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Risk Management, Price Discovery and Forecasting in the Freight Futures Market

by

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A Thesis Submitted for the Degree of PhD in Finance

City University Business School

Department of Shipping, Trade and Finance

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List of Abbreviations

ADF	Augmented Dickey-Fuller Unit Root Test
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average Model
BFI	Baltic Freight Index
BIFFEX	Baltic International Freight Futures Exchange
BPI	Baltic Panamax Index
DGP	Data Generating Process
ECT	Error Correction Term
EG	Engle and Granger Test for Cointegration
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GIR	Generalised Impulse Response
HEGY	Hylleberg, Engle, Granger and Yoo Seasonal Unit Root Test
$I(d)$	Integrated of Order d
LIFFE	London International Financial Futures Exchange
LL	Log Likelihood Function
LR	Likelihood Ratio Test
MAE	Mean Absolute Error
MLE	Maximum Likelihood Estimation
MVHR	Minimum Variance Hedge Ratio
OIR	Orthogonalised Impulse Response
OLS	Ordinary Least Squares
PP	Phillips-Perron Unit Root Test
QMLE	Quasi Maximum Likelihood Estimation
RMSE	Root Mean Squared Error
SBIC	Schwarz Bayesian Information Criterion
SUR	Seamingly Unrelated Regressions
VAR	Vector Autoregressive Model
VECM	Vector Error Correction Model

Table of Symbols

I_n	$n \times n$ Identity Matrix
S_t	Spot (BFI) Price at time t
F_t	Futures (BIFFEX) Price at time t
$F_{t;t-n}$	Futures (BIFFEX) Price at time $t-n$, for delivery at time t
Σ	2×2 Variance Covariance Matrix
H_t	2×2 Time-Varying Variance Covariance Matrix
$h_{SS,t}$	Time-Varying Variance of Spot Returns
$h_{FF,t}$	Time-Varying Variance of Futures Returns
$h_{SF,t}$	Time-Varying Covariance of Spot and Futures 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 $t-1$
\mathbf{X}'	Transpose of Matrix \mathbf{X}
$\text{Rank}(\mathbf{X})$	Rank of Matrix \mathbf{X}
\sim	Distributed as
iid	Independently and Identically 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. $\Delta S_t = S_t - S_{t-1}$
L	Lag operator e.g. $LS_t = S_{t-1}$
\forall	For all
γ	Hedge Ratio
γ_t	Time-Varying Hedge Ratio at time t
ΔP_t	$= \Delta S_t - \gamma \Delta F_t =$ Change in the hedge portfolio from $t-1$ to t
$\sum_{i=1}^T$	Summation Operator from 1 to T

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Nikos Nomikos

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Declaration

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Risk Management, Price Discovery and Forecasting in the Freight Futures Market

Abstract

The success or failure of a futures contract is determined by its ability to provide benefits to economic agents, over and above the benefits they derive from the spot market. These benefits are price discovery and risk management through hedging. The extent to which different commodity and financial futures markets have served as efficient centres of price discovery and risk management has been the focus of considerable empirical research in the literature. The evidence however, on the BIFFEX market is very limited. This thesis therefore, by investigating these issues provides new evidence in the literature for a futures market with some unique characteristics such as the trading of a service and thin trading. Our empirical results are summarised as follows. First, the BIFFEX market performs its price discovery function efficiently since futures prices in the market contribute to the discovery of new information regarding both current and expected BFI prices. Second, futures prices fail to reduce market risk to the extent evidenced in other markets in the literature and, hence, the market does not perform its risk management function satisfactorily; this is thought to be the result of the heterogeneous composition of the underlying index. Sub-period analysis, corresponding to revisions in the composition of the underlying asset, indicates that the effectiveness of the BIFFEX contract as a centre for risk management and price discovery has strengthened over the recent years as a result of the more homogeneous composition of the index. This by itself indicates that the forthcoming elimination from the underlying index of the cargo routes for larger vessels, which will take place in November 1999, may have a beneficial impact on the market.

JEL Classification: G13

Keywords: Futures Markets, Unit Roots, Cointegration, Vector Error Correction Models, Multivariate GARCH Models, Generalised Impulse Response Analysis, Price Discovery, Hedging, Time-Varying Hedge Ratios, Forecasting, Shipping.

Chapter 1 : Introduction

1.1 Introduction

This chapter is an introduction to the thesis. In its four main sections, it considers the following issues. Firstly, it describes the two social benefits that futures markets, in general, provide to economic agents –risk management and price discovery. Secondly, it provides a background to the Baltic International Freight Futures Exchange (BIFFEX) contract, the only exchange-based futures contract available to market agents in the dry-bulk sector of the shipping industry; it describes the composition of its underlying asset, the Baltic Freight Index (BFI) and presents the unique characteristics of this service market that set it apart from other futures markets investigated so far in the literature. Thirdly, it presents the contribution of this thesis to the literature as well as the five research topics that are investigated here; these aim to identify whether the BIFFEX market is serving its risk management and price discovery functions efficiently and to the extent evidenced in other markets in the literature. Finally, this chapter concludes by outlining the organisation of the thesis.

1.2 Social Benefits of Futures Trading

Organised trading in commodity futures markets dates back to the mid 1860's with the opening of the Chicago Board of Trade in the US. Since then, the trading volume as well as the variety of futures contracts available for trading has increased dramatically. Currently, there are 45 futures exchanges world-wide, trading futures contracts for more than 60 different commodities such as agricultural, metallurgical, oil products, and financial securities such as foreign exchange, interest rates and stock indices. This growth in futures trading activity reflects the increased economic benefits that futures markets provide to market agents. These benefits are price discovery and risk management through hedging. Price discovery is the process of revealing information about current and expected spot prices through the futures markets. Risk management refers to hedgers using futures contracts to control their spot price risk. The dual roles of price discovery and hedging provide benefits that cannot be offered in the spot market alone and are often presented as the justification for futures trading (see e.g. Garbade and Silber, 1983).

1.2.1 The Price Discovery Role of Futures Markets

Physical and financial asset prices are determined through the interaction of supply and demand forces in an economy. Futures markets provide a mechanism through which the supply and demand for an asset are brought into alignment, both in present and over time. According to Edwards and Ma (1992), this process of revealing spot price information through the futures markets has two dimensions. First, futures prices provide a mechanism for market agents to form expectations regarding spot prices that will prevail in the future. Second, futures markets also help discover information regarding current spot prices. These two functions are described below.

1.2.1.1 Futures Prices and Expected Spot Prices

Futures contracts are traded for the delivery of an underlying asset at various points in the future, and as such, they reflect the current expectations of the market about the level of spot prices at those points in the future. If futures prices are higher than the current spot prices

then, this reflects the market's expectation that there will be an increased demand for that commodity in the future; lower futures prices, on the other hand, indicate that there will be a relative surplus of that commodity in the future. Therefore, through futures trading, information about the expectations of market participants regarding the future supply and demand balance for a commodity is assimilated to produce a single futures price for a later date.

By reflecting expectations about expected spot prices, futures prices trigger production and consumption decisions that reallocate the temporal supply and demand for a commodity in a way that promotes an efficient allocation of economic resources. In particular, future shortages of a commodity are alleviated by increased future production, while current shortages are alleviated by the deferral of current consumption to a later period when spot prices will be lower. Through the discovery of expected spot prices, futures prices can therefore help to smooth the supply and demand for a commodity over time, and, as a consequence, help to avoid the economic disbenefits that result from shortages in the flow of goods and services.

1.2.1.2 Futures Prices and Current spot prices

For futures markets to provide an efficient pricing mechanism, they must respond to new market information in the same way as the underlying spot prices. For instance, if new market information becomes available which suggests that the future supply of a commodity will be tighter than previously expected, the futures price for a later delivery period would be expected to increase. Also, one expects the spot price which is finally observed in the later period to be higher, given the new information, than it would have been without the new supply information. This suggests that spot and futures markets should price new information the same and that futures prices must lead the changes in the underlying spot prices. Therefore, it is through the futures market that investors send a collective message about how any new information is expected to impact the spot market and, subsequently, this information is transmitted to the spot market.

The existence of a strong causal linkage between futures and spot prices also has implications for the risk management function of the market; the greater the degree of interdependence

between spot and futures prices, the greater the effectiveness of the futures market in terms of hedging. If spot and futures prices respond in like fashion to the arrival of new market information, then they will tend to move closely together over time. As a result, market agents can use futures contracts for controlling efficiently their future spot price risk since, any loss in one market (spot or futures) will be offset by gains in the other market. On the other hand, if the futures and the underlying spot prices are not linked then the transmission of information between them will be impaired, thus reducing the effectiveness of the futures contract as a vehicle for risk management.

In summary, the existence and functioning of futures markets establish and make visible both current and expected spot prices. This availability of information reduces search costs and provides signals that guide production and consumption decisions in ways that contribute to a more efficient allocation of economic resources. Moreover, the benefits of price discovery accrue not only to the futures markets participants, but also to anyone else with an interest in the future value of the underlying asset.

1.2.2 The Risk Management Function of Futures Markets

Market agents are confronted with risks that arise from the ordinary conduct of their businesses. Futures markets provide a way in which these risks may be transferred to other individuals who are willing to bear them. The activity of trading futures contracts with the objective of reducing or controlling future spot price risk is called hedging. Hedging involves taking a position in the futures market that is opposite to the position that one already has in the spot market. For a futures contract to reduce spot price risk effectively, any gains or losses in the value of the spot position, due to changes in the spot prices, will have to be countered by offsetting changes in the value of the futures position.

Hedges are either short or long. A *short* or *selling* hedge involves selling futures contracts as a protection against a perceived decline in spot prices. For instance a shipowner, fearing that freight rates will fall, will always be a seller of futures. A *long* or *buying* hedge, on the other hand, involves buying futures as a protection against a price increase. For instance a charterer will be a buyer of futures contracts; this will enable him to protect his forward freight requirements in case the physical market rises, thus forcing him to pay higher freight rates.

The opportunity to control price risk through futures hedging is, according to Kolb (1997, p. 166), “ ... *perhaps the greatest contribution of futures markets to society*”. If price risk can be controlled efficiently through the futures markets then, profitable investment opportunities involving a high level of price risk, can be pursued and, as a result, society benefits economically.

The extent to which different commodity and financial futures markets have served as efficient centres of price discovery and risk management has been the focus of considerable empirical research in the literature. For instance, Stoll and Whaley (1990), Wahab and Lashgari (1993), Tse (1995) and Hung and Zhang (1995) investigate the price discovery role of the S&P-500, FTSE-100, Nikkei Stock Index and interest rate futures, respectively. Similarly, the issue of risk management has been investigated by Ederington (1979) and Franckle (1980) for the Treasury-bill futures; by Chen, et al. (1987) for the oil futures; by Figlewski (1984) and Lindahl (1992) for stock indices; and by Grammatikos and Saunders (1983) and Malliaris and Urrutia (1991) for currencies. The findings of these studies are discussed more thoroughly in section 1.4.

The evidence, however, on the BIFFEX market is very limited. It is the objective of this study, therefore, to investigate these issues and provide new evidence in the literature regarding a futures market which has some unique characteristics. These are described in more detail in the following section.

1.3 The Freight Futures Market; Introduction

The benefits of providing a futures market in freight rates had been obvious to market practitioners in the shipping industry since the 1960's. However, such a market was eventually established only in 1985. The reason is that the underlying asset of the market - the service of seaborne transportation - is not a physical commodity that can be delivered at the expiry of the futures contract; by its very definition, a futures contract is an agreement to deliver a specified quantity and grade of an identified commodity, at a fixed time in the future. This obstacle was overcome with the introduction of the cash settlement procedure of the stock index futures contracts in 1982.

When the underlying commodity is not suitable for actual physical delivery then an alternative is to deliver the cash value of the commodity at that time ¹. The development of the cash settlement procedure led to the creation, on 1 May 1985, of the Baltic International Freight Futures Exchange (BIFFEX) contract (Gray, 1990). The underlying asset which is delivered at the settlement date is the cash value of a freight rate index, the Baltic Freight Index (BFI). The BFI is a weighted average index of dry-cargo freight rates. Currently, the index is compiled from spot and time-charter freight rates of 11 component routes. The definitions of these routes and their weights in the composition of the BFI as they stand on April 98 - which is the ending period for the empirical analysis undertaken by this study - are presented in Table 1.1.

We can note that two distinct categories of vessels operate on the BFI routes; panamax vessels (routes 1, 1A, 2, 2A, 3, 3A and 9) which make up 70% of the index and capesize vessels (routes 6, 7, 8 and 10) which account for the remaining 30%. These two classes of vessels are used in the transportation of various commodities across different parts of the world. Capesize vessels (around 120,000 dead-weight tons (dwt)) transport iron ore mainly from South America and Australia and coal from North America and Australia. Panamax vessels (around 65,000 dwt) are used primarily to carry grain and coal from North America and Australia. For the period 1985 to November 1993 the BFI also comprised handysize

¹ Although the concept of cash settlement is primarily related to financial futures contracts - such as stock indices, interest rates and currencies - it is also common for physical commodities; for instance the Brent crude oil futures contract is also settled in cash.

vessels (around 30,000 dwt). These transport grain, mainly from North America, Argentina and Australia, and minor bulk products - such as sugar, fertilisers, steel and scrap, forest products, non-ferrous metals and salt - virtually from all over the world ².

Table 1.1

Baltic Freight Index: Definitions of the Constituent Routes as of April 1998

Route	Vessel Size (dwt)	Cargo	Route	Weight in BFI
1	55,000	Light Grain	US Gulf to ARA	10%
1A	70,000	T/C	Trans-Atlantic round T/C (duration 45-60 days)	10%
2	52,000	HSS	US Gulf to South Japan	10%
2A	70,000	T/C	Skaw Passero to Taiwan – Japan (50-60 days)	10%
3	52,000	HSS	US Pacific Coast to South Japan	10%
3A	70,000	T/C	Trans-Pacific round T/C (duration 35-50 days)	10%
6	120,000	Coal	Hampton Roads (US) to South Japan	7.5%
7	110,000	Coal	Hampton Roads (US) to ARA	7.5%
8	130,000	Coal	Queensland (Australia) to Rotterdam	7.5%
9	70,000	T/C	Japan – Korea to Skaw Passero (50-60 days)	10%
10	150,000	Iron Ore	Tubarao (Brazil) to Rotterdam	7.5%

Notes:

1. ARA stands for Amsterdam, Rotterdam (The Netherlands) and Antwerp (Belgium) area.
2. Skaw Passero is the strait between Denmark and Scandinavia. The countries of the remaining ports are in parentheses.
3. T/C denotes Time-Charter Routes.
4. HSS stands for Heavy Grain, Soya and Sorghum.
5. Source : The Baltic Exchange.

