	374.54 [0.000]
Q(12)	751.90 [0.000]	2,904.4 [0.000]	787.45 [0.000]	1,037.5 [0.000]
$Q^2(1)$	4.768 [0.029]	309.69 [0.000]	7.934 [0.005]	1.593 [0.207]
$Q^2(12)$	48.94 [0.000]	450.08 [0.000]	64.53 [0.000]	2.193 [0.999]

Panel C: Post-FFA

	Route 1	Route 1A	Route 2	Route 2A
Q(1)	335.74 [0.000]	402.65 [0.000]	479.12 [0.000]	483.86 [0.000]
Q(12)	879.31 [0.000]	984.23 [0.000]	875.54 [0.000]	1,026.1 [0.000]
$Q^2(1)$	167.03 [0.000]	129.66 [0.000]	108.29 [0.000]	48.948 [0.000]
$Q^2(12)$	77.11 [0.000]	218.18 [0.000]	134.66 [0.000]	104.39 [0.000]

Notes:

- Figures in squared brackets [.] indicate exact significance levels.
- $Q(L)$ and $Q^2(L)$ are the Ljung-Box (1978) Q statistics on the first L lags of the sample autocorrelation function of the series and of the squared series; these tests are distributed as $\chi^2(L)$.
- Standard errors and exact significance levels are adjusted for serial correlation by the Newey-West (1987) correction.

Therefore, autoregressive models are estimated in each route in order to remove any linear temporal predictability. Table 5.4 panels A to C, report the Ljung-Box (1976) portmanteau statistics for the first and twelfth autocorrelation of the residuals series, $Q(L)$, and squared residual series, $Q^2(L)$, of the most parsimonious autoregressive specifications, adjusted for serial correlation by the Newey-West (1987) correction. Panel A to C correspond to the same time periods as in Table 5.3. The results indicate that the autoregressive models capture the serial-correlation in the adjusted residual series, suggesting that the adjustment procedure removes the predictable part of the return series[101]. Significant non-linear temporal dependencies in the squared adjusted residual series, suggest that the volatility of adjusted returns follows an ARCH-type model. Having obtained the unexpected component it is now possible to analyse the impact of the introduction of FFA on the nature and characteristics of volatility.

[101] The only exceptions are in routes 1 and 2A in panel A, and in route 2A in panel C, where serial-correlation cannot be fully removed. Thus, the results of the most parsimonious autoregressive models are presented in those cases.

Table 5.4. Ljung-Box Statistics for Linear and Non-Linear Temporal Dependences in Autoregressive Models

Panel A: Whole Period

	Route 1-AR(4)	Route 1A-AR(3)	Route 2-AR(2)	Route 2A-AR(3)
Q(1)	0.005 [0.942]	0.063 [0.802]	0.038 [0.846]	0.002 [0.964]
Q(12)	26.18 [0.010]	12.96 [0.372]	12.17 [0.432]	26.50 [0.009]
$Q^2(1)$	73.09 [0.000]	161.77 [0.000]	154.57 [0.000]	136.08 [0.000]
$Q^2(12)$	168.21[0.000]	184.32 [0.000]	257.88 [0.000]	150.06 [0.000]

Panel B: Pre-FFA

	Route 1-AR(4)	Route 1A-AR(3)	Route 2-AR(2)	Route 2A-AR(3)
Q(1)	0.007 [0.935]	0.063 [0.802]	0.057 [0.811]	0.013 [0.910]
Q(12)	20.28 [0.062]	12.96 [0.372]	15.85 [0.198]	10.02 [0.614]
$Q^2(1)$	38.02 [0.000]	161.48 [0.000]	62.91 [0.000]	18.14 [0.000]
$Q^2(12)$	96.05 [0.000]	183.95 [0.000]	134.78 [0.000]	18.56 [0.000]

Panel C: Post-FFA

	Route 1-AR(3)	Route 1A-AR(2)	Route 2-AR(1)	Route 2A-AR(2)
Q(1)	0.003 [0.957]	0.006 [0.936]	1.989 [0.158]	0.019 [0.891]
Q(12)	11.81 [0.461]	17.731[0.124]	10.64 [0.568]	33.04 [0.001]
$Q^2(1)$	8.207 [0.004]	55.89 [0.000]	105.75 [0.000]	241.56 [0.000]
$Q^2(12)$	25.39 [0.013]	62.13 [0.000]	135.90 [0.000]	355.74 [0.000]

Notes:

- Figures in squared brackets [.] indicate exact significance levels.
- Q(L) and $Q^2(L)$ are the Ljung-Box (1978) Q statistics on the first L lags of the sample autocorrelation function of the series and of the squared series; these tests are distributed as $\chi^2(L)$.
- Standard errors and exact significance levels are adjusted for serial correlation by the Newey-West (1987) correction.
- The order of the most parsimonious autoregressive models are in parentheses (.).

5.5. EMPIRICAL RESULTS

5.5.1. Impact of FFA Trading on Spot Market Volatility

To assess whether there has been a change in volatility after the inception of FFA trading, GJR-GARCH(1,1) models of conditional volatility are estimated. A dummy variable that takes the value of 0 pre-FFA and 1 post-FFA is included. The most parsimonious specification for each model is estimated by excluding insignificant variables. The QMLE estimates of the GJR-GARCH models of spot freight rates for the whole period of the analysis for each route are presented in Table 5.5[102]. The diagnostic tests, on the standardised residuals and squared standardised residuals, indicate absence of linear and non-linear dependencies, respectively. Thus, the estimated models fit the data very well. The estimated implied kurtosis indicates the presence of excess kurtosis in the standardised residuals in all investigated routes. As a result, the Jarque-Bera (1980) test rejects normality in all routes.

[102] The financial literature has demonstrated that the GARCH(1,1) specification is the most appropriate for a wide variety of markets (see Bollerslev *et al.*, 1992, amongst others).

The results in Table 5.5 indicate that in all routes FFA trading has had a negative impact (stabilising effect) on the level of price volatility of the underlying spot freight market (γ_2 coefficient). However, the magnitude of this negative impact is marginally larger in the voyage routes 1 and 2 and it is in accordance with earlier results that the volatility of the voyage routes has decreased. Thus, the introduction of FFA appears to have a stabilising impact on the level of volatility in the underlying spot routes. The results of the Wald test statistics for the null hypothesis of joint equality to zero of the change in ARCH and GARCH terms indicate that the null hypothesis is rejected in every route. This evidence suggests that the conditional variance of all spot routes underwent some form of change around the date of the FFA introduction. The analysis can be extended to consider the impact of the FFA trading on both the conditional and unconditional variance by testing that the FFA introduction has had no (joint) effect on any variance equation parameters, that is $a_2 = \beta_2 = \gamma_2 = 0$. The results of the Wald tests for the null hypothesis indicate that the relevant coefficients in the variance equation have significantly changed in all trading spot routes.

The results of the γ_1 coefficient of the asymmetric effects suggest statistically significant asymmetric effects in all routes, with the exception in route 2A. In routes 1A and 2 the statistically significant asymmetry coefficients (γ_1) are negative, suggesting that negative shocks elicit a smaller response than positive shocks of an equal magnitude. In route 1 the asymmetry coefficient is significant and positive suggesting that negative shocks elicit a larger response than positive shocks of an equal magnitude. Finally, the persistence estimates of the conditional volatility reveal the presence of a near-Integrated GARCH (IGARCH) process in routes 1 and 2A, with persistence estimates close to but slightly less than unity (see Bollerslev, 1987).

Table 5.5. GJR-GARCH Model Estimates of the Effect of FFA Trading on Spot Market Volatility (Whole Period)

Panel A: Coefficient Estimates

$$\Delta S_t = \varphi_0 + \sum_{i=1}^{p-1} \varphi_i \Delta S_{t-i} + \varepsilon_t \quad ; \quad \varepsilon_t \sim iid(0,h_t) \tag{5.1}$$

$$h_t = a_0 + a_1 h_{t-1} + a_2 D_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \beta_2 D_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1}^- + \gamma_2 D_1 \tag{5.2}$$

	Route 1-AR(3) (29/11/89 – 31/07/00)	Route 1A-AR(3) (07/08/90 – 31/07/00)	Route 2-AR(2) (29/11/89 – 24/08/01)	Route 2A-AR(2) (15/02/91 – 24/08/01)
Mean Equation				
φ_0	1.72E-05 (0.865)	2.11E-05 (0.633)	-4.87E-05 (-0.094)	-1.17E-04 (0.163)
φ_1	0.454* (28.439)	0.566* (23.240)	0.545* (25.221)	0.585* (26.193)
φ_2	0.159* (6.658)	0.166* (5.835)	0.126* (5.997)	0.158* (7.409)
φ_3	0.083* (3.485)	0.06* (2.606)	-	-
Variance Equation				
a_0	6.65E-07* (13.336)	1.69E-05* (15.958)	4.31E-06* (11.241)	8.15E-05* (11.763)
a_1	0.914* (562.23)	0.609* (28.762)	0.881* (114.35)	0.074 (0.947)
a_2	-0.023* (-4.153)	0.056* (2.128)	-0.536* (-11.913)	0.704* (9.586)
β_1	0.030* (15.275)	0.312* (11.820)	0.112* (12.522)	0.153* (5.663)
β_2	0.027* (3.543)	0.047* (1.796)	0.233* (7.584)	0.064* (2.268)
γ_1	0.033* (8.151)	-0.198* (-6.796)	-0.061* (-6.362)	-
γ_2	-6.01E-07* (-7.191)	-4.97E-06* (-3.569)	-1.62E-06* (-9.830)	-8.05E-05* (-11.591)

Panel B: Residual Diagnostic

	Route 1	Route 1A	Route 2	Route 2A
LL	11,665.03	10,942.16	13,033.41	11,274.72
Skewness	0.302 [0.000]	1.418 [0.000]	0.123 [0.006]	3.663 [0.000]
Kurtosis	13.307 [0.000]	17.856 [0.000]	12.821 [0.000]	79.864 [0.000]
J-B	20,481.6 [0.000]	35,289.4 [0.000]	20,801.8 [0.000]	72,868.8 [0.000]
Q(24)	23.845 [0.413]	21.387 [0.557]	32.215 [0.096]	21.995 [0.521]
$Q^2(24)$	31.566 [0.109]	11.073 [0.982]	27.723 [0.226]	0.788 [0.999]]
ARCH(12)	0.921 [0.573]	0.404 [0.963]	1.396 [0.160]	0.017 [0.999]
$a_2 = \beta_2 = 0$	17.864 [0.000]	28.262 [0.000]	142.531 [0.000]	163.753 [0.000]
$a_2 = \beta_2 = \gamma_2 = 0$	153.211 [0.000]	28.661 [0.000]	187.479 [0.000]	420.769 [0.000]
Persistence	0.981	0.826	0.629	0.995
UV	0.000003	0.000069	0.000007	0.000200

Notes:

- Figures in parentheses (.) and in squared brackets [.] indicate *t*-statistics and exact significance levels, respectively.
- * and ** denote significance at the 5% and 10% levels, respectively.
- The GJR-GARCH process is estimated with the QMLE using the BHHH algorithm.
- *LL* is the Log-Likelihood.
- J-B is the Jarque-Bera (1980) normality test.
- Q(24) and $Q^2(24)$ are the Ljung-Box (1978) tests for 24th order serial correlation and heteroskedasticity in the standardised residuals and in the standardised squared residuals, respectively.
- ARCH(12) is the Engle's (1982) *F*-test for Autoregressive Conditional Heteroskedasticity.
- The joint hypothesis tests ($a_2 = \beta_2 = 0$ and $a_2 = \beta_2 = \gamma_2 = 0$) are Wald tests.
- Persistence is defined as the degree of convergence of the conditional volatility to the unconditional volatility after a shock and is calculated as $a_1 + a_2 + \beta_1 + \beta_2 + \gamma_1$.
- UV is the unconditional volatility estimate of the GJR-GARCH models, measured as $(a_0+\gamma_2) / (1-a_1-a_2-\beta_1-\beta_2-\gamma_1)$.

Although the introduction of FFA trading has had an effect on the level of spot market volatility, the interesting issue is whether the introduction of FFA trading had an effect on the way news impacts on volatility; that is, if FFA trading altered the market dynamics. To address this issue the GJR-GARCH models of conditional volatility are estimated for the adjusted return series for the pre- and post-FFA periods. The QMLE estimates of the GJR-GARCH models of spot freight rates for the pre-FFA period for each route are presented in Table 5.6. The standard diagnostic tests of the residuals from the model confirm the absence of any further ARCH effects, suggesting an appropriate model specification. That is, the squared standardised residuals of the modified GJR-GARCH(1,1) models reveal a general absence of significant autocorrelation that Bollerslev and Mikkelsen (1996) argued indicates the model has captured the ARCH effects.

The results of the coefficients of the lagged variance (a_1) and lagged error-terms (β_1) indicate that the conditional volatility in all routes is time-varying, and specifically in route 2A there are ARCH effects only. The results of the asymmetry coefficient (γ_1) suggest that in routes 1A, 2, and 2A there is a statistically significant and negative asymmetric effect, which implies that negative shocks elicit a smaller response than positive shocks of an equal magnitude. In contrast, in route 1 the asymmetry coefficient is significant and positive, which implies that negative shocks elicit a larger response than positive shocks of an equal magnitude. Finally, the persistence of volatilities of the spot markets following a shock, show that unconditional variances are stationary (persistence factors less than one) in all routes.

The issue of the impact of FFA trading on spot market volatility is further investigated by estimating the GJR-GARCH model for spot returns for the post-FFA period. The QMLE estimates of the GJR-GARCH model of spot freight rates for the post-FFA period for each route are presented in Table 5.7. The results of the diagnostics tests report absence of any linear or non-linear dependencies. The impact of FFA introduction on asymmetric market responses may be assessed via consideration of the asymmetry coefficient (γ_1) that captures the nature of any bias in the post-FFA period.

Table 5.6. GJR-GARCH Model Estimates for the Pre-FFA Period

Panel A: Coefficient Estimates

$$\Delta S_t = \varphi_0 + \sum_{i=1}^{p-1} \varphi_i \Delta S_{t-i} + \varepsilon_t \quad ; \quad \varepsilon_t \sim iid(0,h_t) \qquad (5.1)$$

$$h_t = a_0 + a_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1}^- \qquad (5.3)$$

	Route 1-AR(3) (29/11/89 – 01/01/97)	Route 1A-AR(3) (07/08/90 – 01/01/97)	Route 2-AR(2) (29/11/89 – 01/01/97)	Route 2A-AR(3) (15/02/91 – 01/01/97)
Mean Equation				
φ_0	2.34E-05 (0.639)	2.33E-05 (0.651)	-4.80E-06 (-0.261)	-3.76E-05 (-0.054)
φ_1	0.413* (22.218)	0.568* (23.005)	0.483* (19.221)	0.524* (14.722)
φ_2	0.169* (5.737)	0.164* (5.797)	0.135* (4.963)	0.112* (3.151)
φ_3	0.116* (3.963)	0.062* (2.674)	-	0.073* (2.301)
Variance Equation				
a_0	6.04E-07* (13.164)	1.60E-05* (20.351)	4.21E-06* (11.139)	8.03E-5* (10.218)
a_1	0.951* (613.89)	0.619* (38.985)	0.884* (118.721)	0.061 (0.668)
β_1	0.018* (14.495)	0.329* (12.869)	0.112* (12.709)	0.223* (5.486)
γ_1	0.024* (7.137)	-0.191* (-7.018)	-0.071* (-7.671)	-0.124* (-2.452)

Panel B: Residual Diagnostic

	Route 1	Route 1A	Route 2	Route 2A
LL	7,468.70	10,940.23	7,700.19	6,297.11
Skewness	0.596 [0.000]	1.522 [0.000]	0.682 [0.000]	6.654 [0.000]
Kurtosis	16.101 [0.000]	18.395 [0.000]	12.331 [0.000]	138.839 [0.000]
J-B	20,049.5 [0.000]	37,531.30 [0.000]	11,844.1 [0.000]	1,239,341.3 [0.000]
Q(24)	22.082 [0.515]	20.158 [0.632]	23.938 [0.407]	26.518 [0.277]
$Q^2(24)$	22.946 [0.464]	12.088 [0.969]	29.951 [0.151]	0.367 [0.999]
ARCH(12)	1.534 [0.105]	0.403 [0.963]	1.454 [0.213]	0.011 [0.999]
Persistence	0.996	0.757	0.925	0.160
UV	0.000001	0.000021	0.000005	0.000502

Notes:

- See notes in Table 5.5.
- UV is the unconditional volatility estimate of the GJR-GARCH models, measured as $a_0 / (1-a_1-\beta_1-\gamma_1)]$.

The results, presented in Table 5.7, indicate that the post-FFA asymmetry coefficient, in routes 2 and 2A, is statistically insignificant. Thus, the introduction of FFA contracts appears to have had an impact on the asymmetry of volatility in those routes, as a significant asymmetry coefficient in the pre-FFA period results in an insignificant asymmetry coefficient in the post-FFA period. If noise/feedback traders are present in routes 2 and 2A and they overreact to news, especially good news, then the introduction of FFA trading seems to have reduced this overreaction. This could come about either because FFA markets provide more reliable information, and thus, traders become better informed, or because noise traders have less of an impact as a result of more reliable information in the public domain.

Table 5.7. GJR-GARCH Model Estimates for the Post-FFA Period

Panel A: Coefficient Estimates

$$\Delta S_t = \varphi_0 + \sum_{i=1}^{p-1} \varphi_i \Delta S_{t-i} + \varepsilon_t \quad ; \quad \varepsilon_t \sim iid(0,h_t) \qquad (5.1)$$

$$h_t = a_0 + a_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1}^- \qquad (5.3)$$

	Route 1-AR(2) (01/01/97 - 31/07/00)	Route 1A-AR(3) (01/01/97 - 31/07/00)	Route 2-AR(2) (01/01/97 - 24/08/01)	Route 2A-AR(2) (01/01/97 - 24/08/01)
Mean Equation				
φ_0	4.82E-06 (1.702)	-1.85E-05 (-0.967)	-1.05E-04 (-0.417)	-1.88E-04 (-0.133)
φ_1	0.539* (16.339)	0.650* (14.576)	0.675* (15.222)	0.619* (18.963)
φ_2	0.152* (4.289)	0.217* (4.415)	0.072* (1.996)	0.169* (5.548)
φ_3	-	-0.085* (-2.390)	-	-
Variance Equation				
a_0	8.33E-08 (1.094)	1.23E-05* (11.378)	2.11E-05 (13.260)	1.11E-06* (5.028)
a_1	0.902* (115.26)	0.547* (18.021)	0.329* (7.429)	0.726* (88.684)
β_1	0.042* (5.649)	0.502* (6.531)	0.313* (9.652)	0.227* (14.269)
γ_1	0.052* (4.672)	-0.290* (-3.767)	-	-

Panel B: Residual Diagnostic

	Route 1	Route 1A	Route 2	Route 2A
LL	4,182.11	3,832.72	5,298.14	4,942.74
Skewness	-0.210 [0.009]	0.826 [0.000]	-0.783 [0.000]	0.032 [0.649]
Kurtosis	6.289 [0.000]	16.468 [0.000]	13.965 [0.000]	10.332 [0.000]
J-B	1,524.38 [0.000]	10,500.6 [0.000]	9,080.8 [0.000]	5,159.33 [0.000]
Q(24)	31.185 [0.118]	34.518 [0.058]	19.579 [0.667]	25.032 [0.349]
$Q^2(24)$	24.605 [0.371]	14.735 [0.904]	14.731 [0.904]	11.351 [0.979]
ARCH(12)	0.650 [0.799]	0.458 [0.939]	0.268 [0.994]	0.533 [0.894]
Persistence	0.996	0.759	0.642	0.953
UV	0.0000001	0.000016	0.000059	0.000023

See notes in Tables 5.5 and 5.6.

By comparing the coefficients of the lagged variances (a_1) and lagged error-terms (β_1) of the GJR-GARCH models in the pre- and post-FFA periods, it is possible to examine not just the impact of FFA trading in terms of increasing or decreasing spot price volatility, but also the impact of FFA trading on the nature of volatility. For the periods before and after the onset of FFA trading a GJR-GARCH(1,1) representation is the most appropriate in routes 1, 1A, and 2, where statistically significant coefficients of the lagged variance and lagged error-terms imply that the volatility is time-varying. The only exception is in route 2A where the insignificant coefficient of the lagged variance in the pre-FFA period result in a significant coefficient in the post-FFA period. Thus, the onset of FFA trading led to a change in the nature of volatility in route 2A only. The results of the unconditional volatility estimate (UV) indicate that in routes 1, 1A, and 2A there has been a decrease in the unconditional volatility. This finding is consistent with the earlier results of a stabilising impact in the volatilities and with the view that more information is being transmitted to the spot markets. In route 2 the unconditional volatility has increased which is not in accordance with the results of a stabilising impact from the introduction of FFA contracts.

In the context of this analysis the lagged error-term, β_1, relates to changes in the spot price on the previous day which are attributable to market specific factors. Assuming that markets are efficient, then these price changes are due to the arrival in the market of items of information, which are specific to the pricing of the FFA contracts. Thus, the coefficient of the lagged error-term can be viewed as a *new news* coefficient, which relates to the impact of yesterday's market specific price changes on price changes today. Hence, a higher value in the post-FFA period implies that recent news have a greater impact on price changes. The results, from Tables 5.6 and 5.7, indicate that this holds in all routes suggesting that information is being impounded in prices more quickly due to the introduction of FFA trading.

The coefficient of the lagged variance term, a_1, can be thought of as reflecting the impact of *old news*. It is picking up the impact of price changes relating to days prior to the previous day, and thus, to news which arrived before yesterday. A reduction in uncertainty regarding previous news can be regarded as an increase in the rate of information flow with the onset of FFA trading (old news will have less impact on today's price changes). This argument seems to confirm the expectation of increased market efficiency as a consequence of the activity in the FFA market. The results, from Tables 5.6 and 5.7, indicate that this holds in routes 1, 1A, and 2, where the value of the a_1 coefficient has been reduced in the post-FFA period.

5.5.2. Impact of FFA on Spot Market Volatility Considering Market Factors

The next step consists in examining whether the introduction of FFA trading is not the only factor responsible for the reduction in the spot market volatility. To address this issue, the behaviour of the spot variances is adjusted for exposition to additional factors which may affect spot market volatility. The adjustment is obtained by including the conditional volatility (computed by a GARCH process) of economic indicators as explanatory variables in the specification of the spot variance equation[103]. More specifically, the SPI, the SPCI, the BCOI and the WTI are used as economic indicators that can capture major world economic conditions, which may impact the spot market volatility of the investigated freight routes. Thus,

[103] Including the logarithmic first-difference price series of the economic indicators as explanatory variables in the spot mean equation, yielded insignificant coefficients, and therefore, are excluded from the final specification.

we test the hypothesis that FFA trading is the only cause for the diminished volatility, testing the null hypothesis that the FFA *dummy* coefficient (γ_2) is zero.

In the interest of space, we report only those results that we feel are the most relevant to the issue at hand. Thus, the QMLE estimates of the most parsimonious and well-specified (in terms of diagnostic tests) GJR-GARCH model for every spot freight route are presented in Table 5.8. The estimates of the coefficients of the variance equation including: (i) the SPI variable are presented in panel A; (ii) the SPCI variable are presented in panel B; (iii) the BCOI variable are presented in panel C; and (iv) the WTI variable are presented in panel D.

The results in Table 5.8 indicate that the *FFA dummy* variable (γ_2 coefficient) has not been affected by the used economic variables that significantly contribute in the spot market's conditional volatility for voyage routes 1 and 2. This result supports not only the hypothesis of reduced spot volatility but also that the reduction in volatility may be a direct consequence of FFA trading. In contrast, in the time-charter routes 1A and 2A we notice that the FFA *dummy* variable has been affected by most of the economic variables. More specifically, in route 1A the γ_2 coefficient becomes positive and significant with the use of the SPI variable and insignificant with the use of the WTI variable. In route 2A despite the negative sign and significance of the γ_2 coefficient three out of the four economic variables (SPI, SPCI, and BCOI) fail to contribute to the spot market's conditional volatility. Thus, the results do not present a clear answer as to whether reduction in spot volatility, in routes 1A and 2A, is a direct consequence of FFA trading. Although these results are not as consistent as those from the GJR-GARCH models of Equation (5.2), we still observe a propensity for volatility to decrease after the FFA introduction in voyage routes 1 and 2.

We do not deny that these results may be influenced by other factors and advocate some caution in interpreting empirical results. In particular, several points should be considered that may confound the interpretation of the results, and those of all the previous studies in the literature. First, the systematic reporting of FFA rates, from FFA brokers, might also have resulted in more systematic reporting of spot rates, thus leading to the reduction in spot price volatility.

Table 5.8. GJR-GARCH Model Estimates of the Effect of FFA Trading and Other Economic Indicators on Spot Market Volatility (Whole Period)

$$\Delta S_t = \varphi_0 + \sum_{i=1}^{p-1} \varphi_i \Delta S_{t-i} + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{iid}(0,h_t) \tag{5.1}$$

$$h_t = a_0 + a_1 h_{t-1} + a_2 D_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 + \beta_2 D_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 D_{t-1}^- + \gamma_2 D_1 + \delta_1 G_t \tag{5.4}$$

	Route 1-AR(3) (29/11/89 – 31/07/00)	Route 1A-AR(3) (07/08/90 – 31/07/00)	Route 2-AR(2) (29/11/89 – 24/08/01)	Route 2A-AR(2) (15/02/91 – 24/08/01)
Panel A: Coefficient Estimates of Variance Equation with SPI Variable				
a_0	7.12E-07* (12.988)	3.34E-06* (7.890)	3.29E-06* (9.160)	8.15E-05* (11.823)
a_1	0.934* (557.675)	0.659* (38.883)	0.887* (118.087)	0.073 (0.935)
a_2	-0.025* (-3.846)	-0.383* (-7.154)	-0.589* (-13.659)	0.719* (9.654)
β_1	0.031* (15.481)	0.297* (13.075)	0.105* (11.946)	0.143* (5.328)
β_2	0.024* (3.140)	0.108* (3.196)	0.258* (8.051)	0.065* (2.113)
γ_1	0.033* (7.999)	-0.188* (-6.949)	-0.059* (-6.050)	3.81E-03 (0.189)
γ_2	-4.41E-07* (-2.853)	1.65E-05* (3.504)	-1.69E-05* (-10.305)	-7.98E-05* (-11.547)
δ_1	-3.01E-03** (-1.880)	0.192* (14.613)	0.015* (5.932)	-4.93E-03 (-1.607)
Panel B: Coefficient Estimates of Variance Equation with SPCI Variable				
a_0	4.46E-07* (3.899)	8.69E-06* (10.053)	4.69E06* (10.171)	8.15E-05* (11.846)
a_1	0.932* (577.92)	0.644* (33.786)	0.881* (111.49)	0.073 (0.927)
a_2	-0.027* (-4.451)	1.01E-03 (0.041)	-0.542* (-11.968)	0.721* (9.681)
β_1	0.026* (14.670)	0.312* (12.551)	0.111* (12.355)	0.123* (5.318)
β_2	0.030* (3.893)	0.045** (1.737)	0.233* (7.487)	0.066* (2.156)
γ_1	0.032* (8.564)	-0.191* (-6.936)	-0.061* (-6.426)	3.91E-03 (0.188)
γ_2	-6.898* (-7.107)	-3.06E-06* (-2.068)	-1.67E-05* (-10.106)	-8.04E-05* (-11.669)
δ_1	3.36E-03** (1.866)	0.117* (10.938)	-7.32E-03* (-2.199)	-2.60E-03 (-0.486)
Panel C: Coefficient Estimates of Variance Equation with BCOI Variable				
a_0	2.82E-07* (5.273)	8.66E-06* (15.064)	2.51E-05* (16.559)	8.09E-05* (11.685)
a_1	0.931* (552.06)	0.689* (39.201)	0.469* (17.149)	0.075 (0.950)
a_2	-0.041* (-7.413)	0.191* (11.391)	-0.224* (-4.847)	0.724* (9.525)
β_1	0.022* (13.234)	0.217* (13.531)	0.196* (7.095)	0.124* (5.349)
β_2	0.040* (5.634)	-0.086* (-4.855)	0.089* (2.329)	0.071* (2.284)
γ_1	0.036* (9.065)	-0.041* (-2.713)	0.115* (3.644)	1.33E-03 (0.64)
γ_2	-6.91E-07* (-5.845)	-8.63E-06* (-12.317)	-5.76E-06* (-2.612)	-8.02E-05* (-11.541)
δ_1	1.93E-03* (10.169)	7.55E-03* (11.117)	0.016* (13.504)	6.54E-04 (0.566)
Panel D: Coefficient Estimates of Variance Equation with WTI Variable				
a_0	2.04E-07* (4.033)	1.02E-05* (15.759)	2.68E-05* (17.574)	7.98E-05* (11.328)
a_1	0.932* (566.77)	0.634* (34.618)	0.432* (16.246)	0.083 (1.029)
a_2	-0.047* (-8.481)	3.59E-03 (0.169)	-0.229* (-5.189)	0.718* (9.158)
β_1	0.023* (13.469)	0.322* (13.183)	0.206* (7.149)	0.132* (5.441)
β_2	0.057* (6.234)	0.025 (0.959)	0.084* (2.065)	0.070* (2.587)
γ_1	0.031* (8.305)	-0.187* (-6.882)	0.128* (3.786)	-7.05E-03 (-0.286)
γ_2	-6.78E-07* (-5.790)	-3.99E-07 (-0.366)	-6.54E-06* (-3.077)	-7.94E-05* (-11.254)
δ_1	1.25E-03* (9.695)	7.58E-03* (11.102)	0.012* (17.158)	1.54E-03* (2.169)

Notes:

- See notes in Table 5.5.
- SPI is the S&P 500 Composite Index; SPCI is the S&P 500 Commodity Index; BCOI is the London Brent Crude Oil Index; and WTI is the West Texas Intermediate crude oil.