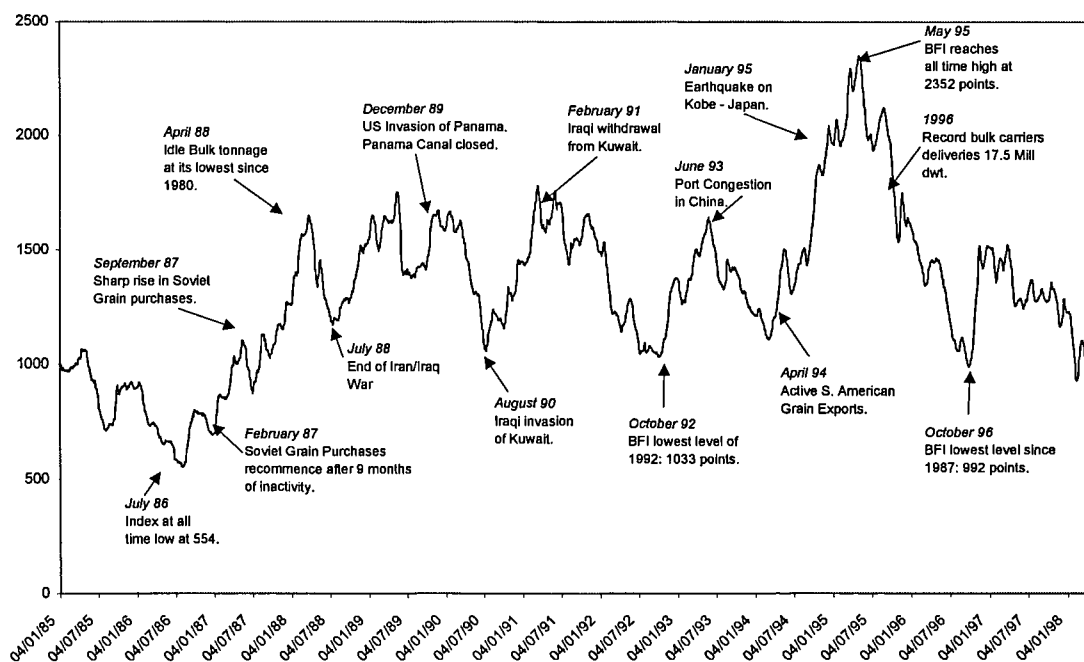
Since its inception, in January 1985, the BFI has been widely recognised by market practitioners as the most reliable indicator of the condition in the dry-bulk shipping markets. As Gray (1990) points out “ *the clarity of vision [provided by the BFI] is a very useful service to the shipping industry* ”. Figure 1.1 presents the history of the BFI over the period January 1985 to April 1998. Starting from an initial value of 1000 on 4 January 1985, the index drifted down over a two year period as a result of the prolonged recession in the dry-bulk market. The BFI reached its all-time low of 554 on 31 July 86. Gray (1990) indicates that this represents the lowest level to which the freight market can possibly go; in other words, the level below which the freight rate revenue earned from a particular voyage is not sufficient to cover the variable costs from the operation of the vessel. From its low point in 1986, the BFI then increased steadily, as the shipping markets were recovering from the recession, to a peak of 1650 in April 1988. Thereafter, the index fluctuated between 1780

² Revisions in the composition of the BFI are discussed in section 1.3.1.

points and 1033 points for a period of almost six years, till April 1994. From that point, freight rates strengthened significantly, primarily due to increased grain shipments from South America, and the BFI reached its all time high of 2352 in May 1995. This high level of freight rates, however, could not be sustained for long as increased deliveries of newly-built vessels - 17.5 m. dwt, the greatest ever level of deliveries, according to the 1996 Annual Shipping Outlook Report of SSY - suppressed the level of freight rates. As a result, the BFI dropped to 992 points in October 1996, its lowest point since 1987. The freight market has not recovered since then and the BFI has fluctuated around the 1000 points level.

Figure 1.1

Developments in the Dry Bulk Market and the Baltic Freight Index (5/01/85 – 30/04/98)



Source: SSY Futures Brokers

1.3.1 Revisions in the composition of the BFI

The underlying trade routes and their respective weightings in the composition of the BFI are under constant review to ensure that the index remains representative of developments and trends in the shipping markets and that it promotes the efficient functioning of the BIFFEX market (see e.g. Gray, 1990 and Cullinane et al., 1999). The major revisions in the definitions of the underlying routes and their weights in the composition of the BFI, since its inception, are presented in Table 1.2; the notes, in the same table, describe some minor amendments to the composition of the index.

We can broadly identify four different periods corresponding to differing compositions of the underlying index. During the first period (January 85 to 3 August 90), the BFI consisted of capesize, panamax and handysize spot freight rates. For the period up to 3 November 1988, the BFI consisted of 13 routes, of which, 3 were capesize routes (routes 6, 8 and 10 representing 15% of the index composition), 5 were panamax routes (routes 1, 2, 3, 7 and 9 which made up 65% of the index) and the remaining 5 were handysize routes (routes 4, 5, 11, 12 and 13 which accounted for the remaining 20%). After 4 November 1988, route 13 was deleted and the number of the BFI constituent routes was reduced to 12. The composition of the BFI was altered again on 6 August 1990 with the introduction of three time-charter routes (routes 1A, 3A and 5). Two additional time-charter routes were introduced on 5 February 1991 (route 2A) and on 5 February 1993 (route 9). The four handysize routes (i.e. routes 4, 5, 11 and 12) were eventually excluded from the composition of the index on 3 November 1993 and the number of the BFI constituent routes was reduced to 11; since then, the BFI represents only panamax and capesize spot and time-charter rates. Finally, in December 1998, the London International Financial Futures Exchange (LIFFE), the authority responsible for regulating the BIFFEX contract, announced that a new shipping index, the Baltic Panamax Index (BPI), will replace the BFI as the underlying asset of the futures contract from November 1999 onwards. The BPI, as its name implies, will consist of the seven panamax spot and time-charter routes (routes 1, 1A, 2, 2A, 3, 3A and 9) that currently compose the BFI. The weights of these routes in the composition of the new index are presented in Table 1.2. The major revisions of the BFI are also presented schematically in Figure 1.2.

Table 1.2
Baltic Freight Index: Changes in its composition since its inception

	Vessel Size (dwt)	Cargo	Route	4/01/85 – 3/11/88	4/11/88 – 3/08/90	6/08/90 – 4/02/91	5/02/91 – 4/02/93	5/02/93 – 2/11/93	3/11/93 – 5/05/98	6/05/98 – 29/10/99	From 1/11/99
1	55,000	Light Grain	US Gulf to ARA	20%	20%	10%	10%	10%	10%	10%	10%
1A	70,000	T/C	Trans-Atlantic round (duration 45 – 60 days)			10%	10%	10%	10%	10%	20%
2	52,000	HSS	US Gulf to South Japan	20%	20%	20%	10%	10%	10%	10%	12.5%
2A	70,000	T/C	Skaw Passero to Taiwan – Japan (50-60 days)				10%	10%	10%	10%	12.5%
3	52,000	HSS	US Pacific Coast to South Japan	15%	15%	7.50%	7.50%	7.50%	10%	10%	10%
3A	70,000	T/C	Trans-Pacific Round (35 – 50 days)			7.50%	7.50%	7.50%	10%	10%	20%
4	21,000	HSS	US Gulf to Venezuela	5%	5%	5%	5%	5%			
5	35,000	Barley	Antwerp to Jeddah (Saudi Arabia)	5%	5%		5%	5%			
	38,000	T/C	South America to Far East			5%					
6	120,000	Coal	Hampton Roads (US) to South Japan	5%	7.50%	7.50%	7.50%	7.50%	7.50%		
7	65,000	Coal	Hampton Roads (US) to ARA	5%	5%						
	110,000	Coal	Hampton Roads (US) to ARA			5%	5%	5%	7.50%	7.50%	
8	130,000	Coal	Queensland (Australia) to Rotterdam	5%	5%	5%	5%	5%	7.50%		
9	55,000	Coke	Vancouver (Canada) to Rotterdam	5%	5%	5%	5%				
	70,000	T/C	Japan – Korea to Skaw Passero (50 – 60 days)					5%	10%	10%	15%
10	90,000	Iron Ore	Monrovia (Liberia) to Rotterdam	5%	5%	5%					
	150,000	Iron Ore	Tubarao (Brazil) to Rotterdam				5%	5%	7.50%	7.50%	
11	25,000	Pig Iron	Vitoria (Brazil) to China	5%							
	25,000	Phosphate	Casablanca (Morocco) to West Coast India		2.50%	2.50%	2.50%	2.50%			
12	20,000	Potash	Hamburg (Germany) to West Coast India	2.50%							
	14,000	Phosphate	Aqaba (Jordan) to West Coast India		5%	5%	5%	5%			
13	14,000	Phosphate	Aqaba (Jordan) to West Coast India	2.50%							
14	140,000	Iron Ore	Tubarao (Brazil) to Beilun and Baoshan (China)							7.50%	
15	140,000	Coal	Richards Bay (US) to Rotterdam							7.50%	

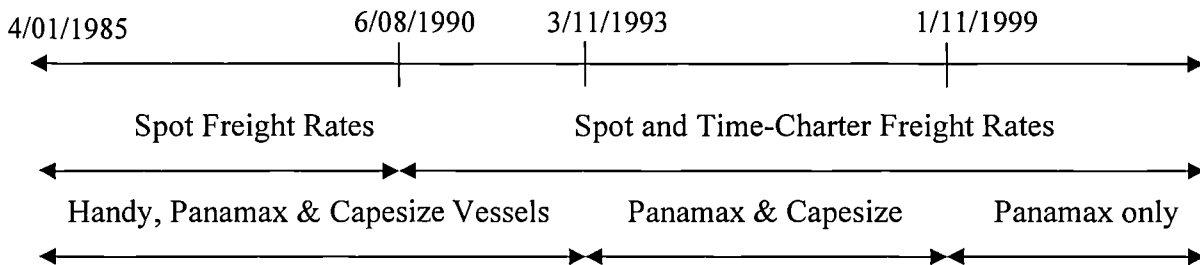
Notes: See the notes in Table 1.1 for the countries of the ports. Source : The Baltic Exchange

The following minor amendments of the Index are not presented in this Table.

1. As of 6 May 1998, Routes 2 and 3 refer to a 54,000 dwt panamax vessel.
2. Routes 1A, 2A, 3A and 9 were based on a 64,000 dwt panamax vessel for the period up to 2 February 1996.
3. Route 5 was 20,000 dwt vessel Barley from Antwerp to Red Sea for the period 1 January 1985 to 4 February 1986.
4. Route 7 was based on a 100,000 dwt vessel for the period 5 February 1991 to 4 February 1993.
5. Route 8 was based on a 110,000 dwt vessel for the period 1 January 1985 to 5 February 1992.
6. Route 10 was based on a 135,000 dwt vessel for the period 5 February 1991 to 2 August 1995.
7. Route 11 was 20,000 dwt Sugar from Recife (Brazil) to US East Coast for the period 1 January 1985 to 8 May 1986.

Figure 1.2

Major revisions of the BFI



These revisions are driven by the intention to generate an underlying index which promotes the effective functioning of the BIFFEX contract. For instance, Gray (1990) indicates that time-charter routes were introduced in order to facilitate market participants who wanted to hedge their freight rate risk on these routes. Similarly, Cullinane et al. (1999) indicate that the exclusion of the handysize routes was implemented in response to pressure from market agents, operating on panamax and capesize trade-routes, who wanted to increase the panamax and capesize representation on the index so as to enhance the performance of their hedges. Finally, the forthcoming exclusion of the capesize routes from the BFI, follows after an extensive review and consultation of LIFFE with BIFFEX market participants, who “*put a Panamax index at the top of their list of requirements*” since this is expected to increase the performance of hedges on the panamax routes ³.

The performance and functioning of a futures contract is dependent upon the contract providing benefits to economic agents, over and above the benefits they can get in the spot market alone. These benefits are price discovery and risk management. Therefore, it is interesting to investigate the temporal variability in the performance of the price discovery and risk management functions in the market, following the revisions in the composition of the BFI, since these revisions are driven by the intention to strengthen the performance of the market. This way, we can assess whether these revisions have actually affected the performance of the market, as it was anticipated by the regulatory authorities. Moreover, investigation of this issue is particularly timely given the imminent introduction of the BPI as

³ Source: “LIFFE to Introduce new BIFFEX Futures and Options Contracts,” LIFFE news, LIFFE Internet Site

the new underlying asset of the BIFFEX contract, since it enables us to provide some preliminary conjectures regarding the possible effect of this radical restructuring on the performance of the market. The impact of the BFI revisions on the functioning and the performance of the market is analysed empirically in chapter 6 of the thesis.

1.3.2 Calculation of the BFI

The BFI is calculated every market day by the Baltic Exchange, from data supplied by a panel of thirteen independent London shipbrokers, and is reported in the market at 1 p.m. London time. The panel is composed of companies who “... *are deemed by the Baltic Exchange to be of sufficient size, reputation and integrity to be good independent arbiters of the market*” Gray (1990; p. 29). Each shipbroking company submits its view of that day’s rate on each of the BFI constituent routes, at 11 a.m. London time. These rates are based either on actual reported fixtures, or in the absence of an actual fixture, reflect the panellist’s expert view of what the rate would be on that day if a fixture had been concluded. As a precautionary measure to prevent any individual broker influencing the market, the highest and lowest assessments for each trade route are excluded and a simple arithmetic average is taken of those that remain.

Table 1.3 shows an example of the BFI calculation, for 30 April 1998. The second column on the table, presents the average freight rate for each route, calculated as the arithmetic mean of the thirteen panellists’s reports of each route, on the day. These average rates are multiplied by a “Weighting Factor” (WF) (column 3 on the table) to return the contribution of each route to the BFI, in column 4.

The WF is a constant, unique for each route, and reflects the importance of each route to the BFI. For example, when the BFI was launched, on 4 January 1985, route 2 had a weighting of 20% (reduced to 10% on 5 February 91 - see Table 1.2). The BFI was set at 1000 points on that day. This meant that the average rate returned by the panellists on that day had to be adjusted so that the contribution of route 2 to the BFI would be 200 points (20% of 1000). The average rate returned by the panellists for this route was 14.286 \$/ton. The weighting

factor applied was therefore, $200/14.286 = 14$. When the weight of route 2 to the BFI was reduced to 10%, the WF was also reduced to 7. The WF for the remaining routes were calculated in a similar fashion. The sum of the contributions of each route then gives the BFI for the day, which is 1004 points.

Table 1.3

BFI and BFI Route Indices Calculation example on 30 April 1998

1 Route	2 Average Rate	3 Weighting Factor (WF)	4 Contribution to the BFI 2 x 3	5 Index Factor (IF)	6 Route Index 5 x 2
1	8.5571	11.01495	94.3	110.14949	943
1A	7,362.5000	0.01320	97.2	0.13203	972
2	18.4643	7.00000	129.2	70.00000	1292
2A	8,331.2500	0.01219	101.6	0.12194	1016
3	11.3286	10.90929	123.6	108.39269	1228
3A	6,681.2500	0.01282	85.7	0.12670	847
6	9.5438	7.10693	67.8	96.95291	925
7	4.0313	17.46321	70.4	205.37931	828
8	8.0875	8.67563	70.2	90.94570	736
9	6,756.2500	0.01489	100.6	0.11435	773
10	4.0188	15.72229	63.2	197.96603	796
BFI on 30/4/98			1004		

Notes:

- Average rates are in \$ / ton for routes 1, 2, 3, 6, 7, 8, and 10 and \$ /day for routes 1A, 2A, 3A, and 9.
- Weighting Factors and Index Factors, are calculated by the Baltic Exchange.
- The contribution of each route (column 4) is the product of the Average Rate (column 2) times the Weighting Factor (column 3). The sum of the contribution in the last row of the table gives the BFI for the day.
- The Route Indices (column 6) are the products of the Average Rate (column 2) times the Index Factor (column 5).

In addition to the BFI, the Baltic Exchange also produces daily route indices on each individual BFI route, presented in column 6 on the table. These route indices were set, like the BFI, at 1000 on 4 January 1985, and are calculated by multiplying the freight rate on each route with an individual “Index Factor” (IF) (column 5 in the table). Like the WF, the IF is a constant, unique for each route, and enables direct conversions from index levels into freight rates and vice versa. For example, on 4 January 1985, the freight rate on route 2 was multiplied by a factor of 70 so as to return a value of 1000 (i.e. $1000/14.286 = 70$). Similarly, an index level of 1292 for route 2 implies a freight rate of 18.4643 \$/ton ($= 1292/70$). The IF for the other routes are calculated in a similar way.