Second, the introduction of FFA contracts is not an entirely exogenous event. The introduction process involved many decisions made by FFABA and FIFC panelists, members of the Baltic Exchange and representatives from FFA broking companies, who may have been influenced by recent or anticipated market conditions. For example, in financial markets the reluctance of regulators to approve the introduction of derivatives contracts during periods of political uncertainty may introduce a selection bias.

Third, given that most financial and commodity markets in developed economies impound information into prices rapidly, the impact of the onset of derivatives trading in terms of the speed of the price change, while significant, is likely to be at the margin. If this change is to be identified, it is necessary to utilise high-frequency intraday data. In this study the most frequent data available are used, namely daily data. This data set proves to be sufficiently frequent to identify the changes resulting from the onset of FFA trading. If information is continually flowing into the spot market then the fact that FFA speeds up this flow may not be identified if the data set used is weekly or monthly, as the increase in the speed of information might by a matter of hours or even days. Fourth, because the events in our sample are not independent draws from a homogeneous population, we cannot interpret this as we would from a traditional event study. Different trading routes have different regulatory and economic conditions. There might have been important political and economic developments that are not captured by our model.

5.6. CONCLUSION

This chapter examines the impact of FFA trading and the activities of speculators on spot market price volatility in panamax voyage routes 1 and 2, and in time-charter routes 1A and 2A. It covers the periods 29 November 1989 to 31 July 2000 in route 1, 7 August 1990 to 31 July 2000 in route 1A, 29 November 1989 to 24 August 2001 in route 2, and 12 February 1991 to 24 August 2001 in route 2A. The daily data are collected from the Baltic Exchange. Most previous studies report mixed evidence. There is evidence consistent with the assertion that speculators in derivatives markets produce destabilising forces (Stein, 1961; Figlewski, 1981). On the other hand, evidence also supports that the introduction of derivatives trading leads to more complete markets, enhanced information flows, and thus, improved investment choices for market agents

(Stoll and Whaley, 1988; and Schwarz and Laatsch, 1991). However, many earlier studies either have not accounted for the interdependence of the time-series of returns in speculative markets (volatility clustering), or have largely ignored the relationship between information and volatility (exceptions are the studies of Antoniou *et al.*, 1998; and McKenzie *et al.*, 2001). The methodology extends the traditional analysis of examining whether FFA trading has increased spot market volatility by considering the link between volatility and information, and of possible asymmetric effects in the conditional volatilities (market dynamics). The results suggest that the onset of FFA trading has had: (i) a stabilising impact on the spot price volatility in all routes; (ii) an impact on the asymmetry of volatility (market dynamics) in routes 2 and 2A; and (iii) substantially improved the quality and speed of information flowing in routes 1, 1A and 2. However, after including in the conditional variance equation other explanatory variables that may affect spot volatility, the results indicate that only in voyage routes 1 and 2 the reduction of volatility may be a direct consequence of FFA trading. The results do not present a clear answer as to whether reduction in spot volatility, in time-charter routes 1A and 2A, is a direct consequence of FFA trading.

The results are consistent with the theoretical arguments of Ross (1989) and the view that derivatives trading increases the flow of information of the spot market. Thus, prices which were already adjusting rapidly, adjust more rapidly with the onset of FFA trading. However, the results disagree somewhat with the arguments of Ross as FFA trading does not subsequently increase the spot price volatility as expected. These findings have implications for the way in which the FFA market is viewed. Contrary to the traditional view of derivatives trading and despite the route-specific nature of the FFA contracts, with the different economic and trading conditions in each route, the results indicate that the introduction of FFA contracts has not had a detrimental effect on the underlying spot market. On the contrary, it appears that there has been an improvement in the way that news is transmitted into prices following the onset of FFA trading. We can conjecture that by attracting more, and possibly better informed, participants into the market, FFA trading has assisted on the incorporation of information into spot prices more quickly. Thus, even those market agents who do not directly use the FFA market have benefited from the introduction of FFA trading.

CHAPTER 6 - THE HEDGING PERFORMANCE OF THE FORWARD FREIGHT MARKET

6.1. INTRODUCTION

The reason for the existence of derivatives markets is to provide instruments for businesses to reduce or control the unwanted risk of price changes by transferring it to others more willing to bear the risk. This function of the derivatives markets is performed through hedging the spot position by holding an equal but opposite position in the derivatives market in order to *neutralise* the impact of adverse price level changes. In practice, it is only rarely possible to offset spot market risks completely with derivatives (futures and forward) contracts. Differences between spot and derivatives prices give rise to basis risk. Thus, the effectiveness of a hedge is influenced by the existence of basis risk, the hedging horizon[104], and the correlation between changes in the spot and derivatives prices. By holding forward contracts until settlement, basis risk is zero, due to the convergence of forward and spot prices. Basis risk is introduced by rebalancing the derivatives position (prior to expiration) in regular time intervals. However, due to changing market and economic conditions the correlation between changes in the forward and spot prices may also change sharply before the expiration date, introducing price risk. Thus, this chapter examines how effective the FFA contracts are in reducing price risk. Moreover, by estimating hedging ratios[105] computed from several model specifications, we also try to identify the hedging model that generates the highest price risk reduction.

[104] Benet (1992) documents the fact that hedging effectiveness tends to increase as the investment horizon increases. Benet offers two explanations for this positive association: (i) the economic rationale is that the arrival of information in the market resolves price uncertainty. More uncertainty is resolved, given a longer amount of time - the basis is reduced; and (ii) noise in the market tends to be cancelled over time - the true underlying relationship between the spot and derivatives prices emerges in long investment horizons. Geppert (1995) argues that neither of these arguments is particularly compelling and shows that the increase in hedging effectiveness follows from cointegration between the spot and derivatives prices.

[105] The hedge ratio, h, is defined as the number of derivatives contracts that an agent must buy or sell for each unit of the spot position on which there is price risk.

The FFA contracts are based on the expected value of the service of seaborne transportation. The physical characteristics of this commodity make it impossible to store it or to carry it forward in time. As a result, FFA prices are not linked to the underlying spot prices through cash-and-carry arbitrage, but rather are driven by the expectations of market agents regarding the expected spot prices, i.e., the spot prices that will prevail at the expiration of the contracts. Therefore, it is expected *a priori* that spot and FFA prices may not be strongly *linked*, as they would be by a no-arbitrage relationship. As an example, increased demand for these contracts at a certain time period may indulge FFA brokers to charge a mark-up on their FFA quotes (weight of money effect) decreasing the correlation between changes in the FFA and spot prices. In that case the hedging effectiveness may be lower than expected. The level of the hedging effectiveness of this market is, thus, an empirical issue.

In chapter 1, we presented the MVHR methodology of Johnson (1960), Stein (1961) and Ederington (1979). The MVHR postulates that the objective of hedging is to minimise the variance of the returns in the hedge portfolio held by the investor. Therefore, the hedge ratio that generates the minimum portfolio variance should be the optimal hedge ratio. As discussed in chapter 1, the hedge ratio that minimises the variance of the returns in the hedge portfolio is equivalent to the ratio of the unconditional covariance between spot and FFA price changes to the variance of FFA price changes; this is equivalent to the slope coefficient, h^*, in the following regression:

$$\Delta S_t = h_0 + h^* \Delta F_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{iid}(0,\sigma^2) \tag{6.1}$$

where $\Delta S_t = S_t - S_{t-1}$ is the logarithmic change in the spot position between t-1 and t; $\Delta F_t = F_t - F_{t-1}$ is the logarithmic change in the FFA position between t-1 and t, and h is the hedge ratio. The degree of variance reduction in the hedged portfolio achieved through hedging is given by the coefficient of determination (R^2) of the regression, since it represents the proportion of risk in the spot market that is eliminated through hedging; the higher the R^2 the greater the effectiveness of the minimum variance hedge.

In the freight futures (BIFFEX) market, the MVHR methodology is applied by Thuong and Vischer (1990) where they estimate the degree of hedging effectiveness achieved by BIFFEX across all the BFI routes from August 1986 to December 1988. They find that the hedging effectiveness of the contract is higher for the panamax routes, compared to the capesize and the handysize routes. Overall, they conclude that the MVHR fails to eliminate the risk of the spot position to the extent in other commodity markets (the higher R^2 being only 32%). They argue that this is due to the heterogeneous composition of the underlying asset, the BFI, which consists of dissimilar shipping routes in terms of vessel size and transported commodities. Futures contacts in different commodity and financial markets are effective in reducing the variability of the spot position by as much as 98%; see Ederington (1979) for interest rates, Figlewski (1984) and Lindahl (1992) for stock indices and Malliaris and Uratia (1991) for currencies. Haralambides (1992) argues that a shipowner, operating on route 3 (of the BFI), can achieve greater risk reduction by using the MVHR compared to a traditional (naïve) hedge (see also Kroner and Sultan, 1993; Gagnon and Lypny, 1995; and Bera *et al.*, 1997, amongst others).

Several points need to be mentioned regarding the performance of the MVHR strategy. First, h^* and R^2 of Equation (6.1) are ex-post measures of hedging effectiveness, since they depend upon the previously explained correlation between the spot and derivatives prices and, as such, give an indication of the historical performance of the hedging strategy (*in-sample* performance). In reality, hedgers in the market use the historical hedge ratios to hedge a position in the future. Hence, a more realistic way to evaluate the effectiveness of alternative hedging strategies is in an *out-of-sample* setting.

Second, Myers and Thompson (1989) and Kroner and Sultan (1993) argue that Equation (6.1) implicitly assumes that the risk in spot and derivatives markets is constant over time. This assumption is too restrictive and contrasts sharply with the empirical evidence in different markets, which indicates that spot and derivatives prices are characterised by time-varying distributions (see for example, Choudhry, 1997; Hogan *et al.*, 1997; and Kavussanos and Nomikos, 2000a, 2000b, amongst others). This in turn, implies that MVHR should be time-varying, as variances and covariances entering the calculations are time-varying (adjusted continuously) as new information arrives in the market and the information set is updated.

Third, economic analysis and intuition suggest that the prices of the spot asset and the derivatives contract are jointly (simultaneously) determined (see Stein, 1961). Consequently, the estimation of Equation (6.1) is subject to simultaneity bias, i.e. the estimated hedge ratio will be upward biased and inconsistent. Furthermore, Equation (6.1) is potentially misspecified because it ignores the existence of a long-run cointegrating relationship between spot and derivatives prices (Engle and Granger, 1987), and fails to capture the short-run dynamics by excluding relevant lagged variables, resulting in downward biased not optimal hedge ratios (see for example, Ghosh, 1993b; Chou *et al.* 1996; and Lien, 1996, amongst others). Since the two biases work in opposite directions, one may hope that they will, on average, cancel each other, even though such a coincidence cannot be assured (Lien and Tse, 2000).

Lien and Luo (1994) argue that although a GARCH process may characterise the price behaviour, the cointegration relationship is the only truly indispensable component when comparing ex post performance of various hedge strategies. Moreover, Herbst, *et al.* (1992) argue that the estimation of the MVHR suffers from the problem of serial correlation in the regression residuals. These issues raise concerns regarding the risk reduction properties of the hedge ratios generated from Equation (6.1). These problems have been empirically addressed in several commodity and financial derivatives markets (see for example, Kroner and Sultan, 1993; Gagnon and Lypny, 1995, 1997; and Kavussanos and Nomikos, 2000a, 2000b, amongst others).

This chapter contributes to the existing literature in a number of ways. First, despite the growing importance of the forward freight market, no effort has been devoted to ascertaining the relative importance and feasibility of the effectiveness of constant and time-varying optimal hedge ratios of this OTC forward market[106]. In a 1985 survey of major US corporations, Khoury and Chan (1988) found that forward contracts were rated as the most often used hedging vehicle by both financial and non-financial respondents. The corporations favoured forward contracts primarily because of their relatively low cost and high degree of flexibility. The lack of any initial financial commitment and the fixed cost (relative to a futures contract) also were deemed to be very attractive attributes.

[106] An essential distinction between futures and forward contracts is the different timing of the settlement of the contracts. Futures losses and gains are settled daily; while those on forward contracts are settled at maturity. This implies that futures positions, unlike forward positions, involve a double speculation on the price of the deliverable asset and on interest rates (Shalen, 1989).

Second, different model specifications are estimated and compared so as to arrive at the most appropriate model, which takes into account the univariate properties of spot and FFA prices. Third, in-sample and out-of sample tests are employed so as to assess the effectiveness of the FFA contracts in minimising the risk in the spot freight market. Market agents (shipowners and charterers) whose physical operations concentrate on specific panamax routes can benefit from using optimal hedge ratios that minimise their freight rate risk.

Finally, the interesting research aspect is to analyse the hedging effectiveness of the FFA contracts and compared it with the hedging effectiveness of the BIFFEX contract, analysed by Kavussanos and Nomikos (2000a, 2000b, 2000c). Kavussanos and Nomikos (2000a, 2000b, 2000c) argue that time-varying hedge ratios outperform alternative specifications and have been found successful in reducing spot market risk in four shipping routes, but they fail to reduce the risk of the spot position to the extent found for other markets in the literature (hedging effectiveness of the BIFFEX contract varies from 23.25% to 4% across the different shipping routes which constitute the BFI).

The model used in this chapter is a VECM (Engle and Granger, 1987 and Johansen, 1988) with a GARCH error structure (Bollerslev, 1986). This framework meets the earlier criticisms of possible model misspecifications and time-varying hedge ratios, since the ECT describes the long-run relationship between spot and FFA prices and the GARCH error structure permits the second moments of their distribution to change over time. Following Kavussanos and Nomikos (2000a, 2000b), the squared lagged ECT of the cointegrated spot and FFA prices in the specification of the conditional variance is included, in what is termed the GARCH-X model (Lee, 1994). A principal feature of cointegrated variables is that their time paths are influenced by the extent of deviations from their long-run equilibrium (Engle and Granger, 1987). As spot and FFA prices respond to the magnitude of disequilibrium, then, in the process of adjusting they may become more volatile. Thus, inclusion of the ECT in the conditional variance specification is appropriate and may lead to the estimation of more accurate hedge ratios.

The time-varying hedge ratios are then calculated from the estimated time-varying variance-covariance matrix using the nearby FFA contract as the hedging instrument. The hedging effectiveness of the dynamic hedge ratios are contrasted with the effectiveness of constant hedge ratios both in-sample and out-of-sample. The selection criterion (loss function) for the optimum model to use is the variance (risk) reduction of the hedged portfolio. In the literature, empirical results concerning the performance of GARCH hedge ratios are generally mixed. In-sample comparisons show that, in some cases, dynamic hedging generates much better performance in terms of risk reduction (see Koutmos and Pericli, 1999) but in others the benefits seem too minimal to warrant the efforts (see Wilkinson *et al.*, 1999). Out-of-sample comparisons are mostly in favour of the conventional hedge strategy, even after updating the second-moment forecasting equations as new data arrived (Lien *et al.*, 1999)[107].

The remainder of this chapter is organised as follows. Section 6.2 presents the derivation of the conditional time-varying hedge ratio. Section 6.3 illustrates the empirical model that is used for determining time-varying hedge ratios. Section 6.4 discusses the properties of the data and presents the empirical results. Section 6.5 evaluates the hedging effectiveness of the proposed strategies. Finally, section 6.6 summarises this chapter.

6.2. ESTIMATION OF TIME-VARYING HEDGE RATIOS

Market participants in derivatives markets choose a hedging strategy that reflects their individual goals and attitudes towards risk. Consider the case of a shipowner who wants to secure his freight rate income in the forward freight market. The return on the shipowner's hedged portfolio of spot and FFA positions, ΔP_t, is given by Equation (1.5) repeated here for convenience:

$$\Delta P_t = \Delta S_t - h_t \Delta F_t \tag{6.2}$$

where $\Delta S_t = S_t - S_{t-1}$ is the logarithmic change in the spot position between t-1 and t; $\Delta F_t = F_t - F_{t-1}$ is the logarithmic change in the FFA position between t-1 and t; and h_t is the hedge ratio at time t. If the joint distribution of spot and FFA returns is time-varying, then the variance of the returns on the hedged portfolio will change as new information arrives in the market; therefore,

[107] Lence (1995) argues that the benefits of sophisticated estimation techniques of the hedge ratio are small. Lence (1995) advocates that hedgers may do better by focusing on simpler and more intuitive hedge models. His concerns appear to be supported by some empirical studies (see, for example, Lien *et al.*, 1999).

the variance of the returns on the hedged portfolio, conditional on the information set available to market agents at time t-1, Ω_{t-1}, is given by:

$$\mathrm{Var}(\Delta P_t \mid \Omega_{t-1}) = \mathrm{Var}(\Delta S_t \mid \Omega_{t-1}) + h_t^2 \mathrm{Var}(\Delta F_t \mid \Omega_{t-1}) - 2h_t \mathrm{Cov}(\Delta S_t, \Delta F_t \mid \Omega_{t-1}) \tag{6.3}$$

where $\mathrm{Var}(\Delta S_t \mid \Omega_{t-1})$, $\mathrm{Var}(\Delta F_t \mid \Omega_{t-1})$ and $\mathrm{Cov}(\Delta S_t, \Delta F_t \mid \Omega_{t-1})$ are, respectively, the conditional variances and covariance of the spot and FFA returns. The hedger must choose the value of h_t that minimises the conditional variance of his hedged portfolio returns i.e. $\min_{h_t} [\mathrm{Var}(\Delta P_t \mid \Omega_{t-1})]$. Taking the partial derivative of Equation (6.3) with respect to h_t, setting it equal to zero and solving for h_t, yields the optimal MVHR, h_t^*, conditional on the information available at t-1:

$$h_t^* \mid \Omega_{t-1} = - \frac{Cov(\Delta S_t, \Delta F_t \mid \Omega_{t-1})}{Var(\Delta F_t \mid \Omega_{t-1})} \tag{6.4}$$

The conditional MVHR of Equation (6.4) is the ratio of the conditional covariance of spot and FFA price changes over the conditional variance of FFA price changes. Since the conditional moments can change as new information arrives in the market and the information set is updated, the time-varying hedge ratios may provide superior risk reduction compared to static hedges. Furthermore, the conditional MVHR, h_t^*, nests the conventional MVHR, h^*, of Equation (6.1); if we replace the conditional moments in Equation (6.3) by their unconditional counterparts and minimise with respect to h then we get the conventional MVHR. The conditional model will reduce to the conventional model if the joint distribution of spot and FFA is constant through time.

6.3. ARCH MODELS AND TIME-VARYING HEDGE RATIOS

To estimate h_t^* in Equation (6.4), the conditional second moments of spot and FFA prices are measured using the family of ARCH models, introduced by Engle (1982). For this purpose, we employ a VECM for the conditional means of spot and FFA returns with a GARCH error structure for the conditional variances. The motivation behind using bivariate GARCH models in the context of hedge ratio estimation is that daily FFA and spot prices react to the same information, and hence, have non-zero covariances conditional on the available information set. Given the time-series nature of the data, the first step in the analysis is to determine the order of integration of each price series using ADF (1981) and PP (1988) tests. Given a set of two $I(1)$[108] series, Johansen (1988, 1991) tests are used to determine whether the series stand in a long-run relationship between them; that is that they are cointegrated. The following VECM (Johansen, 1988) is estimated:

$$\Delta X_t = \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t \mid \Omega_{t-1} \sim \text{dist}(0, H_t) \tag{6.5}$$

where X_t is the 2x1 vector $(S_t, F_t)'$ of log-spot and log-FFA prices, respectively, Δ denotes the first difference operator, and ε_t is a 2x1 vector of residuals $(\varepsilon_{S,t}, \varepsilon_{F,t})'$ that follow an as-yet-unspecified conditional distribution with mean zero and time-varying covariance matrix, H_t. The VECM specification contains information on both the short- and long-run adjustment to changes in X_t, via the estimated parameters in Γ_i and Π, respectively. The significance of incorporating the cointegrating relationship into the statistical modeling of spot and FFA prices is emphasised in studies such as Kroner and Sultan (1993), Ghosh (1993b), Chou *et al.* (1996), Lien (1996), and Kavussanos and Nomikos (2000a, 2000b); hedge ratios and measures of hedging performance may change sharply when this relationship is unduly ignored from the model specification.

Johansen and Juselius (1990) show that the coefficient matrix Π contains the essential information about the relationship between S_t and F_t. Specifically, if rank(Π) = 0, then Π is 2x2 zero matrix implying that there is no cointegration relationship between S_t and $F_{t,t-n}$. In this case the VECM reduces to a VAR model in first differences. If Π has a full rank, that is rank(Π) = 2, then all variables in X_t are $I(0)$ and the appropriate modelling strategy is to estimate a VAR model in levels. If Π has a reduced rank, that is rank(Π) = 1, then there is a single cointegration relationship between S_t and F_t, which is given by any row of matrix Π and the expression ΠX_{t-1} is the ECT. In this case, Π can be factored into two separate matrices α and β, both of dimensions 2x1, where 1 represents the rank of Π, such as $\Pi = \alpha\beta'$, where β' represents the

[108] $I(1)$ stands for a price series which is integrated of order 1; that it is needed to be differenced once to become stationary.

vector of cointegrating parameters and α is the vector of error-correction coefficients measuring the speed of convergence to the long-run steady state[109].

The conditional second moments of spot and FFA returns are specified as a VECM-GARCH-X model using the following Baba *et al.* (1987) augmented positive definite parameterisation (henceforth, BEKK) (see for example, Engle and Kroner, 1995; and Kavussanos and Nomikos, 2000a, 2000c)[110]:

$$H_t = A'A + B'H_{t-1}B + C'\varepsilon_{t-1}\varepsilon_{t-1}'C + E'\,(z_{t-1})^2E \tag{6.6}$$

where A is a 2x2 lower triangular matrix of coefficients, B and C are 2x2 diagonal coefficient matrices, with $\beta^2_{kk} + \gamma^2_{kk} < 1$, k = 1,2 for stationarity, $(z_{t-1})^2$ is the lagged squared basis, and E is a 1x2 vector of coefficients of the lagged squared basis[111]. The B and C matrices are restricted to be diagonal because this results in a more parsimonious representation of the conditional variance (Bollerslev *et al.*, 1994). Moreover, a GARCH(1,1) model is used because of the substantial empirical evidence that this model adequately characterises the dynamics in the second moments of spot and FFA prices (see Kroner and Sultan, 1993; Bera *et al.*, 1997; and Kavussanos and Nomikos, 2000a, 2000c). In this diagonal representation, the conditional variances are a function of their own lagged values (persistence), their own lagged error terms (lagged shocks), and a lagged squared basis parameter, while the conditional covariance is a function of lagged covariances and lagged cross products of the ε_t's.

Moreover, this specification guarantees H_t to be positive-definite almost surely for all t and allows the conditional covariance of spot and FFA returns to be time-varying[112]. As advocated by Baillie and Myers (1991, p. 116), it is vital to let the conditional covariance be time-

[109] Since rank(Π) equals the number of characteristic roots (or eigenvalues) which are different from zero, the number of distinct cointegrating vectors can be obtained by estimating the number of these eigenvalues, which are significantly different from zero. Johansen (1988) proposes the λ_{trace} and λ_{max} statistics to test for the rank of Π.

[110] Several other specifications are also used, such as a bivariate VECM-EGARGH and a VECM-GJR-GARCH, but yield inferior results judged by the evaluation of the log-likelihood and in terms of residual specification tests (not reported).

[111] The use of the lagged square basis specification, instead of the lagged level or the lagged absolute value specifications is justified in the empirical work because it provides uniformly superior results (see Lee, 1994).

[112] For a formal discussion of the properties of this model and alternative multivariate representations of the conditional covariance matrix see Bollerslev *et al.* (1994) and Engle and Kroner (1995).

dependent, as in the bivariate GARCH model, rather than be a constant. Multivariate GARCH models provide more precise estimates of the parameters because they utilise information in the entire variance-covariance matrix of the errors (Conrad *et al.*, 1991). Further, the generated regressor problem associated with univariate models is avoided in multivariate models because it estimates all parameters jointly (Pagan, 1984). The most parsimonious specification for each model is estimated by excluding insignificant variables.

The model incorporates the lagged squared basis as an ECT in order to examine the relation between the two markets, as a factor that influences the variances of the two variables. Engle and Yoo (1987) show that the ECT, which is the short-run adjustment from the long-run cointegrating relationship, has important predictive power for the conditional variances of cointegrated series. This may imply that if the series deviate further from each other they are harder to predict. The main virtue of this model lies in its capability of pointing to a particular feature of cointegrated series, which is the potential relationship between disequilibrium (measured by the ECT) and uncertainty (measured by the conditional variance), (Lee, 1994).

Following Bollerslev (1987), the conditional Student-*t* distribution is used as the density function of the error term, ε_t, and the degrees of freedom, v, is treated as another parameter to be estimated. The general form of the likelihood function becomes:

$$L(H_t, \varepsilon_t, \theta) = \frac{\Gamma[(2+v)/2]}{\Gamma(v/2)[\pi(v-2)]}\left|H(\theta)_t\right|^{-1/2} [1 + \frac{1}{v-2}\, \varepsilon(\theta)_t', H(\theta)_t^{-1}\, \varepsilon(\theta)_t]^{-[(2+v)/2]} \qquad (6.7)$$

$$\text{, for } v > 2$$

where $\Gamma(.)$ is the gamma function, and v denotes the degrees of freedom. This distribution converges to the multivariate normal as $v \rightarrow \infty$, although in empirical applications the two likelihood functions give similar results for values of v above 20. Baillie and Bollerslev (1995) show that for $v < 4$, the Student-*t* distribution has an undefined or infinite degree of kurtosis [the theoretical kurtosis is computed as $3(v\text{-}2)(v\text{-}4)^{-1}$, $v > 4$; see Bollerslev, 1987]. In such cases the QMLE, which estimates robust standard errors, and thus, yields an asymptotically consistent normal covariance matrix, is preferred (Bollerslev and Wooldridge, 1992). For symmetric departures from conditional normality, the QMLE is generally close to the exact MLE. Preliminary evidence on our data set with the Student-*t* distribution reveals that the parameter of the degrees of freedom, v, is greater than 4 in routes 1 ($v = 5.206$) and 1A ($v = 5.765$) and lower than 4 in routes 2 ($v = 3.941$) and 2A ($v = 3.853$). Thus, the Student-*t* distribution is used as the density function of the error term in routes 1 and 1A and the QMLE is used in routes 2 and 2A. The log-likelihood function is highly non-linear and, therefore, numerical maximisation techniques have to be used. The BFGS algorithm, which utilises derivatives to maximise the log-likelihood, is used.