1.3.3 The Relationship Between the BFI and the BFI Routes

The BFI and each of its constituent routes, as they stand on 30 April 1998, are compared visually in Figure 1.3 to Figure 1.13. The graphs are for different time periods, corresponding to the period each route was part of the index (see Table 1.2).

We can see that some of the BFI routes stand either systematically above or systematically below the BFI. Gray (1990) indicates that such a pattern reflects the relative strength of this route compared to the average of the routes in the index. For instance, with the exception of route 6, the capesize routes (routes 7, 8 and 10) stand systematically below the BFI. This reflects the fact that capesize freight rates, in terms of \$/ton are, on average, below the panamax freight rates due to the larger cargo carrying capacity of the capesize vessels. Since the composition of the BFI is dominated by panamax vessels (70% of the index), this explains the observed pattern for the capesize routes.

Comparing next the panamax routes, we can note that all of them move closely together with the BFI, with the exception of routes 2 and 2A which are systematically above the BFI and route 9 which is systematically below the BFI. Routes 2 and 2A are long-haul routes and hence, freight rates for these routes are above freight rates for shorter routes. Route 9, in contrast, represents trade flows from Japan to Continent and is the return leg of route 2A. Since Japan is a major importer of grain and coal (the primary cargoes transported by panamax vessels), there are few dry bulk cargoes originating in Japan and, as a result, freight rates for this routes are low, compared to the other panamax routes ⁴.

⁴ SSY Consultancy, 1999 Annual Shipping Outlook Report.

Figure 1.3

BFI and Route 1 Prices; Daily Data (1/08/88 to 30/04/98)

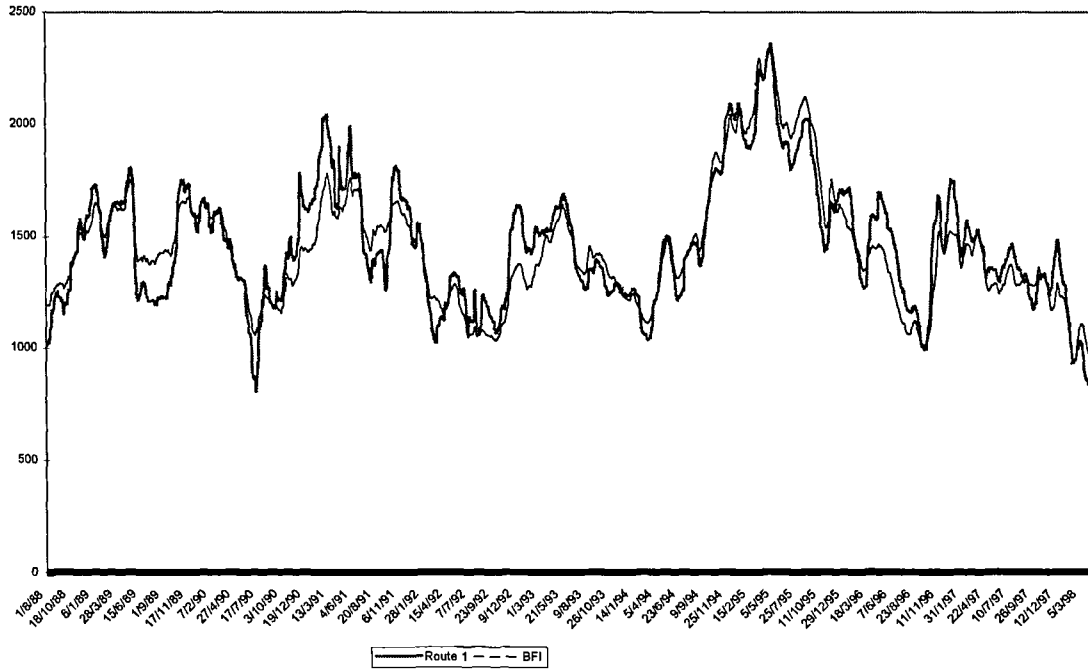


Figure 1.4

BFI and Route 1A Prices; Daily Data (6/08/90 to 30/04/98)

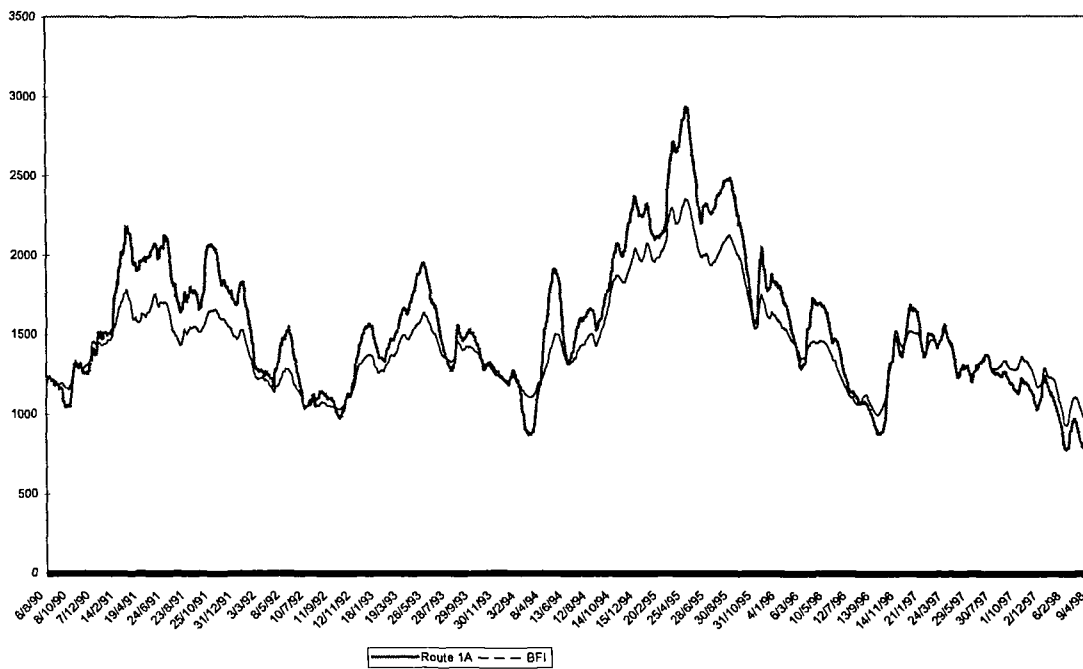


Figure 1.5

BFI and Route 2 Prices; Daily Data (1/08/88 to 30/04/98)

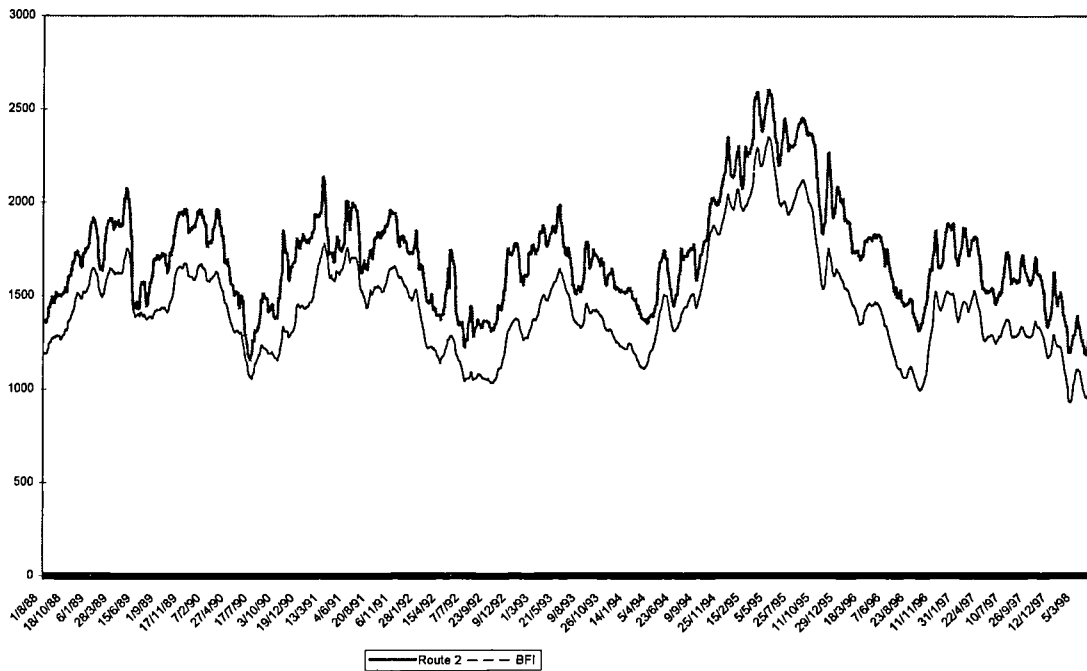


Figure 1.6

BFI and Route 2A Prices; Daily Data (5/02/91 to 30/04/98)

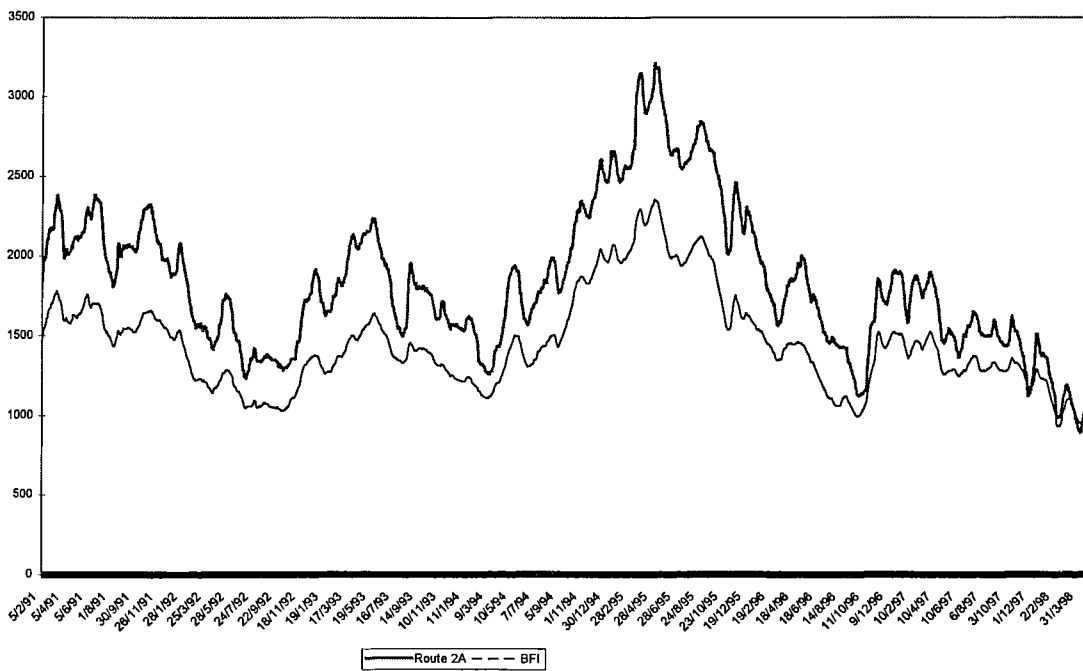


Figure 1.7

BFI and Route 3 Prices; Daily Data (1/08/88 to 30/04/98)

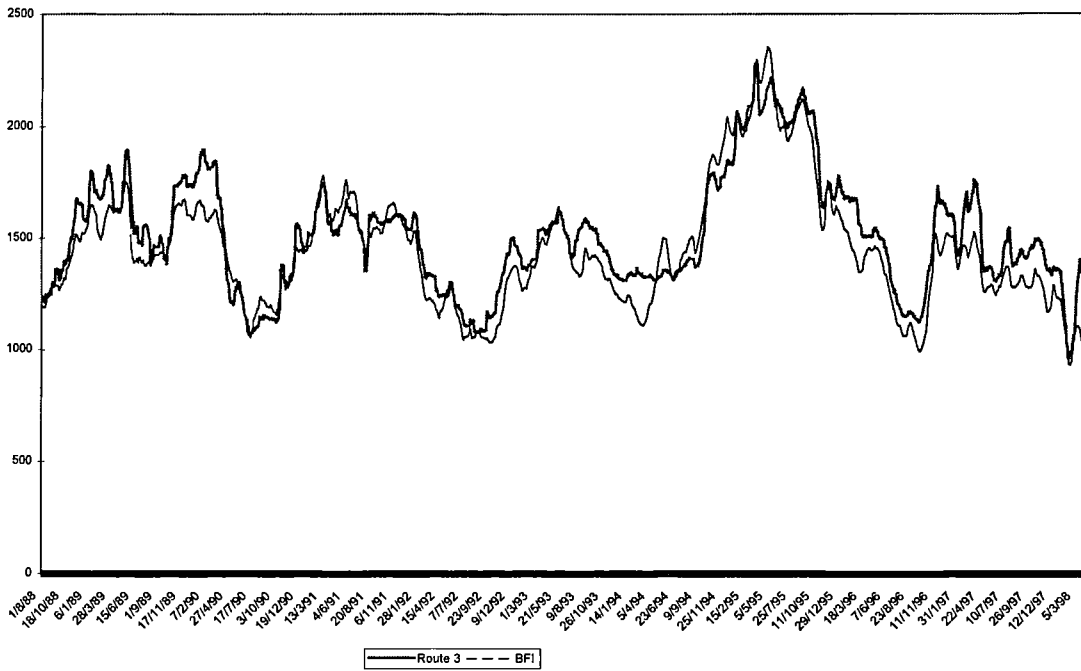


Figure 1.8

BFI and Route 3A Prices; Daily Data (6/08/90 to 30/04/98)

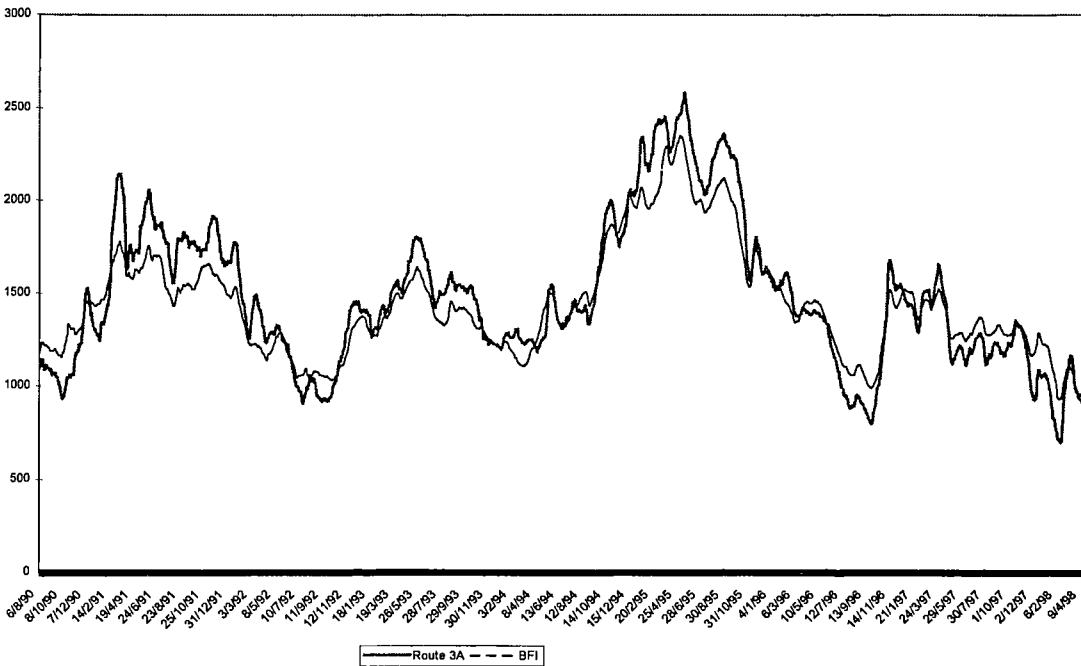


Figure 1.9

BFI and Route 6 Prices; Daily Data (1/08/88 to 30/04/98)

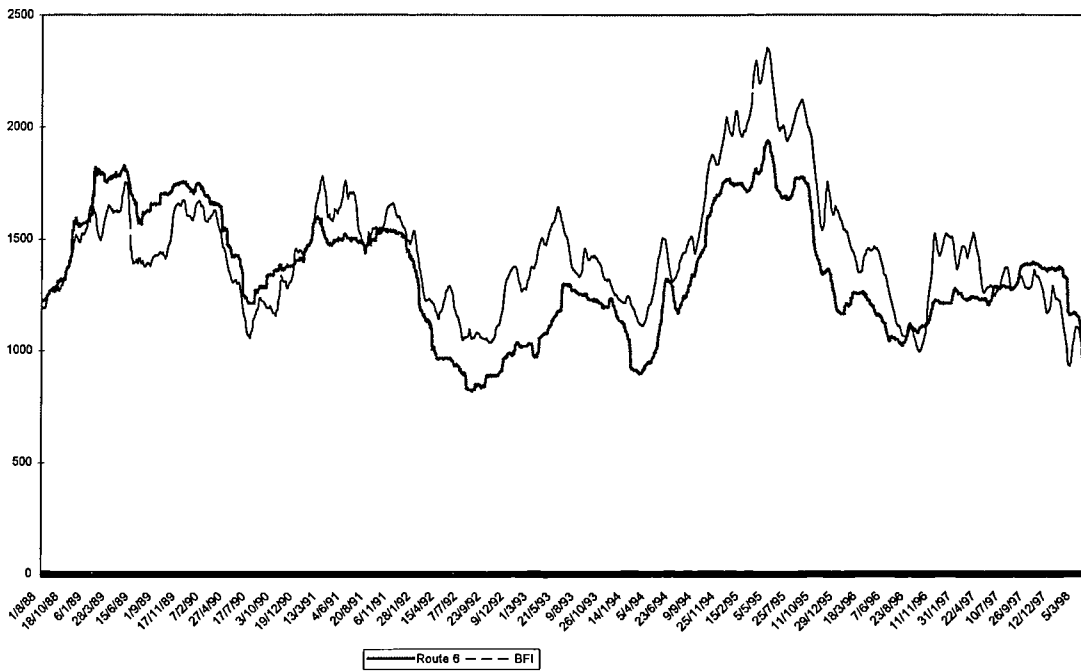


Figure 1.10

BFI and Route 7 Prices; Daily Data (5/02/91 to 30/04/98)

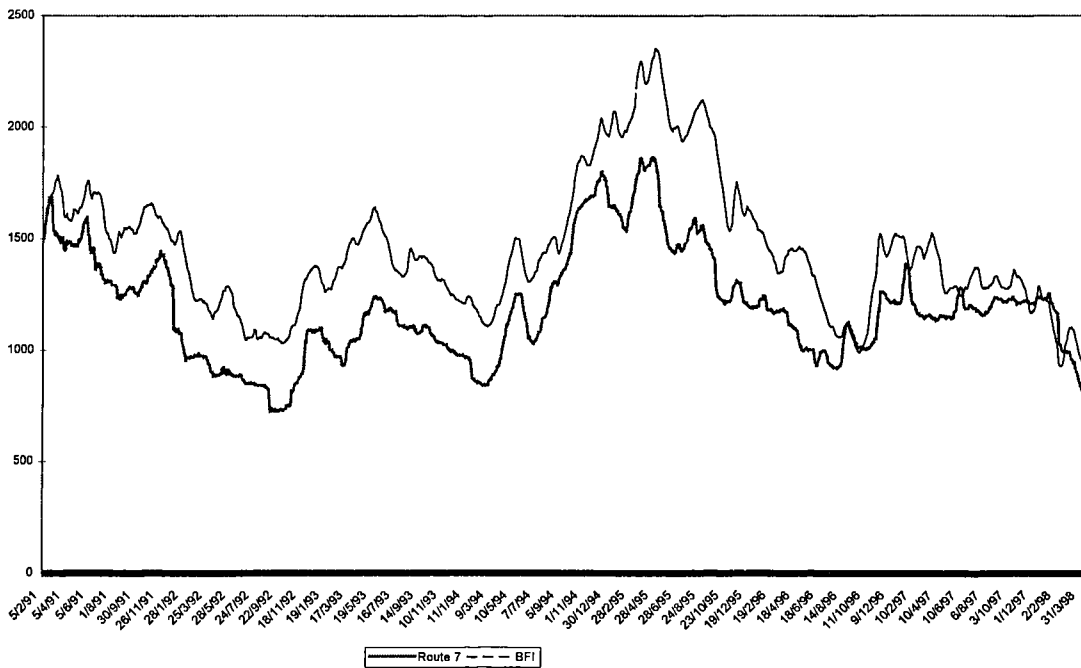


Figure 1.11

BFI and Route 8 Prices; Daily Data (1/08/88 to 30/04/98)

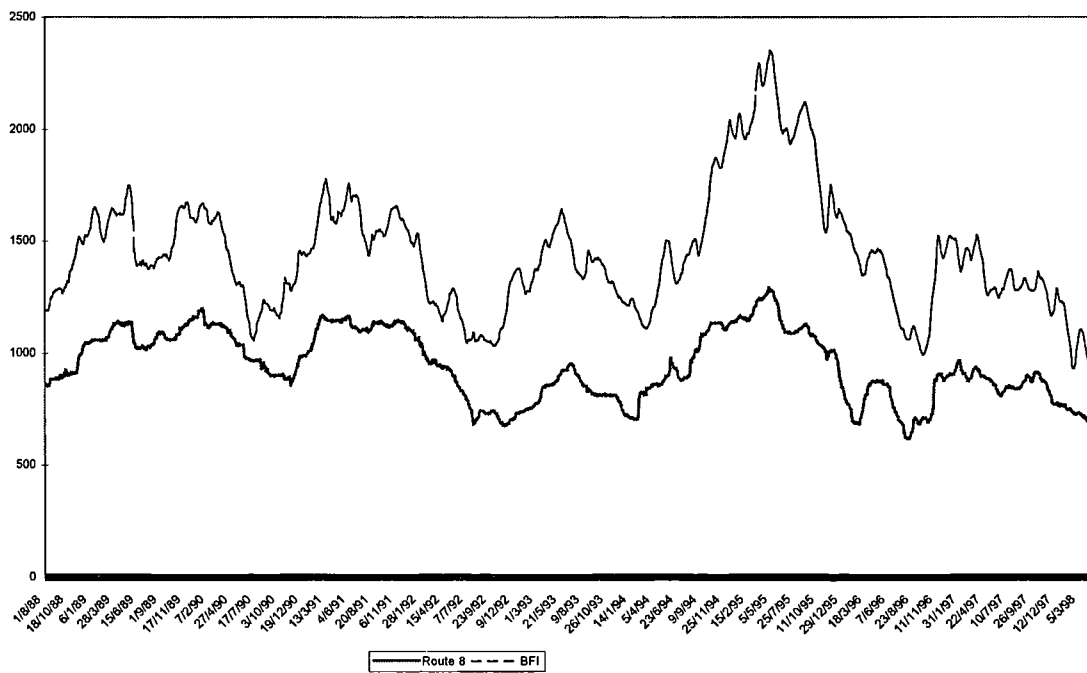


Figure 1.12

BFI and Route 9 Prices; Daily Data (5/02/93 to 30/04/98)

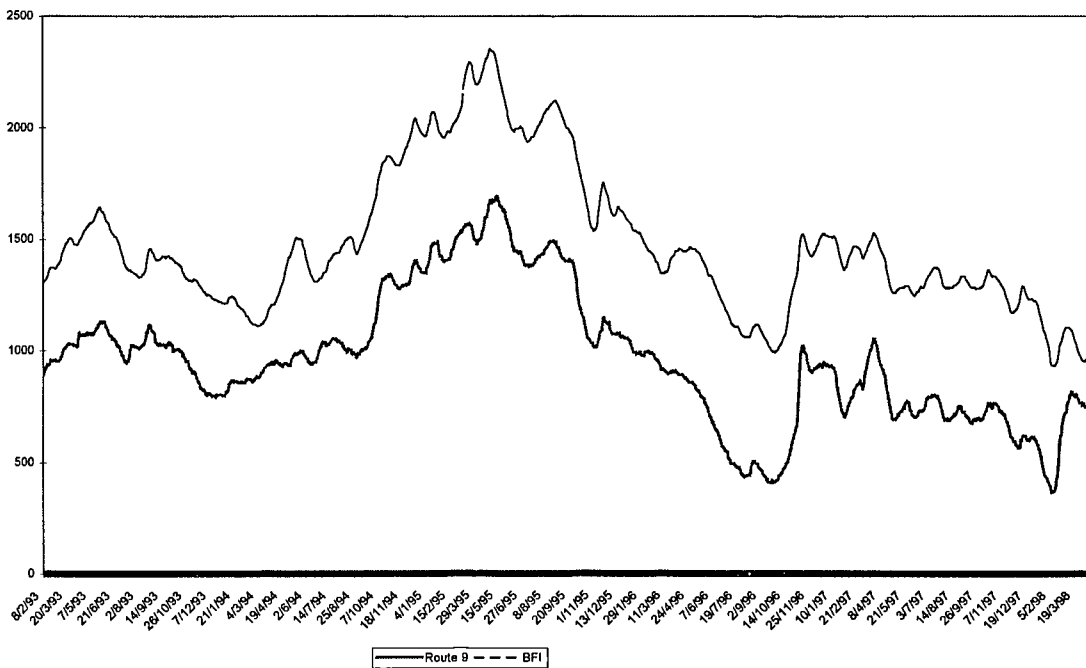
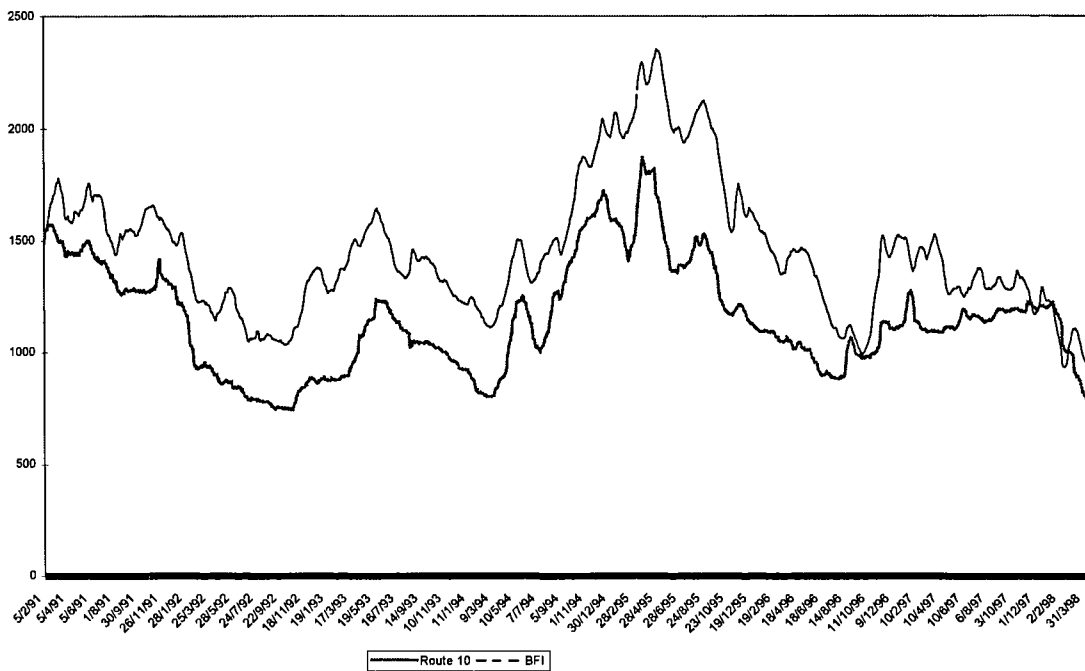


Figure 1.13

BFI and Route 10 Prices; Daily Data (5/02/91 to 30/04/98)



These graphs indicate that there are discrepancies in the levels of freight rates on the routes that constitute the BFI. However, the effectiveness of hedges against freight rate fluctuations on these routes is determined by the correlation of the first differences (not levels) of these routes with the BFI (see Ederington, 1979).

Table 1.4 presents the correlation matrix of the logarithmic price differences of the BFI with the BFI routes; the estimation period runs from 5 February 1993 to 30 April 1998, corresponding to the period after the last revisions in the composition of the BFI (see Table 1.2). The same table, also presents the arithmetic mean of the correlation coefficients across different categories of vessels and cargoes in the BFI. We can see that the panamax routes are more strongly correlated with the BFI than the capesize routes. More specifically, the average correlation of the panamax routes with the BFI, 0.755, is higher than that of the capesize routes, 0.408; this is expected given that the former represent 70% of the index.

Table 1.4

**Correlation Matrix of the logarithmic differences of BFI and BFI routes; Daily Data
(5/02/93 to 30/04/98)**

Route	1	1A	2	2A	3	3A	6	7	8	9	10	BFI
1	-											
1A	0.693	-										
2	0.555	0.624	-									
2A	0.602	0.769	0.719	-								
3	0.384	0.403	0.413	0.445	-							
3A	0.391	0.505	0.432	0.555	0.602	-						
6	0.214	0.261	0.183	0.224	0.201	0.272	-					
7	0.232	0.306	0.203	0.247	0.171	0.236	0.560	-				
8	0.173	0.157	0.110	0.120	0.123	0.193	0.277	0.273	-			
9	0.376	0.486	0.409	0.493	0.585	0.716	0.225	0.235	0.195	-		
10	0.268	0.300	0.207	0.247	0.151	0.218	0.556	0.702	0.293	0.191	-	
BFI	0.729	0.832	0.756	0.841	0.656	0.752	0.430	0.459	0.296	0.715	0.449	-
Arithmetic Mean of the Correlation Coefficients												
BFI with panamax routes					0.755	BFI with coal routes					0.395	
BFI with capesize					0.408	Panamax with panamax routes					0.531	
BFI with time-charter					0.785	Capesize with capesize routes					0.444	
BFI with grain routes					0.714	Panamax with capesize routes					0.209	

Notes:

- The correlation coefficients are based on logarithmic first differences of the daily prices of the BFI and the BFI routes in Table 1.1 for the period 5 February 1993 to 30 April 1998.

When we break down the panamax routes into their component spot grain routes and time-charter routes we can see that the latter are more strongly linked with the BFI. This is due to the following reasons. First, the time-charter routes are strongly correlated with their corresponding spot grain routes - the correlation coefficient of routes 1A and 1 is 69.3%, of routes 2A and 2 is 71.9% and, of routes 3A and 3 is 60.2% - which is in line with the notion that time-charter rates in the shipping freight markets, reflect the expectations of market agents regarding the expected level of spot rates. Second, the time-charter routes are also strongly correlated with each other since three of these routes (routes 2A, 3A and 9) reflect

cargo flows to and from the Far - East. In contrast, the correlation of the BFI with the coal capesize routes is only 39.5%; this reflects the low correlation of route 8, which is the only shipping route that originates in Australia, with the BFI, 29.6%, and the fact that the capesize coal routes account for a small portion, 22.5%, of the BFI.