6.4. DESCRIPTION OF DATA AND EMPIRICAL RESULTS

The data sets that are used consist of weekly spot and FFA prices in panamax routes 1 and 1A from 16 January 1997 to 31 July 2000 and weekly spot and FFA prices in panamax routes 2 and 2A from 16 January 1997 to 31 December 2001. Weekly data are preferred in this chapter for several reasons. First, given the long horizon of operations in the shipping industry, which may extend over a period of two or three months, the choice of weekly hedges is realistic if there is enough liquidity in the market and implies that hedgers in the market rebalance their FFA positions on a weekly basis. Second, weekly data provide us with an adequate number of observations ($N = 184$ in routes 1 and 1A and $N = 258$ in routes 2 and 2A) to investigate the in- and out-of-sample performance of GARCH-based hedge ratios, compared to other frequencies (e.g. two or four weeks). Third, the one-week hedge can be used to reduce risk without incurring excessive transactions costs. Finally, the choice of a weekly hedging horizon is also in line with the empirical studies in other forward markets (see as well Chang *et al.*, 1993 and Islam, 1993).

Spot and FFA price data are Wednesday prices of the four panamax routes. FFA prices are always those of the nearby contract; when a holiday occurs on Wednesday, Tuesday's observation is used in its place. To avoid thin markets and expiration effects, however, we rollover to the next nearest contract one week before the nearby contract expires, as there is sufficient liquidity in the nearby contract up to a few days before its maturity date. The differences in the time to maturity across data points in the nearby FFA price series are rather small. However, it introduces some uncertainty about the difference between the forward price of the contract being closed out the forward price of the new contract that is entered into. At that specific time, hedgers face roll-over basis risk as well as hedge risk. Spot price data are from the Baltic Exchange. FFA price data for the panamax routes are from Clarkson Securities Ltd. All price series are transformed into natural logarithms.

Summary statistics of logarithmic first-differences of weekly spot and FFA prices for the four panamax routes are presented in Table 6.1. The results indicate excess skewness and kurtosis, with the exception of the skewness statistic in routes 1, 1A and 2 FFA price series, and in route 2 spot price series and of the kurtosis statistic in route 1A FFA price series. In turn, Jarque-Bera (1980) tests indicate departures from normality for FFA and spot prices, with the exception in route 1A FFA price series. The Ljung-Box Q(12) statistic (Ljung and Box, 1978) on the first 12 lags of the sample autocorrelation function of the level series indicate significant serial correlation, with the exception of FFA price series in all routes. The existence of serial correlation in spot prices may be attributed in the way shipbroking companies calculate freight rates. These rates are based either on actual fixtures, or in the absence of an actual fixture, on the shipbroker's view of what the rate would be if there was a fixture. In the latter case, shipbrokers submit an assessment, which may be a mark-up over the previous day's rate which, in turn, induces autocorrelation in the spot prices. The $Q^2(12)$ statistic (Ljung and Box, 1978) on the first 12 lags of the sample autocorrelation function of the squared series indicate existence of heteroskedasticity, with the exception of FFA price series in routes 1A, 2 and 2A.

After applying the ADF (1981) and PP (1988) unit root tests on the log-levels and log first-differences of the daily spot and FFA price series, the results indicate that all variables are log first-difference stationary[113]. Having identified that spot and FFA prices are $I(1)$ variables, we next use cointegration techniques to examine the existence of a long-run relationship between these series (Table 6.2). SBIC (1978), used to determine the lag length in the VECM, indicate 2 lags in all routes. The Johansen's (1991) LR test, of Equation (2.36) indicates that an intercept term should be restricted in the cointegrating vector (not reported)[114]. The estimated λ_{max} and

[113] The ADF (1981) and PP (1988) test statistics were undertaken allowing for the presence of an intercept only. Allowing for the presence of a time trend did not affected the results qualitatively.

[114] Johansen (1991) proposes a statistic to test for the appropriateness of including an intercept term in the cointegrating vector against the alternative that there are linear trends in the level of the series: $-T\,[\ln(1 - \hat{\lambda}^*_2) - \ln(1 - \hat{\lambda}_2)]$ where $\hat{\lambda}^*_2$ and $\hat{\lambda}_2$ denote the smallest eigenvalues of the model that includes an intercept term in the cointegrating vector and an intercept term in the short-run model, respectively. Acceptance of the null hypothesis indicates that the VECM in Equation (6.5) should be estimated with an intercept term in the cointegrating vector.

λ_{trace} statistics show that spot and FFA prices in all routes are cointegrated, and thus, stand in a long-run relationship between them.

Table 6.1. Descriptive Statistics of Logarithmic First-Differences of Spot and FFA Prices

Panel A: Route 1 Spot and FFA Price Series (01/97 to 07/00)

	Skew	Kurt	Q(12)	$Q^2(12)$	J-B	ADF (lags) Lev	PP (4) Lev	ADF (lags) 1st Diffs	PP (4) 1st Diffs
Spot	-0.735	2.161	63.267	42.162	48.571	-1.706 (1)	-1.285	-8.225 (1)	-8.111
FFA	-0.306	1.078	13.980	24.149	10.756	-1.429 (0)	-1.201	-14.431 (0)	-15.169

Panel B: Route 1A Spot and FFA Price Series (01/97 to 07/00)

	Skew	Kurt	Q(12)	$Q^2(12)$	J-B	ADF (lags) Lev	PP (4) Lev	ADF (lags) 1st Diffs	PP (4) 1st Diffs
Spot	0.623	2.161	34.935	21.019	44.493	-1.808 (1)	-1.472	-9.831 (0)	-9.986
FFA	0.303	0.622	12.995	12.902	5.261	-1.663 (0)	-1.507	-14.175 (0)	-15.051

Panel C: Route 2 Spot and FFA Price Series (01/97 to 12/01)

	Skew	Kurt	Q(12)	$Q^2(12)$	J-B	ADF (lags) Lev	PP (4) Lev	ADF (lags) 1st Diffs	PP (4) 1st Diffs
Spot	0.211	1.852	38.810	28.194	36.405	-1.514 (3)	-1.602	-10.656 (2)	-12.247
FFA	0.286	1.235	18.752	9.495	18.684	-1.652 (0)	-1.589	-14.836 (0)	-14.870

Panel D: Route 2A Spot and FFA Price Series (01/97 to 12/01)

	Skew	Kurt	Q(12)	$Q^2(12)$	J-B	ADF (lags) Lev	PP (4) Lev	ADF (lags) 1st Diffs	PP (4) 1st Diffs
Spot	0.408	0.731	63.740	81.310	12.416	-1.899 (2)	-1.688	-9.545 (2)	-10.276
FFA	0.841	3.329	13.487	8.999	142.644	-1.928 (0)	-1.719	-15.129 (0)	-15.429

Notes:

- Data series are weekly, measured in logarithmic first-differences.
- Skew and Kurt are the estimated centralised third and fourth moments of the data; their asymptotic distributions under the null are $\sqrt{T}\,\hat{\alpha}_3 \sim N(0,6)$ and $\sqrt{T}\,(\hat{\alpha}_4 - 3) \sim N(0,24)$, respectively.
- Q(12) and $Q^2(12)$ are the Ljung-Box (1978) Q statistics on the first 12 lags of the sample autocorrelation function of the raw series and of the squared series; these statistics are distributed as $\chi^2(24)$.
- J-B is the Jarque-Bera (1980) test for normality; the statistic is distributed as $\chi^2(2)$.
- ADF is the Augmented Dickey-Fuller (1981) test. The ADF regressions include an intercept term; the lag-length of the ADF test (in parentheses) is determined by minimising the SBIC (1978).
- PP is the Phillips and Perron (1988) test; the truncation lag for the test is in parentheses.
- Lev and 1st Diffs correspond to price series in log-levels and log first-differences, respectively.
- The 95% critical value for the ADF (1981) and PP (1988) tests is –2.88.

The normalised coefficient estimates of the cointegrating vector in Equation (6.5) for each route are also presented in Table 6.2. In order to examine whether the exact lagged basis should be included as an ECT in the VECM model, the following cointegrating vector, $z_t = \beta' X_t = (S_t\ \beta_1\ F_t)'$ is examined, with $\beta' = (1, 0, -1)$, implying that the equilibrium regression is the lagged basis, $z_{t-1} = S_{t-1} - F_{t-1}$ (see for example, Viswanath, 1993; Kavussanos and Nomikos, 2000a). The results in Table 6.2 indicate that in voyage routes 1 and 2 the restrictions on the cointegrating vector to represent the exact lagged basis hold, while in time-charter routes 1A and 2A the restrictions are not accepted.

Table 6.2. Johansen (1988) Tests for the Number of Cointegrating Vectors Between Spot and FFA Prices

	Lags	Hypothesis (Maximal)		Test Statistic	Hypothesis (Trace)		Test Statistic	Cointegrating Vector	Hypothesis Test
		H_0	H_1	λ_{max}	H_0	H_1	λ_{trace}	$\beta' = (1, \beta_1, \beta_2)$	$\beta' = (1, 0, -1)$
Route 1	2	$r = 0$	$r = 1$	22.803	$r = 0$	$r >= 1$	25.012	(1, -0.034, -0.979)	2.343 [0.310]
		$r <= 1$	$r = 2$	2.209	$r <= 1$	$r = 2$	2.209		
Route 1A	2	$r = 0$	$r = 1$	29.521	$r = 0$	$r >= 1$	32.163	(1, 0.498, -1.053)	6.790 [0.034]
		$r <= 1$	$r = 2$	2.643	$r <= 1$	$r = 2$	2.643		
Route 2	2	$r = 0$	$r = 1$	63.100	$r = 0$	$r >= 1$	65.917	(1, 0.0206, -1.005)	3.305 [0.192]
		$r <= 1$	$r = 2$	2.817	$r <= 1$	$r = 2$	2.817		
Route 2A	2	$r = 0$	$r = 1$	53.237	$r = 0$	$r >= 1$	57.202	(1, 0.285, -1.029)	6.662 [0.036]
		$r <= 1$	$r = 2$	3.965	$r <= 1$	$r = 2$	3.965		

Notes:

- Lags is the lag length of an VAR model; the lag length is determined using the SBIC (1978).
- Figures in square brackets [.] indicate exact significance levels.
- r represents the number of cointegrating vectors.
- $\lambda_{max}(r,r+1) = -T\ln(1 - \hat{\lambda}_{r+1})$ and $\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1 - \hat{\lambda}_i)$ where $\hat{\lambda}_i$ are the estimated eigenvalues of the Π matrix in Equation (6.5).
- Estimates of the coefficients in the cointegrating vector are normalised with respect to the coefficient of the spot rate, S_t.
- The statistic for the parameter restrictions on the coefficients of the cointegrating vector is $-T\,[\ln(1 - \hat{\lambda}^*_1) - \ln(1 - \hat{\lambda}_1)]$ where $\hat{\lambda}^*_1$ and $\hat{\lambda}_1$ denote the largest eigenvalues of the restricted and the unrestricted models, respectively. The statistic is distributed as χ^2 with degrees of freedom equal to the total number of restrictions minus the number of the just identifying restrictions, which equals the number of restrictions placed on the cointegrating vector.
- In routes 1 and 2 the cointegrating vector is restricted to be $z_t = \beta' X_t = (1, 0, -1)$, while in routes 1A and 2A the cointegrating vector is $z_t = \beta' X_t = (1\ \beta_1\ F_t)'$.

The maximum-likelihood estimates of the preferred VECM-GARCH or VECM-GARCH-X models, selected on the basis of a LR test, for each route are presented in Table 6.3[115]. The estimates of the coefficients of the mean equation, and the variance equation are presented in panels A and B, respectively. Any insignificant variables are excluded from the model to reach a more parsimonious specification. In most cases the GARCH(1,1) specification provides a good description of the joint distribution of spot and FFA price returns, with the exception in route 1A where an ARCH(0,1) model is used.

The results of the mean equations in routes 1, 1A, and 2A indicate that the ECT in the spot equation is found to be significant and negative, while the ECT in the FFA equation is found to be significant and positive. It follows that, both the spot and FFA markets in those routes

[115] LR statistics, testing the VECM-GARCH-X model against the VECM-GARCH (E = 0), indicate that the VECM-GARCH-X model is the preferred specification in routes 1, 2, and 2A. In route 1A the VECM-ARCH is the preferred specification (for a description of the test and results see Table 6.4).

respond to shocks in the system in order for the long-run equilibrium to be restored. For example, in response to a positive deviation from their equilibrium relationship at period *t*-1, the spot price in the next period will decrease in value while the FFA price will increase, thus eliminating any disequilibrium. In the remaining route 2 the results indicate that only the ECT in the spot equation is found to be significant and negative. The ECT in the FFA equation is found to be insignificant. Thus, in route 2 only spot prices respond to shocks in the system in order for the long-run equilibrium to be restored[116].

Focusing next on the parameters describing the conditional variance in each market, it can be seen that in route 1 in both spot and FFA variance equations, the coefficients of the lagged variance are significant, while the coefficients of the lagged error terms are insignificant. The results in routes 2 and 2A indicate that in both spot and FFA variance equations the coefficients of the lagged variance are significant, while only the coefficients of the lagged error terms in the spot variance equations are significant. Thus, the volatility of spot and FFA rates, in routes 2 and 2A, is time-varying. Finally, the results in route 1A indicate that in both spot and FFA variance equations the coefficients of the lagged error terms are significant, which indicate that there is ARCH in both spot and FFA rates.

The coefficients of the lagged error terms in the spot variance equation are higher than those in the FFA variance equation in routes 1, 2, and 2A, implying that past shocks (new news) have a greater impact on the spot rather on the FFA volatility. On the other hand, the coefficient of the lagged variance in the spot variance equation is lower than that in the FFA variance equation in routes 1, 2, and 2A, implying that informed agents use past volatility (old news) more in the FFA market. The results of the coefficients of the lagged squared basis (e_{kk}) in the variance equations indicate that the basis is significant and affects positively the volatility of both spot and FFA markets in routes 1, 1A, and 2A. Therefore, variation in the lagged squared basis for the spot (FFA) market results in increased volatility in the spot (FFA) market.

[116] A possible explanation for this result in route 2 can be the following: FFA prices reflect the changing expectations of market agents regarding the future course of spot prices, and the spot prices in turn converge to this rationally forecasted value.

Table 6.3. Maximum Likelihood Estimates of VECM-GARCH Models (Routes 1 and 1A: 1997:01-1999:12, Routes 2 and 2A:1997:01-2000:12)

$$\Delta S_t = \sum_{i=1}^{p-1} a_{S,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i}\Delta F_{t-i} + a_S z_{t-1} + \varepsilon_{S,t} \tag{6.5a}$$

$$\Delta F_t = \sum_{i=1}^{p-1} a_{F,i}\Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i}\Delta F_{t-i} + a_F z_{t-1} + \varepsilon_{F,t} \; ; \; \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \mid \Omega_{t-1} \sim \text{dist}(0,H_t) \tag{6.5b}$$

$$H_t = A'A + B'H_{t-1}B + C'\varepsilon_{t-1}\varepsilon_{t-1}'C + E'(z_{t-1})^2E \tag{6.6}$$

	VECM-GARCH(1,1)-X		VECM-ARCH(0,1)		VECM-GARCH(1,1)-X		VECM-GARCH(1,1)-X	
Coefficients	Spot 1	FFA 1	Spot 1A	FFA 1A	Spot 2	FFA 2	Spot 2A	FFA 2A
Panel A: Conditional Mean Parameters								
a_j, j = 1, 2	-0.107* (-2.765)	0.138* (2.139)	-0.219* (-3.956)	0.188* (2.936)	-0.346* (-5.886)	0.055 (0.812)	-0.171* (-3.752)	0.168* (3.122)
$a_{j,1}$, j = S, F	0.483* (8.212)	0.173* (1.977)	0.472* (6.737)	0.389* (4.004)	0.127* (2.049)	-	0.203* (2.353)	0.188* (1.804)
$a_{j,2}$, j = S, F	-0.101* (-1.673)		-	-0.176* (-3.239)	-	-	-0.125* (-3.209)	-
$b_{j,1}$, j = S, F	-	-	-	-	0.204* (3.972)	-	0.236* (4.349)	-
$b_{j,2}$, j = S, F	-	-	-	-	-	-	-	-0.164* (-2.441)
Panel B: Conditional Variance Parameters								
a_{11}	0.015* (2.665)		0.047* (13.118)		0.002 (1.427)		0.006* (3.195)	
a_{21}	0.004 (1.332)		0.018* (6.881)		0.004 (1.425)		0.008* (3.826)	
a_{22}	0.009** (1.712)		0.055* (10.767)		0.007 (1.172)		0.011* (2.939)	
b_{kk}, k = 1, 2	0.836* (6.316)	0.944* (31.741)	-	-	0.933* (56.701)	0.962* (43.919)	0.896* (29.261)	0.951* (57.230)
c_{kk}, k = 1, 2	0.095 (0.523)	-0.015 (-0.114)	0.299* (3.312)	0.524* (3.349)	0.289* (3.617)	0.040 (0.642)	-0.271* (4.088)	0.017 (0.313)
e_{kk}, k = 1, 2	0.117** (1.837)	0.229* (3.512)	-	-	0.144** (1.657)	0.215* (2.258)	0.239* (4.037)	0.263* (4.998)
v	5.206		5.765		-		-	

Notes:

- All variables are transformed in natural logarithms.
- * and ** denote significance at the 5% and the 10% levels, respectively.
- Figures in parentheses (.) and in squared brackets [.] indicate *t*-statistics and exact significance levels, respectively.
- The GARCH models are estimated in routes 2 and 2A using the QMLE, while in routes 1 and 1A using the Student-*t* distribution; v is the estimate of degrees of freedom from the Student-*t* distribution. The BFGS algorithm is used to maximise the distributions.
- z_{t-1} represents the lagged ECT ($z_{t-1} = \beta' X_{t-1}$). The ECT is restricted to be the lagged basis ($S_{t-1} - F_{t-1}$) in routes 1 and 2. In the remaining routes the ECT is the following spread: ECT = $S_{t-1} - 1.053 * F_{t-1} + 0.498$ in route 1A; and ECT = $S_{t-1} - 1.029 * F_{t-1} + 0.285$ in route 2A.

Table 6.4 reports the descriptive statistics for the standardised residuals ($\varepsilon_t / \sqrt{h_t}$), the Ljung-Box (1978) statistics for 12th-order serial correlation in the level and squared standardised residuals, as well as the asymmetry test statistics (sign bias, negative size bias, positive size bias, joint test sign and size bias) developed by Engle and Ng (1993). The diagnostic tests indicate the absence of dependencies in the standardised residuals, and the absence of any asymmetries in the standardised squared residuals. The response of volatility to shocks (news) is *symmetric* and is not affected by the magnitude of the shock, providing further evidence that the GARCH specification is appropriate. Thus, the estimated models fit the data very well. The estimated implied kurtosis indicates the presence of excess kurtosis in the standardised residuals in all investigated routes, with the exception of the standardised residuals of the FFA variance equations in routes 1 and 1A.

The persistence of volatility of the spot or FFA market, following a shock in the respective market, measured by $b_{kk}^2 + c_{kk}^2$, where k = 1,2[117], show that the unconditional variances are stationary (persistence factors less than one). In routes 1, 1A and 2A FFA price shocks seem to have a greater effect on FFA volatility, than spot price shocks on spot volatility. This is also seen through the Half-Life measure, estimated as $1 - [\log(2)/\log(b_{kk}^2 + c_{kk}^2)]$ (see Choudhry, 1997), which indicates the time period required for the shocks to reduce to one-half of their original size[118]. According to the results, the shocks reduce to half their original size in approximately 3 days for the spot market and 7 days for the FFA market in route 1, 1 day for the spot market and 2 days for the FFA market in route 1A. and 6 days for the spot market and 8 days for the FFA market in route 2A. In contrast, in route 2, spot price shocks seem to have a greater effect on spot volatility, than FFA price shocks on FFA volatility. The Half-Life measure indicates that shocks reduce to half their original size approximately 16 days for the spot market and 10 days for the FFA market in route 2.

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[117] The volatility persistence factor is defined as the degree of convergence of the conditional volatility to the unconditional volatility after a shock. For example, if the conditional volatility is defined as a GARCH(1,1) process, $h_t = a_0 + b_1 h_{t-1} + c_1 \varepsilon_{t-1}^2$, then the unconditional volatility would be $a_0 / (1 - b_1 - c_1)$. Therefore, the degree of persistence of the conditional volatility can be defined as $(b_1 + c_1)$. The conditional volatility converges to its unconditional value, if and only if $(b_1 + c_1) < 1$. In the BEKK specification persistence is calculated as $(b_1^2 + c_1^2)$.

[118] The closer to unity is the value of the persistence measure, the slower is the decay rate and the longer is the Half-Life measure.

Table 6.4. Diagnostic Tests on Standardised Residuals of VECM-GARCH-X Models

	Spot 1	FFA 1	Spot 1A	FFA 1A	Spot 2	FFA 2	Spot 2A	FFA 2A
System *LL*	578.936		474.424		1,222.92		1,066.69	
Skewness	-0.564 [0.005]	-0.204 [0.315]	0.788 [0.000]	0.010 [0.961]	0.642 [0.000]	0.429 [0.014]	0.475 [0.006]	1.073 [0.000]
Kurtosis	1.981 [0.000]	0.404 [0.326]	3.401 [0.000]	0.079 [0.846]	3.236 [0.000]	1.287 [0.000]	1.339 [0.000]	3.634 [0.000]
Q(12)	10.595 [0.477]	11.201 [0.427]	11.991 [0.364]	14.458 [0.209]	9.502 [0.576]	9.867 [0.542]	9.788 [0.549]	8.720 [0.648]
$Q^2(12)$	12.700 [0.313]	12.796 [0.307]	12.036 [0.361]	8.999 [0.622]	10.413 [0.494]	6.207 [0.859]	9.885 [0.541]	3.497 [0.982]
ARCH(12)	1.263 [0.249]	0.915 [0.534]	0.934 [0.516]	0.709 [0.741]	0.833 [0.616]	0.522 [0.899]	0.863 [0.585]	0.247 [0.995]
Persistence ($b^2_{kk} + c^2_{kk}$)	0.708	0.891	0.089	0.275	0.954	0.927	0.876	0.905
H-L	3.01	7.03	1.29	1.54	15.72	10.15	6.25	7.92
AIC	-1,127.87		-926.846		-2,419.84		-2,101.37	
SBIC	-1,082.81		-893.803		-2,376.89		-2,048.52	
LR (E = 0)	$7.816 \sim \chi^2(2)$		$0.838 \sim \chi^2(2)$		$40.683 \sim \chi^2(2)$		$7.505 \sim \chi^2(2)$	
Sign and Size Bias Tests								
Sign Bias	-0.932 [0.353]	0.225 [0.823]	-0.075 [0.940]	0.296 [0.767]	-0.695 [0.488]	0.656 [0.513]	-0.386 [0.700]	-0.229 [0.819]
Negative Size Bias	-0.577 [0.565]	0.806 [0.422]	0.451 [0.653]	0.825 [0.411]	0.567 [0.572]	0.143 [0.886]	0.072 [0.943]	-0.096 [0.924]
Positive Size Bias	-0.659 [0.510]	0.709 [0.479]	1.924 [0.066]	0.146 [0.884]	1.805 [0.073]	-0.550 [0.583]	1.849 [0.085]	0.075 [0.940]
Joint Test for 3 Effects	2.071 [0.107]	0.988 [0.401]	1.839 [0.143]	0.729 [0.536]	1.132 [0.337]	0.215 [0.886]	1.376 [0.252]	0.059 [0.981]

Notes:

- Figures in squared brackets [.] indicate exact significance levels.
- System *LL* is the System Log-Likelihood.
- Q(12) and $Q^2(12)$ are the Ljung-Box (1978) tests for 12th order serial correlation and heteroskedasticity in the standardised residuals and in the standardised squared residuals, respectively.
- ARCH(12) is the Engle's (1982) *F* test for Autoregressive Conditional Heteroskedasticity.
- The persistence coefficient is calculated as $b^2_{kk} + c^2_{kk}$ (see footnote 117).
- H-L is the Half-Life test, which measures the number of days that it takes for volatility to reduce its size to half its original size after a shock. It is measured as $1 - [\log(2) / \log(b^2_{kk} + c^2_{kk})]$, k = 1, 2.
- AIC and SBIC are the Akaike Information Criterion (1973) and Schwartz Bayesian Information Criterion (1978), respectively.
- LR(E = 0) is the likelihood ratio statistics for the restriction E = 0. Let LLU and LLR be the maximised value of the log-likelihood functions of the unrestricted and the restricted models, respectively. Then the following statistic 2(LLU – LLR) is χ^2 distributed with degrees of freedom equal to the number of restrictions placed in the model.
- The test statistics for the Engle and Ng (1993) tests are the *t*-ratio of *b* in the regressions: $u_t^2 = a_0 + bY^-_{t-1} + \omega_t$ (sign bias test); $u_t^2 = a_0 + bY^-_{t-1}\varepsilon_{t-1} + \omega_t$ (negative size bias test); $u_t^2 = a_0 + bY^+_{t-1}\varepsilon_{t-1} + \omega_t$ (positive size bias test), where u_t^2 are the squared standardised residuals (ε_t^2/h_t). Y^-_{t-1} is a dummy variable taking the value of one when ε_{t-1} is negative and zero otherwise, and $Y^+_{t-1} = 1 - Y^-_{t-1}$. The joint test is based on the regression $u_t^2 = a_0 + b_1Y^-_{t-1} + b_2Y^-_{t-1}\varepsilon_{t-1} + b_3Y^+_{t-1}\varepsilon_{t-1} + \omega_t$. The joint test H_0: $b_1 = b_2 = b_3 = 0$, is an *F*-test with 95% critical value of 2.60.

6.5. COMPARISON OF HEDGE RATIOS AND HEDGE EFFECTIVENESS

6.5.1. In-Sample Hedge Ratios Comparison Results

Following estimation of the GARCH models, measures of time-varying variances and covariances are extracted and used to compute the time-varying hedge ratios of Equation (6.4). Figures 6.1 to 6.4 present the time-varying hedge ratios together with the conventional hedge ratios obtained from the OLS model of Equation (6.1). It can be seen that the conditional hedge ratio is clearly changing as new information arrives in the market. However, it should be noted that beside the two *extreme* hedge ratios there are intermediate possibilities, such as a simple rolling hedge ratio based on the last 30 days of data.