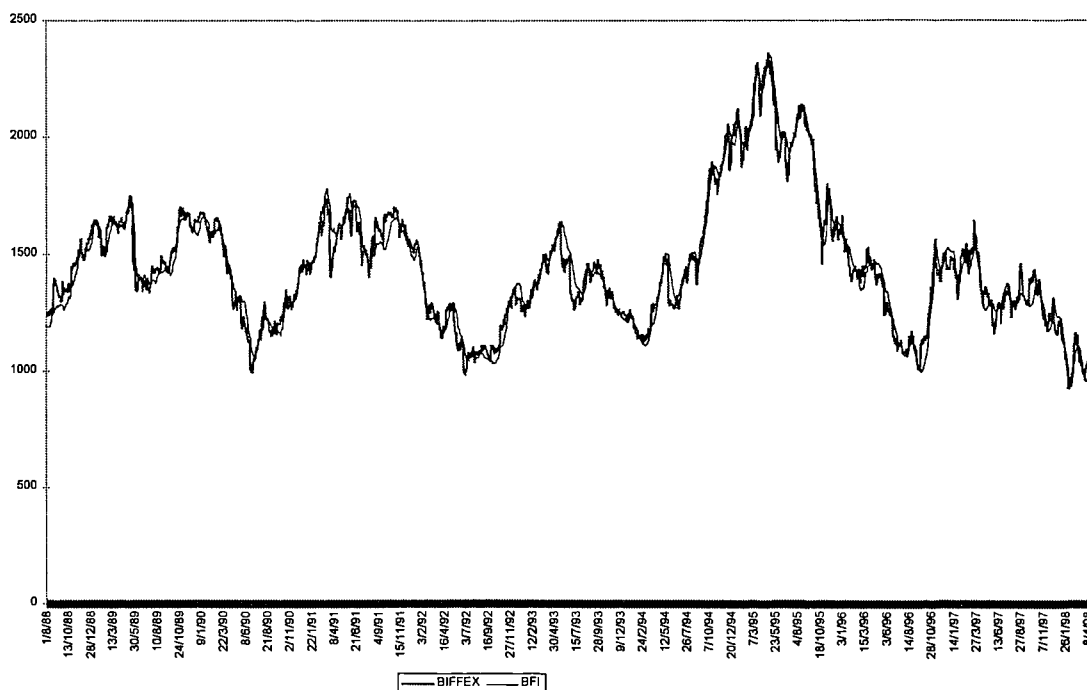
Overall, we can see that the BFI consists of two distinct groups of underlying shipping routes; panamax and capesize. The within-group correlation is strong in both cases although their correlation with the other group is weaker; the average correlation for all the panamax routes is 53.1% while the average correlation for the capesize routes is 44.4%. On the other hand the average correlation between panamax and capesize routes is only 20.9%. The stronger correlation of the panamax routes, compared to the capesize routes, with the BFI, also suggests that freight rate fluctuations on these routes can be hedged more effectively than on the capesize routes. The variability of the futures hedging performance across the different shipping routes as well as across different time-periods, corresponding to revisions in the composition of the underlying index, is an issue which is investigated empirically in this study.

1.3.4 Description and Terms of the BIFFEX Contract

The BIFFEX contract is traded at the London International Financial Futures Exchange (LIFFE). Trading takes place every business day from 10:15 to 12:30 p.m. and from 14:30 to 16:40 p.m. London time. For the period August 1985 to July 1988 there were four contract months traded in the market; January, April, July and October (the “quarterlies”) trading for delivery up to 2 years ahead. From August 1988, trading in “spot” and “prompt” months - i.e. the current month and the following month - was introduced. In other words, since August 1988, at any given month the following contracts were traded; the current month, the following month and January, April, July and October up to 18 months ahead. This trading pattern was altered again in October 1991 when trading in a second “prompt” month was introduced. Therefore, since then, the following contracts are always traded; the current month, the following two months and January, April, July and October up to 18 months ahead. For instance, on May 1, 1998, contracts for delivery in the following months were available in the market; May, June, July, October, January 99, April 99, July 99 and October 99 (8 contracts in total).

Figure 1.14

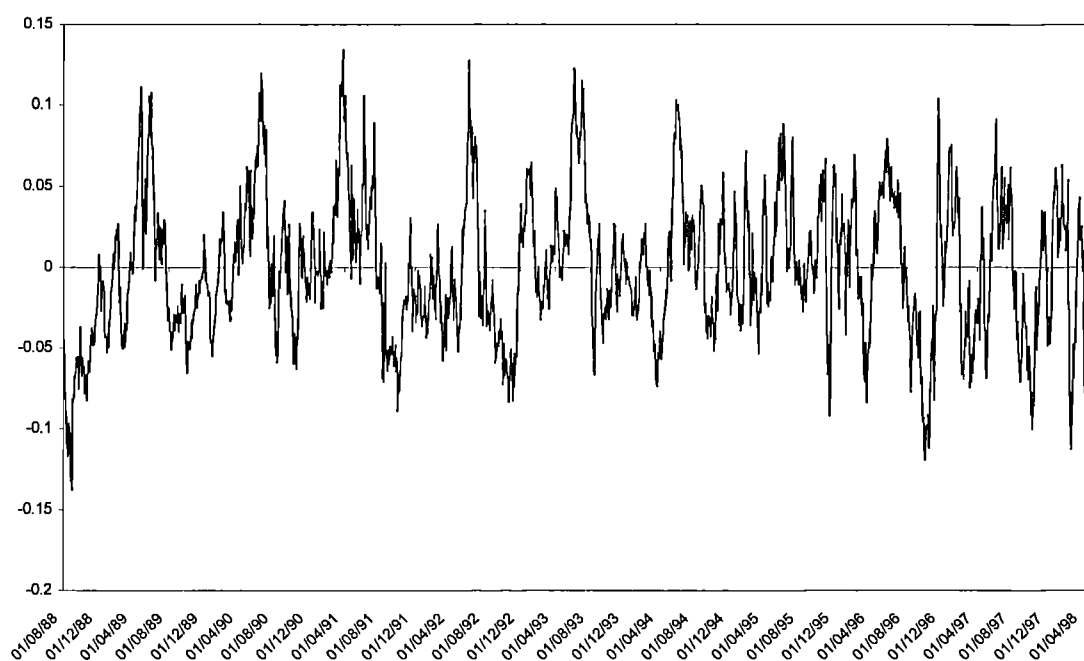
BFI and BIFFEX Prices; Daily Data (1/08/88 to 30/04/98)



A bought (sold) BIFFEX contract can be offset by selling (buying) the same contract at any time before the expiration of the contract in the market. All the contracts that remain open on the last trading day of a particular contract month, which is the last business day of the trading month, or the 20 December for the December contract, are settled in cash. The settlement price is computed as the average of the BFI over the last five trading days of the contract month; the monetary value of the settlement price is \$ 10 per index point. Figure 1.14 presents the near-month BIFFEX prices against the BFI prices. The two series move closely together and the BIFFEX prices capture closely the fluctuations of the BFI. Their close relationship is also evidenced by the high value, of 0.98, of their correlation coefficient.

Figure 1.15

Basis of BFI and Constant Maturity BIFFEX Prices; Daily Data (1/08/88 to 30/04/98)



The basis of a constant maturity BIFFEX contract, measured as the difference in the logarithms of BFI and BIFFEX prices, is presented in Figure 1.15⁵. We can see that the basis fluctuates around zero and there is no evidence of the futures prices being consistently above

⁵ A BIFFEX contract with a constant maturity of 22 days is constructed using a “perpetual” futures contract (Pelletier, 1983). See chapter 4 of the thesis for more on this.

or below the spot prices; this is also confirmed by hypothesis tests for the mean basis which indicate that it is statistically insignificant. This suggests that there is no tendency for the BFI prices to rise or fall over time and is also consistent with Figure 1.14 which shows that BFI and BIFFEX prices are not trending over time.

1.3.5 The Theoretical Relationship between Spot and Futures Prices in the BIFFEX Market

Contemporaneous spot and futures prices for financial and commodity futures markets are related through what is commonly known as the *cost-of-carry* price relationship. The cost-of-carry relationship states that the price, at time $t-n$, of a futures contract for delivery at time t equals the price of the underlying asset at time $t-n$ plus the total costs associated with purchasing and holding the underlying asset from time $t-n$ to t . These costs include the financing costs associated with purchasing the commodity, the storage costs (such as warehouse and insurance costs) as well as any other costs involved in carrying the underlying asset forward in time. Mathematically

$$F_{t,t-n} = S_{t-n} (1 + C) \quad (1.1)$$

Where $F_{t,t-n}$ is the price of the futures contract at time $t-n$, for delivery at time t .

S_{t-n} is the spot price at time $t-n$.

C represents the carrying costs, expressed as a fraction of the spot price, necessary to carry the commodity forward from period $t-n$ to the delivery date of the futures contract, at time t .

For instance, if the spot price of gold is \$ 400 per ounce and the borrowing interest rate is 10% per year, and if for reasons of simplicity we assume that the only charge associated with carrying the commodity forward in time are the financing costs, then the price of the gold futures contract for delivery in one year will be

$$F_{t,t-1} = 400 \times 1.1 = 440$$

The cost-of-carry formula in equation (1.1) determines the price relationship between spot and futures prices and any deviations from this relationship will be restored in the market through riskless arbitrage. Assume, for instance, that the actual price of the futures contract for delivery in one year is \$ 450, i.e. \$ 10 above its fair value, as calculated through the cost-of-carry formula. In this case, market agents can exploit arbitrage profits by purchasing the underlying commodity and selling futures contracts in what is known as the “cash-and-carry” arbitrage. An example of such a strategy, adapted from Kolb (1997), is presented in Table 1.5, Panel A.

Table 1.5

Panel A: Cash-and-Carry Gold Arbitrage Transactions

	Spot Price of Gold	\$ 400
	Cost-of-Carry Future Price of Gold (400×1.1)	\$ 440
	Actual Futures Price of Gold	\$ 450
Time	Transaction	Cash Flow (\$)
t-1	Borrow \$ 400 for one year at 10%	+ 400
	Buy 1 ounce of gold in the spot market for \$ 400	- 400
	Sell a futures contract for \$ 450 for delivery of 1 ounce in one year	0
	Total Cash Flow	0
t	Deliver the ounce of gold against the futures contract	+ 450
	Repay the loan, including interest	- 440
	Total Cash Flow	+ 10

Panel B: Reverse Cash-and-Carry Gold Arbitrage Transactions

	Spot Price of Gold	\$ 420
	Cost-of-Carry Futures Price (420×1.1)	\$ 462
	Actual Futures Price	\$ 450
Time	Transaction	Cash Flow (\$)
t-1	Short Sell 1 ounce of gold in the spot market for \$ 420	+ 420
	Lend the proceeds from sale (\$ 420) for one year at 10%	- 420
	Buy a futures contract for \$ 450 for delivery of 1 ounce in one year	0
	Total Cash Flow	0
t	Collect the proceeds from the loan (420×1.1)	+ 462
t	Accept Delivery of the Futures Contract.	- 450
	Use gold from futures delivery to repay short sale	0
	Total Cash Flow	+ 12

Therefore, through these actions, market agents lock in a profit of \$ 10. This is a risk-free

profit because it is certain when the transaction is made, at time $t-1$. This arbitrage opportunity exists because the difference between the observed futures price and the spot price (i.e. $\$ 450 - 400 = \$ 50$) exceeds the cost-of-carry ($\$ 40$). Such a difference cannot persist in the presence of arbitrage. In the arbitrage transaction described above, futures contracts are sold and the physical commodity is bought. This has the effect of pushing down futures prices, by increasing the supply of futures contracts, and of raising spot prices by increasing the immediate demand for the physical commodity. Both effects result in reducing the difference between futures and cash prices and the arbitrage opportunities will cease to exist when the difference between the futures and the spot prices is equal to the cost-of-carry.

An arbitrage opportunity also arises when the difference between the observed futures price and the spot price exceeds the cost-of-carry. This is called a “Reverse Cash-and-Carry” arbitrage opportunity. As the name implies, the steps necessary to exploit this arbitrage opportunity are just the opposite of those in the cash-and-carry strategy; an example of such strategy is presented in Table 1.5, Panel B.

Assume for instance, that the spot price of gold is $\$ 420$ per ounce. Then, the price of the gold futures contract for delivery in one year will be $F_{t,t+1} = 420 \times 1.1 = 462$, which exceeds the actual price of the futures contract for delivery in one year ($\$ 450$). In this case, market agents will sell the gold short. Short selling, is the process of borrowing the good from another person and promising to repay it at some point in the future; once the good is borrowed, the short seller sells it and takes the proceeds from the sale. This transaction is called short selling because one sells a good that he does not actually own. In this example, the short-seller lends the proceeds from the sale at the interest rate of 10%. He also buys a futures contract to ensure that he can acquire the gold needed to repay the lender at the expiration of the futures contract, in one year.

Through these actions, market agents lock in a profit of $\$ 12$. This is a risk-free profit because it is certain when the transaction is made, at time $t-1$. Such a difference cannot persist in the presence of arbitrage. In the arbitrage transaction described above, futures contracts are bought and the physical commodity is sold. This has the effect of raising futures prices, through the increased demand for futures contracts, and of reducing spot prices by increasing the supply for the physical commodity. Both effects result in reducing the difference between

futures and cash prices and the arbitrage opportunities will cease to exist when the difference between the futures and the spot prices is equal to the cost-of-carry.

The existence of “cash-and-carry” and “reverse cash-and-carry” arbitrage opportunities, is the underlying factor that links spot and futures prices for commodities that can be stored and carried forward over time such as metals, oil, agricultural commodities and financial securities such as interest rates and stock indices. However, the concept of carrying charges does not apply to commodities which are non-storable. Examples of such “commodities” are the electricity futures contracts in the US and contracts that trade a service such as the BIFFEX contract.

The BIFFEX contract trades the expected value of the service of seaborne transportation. The physical characteristics of this commodity make it impossible to store it or carry it forward on time. As a result, BFI and BIFFEX prices are not linked through the cash-and-carry arbitrage trades outlined above. In contrast, futures prices are driven by the expectations of market agents regarding the future spot prices i.e. the spot prices that will prevail at the expiry of the contract. Mathematically

$$F_{t;t-n} = E_{t-n}(S_t | \Omega_{t-n}) \quad (1.2)$$

where $E_{t-n}(.|.)$ is the mathematical conditional expectations operator at time $t-n$ and Ω_{t-n} is the information set available to market participants at period $t-n$. Equation (1.2) states that the price, at time $t-n$, of a futures contract for delivery at time t equals the spot price that market agents expect to prevail at maturity. In forming their expectations, the market agents consider all the relevant information, available to them at time $t-n$ ⁶. This pricing relationship, is also called the unbiasedness hypothesis, since it implies that futures prices are unbiased forecasts of the realised spot prices. Empirical tests of this hypothesis for the BIFFEX market are presented in Chapter 3 of the thesis.

⁶ The time subscripts in the expectations operator denote the time at which expectations are formed. In the subsequent analysis it is assumed that expectations are formed the same time the information set becomes available to market agents and hence, these subscripts are dropped.