Figure 6.1. Constant vs. Time-Varying Hedge Ratios for Spot and FFA in Route 1

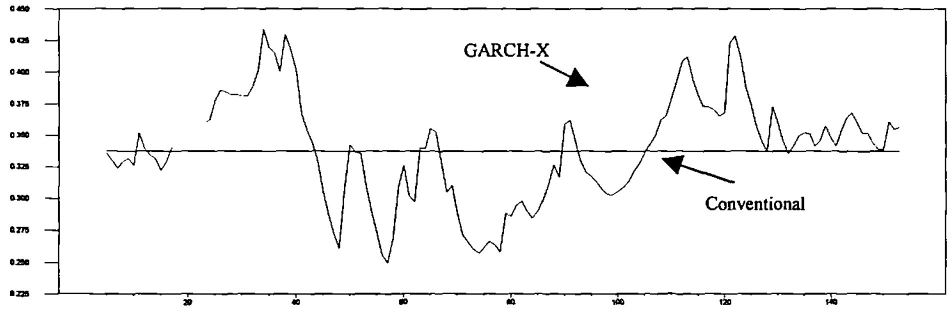


Figure 6.2. Constant vs. Time-Varying Hedge Ratios for Spot and FFA in Route 1A

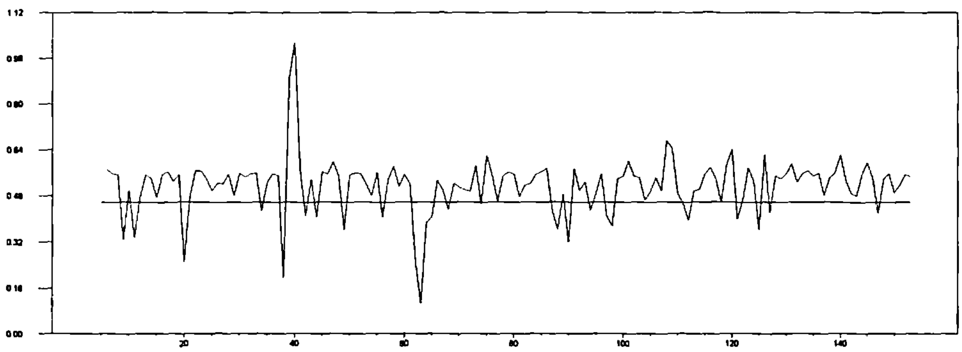


Figure 6.3. Constant vs. Time-Varying Hedge Ratios for Spot and FFA in Route 2

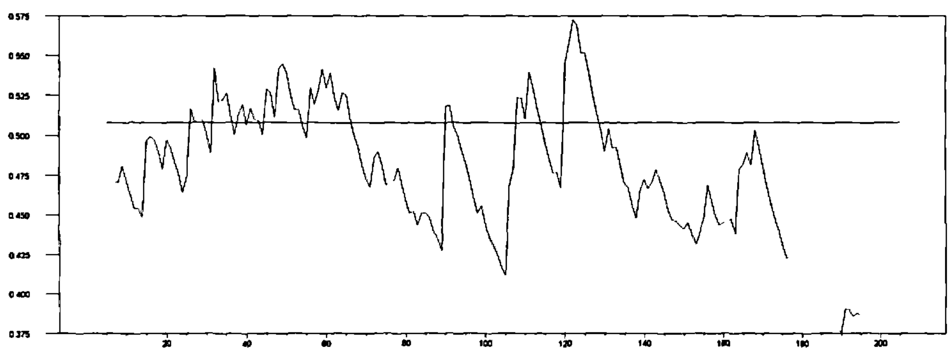
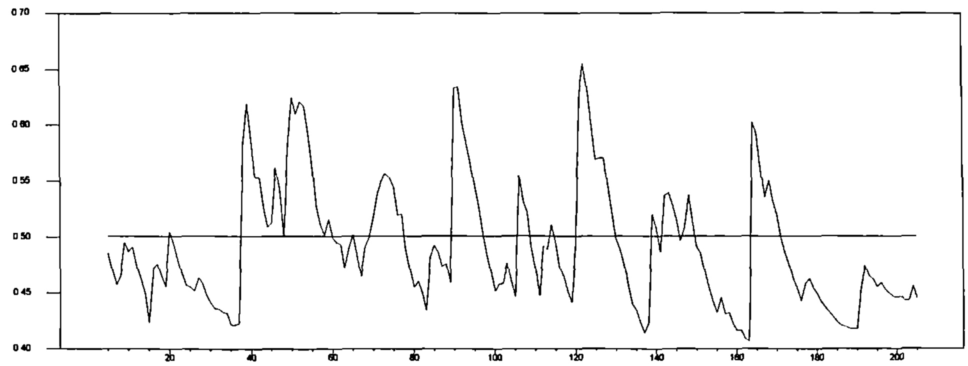


Figure 6.4. Constant vs. Time-Varying Hedge Ratios for Spot and FFA in Route 2A



The descriptive statistics of the hedge ratios are presented in Table 6.5. The conventional hedge ratios have a higher average value than their conditional counterparts in routes 2 and 2A while in contrast, the conventional hedge ratios have a lower average value than their conditional counterparts in routes 1 and 1A. The results of ADF (1981) and PP (1988) unit root tests, on the conditional hedge ratios, indicate that the hedge ratio series are stationary, implying that the time-varying hedge ratios for these routes are mean-reverting, and thus, the impact of a shock to the series eventually becomes negligible.

Table 6.5. Summary Statistics on Hedge Ratios

		Mean	SD	ADF (lags)	PP (4)
Route 1	VECM-GARCH-X	0.339	0.018	-3.242 (1)	-2.950 (4)
	Conventional	0.337	-	-	-
Route 1A	VECM-ARCH	0.516	0.098	-10.034 (0)	-9.910 (4)
	Conventional	0.457	-	-	-
Route 2	VECM-GARCH-X	0.474	0.046	-5.785 (0)	-5.332 (4)
	Conventional	0.508	-	-	-
Route 2A	VECM-GARCH-X	0.492	0.056	-4.912 (1)	-4.521 (4)
	Conventional	0.501	-	-	-

Notes:

- Mean and SD are the mean and standard deviation of the series.
- ADF is the Augmented Dickey-Fuller (1981) test on the level of the series. The ADF regressions include an intercept term; the lag length of the ADF test (in parentheses) is determined by minimising the SBIC (1978).
- PP is the Phillips and Perron (1988) test on the level of the series; the truncation lag for the test is in parentheses.
- The 95% critical value for the ADF (1981) and PP (1988) tests is –2.88.

As indicated by Baillie and Myers (1991) and Park and Switzer (1995) comparison between the effectiveness of different hedge ratios is made by constructing portfolios implied by the computed ratios each week and then comparing the variance of the returns of these constructed portfolios over the sample using Equation (6.2). For each route, we consider five different hedge ratios: the hedge ratios from the VECM-GARCH and VECM-GARCH-X specifications; the hedge ratio generated from a VECM with constant variances, estimated as a SURE system (see Zellner, 1962); the OLS hedge of Equation (6.1); and a naïve hedge by taking a FFA position of the same size as the spot position (i.e. setting the hedge ratio equal to 1). The variance of the hedged portfolios is compared to the variance of the unhedged position, i.e. $Var(\Delta S_t)$. The greater the reduction in the unhedged variance the better the hedging effectiveness[119]. We should notice that by using the variance reduction, instead of the standard deviation reduction, as a measure of hedging performance, the true extent of risk reduction may actually be overestimated. For reasons of consistency and comparison with the literature on derivatives hedging, however, we use the variance reduction as a measure of hedging performance.

The results in Table 6.6 *indicate that time-varying hedge ratios perform better, in terms of* hedging effectiveness, in the time-charter routes 1A and 2A. The ARCH model and the GARCH-X model provide greater variance reduction of the returns of the hedged portfolio, than the alternative models, in routes 1A and 2A, respectively. In contrast, in the voyage routes 1 and 2, the simple conventional OLS model outperforms both GARCH specifications despite the "superior" statistical properties of the latter models. Not surprisingly, we can also notice from the same table that the naïve hedge, where spot market positions are matched dollar for dollar in the FFA market, is the worst hedging strategy.

One final observation is that the best hedging strategy of all the *constant* hedge models is the conventional model. This is expected because the conventional model explicitly solves for the hedge ratio, which minimises the in-sample portfolio variance, and therefore, its resulting in-sample variance must be smaller than any other constant hedge ratio strategy (Kroner and Sultan, 1993). The evidence contrasts with the widely-held belief among practitioners and academics that the naïve approach yields greater variance reduction than the OLS model in some financial markets (Gagnon and Lypny, 1995).

[119] For the conventional hedge ratio, the in-sample variance reduction of the hedged portfolio, in Equation (6.2), is equal to the R^2 of Equation (6.1), (see Ederington, 1979).

Table 6.6. In-Sample Hedging Effectiveness

	Route 1	Route 1A	Route 2	Route 2A
Variance Comparisons				
Unhedged	0.001320	0.003710	0.001440	0.003120
Naïve	0.002230	0.004090	0.001410	0.003110
Conventional	0.001000	0.002780	0.001010	0.002020
VECM	0.001000	0.002820	0.001010	0.002010
VECM-GARCH	0.001020	0.002710	0.001020	0.002000
VECM-GARCH-X	0.001030	0.002720	0.001010	0.002010
Variance Reduction (%)				
Unhedged				
Naïve	-69.01	-10.20	1.88	0.28
Conventional	24.10*	24.99	30.09*	35.45
VECM	24.10	24.12	30.09	35.45
VECM-GARCH	22.67	26.87*	29.44	35.35
VECM-GARCH-X	22.29	26.61	29.66	35.86*

Notes:

- Variance is the variance of the portfolio in Equation (6.2). The results are rounded to 6 decimal places.
- Variance reduction is the variance reduction from the unhedged position from the use of the alternative models. The results are rounded to 4 decimal places.
- * denotes the model with the greatest variance reduction.

6.5.2. Out-of-Sample Hedge Ratios Comparison Results

While the in-sample performance of the alternative hedging strategies gives an indication of their historical performance, investors are more concerned with how well they can do in the future using alternative hedging strategies. Park and Switzer (1995) and Baillie and Myers (1991) further claim that a more reliable and realistic measure of hedging effectiveness is the hedging performance of different methods for out-of-sample periods. Since theory does not indicate how many observations should be used for estimation and for out-of-sample forecasting, we use an initial portion of the sample for estimation and apply the remaining sample for out-of-sample forecasting. For that, in routes 1 and 1A we withhold 30 observations of the sample (5 January 2000 to 26 July 2000, representing a period of seven months), and in routes 2 and 2A we withhold 52 observations of the sample (3 January 2001 to 26 December 2001, representing a period of one year), and estimate the two conditional models using only the data up to this date.

Then, we perform one-step-ahead forecasts of the covariance and the variance as follows:

$$E(h_{SF,t+1}|\Omega_t) = a_{11}a_{12} + b_{11}b_{22}\,h_{SF,t} + c_{11}c_{22}\,\varepsilon_{S,t}\,\varepsilon_{F,t} + e_{11}e_{22}\,z_t^2 \tag{6.8}$$

$$E(h_{F,t+1}|\Omega_t) = a_{12}^2 + a_{22}^2 + b_{22}^2\,h_{F,t} + c_{22}^2\,\varepsilon_{F,t}^2 + e_{22}^2\,z_t^2 \tag{6.9}$$

These are used to estimate the one-step-ahead hedge ratios as follows:

$$E(h^*_{t+1}|\Omega_t) = E(h_{SF,t+1}|\Omega_t) \,/\, E(h_{F,t+1}|\Omega_t) \tag{6.10}$$

The following week this exercise is repeated, with the new observation included in the data set. We continue updating the models and forecasting the hedge ratios until the end of our data set. The results for the out-of-sample hedging effectiveness are presented in Table 6.7.

Table 6.7. Out-of-Sample Hedging Effectiveness

Variance Comparisons				
	Route 1	Route 1A	Route 2	Route 2A
Unhedged	0.000741	0.001980	0.000466	0.001710
Naïve	0.001280	0.002910	0.000591	0.002170
Conventional	0.000585	0.001430	0.000324	0.001240
VECM	0.000586	0.001500	0.000324	0.001240
VECM-GARCH	0.000607	0.001350	0.000332	0.001220
VECM-GARCH-X	0.000596	0.001360	0.000346	0.001210
Variance Reduction (%)				
Unhedged				
Naïve	-72.98	-46.43	-26.76	-27.43
Conventional	21.07*	28.18	30.46*	27.56
VECM	20.95	24.68	30.40	27.47
VECM-GARCH	18.03	32.16*	28.78	28.78
VECM-GARCH-X	19.58	31.61	25.85	29.10*

Notes:

- Variance is the variance of the portfolio in Equation (6.2). The results are rounded to 6 decimal places.
- Variance reduction is the variance reduction from the unhedged position from the use of the alternative models. The results are rounded to 4 decimal places.
- * denotes the model with the greatest variance reduction.

The VECM-GARCH-X model seems to outperform the alternative hedging strategies in route 2A (29.10%); for instance, the variance reduction achieved by the VECM-GARCH-X compared to the OLS model is 2.42% (= 1 – 0.001210 / 0.001240). This suggests that, in route 2A, inclusion of the squared ECT in the conditional variance equation has important implications for the determination of the hedge ratios, and thus, for hedging effectiveness. The short-run error from the cointegrating relationship is therefore a useful variable in modelling the conditional variance as well as the conditional mean of the series.

In route 1A, in line with the in-sample results, the highest variance reduction is achieved by the VECM-ARCH model (32.16%). In routes 1 and 2 the OLS hedge performs better than the GARCH models in reducing the variability of the returns of the hedged portfolio. Myers (1991) and Garcia *et al.* (1995) also report that there are no gains in variance reduction with use of time-varying hedge ratios in the wheat and soybean futures markets, respectively. Tong (1996) finds that in the case of foreign-exchange risk hedging, dynamic hedging is not substantially better than static hedging. He attributes this to the rather stable relationship between the spot asset and the direct hedging instrument. This suggests that the additional complexity of specifying and estimating GARCH models may be justified for some commodities but not in others.

Overall, the results, from both in- and out-of-sample hedging effectiveness, reveal that in voyage routes (1 and 2) the relationship between spot and FFA prices is quite stable and market agents can use simple first-difference regression models in order to obtain optimum hedge ratios. In contrast, in time-charter routes (1A and 2A), it seems that the arrival of new information affects the relationship between spot and FFA prices, and therefore, time-varying hedging models should be preferred. Shipowning companies with vessels operating worldwide or trading companies that transport commodities to different parts of the world can use FFA contracts to reduce their freight rate risk, since the variability of their cash-flows can be explained by the fluctuations of the spot routes.

Despite the mixed evidence provided in favour of the GARCH-based hedge ratios in the forward freight market, all the proposed hedging strategies fail to eliminate a large proportion of the variability of the unhedged portfolio. The highest variance reduction is evidenced in route 1A (32.16%) and the lowest in route 1 (18.03%). The reduction in the out-of-sample portfolio variances by the GARCH specifications relative to the OLS hedges range from 5.60% in route 1A to 2.42% in route 2A[120]. In the freight futures (BIFFEX) market, Kavussanos and Nomikos (2000a) report that the greatest variance reduction is 23.25% in route 1A, and the percentage variance improvements of GARCH hedges, relative to the OLS, are ranging between 5.7% and

[120] We should notice that, our results may be sensitive to the hedging horizon examined (one week). It is well-known that the in-sample hedging effectiveness tends to increase as the investment horizon increases (see footnote 104). This may suggest that our results could be different had we investigated longer hedging horizons (two or three weeks). However, due to the recent creation of the FFA market, a hedging horizon longer than one week could give us an insufficient number of observations.

0.43%. Furthermore, they argue that this is because BIFFEX used to be a cross-hedge instead of a route-specific instrument like FFA contracts. However, the current study shows that route-specific forward freight contracts, despite the fact that provide better hedging opportunities than the BIFFEX contract, fail to reduce freight rate risk to the extent found for other markets in the literature (see Gagnon and Lypny, 1995; Bera *et al.*, 1997; and Koutmos and Pericli, 1999, amongst others).

Despite the trading preferences of participants in the shipping markets, who are now increasingly use FFA contracts, the freight derivatives markets are characterised by a modest trading activity, which can consist a major reason for the poor hedging performance of the investigated contracts. Due to the fact that it is an OTC market, FFA brokers report their FFA quotes based on actual deals, but in the absence of an actual trade they report their expert view (expectations) of what the rate would be if a trade had been concluded. Thus, it may be that in some cases, without any actual trades for several days, the brokers' FFA estimates are not *efficient* enough to *predict* the future spot rates. Furthermore, spot and FFA prices are not linked by a cost-of-carry arbitrage relationship, and therefore, are free to deviate from each other more easily than stock index and stock index futures prices for example. This could provide another explanation about the low hedging effectiveness of the FFA contracts, as shocks in the system could decrease more easily the correlation between changes in the FFA and spot prices. Awareness and increased liquidity of freight derivatives trades may promote the hedging efficiency of the contracts. However, the fact remains that the observed hedging effectiveness is still small, and may not be sufficient to induce market agents to begin to use the market for hedging purposes.

As a policy action, the FFABA, the FIFC and the Baltic Exchange should: first, advertise more this freight derivatives market through marketing campaigns in order to attract the much needed volume; and second, monitor better the way that FFA brokers are conducting their FFA trades in order to verify that the daily FFA quotes are the best available (like a price discovery mechanism) before they are published to market participants.

6.6. CONCLUSION

In this chapter the hedging effectiveness of the forward freight contracts in the voyage routes 1 and 2 and in the time-charter routes 1A and 2A has been examined. The data sets that are used consist of weekly spot and FFA prices in panamax routes 1 and 1A from 16 January 1997 to 31 July 2000 and weekly spot and FFA prices in panamax routes 2 and 2A from 16 January 1997 to 31 December 2001. Spot price data are from the Baltic Exchange. FFA price data for the panamax routes are from Clarkson Securities Ltd. The fact that cointegration exists between spot and FFA prices in all routes is consistent with the literature (see Kavussanos and Nomikos 2000a, 2000b).

Both in-sample and out-of-sample hedging performances are examined for each FFA contract, considering alternative methods, both constant and time-varying, for computing more effective hedge ratios. Results from in- and out-of-sample tests indicate that time-varying hedge ratios marginally outperform alternative specifications in reducing market risk in the time-charter routes 1A (VECM-ARCH model) and 2A (VECM-GARCH-X model). In contrast, the results reveal that the simple first-difference OLS regression is the preferred method for estimating hedge ratios in voyage routes 1 and 2. Moreover, the hedging effectiveness varies from one freight market to the other. This is because freight prices, and consequently FFA quotes, are affected by different trading and regional economic conditions. Market agents can benefit from this result by developing appropriate hedge ratios in each route, and thus, controlling their freight rate risk more efficiently.

However, the extent of risk reduction is less than that found in other commodity and financial markets in the literature. The currently low trading volume, the way that FFA brokers estimate their FFA quotes, and the lack of the cost-of-carry arbitrage relationship of storable assets that keeps spot and derivatives prices close together may provide explanations about the finding that spot price fluctuations of the investigated trading routes are not accurately tracked by the FFA prices.

CHAPTER 7 - THE RELATION BETWEEN BID-ASK SPREADS AND PRICE VOLATILITY IN THE FORWARD FREIGHT MARKET

7.1. INTRODUCTION

Transactions costs are usually ignored in asset pricing theories but are an important consideration in investors' investment decisions. One significant cost is the bid-ask spread (BAS). Brokers match buy and sell contracts and the price charged for this service is known as the bid-ask spread; the difference between the buying (bid) and selling (asked) price per contract. This normally is regarded as compensation to brokers for providing liquidity services in a continuously traded market. The mark-up charged by brokers in the financial markets, as in any other market, is a function of the operational efficiency of the brokers and the nature of the product. Tinic and West (1972) argue that there is a positive relationship between spreads and price volatility on the grounds that the greater the variability in price, the greater the risk associated with performance of the function of the brokers. Intuitively, unambiguous *good* or *bad* news regarding the fundamentals of the price of the asset should have no systematic effect on the spread. Both the bid and the ask prices should adjust in the same direction in response to the traders receiving buy or sell orders that reflect the particular news event. However, greater uncertainty regarding the future price of the asset, as associated with greater volatility of the price of the asset, is likely to result in a widening of the spread (Bollerslev and Melvin, 1994).

The nature and the behaviour of the BASs have been examined thoroughly in the equity (see McInish and Wood, 1992), foreign exchange (see Bollerslev and Melvin, 1994; and Bessembinder, 1994) and bond markets (see Kalimipalli and Warga, 2000). However, knowledge of derivatives spreads is limited, presumably due to the lack of information on bid-ask quotes (with the exception of the studies of Laux and Senchack, 1992; Ma *et al.*, 1992; Wang et al., 1994; Ding, 1999; and Wang and Yau, 2000, amongst others). Transactions costs related to derivatives is an important issue because the low cost of trading is often cited as one rationale for the existence of derivatives markets, high transactions costs will also affect market participants' ability to trade quickly and cheaply and regulators will need to consider how their policy decisions may impact the volatility of the market, and consequently, the BASs. The purpose of this chapter is to investigate what impact an anticipated increase in FFA price volatility will have on transactions costs in terms of BAS. Extant literature that provides some possible answers to the previous question includes those studies on the relationship between BASs and price volatility (see for example, Tinic and West, 1972; Benston and Hagerman, 1974; Stoll, 1978; Copeland and Galai, 1983; and McInish and Wood, 1992, amongst others).

In the OTC FFA market, there is no official organised market, but there is a network of shipbrokers who act as FFA brokers, and transactions occur only when buy and sell orders are matched. The FFA brokers provide the market by quoting daily bid and ask prices simultaneously against which market orders can be executed. In the trading process, interest to buy or sell FFA contracts is send through the telephone or a computerised order-entry system by the FFA brokers to all potential traders. By receiving the replies, the FFA brokers try to match the bid and the ask prices by continuously negotiating with the two parties. If an agreement is reached then the contract is fixed. It should be noted that the forward freight market remains a broker market rather than one in which there are dealers (it is too expensive for individual market-makers to come but not large enough to attract the big professional ones). Enron used to be a major FFA dealer in the past but after its default, during December 2001, the market is cautious in trusting another market-agent. However, the new initiative from IMAREX (described in Chapter 1) is currently following the structure of a dealers market. Moreover, the daily bid and ask prices in the FFA market are directly observable, and therefore, there is no need to estimate them as in other derivatives markets. Several procedures have been proposed for the estimation of the BAS (and its components) when it is not directly observable (see for example, Bhattacharya, 1983; Roll, 1984; Choi *et al.*, 1988; Thompson and Waller, 1988; George *et al.*, 1991; Laux and Senchack, 1992; and Chu *et al.*, 1996). For a formal discussion of the alternative BAS estimators see Ding (1999).

This chapter contributes to existing literature in a number of dimensions. First, we examine the relationship between BAS and price volatility in the FFA market, which offers a unique and directly observable BAS data set. Second, we employ a two-step modeling specification in order to ensure robust inferences on the relationships between variables. In the first-step the GARCH specification is used for modeling the volatility of the FFA prices. This specification is consistent with a return distribution which is leptokurtic (speculative prices), and it also allows for a long-term memory (persistence) in the variance of the conditional return distributions. The

GARCH model is known to be capable of mimicking observed statistical characteristics of many time-series of return on financial assets (see Bollerslev, 1987 and Baillie and Bollerslev, 1989). In the second-step we investigate if the expected conditional volatility (led by one-day) has a significant positive relationship with the current BAS using the General Method of Moments (GMM) approach (Hansen, 1982). Third, volatility in the several markets of the shipping industry are subject to sudden movements which are, at best, only partially predictable. A better understanding of the movements of FFA prices, and the consequent effect in transactions costs, may provide important information and insights for market agents about the timing of trades, the sentiment and the future direction of the FFA market. For example, a widening of the BAS may discourage market agents from participating and trading as it may indicate a period of high volatility. More specifically, traders, speculators, hedgers, and arbitrageurs alike are interested in extracting information from these variables to know how their reaction to new information can be used in predicting future prices. From a policy perspective, the issue is important because of its implications for the analysis of market liquidity and its relationship with risk. Using BAS as a proxy of market liquidity, a market can be considered to be liquid when large transactions can be executed with a small impact on prices (Galati, 2000). Policy makers and regulators (FFABA and FIFC) are interested in knowing how changes in these variables impact the market activity.

The remainder of this chapter is organised as follows. Section 7.2 presents the literature review. Section 7.3 discusses the research methodology. A description of the data and some preliminary statistics are presented in section 7.4. The empirical results are presented in section 7.5. Finally, section 7.6 summarises this chapter.

7.2. LITERATURE REVIEW

Demsetz (1968) characterises the BAS as the cost of obtaining *immediacy*; the right to transact without significant delay. Microstructure theory implies that BASs must cover three costs incurred by providers of immediacy: inventory carrying costs (see Stoll, 1978), asymmetric information costs (see Bagehot, 1971; and Copeland and Galai, 1983), and order processing costs (see Demestz, 1968; and Tinic, 1972). The inventory component should be the cost of the market-maker of maintaining open positions or demanding liquidity from other market participants, which is positively related to risk. According to this view, volatility increases price risk and thereby pushes up spreads (Bollerslev and Melvin, 1994). The asymmetric information costs component may be positively correlated with price volatility, and competition would affect the total size of the spread inversely (Bessembinder, 1994). For a comprehensive guide to the most influential theoretical work in market microstructure literature see O'Hara's (1995) study.

Although there are differences in the theoretical arguments, all the above empirical studies conclude that BASs are positively related to price volatility. In general these studies report a positive relationship between price volatility and BASs when price changes were measured over short intervals (e.g., daily). The relationship became insignificant for price changes measured over longer intervals (e.g., monthly). Of the three different types of costs, the asymmetric information cost is the most relevant in the FFA market. Order processing costs are relatively low and FFA brokers do not sustain any inventory carrying costs, as they do not hold inventories of FFA contracts. Copeland and Galai (1983) argue that the BAS must be wider to protect brokers from the costs of providing liquidity to informed traders, which can affect the brokers unfavorably. In this respect, the BAS may vary with both the timing of information arrival and the uncertainty of the information flow. Glosten and Milgrom (1985) and Hasbrouck (1988) also show that the BAS might be positively related to the amount of information coming to the market.

If information arrives sequentially, the more informed participants will trade first and the less informed participants will trade later. Because informed traders who acquire positive (negative) information are willing to bid (ask) a higher (lower) price to buy (sell), the spread may change according to the trading behaviour of the parties who possess private information. The trader's perceived exposure to private information determines how he will respond to large versus small orders and to arrivals of market-generated and other publicly available information. With regard to the uncertainty of information flows, it has been argued that less informed traders seek protection from the generation and ownership of private information in the market by requiring a higher risk-premium (Glosten and Milgrom, 1985; and Glosten and Harris, 1988). This *adverse selection hypothesis* suggests that the level of BASs should be related to the uncertainty of the information flow in the market. As the broker attributes a positive probability to the order being generated from informed traders, the BAS widens, and therefore, may signal the arrival of new information. From a different perspective, Saar (2000) investigates the role of demand uncertainty, i.e. uncertainty about preferences and endowments of the investors' population, in introducing information content to the order flow. Saar (2000) shows that demand uncertainty increases both the BAS and price volatility.

In the equity market, McInish and Wood (1992) report that NYSE equity BAS widen (decrease) with underlying volatility (trading volume and trade size) over time. Wang *et al.* (1994), using direct estimates of the BAS, examine the intraday relationship of BASs and price volatility in the S&P 500 index futures market and control for information effects. They find that BASs and price volatility are jointly determined and positively related. Furthermore, they demonstrate that OLS estimates of the BAS equation are inconsistent if the standard deviation of transaction price changes is found in the regression.

In the foreign exchange market, Fieleke (1975) reports a positive relationship between the rate of change in the exchange rate and the cost of transacting, and Overturf (1982) finds a positive relation between BAS and price volatility measured by its standard deviations. Overturf (1982) further suggests that the uncertainty regarding the rate of change in exchange rates tends to widen the BAS. Boothe (1988) finds that various measures of risk and transactions volume have an impact on BASs, and in particular he provides evidence for a positive relationship between the level of uncertainty regarding futures prices and BASs. Bollerslev and Melvin (1994) examine the nature of the relationship between BAS for exchange rate quotes and the volatility of the underlying exchange rate process. Using a two-step process, they obtain the GARCH estimates of the underlying volatility of the exchange rate process and then incorporate the volatility estimates as inputs into an ordered probit model. They report a positive relationship between latent volatility and observed BAS on the deutschemark/dollar exchange market. Using a similar framework, Gwilym *et al.* (1998) find a positive relationship between BAS for stock index options traded on LIFFE market and the volatility of the underlying stock market index. Bessembinder (1994) also finds that BAS in the foreign exchange market increases with GARCH-based return volatilities and proxies for liquidity costs.

Ding (1999) investigates intra-day and daily determinants of BASs in the foreign exchange futures market and argues that the number of transactions and the volatility of the prices are the major determinants. The number of transactions is negatively related to the BAS, whereas volatility in general is positively related to the BAS. Galati (2000) reports that the correlation between trading volumes and volatility is positive during *normal* periods but turns negative when volatility increases sharply. Galati (2000) argues that volatility and BAS are positively correlated, as suggested by inventory cost models, but contrary to the prediction of these models, he does not report evidence of a significant impact of trading volumes on BAS.

In the bond market, Kalimipalli and Warga (2000) using an Autoregressive Conditional Duration (ACD) model that provides input for an ordered probit model for observed BAS, find a significant positive (negative) relationship between latent volatility (trading volume proxy) and observed BAS. When repeating the exercise using a GARCH specification, instead of the ACD model they report that their findings are robust to alternative specifications.

Another strand of research on the relationship between BAS and price volatility concentrates on the trading hours of derivatives markets. For example, Amihud and Mendelson (1987) demonstrate that the existence of a positive relationship at the closing hour of the New York Stock Exchange (NYSE). Brock and Kleidon (1992) show that periodic market closure causes greater transactions demand at the open and close of trading. Traders have a greater need to revise portfolios at the opening because they could not trade during the night while information continued to develop. Whereas, near the close, traders are revising their portfolios in anticipation of being unable to trade overnight, again while information continues to arrive. This greater transactions demand at open and close increases asks and lowers bids (widens the spread), so that the spreads follow a U-shaped pattern throughout the day, and increases trading activity (volume). Although, price volatility is not addressed explicitly in this theory, Ma *et al.* (1992) note that the theory implies greater divergence of beliefs during non-trading hours, greater information disparity among traders during the opening period, and higher price volatility in the opening period. Subrahmanyam (1989) and Foster and Viswanathan (1994) predict higher BASs at open and close because the presence of informed traders increases the adverse information component of the spread.

7.3. RESEARCH METHODOLOGY

Most of the previous empirical studies have concentrated on explaining the determinants of BASs utilising two classes of factors. The first class includes: (i) activity variables such as volume and order size; (ii) various measures of risk; (iii) competition in market-making, such as the numbers of brokers trading in the asset; (iv) the number of transactions; and (v) institutional ownership. The second class of factors is related to the features of exchanges and the financial characteristics of assets. Extensive literature reviews are provided by Benston and Hagerman (1974), Hasbrouck (1988), Stoll (1989), and McInish and Wood (1992), amongst others.