1.3.6 Trading Activity of the BIFFEX Contract

Figure 1.16 presents the daily trading volume, measured in number of contracts traded each day, of the BIFFEX contract for the period 1 January 1990 to 30 April 1998 ⁷. For comparison purposes, the plot of BIFFEX prices is presented in the same graph.

Figure 1.16

BIFFEX prices and BIFFEX Daily Trading Volume

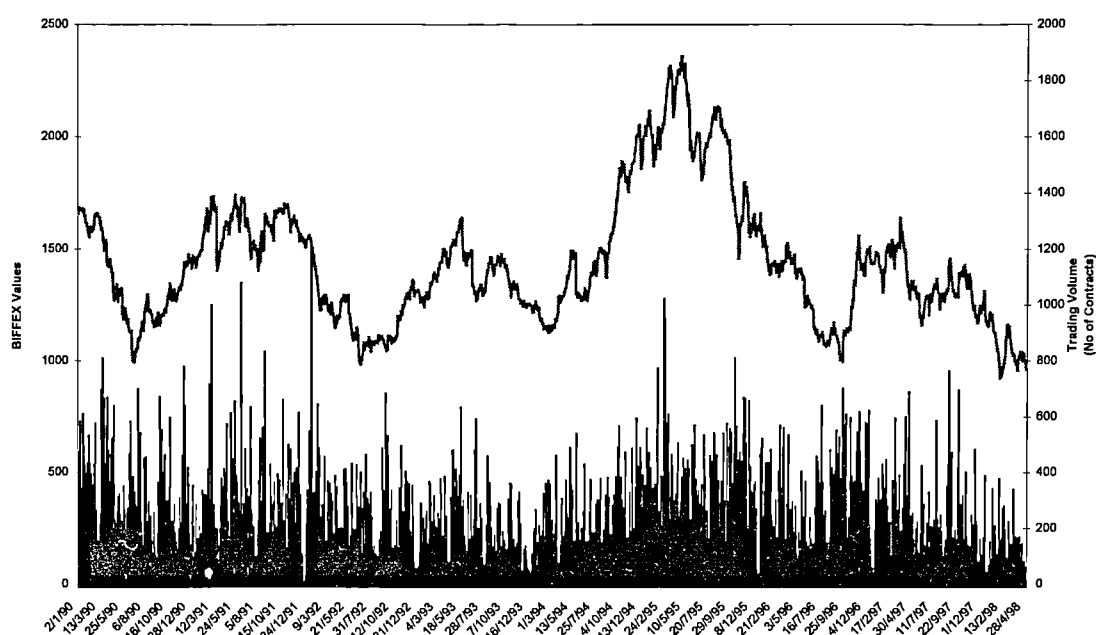


Table 1.6

Average Daily Trading Volume of the BIFFEX contract (1/1/90 – 30/4/98)

Period	1990 – 1998	1990	1991	1992	1993	1994	1995	1996	1997	1998
Contracts per day	218	275	244	203	165	188	291	237	178	110

Source: LIFFE

We can see that trading volume fluctuates widely over the estimation period. Moreover, the average trading activity seems to have declined over the recent years, as indicated in Table

⁷ The starting observation for the volume data is 1 January 1990, because there are no BIFFEX volume data available for the period 1985 to 1989.

1.6. Starting from an average trading volume of 275 contracts per day in 1990, this gradually dropped to 165 in 1993. Thereafter, trading activity in the market increased, following the strengthening of the dry-bulk markets in 1994, and as a result the trading volume peaked in 1995, when, on average, 291 contracts were traded each day. However, after that period, the number of traded contracts declined to reach its lowest level of 110 contracts per day, during the first quarter of 1998.

Overall, during the period from 1 January 1990 to 30 April 1998, the average volume in the market was 218 contracts per day. This compares very poorly to the trading activity, evidenced in other futures markets. For instance, in January 1998, the average trading volume of the wheat, corn and Treasury-Bond futures contracts, at the Chicago Board of Trade, was 17,310, 59,535, and 456,921 contracts per day, respectively. The size of the market is also small, when compared to the size of the dry-bulk sector of the shipping industry. In established futures markets, the total value of futures transactions, exceeds the value of transactions in the underlying market; in the freight futures market however, it is estimated that the value of the BIFFEX transactions represents only 10% of the total chartering activity in the dry-bulk market ⁸.

The issue that arises is to pinpoint why the contract has failed to attract considerable trading interest by the shipping community. There is an impression that dry-bulk shipping market agents abstain from using the BIFFEX contract because they are unfamiliar with its mechanism and functioning ⁹. However, this conjecture contradicts with the findings of Cullinane (1991), who conducted a questionnaire survey to determine the attitudes of shipping market agents with respect to BIFFEX trading, that the shipping community “*is fully aware of the existence of BIFFEX [and] of how to make use of this facility*”.

It is likely that market agents do not use the BIFFEX contract, as a result of the market not performing its risk management and price discovery functions efficiently. The success of a futures contract is dependent upon the contract providing benefits to economic agents, over and above the benefits they can get from the spot market alone. If no such benefits exist, then market agents have no reasons to prefer trading in the futures market instead of the spot

⁸ Lloyd's Shipping Economist, (1996) The Subtle Problem of Selling Freight Derivatives. April, p.10.

⁹ Lloyd's Shipping Economist, (1995) Paper Ships Prepare to Set Sail. April, p.14 – 15.

market. Cullinane et al. (1999) and Haralambides (1992) for instance, indicate that the low volume of BIFFEX contracts is due to the fact that the market does not perform its hedging function efficiently. They argue that using an average index-based contract as a hedge for individual routes implies that fluctuations on these routes are not accurately tracked by the futures prices. This reduces the effectiveness of the futures contract as a hedging instrument and, as a result, market agents who want to control their spot price risk, abstain from using the BIFFEX contract.

This also indicates that, by investigating the price discovery and risk management functions of the BIFFEX contract, we can identify the reasons the contract has failed to attract the trading interest of the shipping agents and hence, suggest policy actions that may be undertaken so as to improve its performance. The issue of trading activity, is also closely related to the viability of the BIFFEX contract. LIFFE derives its revenue by charging a fee for each contract traded on the exchange ¹⁰. The resulting revenues are used to cover all the expenses incurred by the exchange in association to trading a particular contract. As a result, if the trading volume for a contract is low, the exchange may not have an economic incentive to keep this contract and hence, the contract may be withdrawn from the market.

¹⁰ The fee for all the commodity contracts, including BIFFEX, is 62 pence, per traded contract. This fee is charged to the futures broking companies who execute transactions on behalf of their customers.

1.3.7 Uses of the Market

Through the BIFFEX market, information about the expectations of all market participants regarding future developments in the spot and time-charters dry-bulk markets, is assimilated to produce a single forecast of the expected BFI price. This availability of information reduces search costs and provides signals that guide chartering and vessel employment decisions in a more efficient manner. Since BIFFEX contracts are traded for delivery at various points in the future, they reflect the current expectations of the market about the level of the underlying index at those points in the future. For instance, if BIFFEX prices 2 months from maturity are above the current BFI price then this reflects the current expectation of the market that the BFI, two months from now will be above its current level.

Consider the following example; on 31 January 1997, the BFI stands at 1367 points and the BIFFEX contract for delivery in March 97 trades at 1455 points. This suggests that the market expects the BFI to strengthen, over the period January to March 1997, and rise above its current value of 1367 points. On 31 March 1997, the settlement date of the March 97 contract, the BFI stands at 1513 points, which is above its level on 31 January 97. Therefore, through the BIFFEX contract, market agents can get an indication regarding the expected level of freight rates in the future. Moreover, this benefit of price discovery, accrues not only to the charterers and shipowners who are involved in BIFFEX trading but also to all the market agents who have an interest in the future value of the freight rates as a guide for their physical market decisions.

The second benefit that BIFFEX trading provides to market agents is the possibility to control their freight rate risk through hedging. Hedging is the process of eliminating or reducing market price risk through the use of futures contracts and involves setting up an opposite position on the futures market as to that held on the spot market. For instance, the charterer will always be a buyer of futures. This will enable him to protect his forward freight requirements in case the physical market rises and forces him to pay higher freight rates. The shipowner, on the other hand, will be a seller of futures since any loss in the freight market, due to a decline in the level of freight rates, will be compensated through a gain in his futures

position ¹¹.

Table 1.7, presents an example, adapted by Haralambides (1992), illustrating the use of BIFFEX for hedging the freight income of a shipowner. The same example also applies for the case of a charterer with cargoes available for transportation.

On 7 May 1997, a hypothetical shipowner has a 52,000 dwt panamax vessel chartered until the first week of June; the vessel will be delivered in the US Gulf area where it will load grain for delivery to South Japan. The freight index for route 2 (52,000 tons of grain from US Gulf to Japan) stands at 1527 points which represents a freight rate of 21.815 USD/ton¹². The shipowner fears that freight rates will fall within the next month and thus, when he fixes his vessel in 1 month, he will be receiving less freight income compared to today's market; had the shipowner been able to charter the vessel immediately he would be receiving a freight income of $21.815 \text{ \$/ton} \times 52,000 \text{ tons} = \$1,134,380$.

In an effort to protect his income against a market downturn, the shipowner initiates a freight futures hedge, by selling BIFFEX contracts for delivery in June 1997; the current price of the contract is 1290 points, which represents a monetary value of $1290 \times 10 \text{ \$/point} = \$12,900$. In order to determine the magnitude of his futures position, he follows a "naïve" (or *one to one*) hedging strategy i.e. he sets a futures position which matches exactly his exposure in the physical freight market. Therefore, he sells $1,134,380/12,900 \approx 88$ futures contracts.

In order to establish this futures position, the shipowner contacts a LIFFE broking company and places an order to sell 88 June 97 contracts. The broking company communicates the order to its representative broker at LIFFE who executes the transaction on behalf of the shipowner. In return of this service, the broking company charges the shipowner a brokerage fee, which is \$ 15 per contract per "round trip" – that is, the fee covers the transaction costs

¹¹ The role of a hedger is to be differentiated from that of a speculator. A speculator enters the market in pursuit of profit. He may take a long or short position in the futures contract, depending upon his expectations regarding the future level of spot prices. For instance, market agents who believe that freight rates will rise (fall) in the future will buy (sell) futures contract in order to maximise their profits. On the other hand, a hedger has a pre-determined position in the physical market and enters the futures market with the aim of minimising the risk of his physical position. A hedger will always take a futures position which is determined by his position in the physical market; in other words, a hedger shipowner will be a seller of futures contracts and a hedger charterer will be a buyer of futures contracts.

¹² That is, $1527/70 = 21.815 \text{ \$/ton}$, which is the Index Factor for route 2; see Table 1.3 for more on this.

of selling and then buying back the contract. This fee is payable when the transaction is completed i.e. when the shipowner closes his position by buying back 88 contracts.

By the time he fixes the vessel, on 4 June 97, the freight rate has fallen to 21.072 \$/ton. He receives a freight revenue of $21.072 \times 52,000 = \$1,095,744$ thus incurring a loss in the physical market of $1,095,744 - 1,134,380 = -\$38,636$. However, the drop in the freight market, is accompanied by a drop in the price of the June 97 contract which now stands at 1194 points. The shipowner contacts his broker, gives him an order to buy back 88 June 97 contracts and pays the brokerage fee of $15 \times 88 = \$1320$.

Therefore, the shipowner unwinds his hedge, buying back 88 contracts, representing a total amount of $88 \times 11,940 = \$1,050,720$. His futures position generates a profit of $1,135,200 - 1,050,720 = \$84,480$. Combining the loss in the physical market with the gain in the futures market gives an overall profit of \$45,844¹³.

However, despite the realisation of profits from the hedged portfolio, we should note that the performance of this hedge is far from perfect. The objective of a hedger is to reduce the variability of the cash flows of his hedged portfolio. Moreover, any unexpected gains from the hedged position could easily turn into losses. In order to emphasise this point, consider another example presented in Table 1.7, Panel B. On 4 June 1997, our hypothetical shipowner has another panamax vessel which he expects to fix, in route 2, during the first week of July. The shipowner fears that freight rates will fall and initiates a hedge by selling 96 (that is, $1,095,744 / (1135 \times 10)$) futures contracts. By the time he fixes the vessel the freight market has risen thus realising a profit in the physical market of \$94,328. However, the price of the July 97 contract has also risen; his futures position results in a loss of \$124,800 and the total loss on the hedged position becomes \$30,472.

¹³ For reasons of simplicity, brokerage costs are not incorporated in the net outcome from hedging. This is because, brokerage costs represent a small percentage of the shipowner's exposure in the spot market, only 0.1% ($=1320/1,134,380$), and hence, their inclusion in the hedged cash flows does not affect significantly the hedging results.

Table 1.7

Hedging in the Freight Futures Market; An Example**PANEL A: 4-week hedge for the period 7 May to 4 June 1997**

Physical Market	Futures Market
7 May 1997	
Vessel employed till first week of June	
BFI: 1269	June 1997 BIFFEX price : 1290
Route #2 Index : 1527	Shipowner sells 88 June 1997 contracts
Implied Freight Rate : 21.815 \$/ton	Total Value : \$ 1,135,200 (=88*1290*10)
Cargo Size : 52,000 tons	
Freight Income : \$1,134,380	
4 June 1997	
BFI: 1257	June 1997 BIFFEX price : 1194
Route #2 Rate : 1475	Shipowner buys back 88 June 1997 contracts
Implied Freight Rate : 21.072 \$/ton	Total Value : \$ 1,050,720 (=88*1194*10)
Actual Freight Income : \$ 1,095,744	
Profit / Loss in the Physical Market	Profit / Loss from the Futures Transaction
1,095,744 - 1,134,380 = - \$ 38,636	1,135,200 - 1,050,720 = \$ 84,480
Net Result from Hedging = \$ 45,844	
(Transaction Costs = \$ 1320 (=15*88))	

PANEL B: 4-week hedge for the period 4 June to 2 July 1997

Physical Market	Futures Market
4 June 1997	
Vessel employed till first week of July	
BFI: 1257	July 1997 BIFFEX price : 1135
Route #2 Index : 1475	Shipowner sells 96 July 1997 contracts
Implied Freight Rate : 21.072 \$/ton	Total Value : \$ 1,089,600 (=96*1135*10)
Cargo Size : 52,000 tons	
Freight Income : \$1,095,744	
2 July 1997	
BFI: 1334	July 1997 BIFFEX price : 1265
Route #2 Rate : 1602	Shipowner buys back 96 July 1997 contracts
Implied Freight Rate : 22.886 \$/ton	Total Value : \$ 1,214,400 (=96*1265*10)
Actual Freight Income : \$ 1,190,072	
Profit / Loss in the Physical Market	Profit / Loss from the Futures Transaction
1,190,072 - 1,095,744 = \$ 94,328	1,089,600 - 1,214,400 = - \$ 124,800
Net Result from Hedging = - \$ 30,472	
(Transaction Costs = \$ 1440 (=15*96))	

In a perfect hedge, the variability of the cash flows from the hedged position must be zero. In other words, the net result from hedging in the previous cases should have been zero. The fact that this is not the case can be partly attributed to the use of a *one to one* hedge; a one to one hedge is effective as long as freight rates and futures prices change by the same amount. Since spot and futures prices do not always move together, an alternative strategy must be used to determine hedge ratios that minimise the difference between losses in the physical market and gains in the futures market or vice versa. The effectiveness of such a strategy is investigated empirically in chapter 5 of the thesis.