The measurement of price volatility is a difficult task, and many different measurement procedures have been employed in the literature. These can be subdivided into those which have used historical volatility, and those which have used a forecast of the volatility. The latter are those which use the implied volatilities derived through option prices. The definition of historical price volatility employed in any particular study depends on the frequency of the available observations (i.e. transactions data, closing prices) and the length period for which the volatilities are to be computed (i.e. days or months). It is often taken as the variance of the logarithm of the daily price relatives. This has the advantage that, as the level of prices alters over time, the variance of the logarithm of the price relatives is more likely to be stationary than is the variance of alternative volatility measures (Board and Sutcliffe, 1990).

A shortcoming of the earlier studies is the way price volatility is computed. Board and Sutcliffe (1990) have shown that studies based on historical estimates of volatility are sensitive to the measures of volatility used. However, recent studies indicate that most of the financial price series exhibit non-linear price dependencies. For example, it is possible for FFA prices to be linearly unrelated and yet be non-linearly dependent. The general evidence suggests that dependencies work through the conditional variance (and other even-ordered moments), rather than being a result of certain misspecified first-order dynamics (Engle and Rothschild, 1992). The applicability of traditional volatility measures without utilising a procedure that considers these conditions would provide inconsistent estimates in the current study.

The ARCH model of Engle (1982) and the GARCH model of Bollerslev (1986) can capture such time variation in return distributions. In the ARCH model, the conditional error distribution is normal, but the conditional variance is a linear function of past squared errors. The GARCH process allows for a more flexible lag structure, as the conditional variance is a linear function of past squared errors and past variances. There is a great deal of evidence in various financial markets that the conditional variance from ARCH class of models provides a superior estimate of spot price variability (see Bollerslev *et al.*, 1992 for a review). ARCH processes allow the examination of the structure and the characteristics of volatility, explicitly address the issue of time dependence in the variance, and therefore, overcome problems associated with heteroskedasticity in the data.

In order to derive an estimate of the FFA volatility, the following AR-GARCH(1,1) model is employed:

$$\Delta F_t = \varphi_0 + \sum_{i=1}^{p-1} \varphi_i \Delta F_{t-i} + \varepsilon_t \quad ; \quad \varepsilon_t \sim \text{iid}(0,h_t) \tag{7.1a}$$

$$h_t = a_0 + a_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 \tag{7.1b}$$

where F_t is the natural logarithm of the daily FFA price changes (average mid-point of the bid-ask quotes), Δ is the first-difference operator, BAS_t is the difference of the natural logarithm of the ask quote minus the natural logarithm of the bid quote ($\ln(Ask_t) - \ln(Bid_t)$)[121], and ε_t are the residuals that follow a normal distribution with mean zero and time-varying variance, h_t. Bollerslev (1987) shows that GARCH(1,1) adequately fits many economic time-series[122]. After ensuring that the model is well-specified, following Bessembinder (1994) and Galati (2000), we construct one-step ahead conditional volatility estimates (h_{t+1}). Following a common practice in the literature, the GARCH model is fitted on the entire time-series, thus yielding in-sample

[121] Models are also estimated using the percentage BAS, defined as (Ask-Bid)/{(Ask+Bid)/2}. However, the results are qualitatively unaffected, and thus, in the ensuing analysis the models using the differenced BAS are reported.
[122] In order to determine the best GARCH specification several other specifications are used, such as the symmetric GARCH-M (Engle *et al.*, 1987), the asymmetric E-GARCH (Nelson, 1991) and the E-GARCH-M, but yield inferior results judged by the evaluation of the log-likelihood and in terms of residual specification tests (not reported).

forecasts. Ideally, volatility implied in FFA option prices could be used, since there is evidence in other markets that it outperforms GARCH models in providing forecasts of future volatility (Jorion, 1996). However FFA option contracts are currently not very liquid.

To analyse the relationship between expected volatility and current BAS, the BASs are regressed against variables that represent risk, information, a dummy variable that serves to measure non-trading intervals, and a lagged BAS. To evaluate the importance of the approach of non-trading intervals in determining BASs, following Bessembinder (1994), we include a non-trading indicator variable set equal to one on Fridays and on the last trading day before holidays celebrated in UK. However, the results yield insignificant coefficients of the dummy variable in all routes, and therefore, are excluded from the ensuing analysis:

$$BAS_t = \beta_0 + \beta_1 h_{t+1} + \beta_2 BAS_{t-1} + \beta_3 \Delta F_t + u_t \quad ; \quad u_t \sim iid(0,h_t) \tag{7.2}$$

where risk is defined as the one-step ahead conditional volatility (h_{t+1}) from a well-specified AR-GARCH(1,1) model, information effects are evaluated by the first-difference FFA price series (ΔF_t) and BAS_t is defined as previous. Ding (1999) proposes an alternative method to evaluate information effects by using a price dummy variable, calculated as follows: First, the median transaction price is identified from the entire time-series. The FFA price of each day is then compared to the overall median price. If the FFA price is greater than the median price, then the dummy variable is assigned a value of one. Otherwise, a value of zero is assigned. However, Ding (1999) admits that the first-difference price series, rather than the price dummy, may generally provide more information. Thus, only the results containing the first-difference price series are reported here.

Two main problems occur when examining the relationship between volatility and BAS. First, it is readily seen that the use of BAS will result in simultaneity bias leading to inconsistent OLS estimates. In order to overcome the simultaneity problem, Harvey (1989) points out that lagged values of the endogenous variables should be used because they are classified, together with exogenous variables, as predetermined. Therefore, in order to estimate the model, instruments are required for BAS_t, and lagged BAS is used for this purpose. The second difficulty concerns the presence of heteroskedasticity implying inefficient standard errors. Thus, the model is estimated via GMM as proposed by Hansen (1982). The GMM approach allows an instrument to be used for BAS, therefore, avoiding any simultaneity bias. It also has the additional advantage of yielding heteroskedasticity and autocorrelation consistent estimates (as proposed by Newey and West, 1987) in the process. The use of the first-difference FFA price series in the model assists in examining the relationship between informational uncertainty and BASs. If high price levels result from informed trading, then the relationship between price levels and BASs should be positive (Copeland and Galai, 1983). In most empirical studies of BASs a positive price levels-BAS relation has been found (Stoll, 1978). These studies generally attribute their findings of large broker spreads to the risk of adverse selection or uniformed trading. A negative relationship lends support to the presence of scale economies in trading in the FFA market. When prices are high, the dollar volume of transactions rises. This may lead to a lowering of brokers' required BAS to cover their costs (McInish and Wood, 1992).

7.4. DESCRIPTION OF DATA AND PRELIMINARY STATISTICS

The data sets that are used consist of daily FFA and BAS prices in panamax Atlantic routes 1 and 1A from 16 January 1997 to 31 July 2000 and daily FFA and BAS prices in panamax Pacific routes 2 and 2A from 16 January 1997 to 10 August 2001. All price data are from Clarkson Securities Ltd. FFA price series are transformed into natural logarithms. FFA prices are always those of the nearby contract. To avoid thin markets and expiration effects, however, we rollover to the next nearest contract one week before the nearby contract expires as there is sufficient liquidity in the nearby contract up to a few days before its maturity date. Summary statistics of the daily logarithmic first-difference FFA prices and of the BAS prices for the four panamax routes are presented in Table 7.1. Jarque-Bera (1980) tests indicate departures from normality for FFA and BAS prices in all routes. The Ljung-Box Q(24) and $Q^2(24)$ statistics (Ljung and Box, 1978) on the first 24 lags of the sample autocorrelation function of the raw series and of the squared series indicate significant serial correlation and existence of heteroskedasticity, respectively. After applying the ADF (1981) and PP (1988) unit root tests on the daily log first-difference FFA price series, the results indicate that in all routes the log first-difference FFA price series are stationary. The results of the unit root tests on the levels of the BAS series indicate that all BAS price series are stationary.

Table 7.1. Descriptive Statistics of Logarithmic First-Difference FFA Prices and BAS Prices ($\ln(Ask_t) - \ln(Bid_t)$)

Panel A: Route 1 FFA and BAS Price Series (16/01/97 to 31/07/00)

	N	S.D.	Skew	Kurt	Q(24)	$Q^2(24)$	J-B	ADF (lags)	PP(6)
FFA	896	0.0239	-0.151	5.429	44.466	34.183	1,096.7	-31.722 (0)	-32.070
BAS	897	0.0441	1.103	4.327	3,236.0	2,698.3	247.548	-8.773 (0)	-8.517

Panel B: Route 1A FFA and BAS Price Series (16/01/97 to 31/07/00)

	N	S.D.	Skew	Kurt	Q(24)	$Q^2(24)$	J-B	ADF (lags)	PP(6)
FFA	896	0.0301	-0.037	4.708	35.083	50.891	822.28	-29.547 (0)	-29.936
BAS	897	0.0606	0.828	3.813	5,689.8	5,506.7	127.294	-5.516 (2)	-6.792

Panel C: Route 2 FFA and BAS Price Series (16/01/97 to 10/08/01)

	N	S.D.	Skew	Kurt	Q(24)	$Q^2(24)$	J-B	ADF (lags)	PP(6)
FFA	1,150	0.0178	0.285	12.711	45.426	56.827	4,534.59	-31.632 (0)	-31.727
BAS	1,151	0.0105	1.369	6.208	2,452.3	1,420.4	852.907	-12.979 (1)	-16.837

Panel D: Route 2A FFA and BAS Price Series (16/01/97 to 10/08/01)

	N	S.D.	Skew	Kurt	Q(24)	$Q^2(24)$	J-B	ADF (lags)	PP(6)
FFA	1,150	0.0278	0.984	15.266	48.906	50.905	7,394.89	-31.084 (0)	-31.176
BAS	1,151	0.0381	1.534	6.499	8,170.1	7,666.8	1,038.29	-7.113 (2)	-9.628

Notes:

- All series are measured in logarithmic first differences.
- N is the number of observations.
- S.D. is the standard deviation of the series.
- Skew and Kurt are the estimated centralised third and fourth moments of the data; their asymptotic distributions under the null are $\sqrt{T}\,\hat{\alpha}_3 \sim N(0,6)$ and $\sqrt{T}\,(\hat{\alpha}_4 - 3) \sim N(0,24)$, respectively.
- Q(24) and $Q^2(24)$ are the Ljung-Box (1978) Q statistics on the first 24 lags of the sample autocorrelation function of the raw series and of the squared series, respectively; these tests are distributed as $\chi^2(24)$.
- J-B is the Jarque-Bera (1980) test for normality, distributed as $\chi^2(2)$.
- ADF is the Augmented Dickey Fuller (1981) test. The ADF regressions include an intercept term; the lag-length of the ADF test (in parentheses) is determined by minimising the SBIC.
- PP is the Phillips and Perron (1988) test; the truncation lag for the test is in parentheses.
- The 5% critical value for the ADF (1981) and PP (1988) tests is –2.88.

The BASs are presented in Figures 7.1 to 7.4 for routes 1, 1A, 2, and 2A, respectively, providing a visual representation of the transactions costs induced by the FFA brokers. From the figures we can observe that the maximum BAS for route 1 is \$0.25 per ton, for route 1A is \$0.35 per day, for route 2 is \$0.09 per ton, and for route 2A is \$0.29 per day. Moreover, after about September 1999 the BASs for routes 2 and 2A start to narrow significantly. This and the small BAS figures in route 2 can be explained by the fact that routes 2 and 2A concentrate most of the FFA trading interest in the panamax sector. Thus, FFA brokers can report narrow BASs as shipowners and charterers agree to fix FFA contracts after a few negotiations only. Figures 7.5 to 7.8 show the historical volatility (standard deviation) of daily percentage FFA price changes, computed over moving windows of 20 days, and the BASs for routes 1, 1A, 2, and 2A, respectively. From the figures we can observe a positive relationship between volatility and BAS in most cases, which is clearer and more consistent in routes 2 and 2A. However, formal empirical analysis is needed for the significance of the above inference.

Figure 7.1. Route 1 BAS Series; Sample Period 16/01/97 to 31/07/00

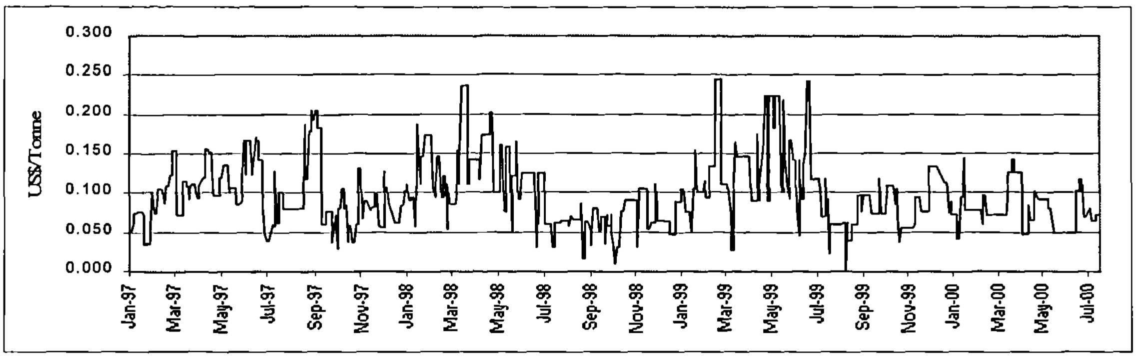


Figure 7.2. Route 1A BAS Series; Sample Period 16/01/97 to 31/07/00

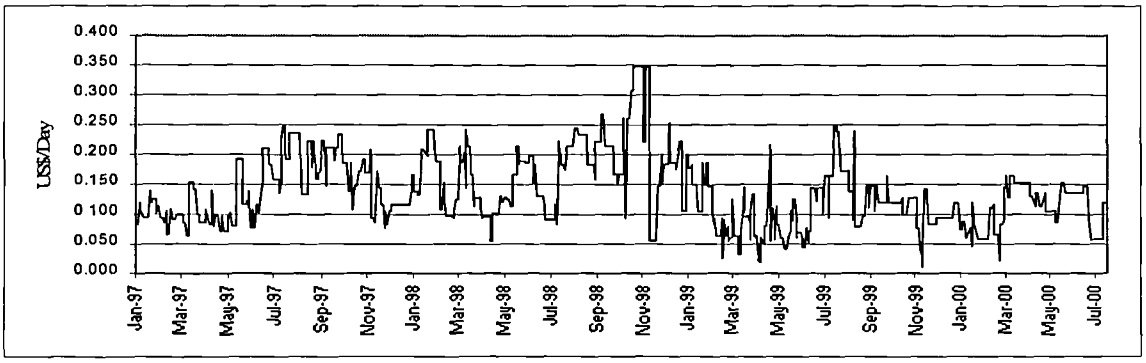


Figure 7.3. Route 2 BAS Series; Sample Period 16/01/97 to 10/08/01

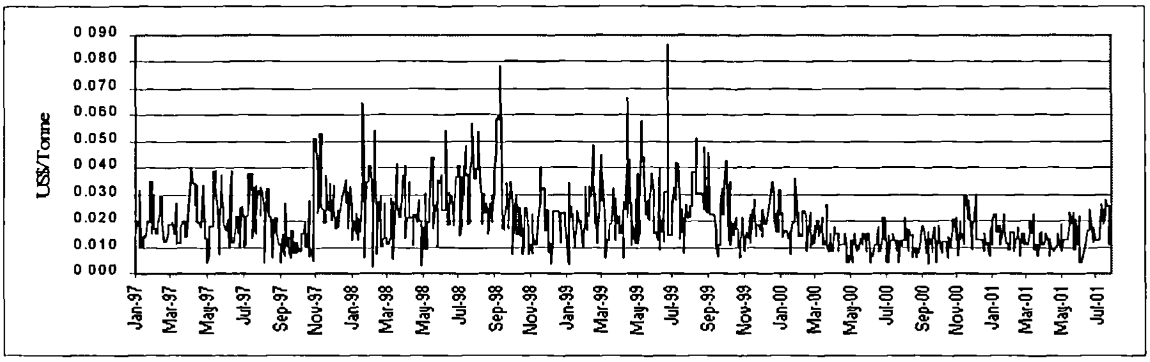


Figure 7.4. Route 2A BAS Series; Sample Period 16/01/97 to 10/08/01

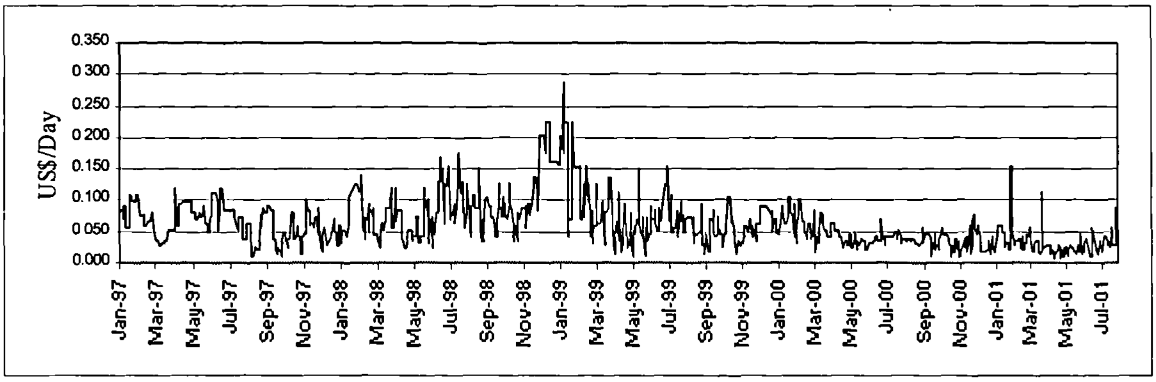


Figure 7.5. Route 1 BAS and Historical Volatility; Sample Period 16/01/97 to 04/07/00

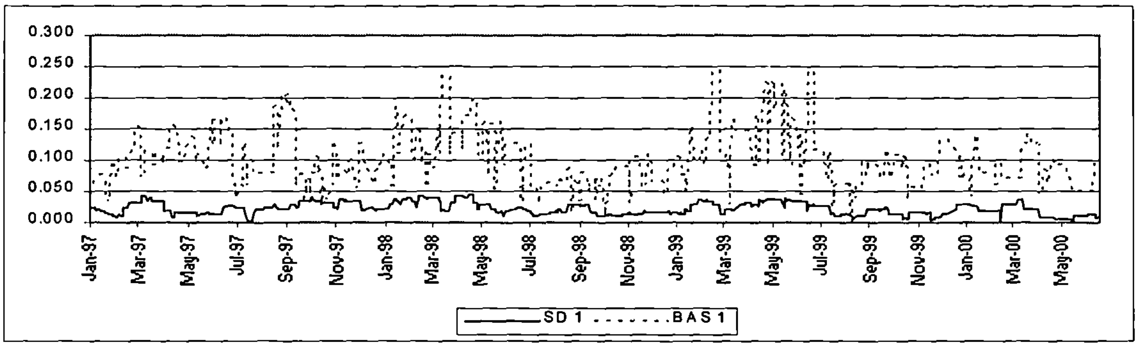


Figure 7.6. Route 1A BAS and Historical Volatility; Sample Period 16/01/97 to 04/07/00

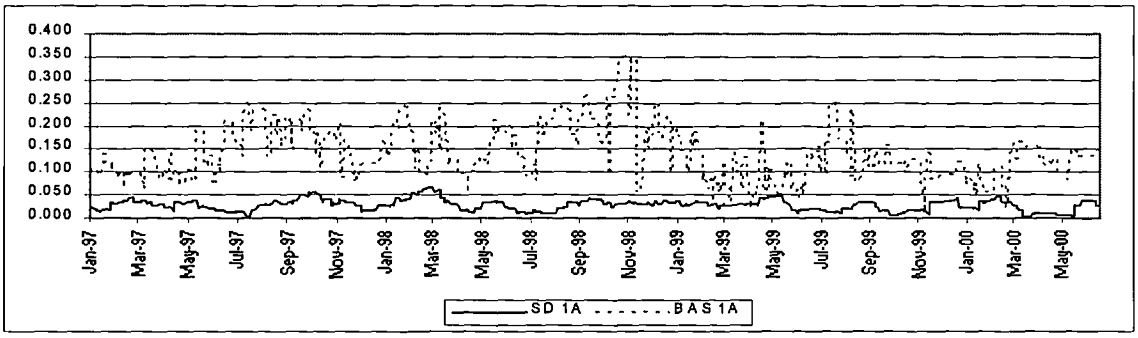


Figure 7.7. Route 2 BAS and Historical Volatility; Sample Period 16/01/97 to 16/07/01

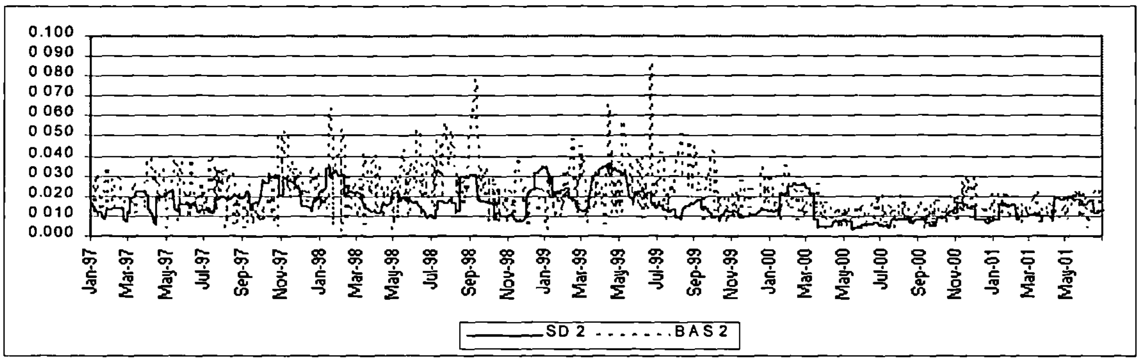
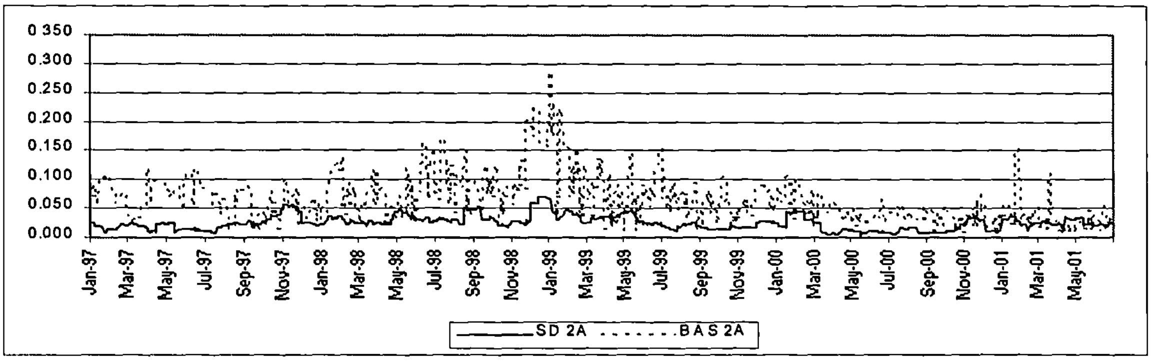


Figure 7.8. Route 2A BAS and Historical Volatility; Sample Period 16/01/97 to 16/07/01



7.5. EMPIRICAL RESULTS

In order to model the volatility of the FFA prices, AR-GARCH(1,1) models are estimated. The most parsimonious specification for each model is estimated by excluding insignificant variables. The QMLE estimates of the GARCH models of FFA rates for each route are presented in Table 7.2. The diagnostic tests, on the standardised residuals and squared standardised residuals, indicate that models are well-specified with no asymmetries and there are no linear and non-linear dependencies, respectively. The estimated implied kurtosis indicates the presence of excess kurtosis in the standardised residuals in all investigated routes. As a result the Jarque-Bera (1980) test rejects normality in all routes.

In routes 1 and 1A the coefficients of the lagged variance (a_1) are significant, suggesting that there is a persistence effect in price volatility, while the coefficients of the lagged error terms (β_1) are insignificant. In routes 2 and 2A the coefficients of the lagged variance and the lagged error terms are significant at conventional significance levels. The persistence estimates of the conditional volatility reveal the presence of a near-IGARCH process in all trading routes, with persistence estimates close to but slightly less than unity (Bollerslev, 1987).

After estimating the GARCH(1,1) models and ensuring that they are well-specified, we extract one-step ahead conditional volatility estimates (h_{t+1}) for each trading route. The results of ADF (1981) and PP (1988) unit root tests on the daily one-step ahead conditional volatility estimates indicate that the conditional volatility series are stationary in all routes (not reported).

The BASs are then regressed against one-step ahead conditional volatilities, current first-difference FFA returns, and lagged BAS, to investigate the relationship between BAS and expected volatility. The results from the GMM regressions are presented in Table 7.3, panel A. The diagnostic tests indicate the existence of serial correlation and heteroskedasticity in most cases, and thus, justify the use of the GMM approach. The adjusted R-squares of 0.711 for route 1, 0.782 for route 1A, 0.407 for route 2, and 0.683 for route 2A show that respectively, 71.1%, 78.2%, 40.7% and 68.3% of the variation in daily BASs are explained by the independent variables.

Table 7.2. GARCH Model Estimates of the FFA Conditional Volatility

Panel A: Coefficient Estimates

$$\Delta F_t = \varphi_0 + \sum_{i=1}^{p-1} \varphi_i \Delta F_{t-i} + \varepsilon_t \quad ; \quad \varepsilon_t \sim iid(0,h_t) \qquad (7.1a)$$

$$h_t = a_0 + a_1 h_{t-1} + \beta_1 \varepsilon_{t-1}^2 \qquad (7.1b)$$

	Route 1 (16/01/97–31/07/00)	Route 1A (16/01/97–31/07/00)	Route 2 (16/01/97–10/08/01)	Route 2A (16/01/97–10/08/01)
Mean Equation				
φ_0	0.012 (0.972)	2.2E-05 (0.021)	-0.0002 (-0.425)	-0.0004 (0.512)
φ_1	-0.079* (-2.541)	-	0.065* (2.339)	0.099* (3.638)
Variance Equation				
a_0	1.1E-05 (0.637)	5.2E-5 (0.844)	1.7E-06 (0.964)	7.1E-06 (1.142)
a_1	0.969* (28.715)	0.925* (12.391)	0.981* (93.471)	0.970* (67.859)
β_1	0.011 (1.362)	0.018 (1.139)	0.013** (1.997)	0.021* (2.459)

Panel B: Residual Diagnostic

	Route 1	Route 1A	Route 2	Route 2A
LL	2,079.5	1,876.7	3,032.7	2,532.7
Skewness	0.004	0.304	0.422	1.207
Kurtosis	13.260	11.275	13.704	16.567
J-B	3,925.8	2,570.4	5,519.8 [0.000]	9,090.9
Q(12)	15.550 [0.159]	10.056 [0.611]	15.288 [0.170]	19.313 [0.056]
$Q^2(12)$	5.046 [0.929]	12.945 [0.373]	4.165 [0.965]	5.131 [0.925]
ARCH(5)	0.259 [0.935]	0.408 [0.843]	0.242 [0.944]	0.712 [0.615]
ARCH(12)	0.386 [0.969]	1.096 [0.359]	0.339 [0.982]	0.417 [0.957]
Persistence	0.980	0.943	0.994	0.991
UV	0.000425	0.000772	0.000283	0.000211
Sign Bias	-0.545 [0.586]	-1.115 [0.265]	-0.924 [0.356]	-0.635 [0.525]
Negative Size Bias	0.627 [0.531]	0.562 [0.575]	0.352 [0.725]	0.298 [0.766]
Positive Size Bias	0.270 [0.787]	-0.086 [0.932]	-0.565 [0.572]	-0.272 [0.786]
Joint Test for 3 Effects	0.161 [0.922]	0.496 [0.685]	0.623 [0.601]	0.215 [0.886]

Notes:

- All variables are transformed in natural logarithms.
- Figures in parentheses (.) and in squared brackets [.] indicate *t*-statistics and exact significance levels, respectively. * and ** denote significance at the 5% and 10% levels, respectively.
- The GARCH process is estimated with the QMLE. The BHHH algorithm maximised the QMLE.
- *LL* is the Log-Likelihood. J-B is the Jarque-Bera (1980) normality test.
- Q(12) and $Q^2(12)$ are the Ljung-Box (1978) tests for 12th order serial correlation and heteroskedasticity in the standardised residuals and in the standardised squared residuals, respectively.
- ARCH(.) is the Engle's (1982) *F*-test for Autoregressive Conditional Heteroskedasticity.
- Persistence is defined as the degree of convergence of the conditional volatility to the unconditional volatility after a shock and is calculated as $a_1 + \beta_1$.
- UV is the unconditional volatility estimate of the GARCH models, measured as $(a_0) / (1-a_1-\beta_1)$.
- The test statistics for the Engle and Ng (1993) tests are the *t*-ratio of *b* in the regressions: $e\sigma_t^2 = a_0 + a_1 Y_{t-1}^- + \omega_t$ (sign bias test); $e\sigma_t^2 = a_0 + a_1 Y_{t-1}^- \varepsilon_{t-1} + \omega_t$ (negative size bias test); $e\sigma_t^2 = a_0 + a_1 Y_{t-1}^+ \varepsilon_{t-1} + \omega_t$ (positive size bias test), where $e\sigma_t^2$ are the squared standardised residuals $(\varepsilon_t^2/\sigma_t)$. Y_{t-1}^- is a dummy variable taking the value of one when ε_{t-1} is negative and zero otherwise, and $Y_{t-1}^+ = 1 - Y_{t-1}^-$. The joint test is based on the regression $e\sigma_t^2 = a_0 + a_1 Y_{t-1}^- + a_2 Y_{t-1}^- \varepsilon_{t-1} + a_3 Y_{t-1}^+ \varepsilon_{t-1} + \omega_t$. The joint test H_0: $a_1 = a_2 = a_3 = 0$, is an *F* test with 95% critical value of 2.60.

Consistent with the findings of the literature, the coefficient on the GARCH variance forecast (β_1) is positive and statistically significant in routes 1, 2, and 2A, suggesting that expected volatility has predictive power in determining BASs through its effect on asymmetric information costs. This result was expected, as anticipated large price changes may be correlated with the presence of information traders, and FFA brokers might increase the BAS to compensate for expected losses when trading with informed traders. In terms of magnitude, the elasticity of BASs with respect to price volatility is higher in route 1 (20.409) than those in routes 2 (13.517) and 2A (5.839). These results are in accordance with Figures 7.1 to 7.4, which indicate that in routes 2 and 2A the BASs are significantly narrower than in route 1, as routes 2 and 2A concentrate most of the FFA trading interest in the panamax sector. The finding of the β_1 coefficient, in route 1A, negative (-3.524) and insignificant is in stark contrast with the findings of the literature, and possibly it is explained by the infrequent FFA trading activity.

The coefficients of lagged BASs (β_2) are positive and significant at the 1% level. This suggests that the dynamic adjustment of the BAS is not usually completed in a one-day period for the selected forward contracts. The coefficient of the first-difference FFA price series (β_3) is found to be negatively significant in route 2 only. In the other three investigated routes the β_3 coefficient is insignificant. This finding, in route 2, dominates the presence of any asymmetric information trading. It is therefore, consistent with the presence of scale economies in trading in the FFA market of route 2 and supports the results of McInish and Wood (1992) for the stock market, and Ding (1999) for the currency futures market. Copeland and Galai (1983) argues that higher price levels in the stock market are associated with larger spreads because of a higher informational uncertainty due to bidding up of prices by informed traders. In contrast, our findings of lower spread levels when prices increase supports the notion of the presence of economies of scale (when prices are high, the dollar volume of transactions rise, leading to a lowering of brokers' required BAS to cover their costs) in trading FFA contracts in route 2.

In order to verify the previous inferences, we further estimate the relationship between BASs and volatility, where as a measure of historical volatility we use the one-step ahead variances of daily percentage FFA price changes, computed over moving-windows of 20 days (approximately one trading month). The results, presented in Table 7.3, panel B are in accordance with previous results as the coefficients of the statistically constructed measure of volatility (β_1) are positive and statistically significant in routes 1, 2 and 2A. In route 1A, as expected, the β_1 coefficient is negative and insignificant. The coefficients of lagged BASs (β_2) are positively significant at the 1% level in all routes, and the coefficient of the first-difference FFA price series (β_3) is found to be negatively significant in route 2 only.

Table 7.3. GMM Estimates of the Relationship Between BAS and Price Volatility

$$BAS_t = \beta_0 + \beta_1 h_{t+1} + \beta_2 BAS_{t-1} + \beta_3 \Delta F_t + u_t \quad ; \quad u_t \sim iid(0,h_t) \qquad (7.2)$$

Panel A: Volatility measured as the Conditional Variance of GARCH Models

Explanatory Variables	Route 1 (16/01/97–30/07/00)	Route 1A (16/01/97–30/07/00)	Route 2 (16/01/97–9/08/01)	Route 2A (16/01/97–9/08/01)
β_0	0.005 (1.095)	0.019* (3.295)	0.004* (6.313)	0.008* (4.452)
β_1	20.409* (2.176)	-3.524 (0.657)	13.517* (4.948)	5.839* (3.175)
β_2	0.827* (31.421)	0.884* (37.958)	0.573* (12.002)	0.801* (27.456)
β_3	-0.098 (-1.191)	0.026 (0.333)	-0.052* (-2.081)	0.068 (1.317)
Diagnostics				
$\bar{R}^2$	0.711	0.782	0.407	0.683
Q(12)	19.048 [0.087]	30.793 [0.002]	45.401 [0.000]	54.154 [0.000]
$Q^2(12)$	64.458 [0.000]	28.599 [0.005]	185.82 [0.000]	140.69 [0.000]

Panel B: Volatility measured as the Rolling Variances

Explanatory Variables	Route 1 (16/01/97–30/07/00)	Route 1A (16/01/97–30/07/00)	Route 2 (16/01/97–9/08/01)	Route 2A (16/01/97–9/08/01)
β_0	0.014* (6.611)	0.017* (5.235)	0.007* (8.929)	0.010* (7.639)
β_1	5.242* (2.640)	-0.120 (-0.121)	2.978* (2.773)	4.530* (5.039)
β_2	0.826* (29.962)	0.883* (36.913)	0.599* (15.206)	0.783* (29.699)
β_3	-0.099 (-1.220)	0.036 (0.472)	-0.040* (-1.993)	0.065 (1.252)
Diagnostics				
$\bar{R}^2$	0.710	0.779	0.392	0.687
Q(12)	18.348 [0.106]	31.310 [0.002]	59.030 [0.000]	54.781 [0.000]
$Q^2(12)$	57.074 [0.000]	27.520 [0.006]	150.01 [0.000]	134.39 [0.000]

Notes:

- Figures in parentheses (.) and in squared brackets [.] indicate *t*-statistics and exact significance levels, respectively.
- * and ** denote significance at the 5% and 10% levels, respectively.
- Volatility, in panel A, is defined as the one-step ahead conditional variance of the FFA prices, computed from a well-specified GARCH(1,1) model.
- Volatility, in panel B, is defined as the one-step ahead variance of percentage FFA price changes, computed over moving-windows of 20 days.
- Q(12) and $Q^2(12)$ are the Ljung-Box (1978) tests for 12th order serial correlation and heteroskedasticity in the residuals and in the squared residuals, respectively.
- $\bar{R}^2$ is the adjusted R-squared of the regression.
- The GMM method uses a weighting matrix ($A = \hat{\Omega}^{-1}$) that is robust to heteroskedasticity and autocorrelation of unknown form. The covariance matrix ($\hat{\Omega}$) is defined as:

  $\hat{\Omega}=\hat{\Gamma}(0)+(\sum_{j=1}^{T-1}k(j,q)(\hat{\Gamma}(j)-\hat{\Gamma}'(j))$ where $\hat{\Gamma}(j)=\frac{1}{T-k}(\sum_{i=j+1}^{T}Z'i-jUiU'i-jZi)$, the kernel ($k$) is set to Bartlett functional form, and the truncation lag window (q) is set to Newey-West fixed bandwidth selection criterion.

7.6. CONCLUSION

The microstructure of the FFA market differs in several ways from that of the often examined derivatives markets, providing an interesting alternate market for developing and testing microstructure theories. This chapter utilises a two-step model that attempts to explain some of the empirical regularities cited in the microstructure literature. We provide some new evidence on interactions between expected volatility and bid-ask spreads, by finding that FFA spreads vary with proxies for asymmetric information costs, including alternative risk forecasts. More specifically, results indicate that there is a positive relationship between BASs and expected price volatility in routes 1, 2, and 2A, after other factors are controlled. In contrast, in route 1A we do not observe a significant relationship between BASs and expected volatility, and this finding may be explained by the thin trading of the FFA contracts in the latter route.

The results of this chapter can provide a better understanding of the movements of FFA prices, and the consequent effect in transactions costs. Market agents using the information of the behaviour of the BASs can have a better insight about the timing of their FFA transactions and the future direction of the FFA market, as a widening BAS corresponds to an anticipation of increased future volatility. As a policy implication, FFABA and the FIFC should consider how their future policy decisions may impact the volatility of the market, and consequently, the bid-ask spreads.

Although this chapter investigated and identified some key determinants of BASs in the FFA market, it recognises the possibility that other may exist (i.e. trading volume). In general, however, risk is thought to be a stable determinant and is found to support the findings of previous studies.

CHAPTER 8 – FORECASTING PERFORMANCE OF SPOT AND FORWARD PRICES IN THE FORWARD FREIGHT MARKET

8.1. INTRODUCTION

In this chapter, we compare the performance of multivariate and univariate time-series models in generating short-term forecasts of spot and FFA freight rates. In particular, we investigate if FFA prices provide more accurate short-term forecasts of the spot prices than forecasts generated by time-series models. Market agents can benefit from having accurate short-term forecasts of the spot and FFA prices, since availability of such forecasts will enable them to design more efficient trading strategies. In order to identify the model that provides the most accurate forecasts, we estimate alternative multivariate and univariate specifications and assess their forecasting performance.

This exercise is interesting for three reasons. First, unlike markets in financial assets and most non-agricultural commodities, the freight market trades a non-storable service. This means that FFA rates are not tied to spot rates by an arbitrage condition, but are free to be determined by speculative activity. In a speculatively efficient market we would expect that a FFA rate would incorporate all available information about the likely future spot rate, and hence provide a good basis for forecasting future spot rates. Second, the asymmetric transactions costs between spot and FFA markets. These costs are believed to be higher in the spot freight market (in relation to the FFA market) as they involve the physical asset (vessel). Third, the FFA market is relatively new, and like all forward markets has developed primarily in response to the needs of hedgers. It is an empirical question – partially answered in this chapter - whether liquidity on all the routes covered by the market is indeed sufficient to make the FFA prices speculatively efficient, or whether they are dominated by hedging pressure.

Our multivariate specifications are motivated by the causality results between contemporaneous spot and FFA prices, in chapter 4. We found that spot and FFA prices are cointegrated. Thus, incorporating the information contained in the cointegrating relationship in the model may improve the predictability of spot and FFA prices (Engle and Yoo, 1987). We therefore, compare the forecasting performance of a VECM, to that of a standard VAR, and univariate ARIMA and Random Walk models, which do not exploit the interdependencies between the two price series. If the univariate models outperform the multivariate model in predicting the spot price, this would be evidence against the speculative efficiency of the FFA market.

Kavussanos and Nomikos (2001) apply these models to data from the now defunct exchange-based BIFFEX market, and conclude that the VECM generates significantly the most accurate forecasts of BFI prices, for a period up to 15 days ahead, and therefore, BIFFEX prices help in improving the forecasting performance of spot prices. For the BIFFEX prices however, they report that the increase in forecasting performance, through the VECM, is insignificant across all the forecasting horizons. This suggests that the prior of market efficiency is reasonable. However, our data come from the new OTC market. Moreover, Tashman (2000) argues that non-independent forecasts are biased and can invalidate the forecasting results. Thus, in making the model comparisons we are careful to estimate the models recursively, using only data up to each base date for the forecasts, and to use non-overlapping sets of forecasts for each forecast horizon, as advocated in Tashman (2000). This lets us conduct formal (Diebold and Mariano, 1995) tests for comparative forecast accuracy.

The remainder of this chapter is organised as follows. Section 8.2 describes the data used and the models that are used to generate the forecasts. Section 8.3 evaluates the forecasting performance of the alternative model specifications. Finally, section 8.4 summarises this chapter.

8.2. DATA AND ESTIMATION OF ALTERNATIVE TIME-SERIES MODELS FOR FORECASTING

The data sets used are daily spot and FFA prices in panamax Atlantic routes 1 and 1A from 16 January 1997 to 31 July 2000 and daily spot and FFA prices in panamax Pacific routes 2 and 2A from 16 January 1997 to 30 April 2001. Spot price data are from the Baltic Exchange. FFA price data for the four panamax routes are from Clarkson Securities Ltd. The FFA prices are from the contract which is closest to expiry until five working days before the maturity of the contract, in which case the next nearest contract is considered. In order to identify the model that provides the most accurate short-term forecasts of spot and FFA prices in the market and to perform a comprehensive comparison of the forecasting performance of the prices, five alternative models for predicting the spot and FFA prices are considered. The alternative time-series models are initially estimated over the period 16 January 1997 to 30 June 1998 for all routes (the first *estimation* period corresponding to one and a half year). The end observation in the first estimation period (T) is 30 June 1998 which is the *forecasting* origin – the observation from which the forecasts are generated. Following Tashman (2000), the period from 1 July 1998 to 31 July 2000 for the Atlantic routes and the period from 1 July 1998 to 30 April 2001 for the Pacific routes are used to generate independent out-of-sample N-period ahead forecasts over the *test data* period.

In making the forecast comparisons we are careful to avoid the biases in error measures which can arise if forecasts are for overlapping forecast periods. Overlapping forecast periods means non-independent forecasts errors (a shock in a specific forecast horizon may affect all other forecast horizons), which in turn violate the assumptions underlying standard tests of the statistical significance of differences in mean square errors. Our methodology is to recursively augment our estimation period by *N-period* ahead forecasts by N observations every time. For example, in order to compute 5 steps-ahead forecasts, we augment our estimation period by N = 5 observations each time. Thus, this method yields 104 and 141 independent (non-overlapping) forecasts in the Atlantic and Pacific routes, respectively. Similarly, in order to compute 10 steps-ahead forecasts, this method yields 52 and 70 independent forecasts in the Atlantic and Pacific routes, respectively. As discussed in Tashman (2000), this procedure provides two desirable characteristics for an out-of-sample accuracy test - *adequacy* (enough forecasts at each forecasting horizon), and *diversity* (desensitising forecast error measures to special events and specific phases of business).

Estimated parameters for the VECM are presented for the first estimation period in Tables 8.1 to 8.4 for routes 1, 1A, 2, and 2A, respectively, under the column VECM. VECM models offer an interesting alternative to Box-Jenkins (1970) ARIMA models for problems in which simultaneous forecasts are required for a collection of related economic variables, such as spot and FFA prices forecasting. The second model is a parsimonious VECM which is derived by eliminating the insignificant coefficients from the original VECM. The selected model has different regressors in the two equations, and is therefore, estimated as a system of SURE since this method yields more efficient estimates than OLS (see Zellner, 1962). The estimation results for this model are presented in the same tables under the column SURE-VECM (for the fit period).

The third model is a VAR model in first differences without any ECTs and is presented in the same tables under the column VAR (for the fit period). The use of VAR models for economic forecasting was proposed by Sims (1980), motivated in part by questions related to the validity of the way in which economic theory is used to provide *a priori* justification for the inclusion of a restricted subset of variables in the *structural* specification of each dependent variable. Strictly speaking this is a misspecified VECM and the number of parameters to be estimated may be very large. This lack of parsimony may present serious problems when the model is to be used in a forecasting application[123]. Thus, it is employed here as a benchmark for the contribution of the ECT in forecasting accuracy. Fourth, ARIMA models (Box-Jenkins, 1970) are also used, which have been proposed by Cullinane (1992) as tools for forecasting freight rates. The most parsimonious and well-specified models for the spot and FFA returns, selected using the SBIC (1978) and ensuring that residuals are free of serial correlation, are presented in Tables 8.1 to 8.4 for routes 1, 1A, 2, and 2A, respectively, under the column ARIMA (for the fit period).

The alternative model specifications are estimated during the out-of-sample period and generate independent forecasts of the spot and FFA prices up to 20-steps ahead. Finally, the Random-Walk (RW) model is also considered for benchmark comparison; this model postulates the spot (FFA) prices at time t-n, $S_{t\text{-n}}$ ($F_{t\text{-n}}$), are the most accurate predictors of spot (FFA) prices at time t, S_t (F_t). Therefore, it uses the current spot or FFA prices to generate forecasts of these prices, and thus, requires no estimation. The results of the ADF (1981) and PP (1988) unit root tests on the log-levels and log first-differences of the daily spot and FFA price series indicate that all variables are log first-difference stationary, all having a unit root on the log-levels representation (not reported).

[123] Apart from the multicollinearity between the different lagged variables leading to imprecise coefficient estimates, the large number of parameters leads to a good within-sample fit but poor forecasting accuracy because, according to Litterman (1986, p.2), "*parameters fit not only the systematic relationships ... but also the random variation*".

Table 8.1. Estimates of the Models in Route 1 for the Out-of-Sample Forecasts; Sample Period 16/01/97 to 30/06/98

	VAR		VECM		SURE-VECM		ARIMA	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
z_{t-1}	-	-	-0.007 (-1.016)	0.056* (2.385)	-0.008 (-1.266)	0.061* (2.832)	-	-
ΔS_{t-1}	0.348* (6.354)	0.601* (3.213)	0.350* (6.385)	0.585* (3.152)	0.360* (7.579)	0.412* (3.039)	0.451* (8.682)	-
ΔS_{t-2}	-0.002 (-0.032)	-0.128 (-0.669)	13E-04 (24E-04)	-0.142 (-0.749)	-	-	0.041 (0.709)	-
ΔS_{t-3}	0.233* (4.174)	0.167 (0.877)	0.234* (4.203)	0.153 (0.811)	0.244* (5.823)	-	0.212* (4.074)	-
ΔS_{t-4}	-0.012 (-0.229)	-0.223 (-1.302)	-0.010 (-0.209)	-0.231 (-1.358)	-	-	-	-
ΔF_{t-1}	0.107* (6.704)	-0.090** (-1.651)	0.102* (6.193)	-0.054 (-0.968)	0.104* (6.623)	-	-	-0.052 (-0.981)
ΔF_{t-2}	0.039* (2.261)	-0.076 (-1.299)	0.035* (1.989)	-0.046 (-0.763)	0.033* (2.039)	-	-	0.003 (0.062)
ΔF_{t-3}	0.034* (1.995)	0.055 (0.944)	0.031** (1.773)	0.081 (1.374)	-	-	-	0.109** (1.931)
ΔF_{t-4}	0.003 (0.161)	-0.087 (-1.510)	0.001 (-0.004)	-0.065 (-1.117)	-	-	-	-
$\bar{R}^2$	0.4215	0.0258	0.4216	0.0385	0.4219	0.0355	0.3536	0.0047
Q(12)	2.705 [0.994]	12.099 [0.356]	2.740 [0.994]	10.048 [0.526]	3.117 [0.989]	19.536 [0.052]	2.245 [0.997]	9.956 [0.534]

Notes:

- * and ** denote significance at the 5% and 10% levels, respectively.
- Figures in parentheses (.) and in squared brackets [.] indicate *t*-statistics and exact significance levels, respectively.
- *t*-statistics are adjusted using the White (1980) heteroskedasticity consistent variance-covariance matrix.
- The cointegrating vector is restricted to be the lagged basis in routes 1 and 2A. In the remaining routes it is the following spread: $S_{t-1}-1.0143*F_{t-1}+0.1585$ in route 1A; and $S_{t-1}-1.0067*F_{t-1}+0.0324$ in route 2.
- Q(12) is the Ljung-Box (1978) Q statistics for 12^{th} order serial correlation in the residuals.

Table 8.2. Estimates of the Models in Route 1A for the Out-of-Sample Forecasts; Sample Period 16/01/97 to 30/06/98

	VAR		VECM		SURE-VECM		ARIMA	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
z_{t-1}	-	-	-0.014** (-1.783)	0.093* (3.051)	-0.013** (-1.660)	0.108* (3.857)	-	-
ΔS_{t-1}	0.601* (11.171)	0.481* (2.230)	0.596* (11.114)	0.510* (2.392)	0.602* (11.586)	0.596* (4.223)	0.643* 12.275	-
ΔS_{t-2}	0.121* (2.320)	0.219 (1.048)	0.121* (2.321)	0.221 (1.071)	0.104* (2.116)	-	0.126* 2.399	-
ΔF_{t-1}	0.033* (2.410)	-0.089 (-1.648)	0.024** (1.708)	-0.033 (-0.586)	0.027* (1.976)	-	-	0.138* (4.625)
ΔF_{t-2}	0.031* (2.324)	-0.135* (-2.498)	0.025** (1.780)	-0.091 (-1.635)	0.031* (2.371)	-	-	-
$\bar{R}^2$	0.5551	0.0425	0.5578	0.0641	0.5574	0.0626	0.5450	0.0096
Q(12)	15.119 [0.177]	14.797 [0.192]	14.217 [0.221]	10.210 [0.512]	14.270 [0.218]	12.874 [0.302]	15.663 [0.154]	10.079 [0.523]

See Notes of Table 8.1.

Table 8.3. Estimates of the Models in Route 2 for the Out-of-Sample Forecasts; Sample Period 16/01/97 to 30/06/98

	VAR		VECM		SURE-VECM		ARIMA	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
z_{t-1}	-	-	-0.052* (-4.544)	0.029 (0.986)	-0.052* (-4.574)	0.031 (1.105)	-	-
ΔS_{t-1}	0.611* (14.376)	0.434* (4.107)	0.556* (12.911)	0.464* (4.219)	0.555* (13.057)	0.457* (4.392)	0.668* (17.012)	-
ΔF_{t-1}	0.079* (3.452)	-0.030 (-0.531)	0.047* (2.012)	-0.012 (-0.209)	0.049* (2.343)	-	-	0.161* (4.443)
$\overline{R}^2$	0.4592	0.0417	0.4872	0.0417	0.4871	0.0442	0.443	0.0161
Q(12)	12.239 [0.346]	7.553 [0.723]	9.747 [0.553]	6.761 [0.818]	9.841 [0.545]	6.601 [0.830]	8.717 [0.648]	6.843 [0.812]

See Notes of Table 8.1.

Table 8.4. Estimates of the Models in Route 2A for the Out-of-Sample Forecasts; Sample Period 16/01/97 to 30/06/98

	VAR		VECM		SURE-VECM		ARIMA	
	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t	ΔS_t	ΔF_t
z_{t-1}	-	-	-0.032* (-2.479)	0.088* (2.362)	-0.030* (-2.444)	0.101* (3.145)	- -	-
ΔS_{t-1}	0.558* (10.072)	0.416* (2.571)	0.558* (10.141)	0.416* (2.590)	0.570* (13.289)	0.401* (3.783)	0.739* (20.621)	-
ΔS_{t-2}	0.043 (0.681)	0.034 (0.185)	0.052 (0.827)	0.009 (0.051)	-	-	-	-
ΔS_{t-3}	-0.053 (-0.839)	0.108 (0.593)	-0.044 (-0.710)	0.085 (0.468)	-	-	-	-
ΔS_{t-4}	0.006 (0.118)	-0.046 (-0.306)	0.013 (0.255)	-0.065 (-0.438)	-	-	-	-
ΔF_{t-1}	0.087* (4.537)	0.106** (1.889)	0.065* (3.090)	0.167* (2.723)	0.066* (3.181)	0.174* (3.026)	-	0.169* (3.263)
ΔF_{t-2}	0.056* (2.819)	-0.109** (-1.879)	0.036** (1.710)	-0.054 (-0.873)	0.046* (2.380)	-	-	-
ΔF_{t-3}	0.053* (2.635)	-0.061 (-1.042)	0.037** (1.799)	-0.018 (-0.301)	0.038* (2.063)	-	-	-
ΔF_{t-4}	0.068* (3.399)	-0.037 (-0.629)	0.055* (2.677)	-0.001 (-0.009)	0.056* (3.071)	- -	-	-
$\overline{R}^2$	0.5808	0.0467	0.5868	0.0588	0.5892	0.0715	0.5396	0.0259
Q(12)	17.264 [0.100]	12.469 [0.329]	16.952 [0.109]	9.977 [0.532]	17.396 [0.097]	10.433 [0.492]	14.047 [0.230]	10.209 [0.512]

See Notes of Table 8.1.

The Johansen (1988) test indicates that spot and FFA prices are cointegrated in all routes. The cointegrating vector $z_{t-1} = \beta' X_{t-1}$ is simply the lagged basis ($S_{t-1} - F_{t-1}$) in routes 1 and 2A. In the other routes this is restricted in favour of ($S_{t-1} - 1.0143*F_{t-1} + 0.1585$) in route 1A and ($S_{t-1} - 1.0067*F_{t-1} + 0.0324$) in route 2[124]. The results of the LR tests applied on the cointegrating vector to test the restrictions are: 4.901 [0.086] in route 1; 8.011 [0.018] in route 1A; 8.481 [0.014] in route 2; and 3.581 [0.167] in route 2A.

[124] Restricting the cointegrating vector to be the lagged basis, in routes 1A and 2, yields downward biased RMSEs in all cases. Thus, in routes 1A and 2 the cointegrating vector is not restricted to be the lagged basis in the ensuing analysis.

8.3. FORECASTING PERFORMANCE OF THE TIME-SERIES MODELS

We compare forecasts from all models at N = 1, 2, 3, 4, 5, 10, 15, and 20 day horizons, using the Root Mean Square Error (RMSE) as our error metric. Other measures of the seriousness of error may be relevant in this market – for example, monetary gains and losses from trading on the model forecasts. However, the RMSE is conventional, and consistent with the quadratic loss function implicitly used when parameterising the models by least squares and maximum-likelihood methods. The forecasting performance for each model, across the different forecast horizons, are presented in matrix form in Tables 8.5, 8.7, 8.9, and 8.11 for the spot prices in routes 1, 1A, 2, and 2A, respectively, and in Tables 8.6, 8.8, 8.10, and 8.12 for the FFA prices in routes 1, 1A, 2, and 2A, respectively. Numbers on the principal diagonal are the RMSEs[125] from each model and the off-diagonal numbers are the ratios of the RMSE of the model on the column to the RMSE of the model on the row. When this ratio is less than one, the model on the column of the matrix provides a more accurate forecast than the model on the row. We employ Diebold and Mariano's (1995) pairwise test of the hypothesis that the RMSEs from two competing models are equal. This statistic is constructed as follows. Let the average difference between the squared forecast errors from two models at time t, $u_{1,t}^2$, $u_{2,t}^2$, be given by $\bar{d} = \frac{1}{N}\sum_{t=1}^{N}(u_{1,t}^2 - u_{2,t}^2)$ where N is the number of forecasts. Under the null hypothesis of equal forecast accuracy the following statistic has an asymptotic standard normal distribution:

$$\mathrm{DM} = \frac{\bar{d}}{\sqrt{\dfrac{2\pi f_d(0)}{N}}} \sim N(0,1) \qquad (8.1)$$

where $f_d(0)$ is the spectral density of $(u_{1,t}^2 - u_{2,t}^2)$ at frequency 0. Following Diebold and Mariano (1995), a consistent estimate of $f_d(0)$ can be obtained by calculating the weighted sum of the sample autocovariances of $(u_{1,t}^2 - u_{2,t}^2)$ using a Bartlett weighting scheme as in Newey and West

[125] The forecast accuracy of each model is assessed using the RMSE which attaches a higher weight to larger forecast errors. The RMSE is calculated as follows: RMSE = $\sqrt{\frac{1}{N}\sum_{t=1}^{N}(R_t - Z_t)^2}$; where R_t are the realised values of the spot (FFA) prices, Z_t are the forecasted values of the spot (FFA) prices, and N is the number of forecasts.

(1987). The truncation lag equals one-third of the corresponding out-of-sample observations each time (see Andrrews, 1991). This test statistic is shown to be robust to the presence of non-normality and serial correlation in the forecast errors. Hypothesis tests for the equality of the RMSEs are conducted for each pair of models and the significance of the tests are indicated (as * and ** - see Table 8.5 notes) next to the RMSE ratios.