1.4 Aims of the Thesis and its Contribution to the Literature

In this section we present the research issues, addressed in this thesis, along with its contribution to the literature. The aim of this study is to examine whether the BIFFEX market is serving its price discovery and risk management functions efficiently and to the extent evidenced in other markets in the literature. In addition, it considers how the performance of these functions has changed over time, in response to changes in the compositions of the BFI. These issues are examined in chapters 3 to 7. In chapter 3, we investigate the unbiasedness hypothesis, that is the relationship between futures prices and expected spot prices. Chapter 4, examines the pricing relationship between contemporaneous spot and futures prices. These two chapters provide evidence regarding the price discovery function of the market. The risk management (hedging) function of the market is investigated in chapter 5. Chapter 6 examines the impact of revisions in the composition of the BFI on the price discovery and risk management function of the market, and, finally, in chapter 7, we develop a multivariate time-series model for forecasting spot and futures prices in the market. These research topics are described in more detail, below.

1.4.1 The Unbiasedness Hypothesis of Futures Markets

In section 1.2.1.2, we proposed a linking relationship between futures prices and expected spot prices for futures markets of non-storable commodities. In particular, we mentioned that futures prices in the BIFFEX market are linked with the underlying BFI prices through the equation (1.2), repeated here for convenience

$$F_{t;t-n} = E(S_t | \Omega_{t-n}) \quad (1.3)$$

where $F_{t;t-n}$ is the price, at time $t-n$, of the futures (BIFFEX) contract maturing at time t , S_t is the spot (BFI) price prevailing at period t , Ω_{t-n} is the information set available to market agents at period $t-n$ and $E(.|.)$ is the mathematical conditional expectations operator. This pricing relationship, is also called the unbiasedness hypothesis, since it implies that futures prices are unbiased forecasts of the realised spot prices.

The extent to which futures prices in the BIFFEX market provide unbiased expectations forecasts of the realised BFI prices is of particular interest to participants in the market because it is closely related with the two other functions of the BIFFEX market namely risk management and price discovery. First, the existence of a bias in futures prices increases the cost of hedging. For instance, when futures prices are well above (below) the expected spot prices, long (short) hedgers are obliged to buy (sell) the futures contracts at a premium (discount) over the price they expect to prevail on maturity. Second, if futures prices are not unbiased forecasts then, they may not perform their price discovery function efficiently, as they do not represent accurate predictors of expected spot prices. This bias is called the risk premium and represents the compensation that speculators in the market demand in order to assume the risk that hedgers wish to eliminate.

In order to test empirically the unbiasedness hypothesis, an assumption regarding the formation of expectations in the market needs to be made. If we assume that expectations in the market are formed rationally, in the sense of Muth (1961), then market agents have access to the correct information set at time $t-n$ which they take into account when forming their predictions. Hence, market agents are, on average, correct in their forecasts and make no systematic mistakes in the formation of their expectations. Therefore, conditional on the assumption of rational expectations, the realised spot price at time t , will differ from its conditional expectation at time $t-n$ by a white noise error process, u_t

$$S_t = E(S_t | \Omega_{t-n}) + u_t \quad ; \quad u_t \sim \text{iid}(0, \sigma^2) \quad (1.4)$$

and (1.3) can be written as

$$S_t = F_{t,t-n} + u_t \quad ; \quad u_t \sim \text{iid}(0, \sigma^2) \quad (1.5)$$

The empirical investigation of the equilibrium relationship described in (1.5) can then be carried out by regressing the realised spot price S_t on the futures prices, n periods before maturity, $F_{t,t-n}$, as in the following model

$$S_t = \beta_1 + \beta_2 F_{t,t-n} + u_t \quad ; \quad u_t \sim \text{iid}(0, \sigma^2) \quad (1.6)$$

Under the joint hypothesis of unbiasedness and rational expectations, the price of a futures contract should be equal to the spot market price realised on the contract delivery date. This implies the joint parameter restriction $(\beta_1, \beta_2) = (0, 1)$. Longworth (1981) for instance, estimates equation (1.6) using Ordinary Least Squares (OLS) and tests the unbiasedness hypothesis for the 1-month forward Canadian Dollar exchange rates. Using an ordinary F-test for the joint restriction $(\beta_1, \beta_2) = (0, 1)$, he concludes that the forward exchange rate is an unbiased predictor of the future spot rate for the period 1970 to 1978.

The test of equation (1.6) is considered as a “weak form” efficiency test, in the sense of Fama (1970), since it investigates whether price changes from one period to the next are unpredictable given the current information set. If the futures price, $F_{t,t-n}$, contains all relevant information to forecast the next period’s spot price, S_t , then $F_{t,t-n}$ should be an unbiased predictor of the future spot price. Of course, this test examines the joint hypothesis of risk neutrality (or no risk premium) and rationality of expectations. This represents what Fama (1991) calls the “joint hypothesis problem”. Since the rational expectations mechanism is tested jointly with a particular assumption regarding the long-run equilibrium relationship between spot and futures prices, if the unbiasedness hypothesis is rejected, it is not clear whether its rejection derives from a breakdown of the expectations mechanism or from the existence of a risk premium, since a violation of either hypothesis can lead to the rejection of the joint hypothesis. Furthermore, these two hypotheses cannot be separated without further assumptions regarding the formation of expectations or the risk preferences of market agents.

The unbiasedness hypothesis is also closely linked with the accuracy with which futures prices can forecast the realised spot prices. If futures prices are to fulfil their price discovery role, they must provide accurate forecasts of the realised spot prices and the more accurate futures prices are in predicting these prices, the more efficient they are in conveying new information in the market and in allocating economic resources (Stein, 1981). In order to determine the accuracy of futures price forecasts, comparisons must be made against some alternative methods of predicting the realised spot prices. This is an issue which has been investigated for different futures markets in the literature. For instance, Ma (1989) and Kumar (1992) compare the forecasting accuracy of oil futures prices to forecasts generated from time-series and random walk models, while Hafer et al. (1992) compare the forecasting performance of Treasury-Bill futures prices to that of forward prices and survey data. Broadly

speaking, these studies find that futures prices provide superior forecasts of the realised spot prices than forecasts generated from alternative methods, although their forecasting performance diminishes as the forecast horizon increases.

Although these issues have been examined extensively for different futures and forward markets, very little empirical evidence is available on the BIFFEX market. The exception to that are the studies of Chang (1991) and Chang and Chang (1996) who investigate the unbiasedness hypothesis and the forecasting performance of futures prices, respectively. Chang (1991), uses the model specification of equation (1.6) to test the unbiasedness property of BIFFEX prices during the period April 1985 to October 1990. He estimates the equation using OLS and employs an F-test to examine the joint significance of the restrictions posited by the unbiased expectations hypothesis. He finds that BIFFEX prices with maturity up to 12 months provide unbiased expectations forecasts of the future BFI prices. Chang and Chang (1996) also employ equation (1.6) and perform hypothesis tests on the significance of the slope coefficient, β_2 . If the slope coefficient is found to be significant, then futures prices are considered as being accurate forecasts of the realised spot prices with the degree of forecasting performance being measured by the R^2 of the regression. They find that futures prices up to 6 months before maturity are accurate forecasts of the realised spot prices with the R^2 's ranging from 89%, in the case of 1-month futures, to 23% for futures prices 6 months from maturity.

However, the findings of these studies can be criticised on the grounds that no attempt has been made to test whether spot and futures prices are stationary¹⁴. The stationarity property of the underlying price series is crucial since, as shown by Granger and Newbold (1974), using standard regression techniques 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. Thus, a regression involving non-stationary series does not imply the kind of causal relationship that might be inferred from stationary series. This also indicates that examination of the unbiasedness hypothesis should be done on the basis of a correctly specified model that takes into account the stochastic properties of the

¹⁴ A stochastic process, S_t , is stationary if: 1) its mean value is constant for all t, that is $E(S_t) = \text{constant}$, $\forall t$; 2) its variance is constant for all t, that is $\text{Var}(S_t) = \text{constant}$, $\forall t$; 3) its autocovariances depend only on the distance between two observation points, that is $\text{Cov}(S_t, S_{t-k}) = \gamma_k$, $\forall t$. If a stochastic series must be differenced once in order to become stationary, then the series contains 1 unit root and is said to be integrated of order 1, denoted as

underlying variables. A second criticism is that, in the study of Chang and Chang (1996), no comparisons are being made against alternative methods of predicting the realised spot prices. Such comparisons are essential since futures forecasts may be inferior to forecasts generated from other sources and, as a result, futures prices may not fulfil their price discovery role.

The preceding discussion highlights the deficiencies of earlier studies in the literature and indicates the need for new empirical evidence on the issues of unbiasedness and futures forecasting performance in the BIFFEX market. In order to accommodate the aforementioned comments we explicitly test for the order of integration of spot and futures prices and we examine the unbiasedness hypothesis using the cointegration methodology which provides a framework for valid inference in the presence of non-stationary price series ¹⁵. Moreover, we provide robust evidence on the forecasting performance of futures prices by comparing the accuracy of the forecasts implied by the futures prices with forecasts generated from error correction, ARIMA, exponential smoothing and random walk models. This way we avoid the shortcomings evidenced in the studies of Chang (1991) and Chang and Chang (1996).

I(1). See chapter 2 of the thesis for more details on this.

¹⁵ If S_t and F_t are *I*(1) series then, any linear combination among these two series will also be *I*(1). However, there may be a number β such that $S_t - \beta F_t = \varepsilon_t$ is stationary. In this special case, Engle and Granger(1987) define the series S_t and F_t as cointegrated of order (1,1) (denoted as *CI*(1,1)) and the regression $S_t - \beta F_t = \varepsilon_t$ is called the cointegrating or equilibrium regression. See chapter 2 of the thesis for more details on this.

1.4.2 The Causal Relationship between Contemporaneous Spot and Futures Prices in the BIFFEX Market

In addition to providing a mechanism for market agents to form expectations regarding spot prices that will prevail in the future, trading in futures markets also provides information regarding current spot prices. The relationship between contemporaneous spot and futures prices has been investigated extensively in different commodity and financial futures markets. The focus of attention, in particular, has been on the lead-lag relationship between futures returns and the underlying spot returns; for the futures prices to fulfil their price discovery role they must respond rapidly to new market information and must lead the underlying spot prices. For instance, Stoll and Whaley (1990) report the existence of a two-way feedback relationship between futures returns and stock index returns in the S&P-500 and the Major Market Index contracts with the lead from futures to spot being stronger. Similar conclusions are drawn by Wahab and Lashgari (1993) and Hung and Zhang (1995) in the examination of stock index futures (FTSE-100 and S&P-500) and interest rate futures, respectively. Finally, Tse (1995) finds that futures returns lead the spot price returns in the Nikkei Stock Index contract. Overall, the findings of these studies indicate that futures prices contribute to the discovery of new information regarding the current level of spot prices.

Despite this plethora of studies, however, there exists no empirical evidence on the causal relationship between spot and futures prices in the BIFFEX market. Investigation of this issue not only provides, for the first time, evidence on the price discovery function of the BIFFEX contract but also contributes to the existing financial literature since tests on the causal relationship between spot and futures prices are extended to a market which trades a non-storable commodity and is characterised by low trading activity. From that respect, it is therefore interesting to investigate whether futures prices in the BIFFEX market contribute to the discovery of new information to the extent evidenced in the more liquid markets of storable commodities which have received the focus of attention in the literature. These issues are addressed using both Granger causality tests (Granger, 1969) and generalised impulse response analysis (Pesaran and Shin, 1997) so as to identify the flow of information and the speed with which BFI and BIFFEX prices respond to the arrival of new information in the market.

1.4.3 Hedging Effectiveness and Minimum Variance Hedge Ratios

Futures markets provide a mechanism through which market agents can reduce their spot price risk. Therefore, it is desirable to assess the degree of practical success that has been achieved by BIFFEX in fulfilling this objective. In this section we present the minimum variance hedge ratio methodology. This methodology avoids the problems associated with the use of *one to one* hedging strategies and was first applied in the BIFFEX market by Thuong and Vischer (1990) and Haralambides (1992). We also discuss the limitations of this hedging strategy when futures and spot prices follow time-varying distributions and propose the use of a new model for calculating hedge ratios in the BIFFEX market.

1.4.3.1 The Minimum Risk Hedge Ratio Methodology

The primary purpose of hedging is to reduce or control the risk of adverse price changes in the spot market. To achieve this objective, the hedger has to determine a hedge ratio, i.e. the number of futures contracts to buy or sell for each unit of spot commodity on which he bears price risk. Johnson (1960), Stein (1961) and Ederington (1979) apply the principles 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 futures price changes over the unconditional variance of futures price changes. This is derived as follows.

Consider the case of a shipowner who wants to secure his freight rate income in the freight futures market. The change on the shipowner's portfolio of spot and futures positions, ΔP_t , is given by

$$\Delta P_t = \Delta S_t - \gamma \Delta F_t \quad (1.7)$$

where, $\Delta S_t = S_t - S_{t-1}$ is the change in the spot position between t-1 and t; $\Delta F_t = F_t - F_{t-1}$ is the change in the futures position between t-1 and t; and γ is the hedge ratio¹⁶. Using the formula for the portfolio variance of two risky assets (see e.g. Weston and Copeland, 1988; p. 339),

¹⁶ Spot and futures prices are measured in natural logarithms. Hence, ΔS_t and ΔF_t approximate the continuously compounded spot and futures returns, respectively.

the variance of the returns of the hedged portfolio is given by

$$\text{Var}(\Delta P_t) = \text{Var}(\Delta S_t) - 2\gamma \text{Cov}(\Delta S_t, \Delta F_t) + \gamma^2 \text{Var}(\Delta F_t) \quad (1.8)$$

where $\text{Var}(\Delta S_t)$, $\text{Var}(\Delta F_t)$ and $\text{Cov}(\Delta S_t, \Delta F_t)$ are, respectively, the unconditional variance of the spot and futures price changes and their unconditional covariance. The hedger must choose the value of γ that minimises the variance of his portfolio returns i.e. $\min_{\gamma} [\text{Var}(\Delta P_t)]$.

Taking the partial derivative of equation (1.8) with respect to γ , setting it equal to zero and solving for γ , yields the minimum variance hedge ratio (MVHR), γ^*

$$\gamma^* = \frac{\text{Cov}(\Delta S_t, \Delta F_t)}{\text{Var}(\Delta F_t)} \quad (1.9)$$

The MVHR, γ^* , is equivalent to the slope coefficient, γ , in the following regression

$$\Delta S_t = \gamma_0 + \gamma^* \Delta F_t + u_t \quad ; u_t \sim \text{iid}(0, \sigma^2) \quad (1.10)$$

Within this specification, the degree of variance reduction in the hedged portfolio achieved through hedging is given by the 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.