Consider first the route 1 spot price forecasts in Table 8.5. The RMSEs of the VECM and the SURE-VECM specifications are almost identical in most forecast horizons. This is confirmed by Diebold and Mariano's (1995) test which indicates that the difference between the RMSE from the two models is not significant, with the exceptions of the 1-day, 2-days, 15-days and 20-days ahead forecasts. The VECM produces forecasts which are significantly more accurate than the VAR, ARIMA and the RW for all forecast horizons. The only exceptions are in the 10-days and 20-days ahead forecasts where the ARIMA is as good as the VECM. Regarding the performance of the VAR and ARIMA models they outperform the RW model for all forecast horizons. Therefore, it seems that conditioning spot returns on lagged FFA returns and on the lagged basis significantly enhances the predictive accuracy of the model. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 8.88% (i.e. 1 – 0.91121). This is in accordance with the findings in other markets; Tse (1995) finds that the ECM outperforms the naïve model by 3% in the Nikkei stock index market.

Turning next to the route 1 FFA price forecasts in Table 8.6, it can be seen that the RMSEs of the VECM and the SURE-VECM specifications are almost identical for all the forecast horizons, with the exception of the 2-days ahead forecasts. The VECM outperforms the RW model up to 10-days ahead forecasts. Furthermore, the VECM significantly outperforms the VAR and the ARIMA up to 4-days ahead. For the 5-days ahead forecasts the VAR significantly outperforms the VECM and the RW but not the ARIMA, and for 10-days up to 20-days ahead forecasts the ARIMA outperforms all other specifications. Thus, it seems that conditioning FFA returns on lagged spot returns and on the lagged basis generates the most accurate forecasts up to 4-days ahead. For longer forecast horizons the ARIMA seems to generate the most accurate forecasts. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 34.25% (i.e. 1 – 0.65752).

Table 8.5. Route 1 Spot Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	520	VECM	0.00585				
		SURE-VECM	0.98817*	0.00592			
		VAR	0.99152*	1.00338	0.00590		
		ARIMA	0.81703*	0.82681*	0.82402*	0.00716	
		RW	0.91121*	0.92211**	0.91900**	1.11526*	0.00642
2	260	VECM	0.00559				
		SURE-VECM	0.98763*	0.00566			
		VAR	0.98763*	1*	0.00566		
		ARIMA	0.79516*	0.80512*	0.80512*	0.00703	
		RW	0.77639*	0.78611*	0.78611*	0.97638*	0.00720
3	173	VECM	0.00584				
		SURE-VECM	0.98648	0.00592			
		VAR	0.99488*	1.00851*	0.00587		
		ARIMA	0.77248*	0.78306*	0.77645*	0.00756	
		RW	0.63755*	0.64628*	0.64082*	0.82532*	0.00916
4	130	VECM	0.00579				
		SURE-VECM	0.98135	0.00590			
		VAR	0.98974*	1.00854*	0.00585		
		ARIMA	0.75984*	0.77427**	0.76771*	0.00762	
		RW	0.58722*	0.59837*	0.59330*	0.77281*	0.00986
5	104	VECM	0.00699				
		SURE-VECM	0.98868	0.00707			
		VAR	0.98868*	1	0.00707		
		ARIMA	0.86296*	0.87283*	0.87283*	0.00810	
		RW	0.60311*	0.61000*	0.61000*	0.69887*	0.01159
10	52	VECM	0.00464				
		SURE-VECM	1.00869	0.00460			
		VAR	0.96868*	0.96033**	0.00479		
		ARIMA	0.95670	0.94845	0.98762	0.00485	
		RW	0.53456*	0.52995*	0.55184*	0.55875*	0.00868
15	34	VECM	0.00710				
		SURE-VECM	0.97796**	0.00726			
		VAR	0.99440*	1.01680	0.00714		
		ARIMA	0.80225*	0.82033*	0.80677*	0.00885	
		RW	0.46254*	0.47296*	0.46514*	0.57654*	0.01535
20	26	VECM	0.00518				
		SURE-VECM	0.99807*	0.00519			
		VAR	0.97003*	0.97191	0.00534*		
		ARIMA	0.92998	0.93177	0.95870	0.00557	
		RW	0.49007*	0.49101*	0.50520*	0.52696*	0.01057

Notes:

- Forecasts are generated by the models in Tables 8.1 to 8.4.
- *N* is the number of forecasts.
- * and ** denote significance at the 5% and 10% levels, respectively.
- Numbers on the principal diagonal are the RMSE from each model and the off-diagonal numbers are the ratios of the RMSE of the model on the column to the RMSE of the model on the row.
- The Diebold and Mariano (1995) pairwise test of the hypothesis that the RMSEs from two competing models are equal is estimated using a Newey-West (1987) covariance estimator with a truncation lag equal to one-third of the corresponding out-of-sample observations each time.

Table 8.6. Route 1 FFA Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	520	VECM	0.02060				
		SURE-VECM	0.99757	0.02065			
		VAR	0.99133*	0.99374	0.02078		
		ARIMA	0.97815*	0.98053*	0.98670*	0.02106	
		RW	0.65752*	0.65911*	0.66326*	0.67220*	0.03133
2	260	VECM	0.02152				
		SURE-VECM	0.99079*	0.02172			
		VAR	0.99491*	1.00416	0.02163		
		ARIMA	0.97200*	0.98102*	0.97696*	0.02214	
		RW	0.67737*	0.68366*	0.68083*	0.69688*	0.03177
3	173	VECM	0.01789				
		SURE-VECM	0.99721	0.01794			
		VAR	0.98730*	0.99006	0.01812		
		ARIMA	0.99003*	0.99280*	1.00276	0.01807	
		RW	0.68702*	0.68894*	0.69585*	0.69393*	0.02604
4	130	VECM	0.02222				
		SURE-VECM	0.99865	0.02225			
		VAR	0.99285*	0.99419	0.02238		
		ARIMA	0.97541*	0.97673*	0.98244*	0.02278	
		RW	0.69114*	0.69206*	0.69611	0.70855	0.03215
5	104	VECM	0.01674				
		SURE-VECM	0.99053	0.01690			
		VAR	1.01086*	1.02053	0.01656		
		ARIMA	0.99761	1.00715	0.98688	0.01678	
		RW	0.69461**	0.70124**	0.68713**	0.69626**	0.02410
10	52	VECM	0.01015				
		SURE-VECM	0.96300	0.01054			
		VAR	1.02628*	1.06572**	0.00989		
		ARIMA	1.04639**	1.08660**	1.01958*	0.00970	
		RW	0.68860*	0.71506*	0.67096*	0.65807*	0.01474
15	34	VECM	0.00647				
		SURE-VECM	1.09475	0.00591			
		VAR	1.05374	0.96254	0.00614		
		ARIMA	1.25875*	1.14980*	1.19455*	0.00514	
		RW	0.79680	0.72783	0.75615	0.63300*	0.00812
20	26	VECM	0.00994				
		SURE-VECM	1.01635	0.00978			
		VAR	1.00607	0.98987	0.00988		
		ARIMA	1.11185**	1.09395*	1.10514**	0.00894	
		RW	0.73575	0.72390	0.73131	0.66173*	0.01351

See Notes in Table 8.5.

For the route 1A spot price forecasts in Table 8.7, the results indicate that the RMSEs of the VECM and SURE-VECM models are not significantly different than those of the VAR model for all forecast horizons, with the exception of the 1-day ahead forecasts. However, the VECM and SURE-VECM significantly outperform the ARIMA and the RW for all forecast horizons. The VAR significantly outperforms the ARIMA and the RW for all forecast horizons, with the exception of the 10-days and 20 days ahead ARIMA based forecasts. Thus, it seems that the VAR model produces forecasts with similar accuracy as those produced by VECM and SURE-VECM models. Only in 1-day ahead forecasts the SURE-VECM significantly outperforms all other specifications. These results are in accordance with earlier cointegration results which reject the hypothesis that the cointegrating vector can be restricted to be the lagged basis in route 1A. Thus, lack of restricting the cointegrating vector to be the lagged basis may explain why forecasts produced by the VAR model are as accurate as those produced by VECM and SURE-VECM models. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 14.32% (i.e. 1 – 0.85681).

Turning next to the route 1A FFA price forecasts in Table 8.8, the results indicate that the difference between the RMSE from the VECM and SURE-VECM specifications is not significant, with the exception of the 1-day ahead forecasts. However, the RMSEs of the VECM and SURE-VECM specifications are not significantly different than those of the VAR model for all forecast horizons, with the exception of the 1-day ahead forecasts. Finally, the differences between the RMSEs from the ARIMA and from the other time-series models are significant up to 4-days ahead forecasts. For longer forecast horizons conditioning FFA returns on lagged spot returns does not enhance the forecasting accuracy of FFA prices. All specifications significantly outperform the RW model. Thus, it seems that for 1-day ahead forecasts the VECM model produces the most accurate forecasts amongst all other specifications. For 2-days up to 4-days ahead forecasts the VAR model produces forecasts as accurate as those by VECM and SURE-VECM models. For longer forecast horizons the ARIMA model produces forecasts as accurate as those by the other time-series models. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 31.19% (i.e. 1 – 0.68807).

Table 8.7. Route 1A Spot Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	520	VECM	0.01119				
		SURE-VECM	1	0.01119			
		VAR	0.98764*	0.98764*	0.01133		
		ARIMA	0.85290*	0.85290*	0.86356*	0.01312	
		RW	0.85681*	0.85681*	0.86753*	1.00459	0.01306
2	260	VECM	0.00979				
		SURE-VECM	1	0.00979			
		VAR	0.99089	0.99089	0.00988		
		ARIMA	0.78320*	0.78320*	0.79040*	0.01250	
		RW	0.67751*	0.67751*	0.68374*	0.86505*	0.01445
3	173	VECM	0.01038				
		SURE-VECM	1.00387	0.01034			
		VAR	0.99904	0.99519	0.01039		
		ARIMA	0.77003*	0.76706*	0.77077*	0.01348	
		RW	0.59179*	0.58951*	0.59236*	0.76853*	0.01754
4	130	VECM	0.00878				
		SURE-VECM	1	0.00878			
		VAR	1.00228	1.00228	0.00876		
		ARIMA	0.73167*	0.73167*	0.73000*	0.01200	
		RW	0.52606*	0.52606*	0.52487*	0.71899*	0.01669
5	104	VECM	0.01334				
		SURE-VECM	0.99627*	0.01339			
		VAR	0.99330	0.99702	0.01343		
		ARIMA	0.92382*	0.92729*	0.93006*	0.01444	
		RW	0.57950*	0.58167*	0.58341*	0.62728*	0.02302
10	52	VECM	0.01097				
		SURE-VECM	0.99546*	0.01102			
		VAR	1.00183	1.00639	0.01095		
		ARIMA	0.98034*	0.98481*	0.97855	0.01119	
		RW	0.57285*	0.57546*	0.57180*	0.58433*	0.01915
15	34	VECM	0.01463				
		SURE-VECM	0.99932	0.01464			
		VAR	1.00688	1.00757	0.01453		
		ARIMA	0.91323*	0.91386*	0.90699*	0.01602	
		RW	0.56926*	0.56965*	0.56537*	0.62335*	0.02570
20	26	VECM	0.00606				
		SURE-VECM	0.98058	0.00618			
		VAR	0.95886	0.97785	0.00632		
		ARIMA	0.93519*	0.95370*	0.97531	0.00648	
		RW	0.36179*	0.36896*	0.37731*	0.38687*	0.01675

See Notes in Table 8.5.

Table 8.8. Route 1A FFA Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	520	VECM	0.02636				
		SURE-VECM	0.99172**	0.02658			
		VAR	0.98986*	0.99812*	0.02663		
		ARIMA	0.96310*	0.97114*	0.97296*	0.02737	
		RW	0.68807*	0.69381*	0.69512*	0.71443*	0.03831
2	260	VECM	0.02709				
		SURE-VECM	0.99376	0.02726			
		VAR	0.99963	1.00590	0.02710		
		ARIMA	0.98438*	0.99055*	0.98474*	0.02752	
		RW	0.65993*	0.66407*	0.66017*	0.67040*	0.04105
3	173	VECM	0.02866				
		SURE-VECM	0.99204	0.02889			
		VAR	0.98794	0.99586	0.02901		
		ARIMA	0.95757*	0.96525*	0.96926*	0.02993	
		RW	0.68647*	0.69198*	0.69485*	0.71689*	0.04175
4	130	VECM	0.02886				
		SURE-VECM	0.99209	0.02909			
		VAR	0.97930	0.98711	0.02947		
		ARIMA	0.93338*	0.94082*	0.95310*	0.03092	
		RW	0.60912*	0.61397*	0.62199*	0.65260*	0.04738
5	104	VECM	0.02551				
		SURE-VECM	0.98953	0.02578			
		VAR	0.99648	1.00703	0.02560		
		ARIMA	0.96702	0.97726	0.97043	0.02638	
		RW	0.70450*	0.71196*	0.70699*	0.72853*	0.03621
10	52	VECM	0.02326				
		SURE-VECM	0.96836	0.02402			
		VAR	0.99402	1.02650	0.02340		
		ARIMA	0.96474	0.99627	0.97055	0.02411	
		RW	0.68878*	0.71128*	0.69292*	0.71395*	0.03377
15	34	VECM	0.02927				
		SURE-VECM	0.99187	0.02951			
		VAR	1.00827	1.01653	0.02903		
		ARIMA	0.95280	0.96061	0.94499	0.03072	
		RW	0.65628*	0.66166*	0.65090*	0.68879*	0.04460
20	26	VECM	0.01839				
		SURE-VECM	1.00109	0.01837			
		VAR	1.01434	1.01324	0.01813		
		ARIMA	0.98132	0.98026	0.96745	0.01874	
		RW	0.67486**	0.67413**	0.66532**	0.68771**	0.02725

See Notes in Table 8.5.

For the route 2 spot price forecasts in Table 8.9, the results indicate that the RMSEs of the VECM and the SURE-VECM specifications are almost identical in all forecast horizons. This is confirmed by Diebold and Mariano's (1995) test which indicates that the difference between the RMSE from the two models is not significant. Moreover, both models outperform the RW model. However, the RMSEs of the VECM and SURE-VECM models are not significantly different than those of the VAR model for all forecast horizons, with the exceptions of the 1-day and 2-day ahead forecasts. This is expected as lack of restricting the cointegrating vector to be the lagged basis in route 2 may explain why forecasts produced by the VAR model are as accurate as those produced by VECM and SURE-VECM models. Furthermore, the VAR outperforms the ARIMA and RW models for all forecast horizons. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 14.67% (i.e. 1 – 0.85335).

Turning next to the route 2 FFA price forecasts in Table 8.10, the results indicate that the RMSEs of the VECM and the SURE-VECM specifications are significantly different up to 4-days ahead forecasts. For longer forecast horizons the VECM produces forecasts as accurate as the SURE-VECM. However, the RMSEs of the VECM and SURE-VECM models are not significantly different than those of the VAR model for all forecast horizons, with the exception of the 1-day ahead forecasts. For up to 4-days ahead forecasts the VAR model outperforms the ARIMA and RW. For longer forecast horizons the ARIMA model produces forecasts as accurate as those by the VAR, VECM, and SURE-VECM models. Finally, the ARIMA model outperforms the RW for all forecast horizons. Thus, for 2-days, 3-days, and 4-days ahead forecasts the VAR model produces forecasts as accurate as those by VECM and SURE-VECM models. For longer forecast horizons the ARIMA model produces forecasts as accurate as those by the other time-series models. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 28.01% (i.e. 1 – 0.71986).

Table 8.9. Route 2 Spot Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	707	VECM	0.00675				
		SURE-VECM	1.00148	0.00674			
		VAR	0.98253*	0.98108*	0.00687		
		ARIMA	0.94803*	0.94663*	0.96489*	0.00712	
		RW	0.85335*	0.85209*	0.86852*	0.90013	0.00791
2	353	VECM	0.00652				
		SURE-VECM	1	0.00652			
		VAR	0.97024*	0.97024*	0.00672		
		ARIMA	0.91961*	0.91961*	0.94781**	0.00709	
		RW	0.65859*	0.65859*	0.67879*	0.71616*	0.00990
3	235	VECM	0.00639				
		SURE-VECM	1.00157	0.00638			
		VAR	0.97557	0.97405	0.00655		
		ARIMA	0.96235	0.96084	0.98645**	0.00664	
		RW	0.60626*	0.60531*	0.62144*	0.62998*	0.01054
4	176	VECM	0.00682				
		SURE-VECM	1	0.00682			
		VAR	0.97708	0.97708	0.00698		
		ARIMA	0.92162**	0.92162**	0.94324**	0.00740	
		RW	0.53240**	0.53240**	0.54489**	0.57767**	0.01281
5	141	VECM	0.00629				
		SURE-VECM	1	0.00629			
		VAR	0.99055	0.99055	0.00635		
		ARIMA	0.93881*	0.93881*	0.94776**	0.00670	
		RW	0.53260*	0.53260*	0.53768*	0.56732*	0.01181
10	70	VECM	0.00448				
		SURE-VECM	1	0.00448			
		VAR	0.93333	0.93333	0.00480		
		ARIMA	0.88363	0.88363	0.94675*	0.00507	
		RW	0.48643*	0.48643*	0.52117*	0.55049*	0.00921
15	47	VECM	0.00629				
		SURE-VECM	1	0.00629			
		VAR	0.98589	0.98589	0.00638		
		ARIMA	0.96621	0.96621	0.98003*	0.00651	
		RW	0.51727*	0.51727*	0.52467*	0.53536*	0.01216
20	35	VECM	0.00518				
		SURE-VECM	1	0.00518			
		VAR	0.91519	0.91519	0.00566		
		ARIMA	0.88245	0.88245	0.96422*	0.00587	
		RW	0.56243**	0.56243**	0.61455**	0.63735**	0.00921

See Notes in Table 8.5.

Table 8.10. Route 2 FFA Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	707	VECM	0.01642				
		SURE-VECM	0.99818*	0.01645			
		VAR	0.99274*	0.99456*	0.01654		
		ARIMA	0.98382*	0.98562*	0.99101*	0.01669	
		RW	0.71986*	0.72117*	0.72512*	0.73170*	0.02281
2	353	VECM	0.01501				
		SURE-VECM	0.99602*	0.01507			
		VAR	0.99404	0.99801	0.01510		
		ARIMA	0.98945	0.99341	0.99539*	0.01517	
		RW	0.63900*	0.64155*	0.64283*	0.64581*	0.02349
3	235	VECM	0.01743				
		SURE-VECM	0.99828*	0.01746			
		VAR	0.98754	0.98924	0.01765		
		ARIMA	0.95350**	0.95514**	0.96554**	0.01828	
		RW	0.68460*	0.68578*	0.69324*	0.71799*	0.02546
4	176	VECM	0.01642				
		SURE-VECM	0.99576*	0.01649			
		VAR	0.98737	0.99158	0.01663		
		ARIMA	0.93402	0.93800	0.94596*	0.01758	
		RW	0.63742*	0.64014*	0.64557*	0.68245*	0.02576
5	141	VECM	0.01422				
		SURE-VECM	1.00141	0.01420			
		VAR	1.00566	1.00424	0.01414		
		ARIMA	1.00424	1.00282	0.99859	0.01416	
		RW	0.72366*	0.72265*	0.71959*	0.72061*	0.01965
10	70	VECM	0.01416				
		SURE-VECM	1	0.01416			
		VAR	1.01215	1.01215	0.01399		
		ARIMA	1.01143	1.01143	0.99929	0.01400	
		RW	0.69651*	0.69651*	0.68815*	0.68864*	0.02033
15	47	VECM	0.01466				
		SURE-VECM	1.00068	0.01465			
		VAR	1.00068	1	0.01465		
		ARIMA	0.96638	0.96572	0.96572	0.01517	
		RW	0.70211**	0.70163**	0.70163**	0.72653**	0.02088
20	35	VECM	0.01417				
		SURE-VECM	0.99719	0.01421			
		VAR	1.00496	1.0078	0.01410		
		ARIMA	0.96856	0.97129	0.96377	0.01463	
		RW	0.59865*	0.60034*	0.59569*	0.61808*	0.02367

See Notes in Table 8.5.

For the route 2A spot price forecasts in Table 8.11, the results indicate that the difference of the RMSE from the VECM and the SURE-VECM specifications is not significant up to 4-days ahead forecasts. For longer forecast horizons the VECM significantly outperform the SURE-VECM. Moreover, the VECM outperforms the VAR, ARIMA, and RW models for all forecast horizons, with the exception in the 10-days ahead forecasts where the ARIMA is as good as the VECM. Regarding the performance of the VAR and ARIMA models they outperform the RW model for all forecast horizons. Therefore, it seems that conditioning spot returns on lagged FFA returns and on the lagged basis significantly enhances the predictive accuracy of the model. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 19.37% (i.e. 1 – 0.80626).

Turning next to the route 2A FFA price forecasts in Table 8.12, the results indicate that the difference of the RMSE from the VECM and the SURE-VECM specifications is significant in most forecast horizons, with the exceptions of the 3-days and 4-days ahead forecasts. The VECM significantly outperforms all other specifications up to 4-days ahead forecasts. For 5-days and 10-days ahead forecasts the VAR significantly outperforms the SURE-VECM, ARIMA and RW specifications. However, the difference of the RMSE from the VECM and the VAR specifications is not significant for these forecast horizons. Thus, the VECM model produces forecasts as accurate as those by the VAR for 5-days and 10-days ahead forecasts. For longer forecast horizons the ARIMA model produces forecasts as accurate as those by the other time-series models. Finally, the ARIMA model outperforms the RW model for all forecast horizons. The reduction in the RMSE achieved by the VECM over the RW model for the 1-day ahead forecasts is 29.71% (i.e. 1 – 0.70294).

Table 8.11. Route 2A Spot Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	707	VECM	0.01082				
		SURE-VECM	0.98453	0.01099			
		VAR	0.98543**	1.00091	0.01098		
		ARIMA	0.91077**	0.92508**	0.92424	0.01188	
		RW	0.80626**	0.81893**	0.81818**	0.88525**	0.01342
2	353	VECM	0.01021				
		SURE-VECM	0.99416	0.01027			
		VAR	0.97891**	0.98466	0.01043		
		ARIMA	0.90354*	0.90885*	0.92301	0.01130	
		RW	0.58044*	0.58385*	0.59295*	0.64241*	0.01759
3	235	VECM	0.00979				
		SURE-VECM	0.99089	0.00988			
		VAR	0.98491**	0.99396	0.00994		
		ARIMA	0.95980*	0.96863*	0.97451	0.01020	
		RW	0.59369*	0.59915*	0.60279*	0.61856*	0.01649
4	176	VECM	0.01098				
		SURE-VECM	1	0.01098			
		VAR	0.98741**	0.98741	0.01112		
		ARIMA	0.89196*	0.89196*	0.90333	0.01231	
		RW	0.46823**	0.46823**	0.47420**	0.52495**	0.02345
5	141	VECM	0.01124				
		SURE-VECM	0.97654**	0.01151			
		VAR	0.98944**	1.01320	0.01136		
		ARIMA	0.95823**	0.98124	0.96846	0.01173	
		RW	0.58088*	0.59483*	0.58708*	0.60620*	0.01935
10	70	VECM	0.00665				
		SURE-VECM	0.97651*	0.00681			
		VAR	0.94729**	0.97009	0.00702		
		ARIMA	0.94326	0.96596	0.99574	0.00705	
		RW	0.49627*	0.50821*	0.52388*	0.52612*	0.01340
15	47	VECM	0.01223				
		SURE-VECM	0.97295*	0.01257			
		VAR	0.97918*	1.00641	0.01249		
		ARIMA	0.93216*	0.95808*	0.95198**	0.01312	
		RW	0.51150*	0.52572*	0.52238*	0.54872*	0.02391
20	35	VECM	0.00706				
		SURE-VECM	0.98056*	0.00720			
		VAR	0.93386*	0.95238	0.00756		
		ARIMA	0.90281*	0.92072**	0.96675	0.00782	
		RW	0.40297*	0.41096*	0.43151*	0.44635*	0.01752

See Notes in Table 8.5.

Table 8.12. Route 2A FFA Price Forecasts for Out-of-Sample Period

Horizon (days)	N	RMSEs	VECM	SURE-VECM	VAR	ARIMA	RW
1	707	VECM	0.02726				
		SURE-VECM	0.99055**	0.02752			
		VAR	0.99489*	1.00438	0.02740		
		ARIMA	0.97322*	0.98251*	0.97822*	0.02801	
		RW	0.70294*	0.70964*	0.70655*	0.72228*	0.03878
2	353	VECM	0.02284				
		SURE-VECM	0.99434*	0.02297			
		VAR	0.99651*	1.00218	0.02292		
		ARIMA	0.97316*	0.97870*	0.97657*	0.02347	
		RW	0.67395*	0.67778*	0.67631*	0.69253*	0.03389
3	235	VECM	0.03187				
		SURE-VECM	0.99160	0.03214			
		VAR	0.99438*	1.00281	0.03205		
		ARIMA	0.96517**	0.97335**	0.97062	0.03302	
		RW	0.68938*	0.69522*	0.69327*	0.71425*	0.04623
4	176	VECM	0.02434				
		SURE-VECM	1.00165	0.02430			
		VAR	0.98463*	0.98301**	0.02472		
		ARIMA	0.95115*	0.94959*	0.96600*	0.02559	
		RW	0.63106*	0.63002*	0.64091*	0.66347*	0.03857
5	141	VECM	0.03105				
		SURE-VECM	0.98197**	0.03162			
		VAR	1.00064	1.01901**	0.03103		
		ARIMA	0.95421**	0.97173	0.95360*	0.03254	
		RW	0.76403*	0.77805*	0.76353*	0.80069*	0.04064
10	70	VECM	0.02670				
		SURE-VECM	0.98126**	0.02721			
		VAR	1.01022	1.02951**	0.02643		
		ARIMA	0.95802*	0.97632	0.94833*	0.02787	
		RW	0.63195*	0.64402*	0.62556*	0.65964*	0.04225
15	47	VECM	0.03822				
		SURE-VECM	0.98454*	0.03882			
		VAR	1.00738	1.02319	0.03794		
		ARIMA	0.97301	0.98829	0.96589	0.03928	
		RW	0.66713*	0.67761*	0.66224*	0.68563*	0.05729
20	35	VECM	0.02546				
		SURE-VECM	1.00118*	0.02543			
		VAR	0.99337	0.99220	0.02563		
		ARIMA	0.95071	0.94959	0.95706	0.02678	
		RW	0.58949*	0.58879*	0.59342*	0.62005*	0.04319

See Notes in Table 8.5.

To conclude, there are four major findings from this forecast exercise. First, restricting the cointegrating vector to represent the exact lagged basis significantly affects the forecast performance of the VECM model. In routes 1 and 2A (where the restriction is accepted) the VECM provides more accurate forecasts than the VAR specification. In contrast, in routes 1A and 2 (where the restriction is not accepted) the VAR provides more accurate forecasts than the VECM specification, with the exception of the 1-day ahead forecasts.

Second, while conditioning spot returns on lagged FFA returns generates more accurate forecasts of the spot prices for all forecast horizons, conditioning FFA returns on lagged spot returns enhance the forecasting accuracy of FFA prices up to 4-days ahead forecasts in routes 1, 1A, and 2 and up to 10-days ahead forecasts in route 2A. For longer forecast horizons the univariate Box-Jenkins (1970) ARIMA model produces forecasts as accurate as those by the other time-series models in all trading routes, and therefore, there is little gain in forecasting accuracy by employing multivariate time-series models.

Third, the reduction in the RMSE achieved by the VECM over the RW for the 1-day ahead spot forecasts is lower than the RMSE achieved by the VECM over the RW for the 1-day ahead FFA forecasts in all trading routes. This compares favourably to the findings in other markets. For example, Ghosh (1993a) reports reductions in RMSE for the 1-day ahead spot forecasts ranging from 15% to 34% for the S&P 500 and the Commodity Research Bureau (CRB) spot indices, respectively, while reports reductions in RMSE for the 1-day ahead futures forecasts ranging from 24% and 39% for the S&P 500 and the CRB futures markets, respectively. However, the studies of Ghosh (1993a) and Tse (1995) use only 1-step ahead forecasts and do not test statistically the equality of the RMSE. Investigation of longer forecast horizons and hypothesis tests for the RMSE in this study, are important because they allow market agents in the FFA market to find the appropriate time-series specification in order to generate accurate forecasts of the spot and the FFA prices, and hence design more efficient investment and speculative trading strategies.

Finally, all time-series models generate more accurate spot and FFA forecasts than the forecasts obtained by the RW model in all routes. Thus, there is much gain in forecasting accuracy by employing time-series models rather than using the readily available information provided by the current spot and FFA prices.

8.4. CONCLUSION

In this chapter, we investigated the performance of alternative time-series models in generating short-term forecasts of the spot and FFA prices. We examine the forecasting performance of a VECM of spot and FFA prices where the cointegrating vector is restricted to be the lagged basis in routes 1 and 2A only. The forecasts from this model are compared to forecasts generated by SURE-VECM, ARIMA, VAR and the RW models.

We find that in routes (1 and 2A) where the cointegrating vector is restricted to be the lagged basis, the VECM outperforms the VAR model and in routes (1A and 2) where the cointegrating vector is not restricted to be the lagged basis, the VAR outperforms the VECM model. More specifically, while conditioning spot returns to lagged FFA returns generates more accurate forecasts of the spot prices for all forecast horizons, conditioning FFA returns to lagged spot returns enhance the forecasting accuracy of FFA prices up to 4-days ahead forecasts in routes 1, 1A, and 2 and up to 10-days ahead forecasts in route 2A. For longer forecast horizons the univariate Box-Jenkins (1970) ARIMA model produces forecasts as accurate as those by the other time-series models in all trading routes, and therefore, there is little gain in forecasting accuracy by employing multivariate time-series models. Thus, market agents by selecting the appropriate time-series model for forecasting purposes can design more efficient investment and speculative trading strategies.

CHAPTER 9 – CONCLUSIONS AND FURTHER RESEARCH

9.1. INTRODUCTION

This chapter concludes the thesis. The main subject of the thesis is the investigation of the price discovery, and risk management functions of the FFA market. These are the most important functions of any derivatives (futures or forward) market and are often presented as the justification for derivatives trading (see Garbade and Silber, 1983). Moreover, we investigate the impact of the introduction of FFA trading on the spot market price volatility and the relationship between bid-ask spreads and expected volatility in the FFA market. Finally, we also address the issue of forecasting spot and FFA prices and propose a model which outperforms all the other models considered so far in the literature.

A considerable amount of empirical research has been directed towards examining these hypotheses in different exchange-based financial and commodity derivatives markets. In forward markets, to the best of our knowledge, there have been only few studies investigating the economic functions of OTC derivatives contracts (with the exeption of currency forwards), primarily due to the unavailability of data. The possession of daily data that were manually gathered and processed in an electronic format and the use of critically selected econometric methodologies enable us for the first time to introduce empirical evidence for the FFA market. It is has been therefore, the objective of this thesis to fill this gap in the literature. The uniqueness of this thesis lies in the fact that its concern is with a market that has been subject to extremely limited, if any, coverage.

The special features of this market, in comparison to the existing literature on futures and forward markets, are: (i) the non-storable nature of the underlying commodity, being that of a service. The theory of intertemporal relationships between spot and derivatives prices of continuously storable commodities is well developed (Working 1970), in contrast to that of non-storable commodities (e.g. freight services). The non-storable nature of FFA market implies that spot and FFA prices are not linked by a cost-of-carry (storage) relationship, as in financial and agricultural derivatives markets. Thus, inter-dependence between spot and FFA prices may not be as strong as for storable commodities; and (ii) the asymmetric transactions costs between spot and FFA markets. These costs are believed to be higher in the spot freight market (in relation to the FFA market) as they involve the physical asset (vessel).

Due to space and time constraints we selected four trading routes of the panamax sector of the dry-bulk shipping industry, which are constituent routes of the BPI; the Atlantic voyage route 1 (US Gulf/Antwerp-Rotterdam-Amsterdam), the Atlantic time-charter route 1A (Transatlantic round to Skaw-Gibraltar range), the Pacific voyage route 2 (US Gulf/Japan) and the Pacific time-charter route 2A (Skaw Passero-Gibraltar/Taiwan-Japan). The choice of the above routes was based on the FFA trading interest of the market agents for those routes, where routes 1 and 1A are characterised by low trading interest and, in contrast, routes 2 and 2A concentrate the highest trading interest at the time of writing. Thus, by comparing less liquid and highly liquid trading routes, robust conclusions can be reached.

The structure of this chapter is as follows. In section 9.2 we report the conclusions for each chapter. In section 9.3 we discuss the policy implications of our findings. Finally, section 9.4 presents some topics for further research, which, due to space and time constraints, are not investigated here.

9.2. SUMMARY OF THE FINDINGS AND CONCLUSIONS

In the first chapter, we described the two benefits that derivatives markets, in general, provide to economic agents – price discovery and risk management; a description of the dry-bulk and wet-bulk spot and FFA markets is also examined. The contribution of the thesis to the literature was also identified. In the second chapter, we presented time-series techniques for investigating equilibrium relationships involving non-stationary price series. The properties of stationary and non-stationary processes were discussed and the Dickey and Fuller (1979 and 1981) and the Phillips and Perron (1988) unit root tests were presented. Furthermore, we presented the cointegration methodology and described the Engle and Granger (1987), and Johansen (1988) testing procedures. The Johansen (1988) test is more powerful than the Engle and Granger (1987) test, it provides a test statistic which has an exact limiting distribution, and enables us to perform hypothesis tests for restricted versions of the cointegrating relationships. Finally, the theory of ARCH and GARCH models was presented and various univariate and multivariate specifications were analysed.

The empirical analysis of the thesis is presented in chapters 3 through 8. In chapters 3 and 4 we investigated two different aspects of the price discovery function of the market, namely the relationship between current forward prices and expected spot prices – the unbiasedness hypothesis – and the lead-lag relationship in returns and volatility between spot and forward prices. More specifically, in chapter 3, we investigated the unbiased expectations property of the forward prices in the market using cointegration techniques. Parameter restriction tests on the cointegrating relationship between spot and FFA prices indicate that FFA prices one- and two-months prior to maturity are unbiased predictors of the realised spot prices in all investigated routes. However, the efficiency of the FFA prices three-months prior to maturity gives mixed evidence, with routes 2 and 2A being unbiased estimators and with routes 1 and 1A being biased estimators of the realised spot prices. Thus, it seems that unbiasedness depends on the market and type of contract under investigation. For the investigated routes and maturities for which unbiasedness holds, market agents can use the FFA prices as indicators of the future course of spot prices, in order to guide their physical market decisions. Our results are consistent with those of Kavussanos and Nomikos (1999) who examine the BIFFEX market using cointegration techniques and find that futures prices one- and two-months from maturity provide unbiased forecasts of the realised spot prices. On the other hand, futures prices three-months from maturity seem to be biased estimates of the realised spot prices.

In chapter 4, we investigated the lead-lag relationship between FFA and spot markets, both in terms of returns and volatility - which represent the second dimension of the price discovery role of derivatives markets. After using a SURE-VECM model and GIR analysis, to investigate the short-run dynamics and the price movements in the two markets, causality tests indicate that there is a bi-directional causal relationship in all routes, implying that FFA prices can be equally important as informational sources as the spot prices, in commodity markets (Yang *et al.*, 2001). However, FFA prices tend to discover new information more rapidly than spot prices in all routes. This pattern is thought to reflect the fundamentals of the underlying asset since, due to the limitations of short-selling and higher transactions costs of the underlying spot rate, investors who have collected and analysed new information would prefer to trade in the FFA rather than in the spot market. In order to investigate for volatility spillovers between the spot and FFA markets, we utilised an extended bivariate VECM-GARCH-X model. The results indicate that the FFA market volatility spills information to the spot market volatility in route 1. In route 1A the results indicate no volatility spillovers in either market. In routes 2 and 2A there is a bi-directional relationship as each market transmits volatility in the other. The previous results, in all routes, indicate that informed agents are not indifferent between trading in the FFA and the spot market, as new market information disseminates in the FFA market before the spot market. Thus, it seems that FFA prices contain useful information about subsequent spot prices, beyond that already embedded in the current spot price, and therefore, can be used as price discovery vehicles, since such information may be used in decision making. Furthermore, the FFA contracts in routes 1, 2, and 2A contribute in the volatility of the relevant spot rate, and therefore, further support the notion of price discovery. Kavussanos and Nomikos (2001) examine the lead-lag relationship between BFI and BIFFEX markets in terms of returns only and conclude that there is a bi-directional causal relationship between the BIFFEX and BFI prices, and that this relationship is stronger from BIFFEX to BFI prices.

In chapter 5, we investigated the impact of FFA trading and the activities of speculators on spot market price volatility. The results suggest that the onset of FFA trading has had: (i) a stabilising impact on the spot price volatility in all routes; (ii) an impact on the asymmetry of volatility (market dynamics) in routes 2 and 2A; and (iii) substantially improved the quality and speed of information flowing in routes 1, 1A and 2. However, after including in the conditional variance equation other explanatory variables that may affect spot volatility, the results indicate that only in voyage routes 1 and 2 the reduction of volatility may be a direct consequence of FFA trading. The results do not present a clear answer as to whether reduction in spot volatility, in time-charter routes 1A and 2A, is a direct consequence of FFA trading. These findings have implications for the way in which the FFA market is viewed. Contrary to the traditional view of derivatives trading and despite the route-specific nature of the FFA contracts, with the different economic and trading conditions of each route, the results indicate that the introduction of FFA contracts has not had a detrimental effect on the underlying spot market. On the contrary, it appears that there has been an improvement in the way that news is transmitted into prices following the onset of FFA trading. We can conjecture that by attracting more, and possibly better informed, participants into the market, FFA trading has assisted on the incorporation of information into spot prices more quickly. Thus, even those market agents who do not directly use the FFA market have benefited from the introduction of FFA trading.

In chapter 6, we investigated the risk management function of the FFA market. We examined the effectiveness of time-varying hedge ratios in reducing freight rate risk in four routes of the BPI. In- and out-of-sample tests indicate that in voyage routes (1 and 2) the relationship between spot and FFA prices is quite stable and market agents can use simple first-difference regression models in order to obtain optimum hedge ratios. In contrast, in time-charter routes (1A and 2A), it seems that the arrival of new information affects the relationship between spot and FFA prices, and therefore, time-varying hedging models should be preferred. Also the hedging effectiveness varies from one freight market to the other. This is because spot prices, and consequently FFA quotes, are affected by different trading and regional economic conditions. Market agents can benefit from this result by developing appropriate hedge ratios in each route, and thus, controlling their freight rate risk more efficiently. Shipowning companies with vessels operating worldwide or trading companies that transport commodities to different parts of the world can use the FFA contracts to reduce their freight rate risk, since the variability of their cash-flows can be explained by the fluctuations of the spot routes.

Despite the mixed evidence provided in favour of the time-varying hedge ratios in the FFA market, and despite the fact that FFA contracts provide better hedging opportunities than the BIFFEX contract examined by Kavussanos and Nomikos (2000a, 2000b), the freight rate risk reduction across the four investigated routes is lower than that evidenced in other commodity and financial markets in the literature. The currently low trading volume, the way that FFA brokers estimate their FFA quotes, and the lack of the cost-of-carry arbitrage relationship of storable assets, that keeps spot and derivatives prices close together, may provide explanations about the finding that spot price fluctuations of the investigated trading routes are not accurately tracked by the FFA prices.

In chapter 7, we examined the relationship between expected volatility and bid-ask spreads. The results indicate that there is a positive relationship between bid-ask spreads and expected price volatility in routes 1, 2, and 2A, after other factors are controlled. In contrast, in route 1A we do not observe a significant relationship between bid-ask spreads and expected volatility, and this finding may be explained by the thin trading of the FFA contracts in the latter route. The results of this study provide a better understanding of the movements of FFA prices, and the consequent effect in transactions costs. Market agents using the information of the behaviour of the bid-ask spreads can have a better insight about the timing of their FFA transactions and the future direction of the FFA market, as a widening bid-ask spreads corresponds to an anticipation of increased future volatility. More specifically, traders, speculators, hedgers, and arbitrageurs alike are interested in extracting information from these variables to know how their reaction to new information can be used in predicting future prices.

Finally, in chapter 8, we investigated the performance of different time-series models in generating short-term forecasts of the spot and FFA prices. More specifically, we examined the forecasting performance of a VECM of spot and FFA prices. The forecasts from this model were compared to forecasts generated by VAR, SURE-VECM, ARIMA, and the RW model. Following Tashman (2000), we created independent non-overlapping forecasts by generating *N*-period ahead multiple forecast sets, generated from recursively estimated model parameters.

We find that in the routes (1 and 2A) where the cointegrating vector is restricted to be the lagged basis, the VECM outperforms the VAR model and in the routes (1A and 2) where the cointegrating vector is not restricted to be the lagged basis, the VAR outperforms the VECM. More specifically, while conditioning spot returns on lagged FFA returns generates more accurate forecasts of the spot prices for all forecast horizons, conditioning FFA returns on lagged spot returns enhance the forecasting accuracy of FFA prices up to 4-days ahead forecasts in routes 1, 1A, and 2A and up to 10-days ahead forecasts in route 2A. For longer forecast horizons the univariate Box-Jenkins (1970) ARIMA model produces forecasts as accurate as those by the other time-series models in all trading routes, and therefore, there is little gain in forecasting accuracy by employing multivariate time-series models. Thus, market agents by selecting the appropriate time-series model for forecasting purposes can design more efficient investment and speculative trading strategies.

Concluding, this thesis examines the performance of the price discovery and risk management functions of the FFA market. These two functions represent the major benefits that derivatives markets provide to economic agents and are often presented as the justification for derivatives trading. The thesis also investigates the impact of the introduction of FFA trading in spot market price volatility, the relationship between bid-ask spreads and expected FFA volatility, and whether the forecastability of spot prices can be improved by incorporating the information contained in the FFA prices, thus providing further evidence on the informational properties of FFA prices in the market.

9.3. POLICY IMPLICATIONS

The success of a derivatives (futures or forward) contract is dependent upon the contract providing benefits to economic agents, over and above the benefits they can get from the spot market alone. These benefits are price discovery and risk management through hedging. If the market does not perform one or both of these functions satisfactorily, then market agents have no reasons to trade in the derivatives market, which eventually leads to loss of trading interest by the market agents.

The results of this thesis indicate that the FFA market performs its price discovery function efficiently. FFA prices contribute to the discovery of new information about current and expected spot prices. Therefore, market agents receive accurate signals from the FFA prices, regarding the future course of spot prices, and can use the information generated by these prices so as to guide their decisions in the physical market.

Moreover, it appears that there has been an improvement in the way that news is transmitted into prices following the onset of FFA trading. We can conjecture that by attracting more, and possibly better informed, participants into the market, FFA trading has assisted on the incorporation of information into spot prices more quickly. Our findings provide regulators and practitioners with important insights into the FFA trading - spot market price volatility relationship as FFA trading lead to new channels of information being provided, more information due to more traders, and a reduction in uniformed investors. Thus, the FFA contracts provide a useful service and calls for their regulation, by the FFABA and the FIFC, are unwarranted.

On the contrary, the findings for the risk management function of the FFA market are not so promising. The risk reduction in the spot routes compares very poorly to the risk reduction evidenced in other commodity and financial derivatives market; for instance, the greatest in-sample variance reduction is 35.86% in route 2A and the highest out-of-sample variance reduction is 32.16% in route 1A, while the variance reductions evidenced in other markets in the literature range from 57.06% to 97.91%. The underlying reasons for this poor hedging performance are the currently low trading volume, the way that FFA brokers estimate their FFA quotes, and the lack of the cost-of-carry arbitrage relationship of storable assets, that keeps spot and derivatives prices close together. As a result, the FFA contract cannot provide risk reduction to the extent that is observed in other markets. Awareness and increased trading activity of freight derivatives trades may promote the hedging efficiency of the contracts. As a policy action, the FFABA, the FIFC, and the Baltic Exchange should: first, advertise more this derivatives market through marketing campaigns in order to attract the much needed volume; and second, monitor more the way that FFA brokers are conducting their FFA trades in order to verify that the daily FFA quotes are the best available (like a price discovery mechanism) before they are published to market participants.

The results of this thesis also indicate that there is a positive relationship between bid-ask spreads and expected price volatility in most of the investigated routes, after other factors are controlled. From a policy perspective, the issue is important because of its implications for the analysis of market liquidity and its relationship with risk. Using bid-ask spreads as a proxy of market liquidity, a market can be considered to be liquid when large transactions can be executed with a small impact on prices (Galati, 2000). Policy makers and regulators are interested in knowing how changes in these variables impact the market activity.

Concluding, the Baltic Exchange, the FFA brokers, the FFABA, and the FIFC are thinking ways to improve the use of the FFA contract and increase its trading activity, by a possible launch of a FFA information system, a revision of the contract and other initiatives. As an example, IMAREX, a web-based exchange for trading OTC freight derivatives, started trading during November 2001. IMAREX uses a clearing-house for the clearing of standardised listed and other OTC derivatives. Moreover, the FFABA revised the FFA contract during August 2002 in order to include default and termination procedures. It is clear that there is considerable interest in the shipping industry for the introduction of risk management facilities and a considerable amount of time, effort and money is being channeled into the establishment of the provision of this service.

9.4. SUGGESTIONS FOR FURTHER RESEARCH

The theme of the research in this thesis was to investigate the price discovery and risk management functions of the FFA market using four panamax trading routes (1, 1A, 2, and 2A). This thesis also considered the impact of the introduction of FFA trading on the spot market price volatility, the relationship between bid-ask spreads and expected volatility in the FFA market, and the issue of forecasting spot and FFA prices. The motivation for investigating these issues derives from the fact that these are the most important functions of any derivatives market, and hence, the findings of this thesis are of particular importance to those involved in trading and regulating the FFA market. Empirical investigation presented in chapters 3 to 8 of this thesis, although quite comprehensive, is subjected to certain limitations due to space and time constraints and availability of data. Therefore, the aim of this section is to suggest directions in which fruitful future research can be undertaken to improve and enhance our knowledge in the area of freight derivatives.

A natural suggestion for further research would involve undertaking similar investigations for the remaining BPI routes (3, 3A and 4), the constituent trading routes of the BCI and BHMI indices of the dry-bulk sector, and the constituent trading routes of the BITR index of the wet-bulk sector, as tanker FFA contracts have become important risk management tools in the oil and energy industries, provided that sufficient data will be available. This would enhance our understanding of the role and functioning of the FFA contracts in general and provide investors and policy makers with important information. It would be interesting to further develop the work carried out in this thesis. Regarding the price discovery function of the market, future research should study the ability of end of month FFA prices to predict the realised spot prices on the maturity day of the contract. Thus, the purpose of such forecasting exercise is to investigate whether one can obtain more accurate forecasts of the settlement prices one-, two-, and three-months ahead by employing time-series models rather using the readily available information provided by FFA prices.

For the impact of the introduction of FFA trading on spot market price volatility it would be interesting to incorporate in the model more market-wide factors that represent major world economic conditions, which are likely to impact spot price volatility, such as the industrial production, grain exports and international trade. Thus, we could have a greater understanding whether the introduction of FFA trading is the only factor responsible for the reduction in the spot market volatility. Furthermore, it would be worthy of note if proxies for political and economic developments could be incorporated in the model, because different trading routes are subject to different regulatory and economic conditions and regimes.

There is also ample scope for further research in the hedging performance of the market. The current study can be extended to investigate the effectiveness of time-varying ratios in reducing freight rate risk in a portfolio of freight routes, rather than in a single route. Shipowners who operate a fleet of vessels across different shipping routes or charterers who want to transport their commodities to different parts of the world would be interested with the findings of such hedging exercise. For example, Gagnon *et al.* (1998) examine the effectiveness of time-varying hedge ratios in hedging a portfolio of foreign currencies and compare the performance of these hedges to the case where the currencies are hedged in isolation. They report, however, that by taking the portfolio effects into consideration, the increase in the hedging effectiveness is small, only 1.88%. Whether similar findings will emerge by considering, for instance, a portfolio of voyage routes, or a portfolio of time-charter routes is an issue worth investigating.

Turning next into the relationship between bid-ask spreads and expected volatility, the current study can be extended by computing several alternative measures of historical volatility or implied volatility extracted from FFA option prices and see whether similar findings with this study emerge. Moreover, FFA volume can be used as a measure of trading activity and can be included in the proposed model in order to examine the relationships between bid-ask spreads, volume and expected volatility, provided that volume data will be publicly available. Finally, it would be interesting in the area of forecasting to investigate the performance of alternative models for predicting spot and FFA price volatility. The alternative models can contain both simple models such as the random walk and smoothing models and complex models such as ARCH-type and stochastic volatility models. Market agents can potentially benefit by having accurate forecasts of both spot and FFA volatilities since they will be able to design more effective investment and speculative strategies. For example, Yu (2002) uses nine alternative models for predicting stock price volatility and argues that the stochastic volatility model provides the best performance among all the candidates and the simple regression and exponentially moving average models perform the worst, in contrast to the results found in various markets.

APPENDIX

FORWARD FREIGHT AGREEMENT BROKERS ASSOCIATION ("FFABA") FORWARD FREIGHT AGREEMENT (AUGUST 2002)

File Ref: «REF» **Contract Date:** «DATE»

This Forward Freight Agreement is made this day of «DATE» in London between:

1. **«BUYER»** and 2. **«SELLER»**
("the Buyer") ("the Seller") on the following terms and conditions.

1) Contract Route: As per Route(s) XX of the [Baltic Panamax Index] [Baltic Handy Index] [Baltic Cape Size Index] as defined on the Contract Date including any forthcoming amendments published at the Contract Date which will become effective prior to the settlement of this Agreement.

2) Contract Rate: USD «RATE» per [ton]/[day]

3) Contract Quantity: «QUANTITY» [tons] [[days] each Contract Month]

4) Contract Month(s): «MONTH»

5) Settlement Date(s): «MONTH»

6) Settlement Period: Settlement Period defined as all the Baltic Exchange Index publication days of the Contract Month **(or state the number of days)** up to and including the Settlement Date.

7) Settlement Rate: The Settlement Rate shall be the average of the rates for the Contract Route published by the Baltic Exchange over each Settlement Period. If for any reason the Baltic Exchange cannot provide any rate required for establishing the Settlement Rate, then the current Chairman of the Forward Freight Agreement Brokers Association ("FFABA") shall be instructed by either party to form a panel comprising of a minimum of three independent brokers (the "Panel") to establish an appropriate rate which will be final and binding on both parties. The parties agree not to bring any proceedings of any kind and to jointly and severally indemnify and hold harmless this Panel, the Baltic Exchange, the FFABA and their members against all liability, claims, demands, costs and expenses arising directly or indirectly as a result of the Panel's decision.

8) Settlement Sum: The Settlement Sum is the difference between the Contract Rate and the Settlement Rate multiplied by the Contract Quantity. If the Settlement Rate is greater than the Contract Rate, the Seller shall pay the Buyer the Settlement Sum. If the Settlement Rate is less than the Contract Rate, the Buyer shall pay the Seller the Settlement Sum.

9) Payment Procedure and Obligations:

(a) The payment obligation of each party as provided below is subject to the condition precedent that no Termination Event(s) (or notice period provided for in clause 12 (i)) with respect to the other party has occurred and is continuing. In the event that a Termination Event does not result in the termination of this Agreement (as provided for in clause 12) this condition precedent will no longer apply.

(b) The Settlement Sum must be received within five clear London Banking Days (to mean between the hours of ten am until four pm) after the Settlement Date. The parties are obliged to provide each other with their respective bank remittance details, and invoice if requested, in order to facilitate timely payment. Payment of the settlement sum shall be made telegraphically in full in United States Dollars. Payment shall be made without deduction, set off or counterclaim save as provided for under clause 11 below. The costs incurred in effective payment shall be for the account of the payor. Payment may only be effected directly between the parties.

(c) Payment is "received" for the purposes of clause 9(b) when the Settlement Sum has been received into the bank account designated by the payee.

(d) If receipt of payment is delayed beyond the period referred to in clause 9(b) above solely as a result of proven clerical and/or banking error then the payee shall give the payor written notice granting the payor the opportunity to rectify the error within three clear London Banking Days of such written notice.

10) Capacity and Solvency: Each party warrants (which warranty shall continue to apply throughout the duration of this Agreement) at the time of entering into this Agreement that:

(a) It is duly incorporated and validly exists under the laws of its domicile and is solvent;

(b) It has the power to execute, deliver and perform this Agreement;

(c) All regulatory, governmental and other consents that are required to have been obtained by it with respect to this Agreement have been obtained and are in full force and effect and all conditions of any such consents have been complied with.

(d) In the event that either party to this Agreement is a person domiciled in the United States, or a corporation incorporated in the United States for a body [[corporation]] with its principal place of business in the United States], that party represents to the other party that its is an 'eligible swap participant' as defined by the United States Commodities Futures Trading Commission in C.F.R. Section 35.1(b) (2).

11) Payment Netting: If the Settlement Date(s) for this Agreement and any other forward freight Agreement(s) entered into between the parties shall fall on the same day and in the same currency, payments shall be made on a net basis.

12) Termination Events: In the event either party (the "Non-Performing Party") shall:

(i) Fail to honour its obligations (whether totally or partially) the other party in accordance with clause 9 if such failure is not remedied within four clear London Banking Days after written notice of such failure (pursuant to this sub paragraph) is given to the party; or

(ii) be proven to have made a warranty under clause 10 that was incorrect or misleading in any material respect or be proven to have made a warranty under clause 10 which is no longer sustainable; or

(iii) petition or otherwise commence or authorize the commencement of proceedings under any bankruptcy or similar insolvency law for the protection of creditors or have any such petition filed or proceedings commenced against it or its assets; or

(iv) institute or have instituted against it a proceeding seeking a judgment of bankruptcy or insolvency or a petition is presented for its winding up or liquidation; or

(v) fail to honour its obligations to the other party in accordance with clause 19 below (if clause 19 applies)

(each event (i), (ii), (iii), (iv), (v) shall be referred to as the "Termination Event").

the other party (the "Performing Party") shall (save in the case of a Termination Event (iii) or (iv) where this Agreement shall be automatically terminated (and any overall monetary gains or losses, costs and expenses calculated) immediately preceding the presentation of the relevant petition or the institution of the relevant proceedings if the Termination Event specified in (iii) and (iv) is governed by a system of law that does not permit termination to take place after the occurrence of a Termination Event) have the right immediately (but latest within seven clear London Banking Days from the Termination Event) to terminate this Agreement and to calculate in good faith its overall monetary gains or losses under this Agreement and its costs and expenses reasonably incurred in terminating this Agreement. The Performing Party shall aggregate any monetary gains or losses, costs and expenses with respect to this Agreement into a single amount. The Performing Party will arrange for such single amount to be certified, as commercially reasonable, by an impartial FFABA broker (the "Certified Amount"). The Certified Amount will be final and binding on both parties. The Performing Party shall notify in writing the Non-Performing Party of any Certified Amount owed. The Non-Performing party shall arrange prompt remittance. The Performing party shall be entitled, in its option and discretion, to set off against any Certified Amount owed by it, any amounts payable to the Non-Performing Party under this Agreement or any other agreement to prompt remittance.

13) Commission: Each of the parties is jointly and severally liable to pay brokers' commission within five clear banking days of the Contract Date. An invoice will be provided.

14) Non-Assignability: This Agreement is non-assignable unless otherwise agreed in writing between the parties.

15) Principal to Principal: This is a principal to principal Agreement with settlement directly between the two parties. Both parties agree that [brokers name] and any impartial FFABA broker (referred to clause 12) shall be under no legal liability in relation to this Agreement. Both parties agree jointly and severally to indemnify and hold harmless [brokers name] and any impartial FFABA broker against all actions, including but not limited to all claims, demands, liabilities, damages, costs and expenses both from the two parties and any third party. Claims, demands, liabilities, damages, costs and expenses suffered or incurred are to be settled directly by or between the two parties.

16) Entire Agreement: Each party confirms that it has taken its own independent financial, legal and tax counsel prior to entering into this Agreement and is not relying upon any advice, counsel or representations made by the other party.

17) Telephone Recording: Each party reiterates their consent to the recording of telephone conversations in connection with this Agreement.

18) Law and Jurisdiction: This Agreement shall be governed by and construed in accordance with English law and subject to the non-exclusive jurisdiction of the High Court of Justice in London, England. Proceedings may be validly served upon either party by sending the same by ordinary post and/or by fax to the addresses and/or fax numbers for each party given above.

19) Guarantee Clause: The Seller [Buyer] shall procure promptly the generation of a guarantee from [specify guarantor] in the attached form. The guarantee must be finalized and signed by [state date] latest. Clause 19 only applies if completed.

Signed for the Buyer by........................	Signed for the Seller by..........................
[printed name]	[printed name]
Duly authorised signatory	Duly authorised signatory
Date:	Date:
(Company Seal or Stamp)	(Company Seal or Stamp)

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