The following example demonstrates an application of the MVHR methodology to the hedging problem, presented in Table 1.7. The shipowner has collected the historical price changes of route 2 and futures prices for the period 1 August 1988 to 7 May 1997, i.e. the date at which he initiates the hedge. He uses these observations to estimate the regression equation (1.10); this gives the following parameter estimates (standard errors are in parentheses)

$$\Delta S_t = -1.832 + 0.941 \Delta F_t \quad R^2 = 0.724$$

(11.27) (0.079)

Table 1.8

Hedging in the Freight Futures Market using the Minimum-Variance Hedge Ratio**PANEL A: 4-week hedge for the period 7 May to 4 June 1997**

Physical Market	Futures Market
	7 May 1997
Vessel employed till first week of June	
BFI: 1269	June 1997 BIFFEX price : 1290
Route #2 Index : 1527	Shipowner sells $88 \times 0.941 = 83$ June 97 contracts
Implied Freight Rate : 21.815 \$/ton	Total Value : \$ 1,070,700 ($=83 \times 1290 \times 10$)
Cargo Size : 52,000 tons	
Freight Income : \$1,134,380	
	4 June 1997
Route #2 Rate : 1475	June 1997 BIFFEX price : 1194
Implied Freight Rate : 21.072 \$/ton	Shipowner buys back 83 June 1997 contracts
Actual Freight Income : \$ 1,095,744	Total Value : \$ 991,020 ($=83 \times 1194 \times 10$)
Profit / Loss in the Physical Market	Profit / Loss from the Futures Transaction
1,095,744 - 1,134,380 = - \$ 38,636	1,070,700 - 991,020 = \$ 79,680

Net Result from Hedging = \$ 41,044**PANEL B: 4-week hedge for the period 4 June to 2 July 1997**

Physical Market	Futures Market
	4 June 1997
Vessel employed till first week of July	
BFI: 1257	July 1997 BIFFEX price : 1135
Route #2 Index : 1475	Shipowner sells $96 \times 0.941 = 90$ July 97 contracts
Implied Freight Rate : 21.072 \$/ton	Total Value : \$ 1,021,500 ($=90 \times 1135 \times 10$)
Cargo Size : 52,000 tons	
Freight Income : \$1,095,744	
	2 July 1997
Route #2 Rate : 1602	July 1997 BIFFEX price : 1265
Implied Freight Rate : 22.886 \$/ton	Shipowner buys back 90 July 1997 contracts
Actual Freight Income : \$ 1,190,072	Total Value : \$ 1,138,500 ($=90 \times 1265 \times 10$)
Profit / Loss in the Physical Market	Profit / Loss from the Futures Transaction
1,190,072 - 1,095,744 = \$ 94,328	1,021,500 - 1,138,500 = - \$ 117,000

Net Result from Hedging = - \$ 22,672**PANEL C: Variance Comparisons of the Cash-Flows from the Hedged Portfolio**

	Unhedged (ΔS_t)	One to One Hedge ($\Delta S_t - \Delta F_t$)	Min. Variance Hedge ($\Delta S_t - 0.941 \times \Delta F_t$)
7 May to 4 June	- \$ 38,636	\$ 45,844	\$ 41,044
4 June to 2 July	\$ 94,328	- \$ 30,472	- \$ 22,672
Portfolio Mean	\$ 27,846	\$ 7,686	\$ 9,186
Portfolio Variance	8.84×10^9	2.9×10^9	2×10^9
Var. Reduction compared to Unhedged		67.06%	77.04%

The estimated hedge ratio is $\gamma^* = 0.941$; this implies that the shipowner should sell \$ 0.941 worth of futures contract for each USD of freight rate income. From the regression model, we can also note that futures prices explain 72.4% of the variability of freight rates in route 2. This suggests that if the shipowner had used a hedge ratio of 0.941 during the sample period, he would have reduced the variance of his unhedged position by 72.4%.

The estimated hedge ratio is applied next to the hedging example presented in Table 1.7. The results are in Table 1.8. For the period 7 May to 4 June 1997, the shipowner sells $[1,134,380/(1290*10)]*0.941 = 88*0.941 = 83$, June 97 contracts, instead of the 88 contracts sold using the *one to one* hedge. When he fixes his vessel, on 4 June 1997, he buys back 83 contracts at a price of 1194 points thus realising a profit of $\$1,070,700 - \$991,020 = \$79,680$ in the futures market. Combining his loss in the physical market with the gain in the futures market, gives an overall profit of $-\$38,636 + \$79,680 = \$41,044$. The same hedge ratio is used for the period 4 June to 2 July 1997. The shipowner sells $(1,095,744/(1135*10))*0.941 = 96*0.941 = 90$, July 97 contracts, on 4 June 1997, and closes his position when he fixes his vessel, on 2 July 1997, thus realising a loss in his hedged position on the amount of $-\$22,672$.

A summary of the shipowner's cash flow from the different hedging strategies is presented in Table 1.8, Panel C. We can see that when the shipowner leaves his position unhedged (i.e. ΔS_t) he incurs a loss in the freight market of $-\$38,636$, in the first period, and a profit of $\$94,328$ in the second period. When he initiates a *one to one* hedge his cash flow position (i.e. $\Delta S_t - \Delta F_t$) becomes $\$45,844$ and $-\$30,472$, respectively. Finally, the use of the MVHR (i.e. $\Delta S_t - 0.941*\Delta F_t$) results in cash flows of $\$41,044$ and $-\$22,672$, respectively.

Several points need to be mentioned regarding the performance of these hedges. First, the cash flows generated by the MVHR have the lowest variance among the other strategies considered; using the MVHR reduces the variability of the unhedged position by 77.04% ($= 1 - 2*10^9/8.84*10^9$). In contrast, the *one to one* hedge provides a variance reduction of 67.06% ($= 1 - 2.9*10^9/8.84*10^9$).

Second, the variance reduction achieved by the MVHR, 77.04%, is different than the R^2 of equation (1.10), 72.4%¹⁷. This is expected since the latter refers to the variance reduction that would have been achieved during the estimation period (i.e. 1 August 1988 to 7 May 1997) if the shipowner had employed a hedge ratio of 0.941; it is therefore an ex-post measure of hedging effectiveness and, as such, gives an indication of the *historical* performance of the hedging strategy. In reality, hedgers in the market use the historical hedge ratios to hedge a position in the future, and the performance of these hedges is different than their in-sample performance, as is evidenced by this example.

Finally, using the MVHR reduces the average profits of the unhedged position from \$27,846 to \$9,186. This is expected and is also consistent with the objective of hedging which is to minimise the variability (riskiness) of the hedged position, rather than to maximise the profits from this position; hedging is aimed at minimising risk, not generating profits.

Since the seminal work of Ederington (1979), minimum risk hedge ratios and measures of hedging effectiveness have been estimated for numerous financial and commodity futures markets; for Treasury-bill futures by Ederington (1979) and Franckle (1980); for the oil futures by Chen, et al. (1987); for stock indices by Figlewski (1984) and Lindahl (1992); for currencies by Grammatikos and Saunders (1983) and by Malliaris and Urrutia (1991). The major conclusion of these studies is that futures contracts perform well as hedging vehicles with R^2 's ranging from 80% to 99%.

The MVHR methodology is applied in the BIFFEX market by Haralambides (1992) who finds that a shipowner, operating on route 3, can achieve greater risk reduction by using the MVHR compared to a naive hedge. In a related study, Thuong and Vischer (1990) estimate the degree of hedging effectiveness achieved by the BIFFEX contract across all the BFI routes for the period 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; for the latter routes, in particular, they find that the futures contract is marginally effective, with R^2 's ranging from 10.00% to 0.74%. Overall, however, they find that the minimum variance hedges fail to eliminate the riskiness of the spot position to the

¹⁷ Ederington (1979) shows that for within-sample hedges, this measure of hedging performance is identical to the R^2 of equation (1.10). A proof of this is presented in Appendix 5.A.

extent evidenced in other markets; the highest R^2 being only 32%. They argue that this poor hedging performance of the BIFFEX contract is thought to reflect the heterogeneous composition of the BFI, which consists of shipping routes which are dissimilar in terms of vessel sizes and transported commodities.

However, estimating hedge ratios using equation (1.10) is demonstrated by Myers and Thompson (1989) and Kroner and Sultan (1993) to be lacking in several respects. The first objection relates to the implicit assumption in equation (1.10) that the risk in spot and futures 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 futures prices are characterised by time-varying distributions; see for instance Choudhry (1997) and Hogan et al. (1997) for evidence on this. This in turn, implies that optimal, risk minimising hedge ratios should be time varying, as variances and covariances entering the calculations are time-varying. A second problem is that equation (1.10) is potentially misspecified because it ignores the existence of a long-run cointegrating relationship between spot and futures prices (Engle and Granger, 1987). The empirical consequence of omitting this relationship from the model specification is that the estimated hedge ratios are downward biased and as a result, the futures position is less than optimal; see for instance Ghosh (1993b), Chou et al. (1996) and Lien (1996). Finally, both γ^* and R^2 from equation (1.10) are ex-post measures of hedging effectiveness, since they depend upon the previously explained correlation between the spot and futures prices, and as such they give an indication of the *historical* performance of the hedging strategies. However, 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.

The preceding discussion highlights the deficiencies of earlier studies in the literature and emphasises the need for new empirical evidence on the risk management function of the BIFFEX contract. In order to address these issues, we model the spot and futures returns as a Vector Error-Correction Model (Johansen, 1988) (VECM) with a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) error structure (Engle, 1982 and Bollerslev, 1986). The error correction term describes the long-run relationship between spot and futures prices and the GARCH error structure permits the second moments of their distribution to change over time. The time-varying hedge ratios are then calculated from the estimated covariance

matrix of the model and their in-sample and out-of-sample hedging performance is compared to that of hedge ratios estimated using equation (1.10) and to one-to-one hedges. We also extend previous research in other futures markets by including the squared lagged error correction term of the cointegrated spot and futures prices in the specification of the conditional variance, in what is termed the GARCH-X model (Lee, 1994), and investigate its hedging performance against the alternative specifications.

1.4.4 The Effect of Revisions in the Composition of the BFI to the Price Discovery and Risk Management Functions of the BIFFEX Market

This thesis also investigates the temporal variability of the price discovery and risk management functions in the market, following major revisions in the composition of the BFI. The motivation for this, derives from the interesting policy issues surrounding the composition of the BFI. All the major revisions in the BFI - such as the introduction of time-charter routes or the exclusion of the handy-size routes - are driven by the intention to generate an underlying index that promotes the more effective functioning of the BIFFEX contract; it is therefore, interesting to investigate whether these revisions have achieved their intended objective. This is also related to the introduction of the BPI as the new underlying asset of the BIFFEX contract from November 1999 onwards. By investigating the effect that previous revisions in the composition of the BFI had on the two functions of the BIFFEX contract, we can thus provide some preliminary conjectures regarding the possible effects following this new restructuring. Finally, investigation of the price discovery and hedging effectiveness functions of the market over different sub-periods, provides additional supporting evidence to our results from the analysis of the entire sample and enables us to rule out the possibility that these results are sensitive to the period of time examined.

The effect of the revisions in the BFI is also investigated by Cullinane et al. (1999) who examine whether the exclusion of the handysize routes from the composition of the BFI has altered the fundamental characteristics of the index. They argue that if such a structural change has taken place then it will manifest itself in the fact that previous forecasting models of the BFI, such as the Autoregressive (AR) model of order 3 which was estimated by Cullinane (1992) using BFI data for the period 1985 to 1988, will not provide accurate forecasts for the period after the exclusion of the handysize routes. In order to investigate this conjecture, they compare the forecasting performance of the AR(3) model of Cullinane (1992) to that of an AR(2) model, estimated using BFI data for the post handysize period. They find that the Cullinane (1992) model is consistently more accurate than the new (post handysize) AR(2) model, for lead times up to 20 days ahead; this suggests that the exclusion of the handysize routes did not affect the fundamentals of the BFI.

Our focus in this study, however, is different for the following reasons. First, we investigate the impact of the revisions in the BFI on the functions of the BIFFEX contract, rather than on the structural composition of the BFI, since investigation of this issue is closely linked with the objective of the thesis which is to examine the performance of the price discovery and risk management functions in the BIFFEX market. Second, in addition to the exclusion of the handysize routes, this thesis also investigates the impact from the introduction of the time-charter routes on the index. To address these issues, we perform causality tests and assess the hedging performance of constant and time-varying hedge ratios over different sub-periods, which are dictated by the revisions of the composition of the BFI.

1.4.5 A Time-Series Model for Forecasting Spot and Futures Prices in the BIFFEX Market

The social and economic benefits of having more accurate forecasts are well-known; better forecasts provide superior signals that guide future supply and demand decisions in ways that contribute to a more efficient allocation of economic resources. As in the case of other commodity and financial futures markets, economic agents in the BIFFEX market can potentially benefit through the use of more accurate forecasts. For that, we estimate and compare alternative forecasting models of BFI and BIFFEX prices so as to arrive at the model specification that generates the most accurate forecasts of these price series.

The use of time-series models for forecasting the BFI is proposed, for the first time, by Cullinane (1992). He applies Box-Jenkins (1970) techniques to identify the best ARIMA (Autoregressive Integrated Moving Average) model for the BFI over the period January 1985 to December 1988; his selected model is an AR specification with autoregressive terms at lags 1 and 3. 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 the Holt - Winters (Holt, 1957 and Winters, 1960) exponential smoothing model. He finds that the 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.

We extend the findings of this study and propose a multivariate forecasting model of the BFI and BIFFEX prices. This model combines the information provided by the spot and futures prices and the spot-futures differential (i.e. the basis) to generate simultaneous forecasts of the BFI and BIFFEX prices. The forecasting performance of our proposed model is then compared to forecasts generated from Vector Autoregressive (VAR), ARIMA and Random-Walk models and the statistical test of Diebold and Mariano (1995) is used to assess whether the forecasts from the competing models are equally accurate. Our empirical results, in chapter 7, indicate that the proposed model outperforms all the other forecasting models, thus providing a further dimension to the contribution of this thesis to the literature.

1.5 Organisation of the Thesis

Having put forward the aims of this study we now proceed to describe the organisation of the thesis. This thesis consists of eight chapters, including the present one. 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.

Chapter 2 is devoted to a discussion of the time-series techniques, employed in this study. Two of the most popular unit root tests are presented and the tests for cointegration developed by Engle and Granger (1987) and Johansen (1988) are also discussed. The discussion focuses primarily on the Johansen (1988) tests which, due to their superior properties, are employed in this study. The use of impulse response analysis for investigating the dynamic relationship between the variables in a system of equations is also presented. Our discussion focuses both on Sims' (1980) "orthogonalised" impulse responses as well as on the "generalised" impulse responses, developed by Pesaran and Shin (1997), which avoid some deficiencies evidenced in Sims' approach.

The relationship between futures prices and expected spot prices in the freight futures market is examined in chapter 3. Two related hypotheses are investigated in this chapter; the unbiasedness hypothesis and the forecasting performance of futures prices. The unbiasedness hypothesis is examined using cointegration techniques so as to account for the stochastic properties of the underlying spot and futures price series. The forecasting performance, is analysed by comparing the futures price forecasts with forecasts generated from error correction, ARIMA, exponential smoothing and random walk models.

In chapter 4, we investigate the causal relationship between contemporaneous spot and futures prices. We employ Granger causality tests (Granger, 1969) and generalised impulse response analysis so as to identify the flow of information and the speed with which spot and futures prices respond to the arrival of new information in the market.

The hedging function of the market is analysed in chapter 5. The constant minimum-variance hedge ratio methodology is extended to a time-varying framework and, GARCH and

augmented GARCH models are introduced to investigate the hedging effectiveness of the futures contract across the different shipping routes. The hedging performance of these models is then investigated so as to arrive at the specification that offers the greater variance reduction both in an in-sample and in an out-of-sample setting.

Chapter 6 examines the temporal variability of the price discovery and risk management functions in the market, following major revisions in the composition of the BFI. Causality tests are performed over sub-periods so as to investigate whether the causal relationship between spot and futures prices has strengthened as a result of the more homogeneous composition of the index in the recent years. The effectiveness of constant and dynamic hedging strategies across different sub-periods is also examined so as to identify whether past revisions in the composition of the index had an impact on the effectiveness of the futures contract as a hedging instrument.

A multivariate time-series model for forecasting spot and futures prices is presented in Section 7. This model builds on our empirical results from chapter 4 and combines the information provided by the spot and futures prices as well as the basis to generate simultaneous forecasts of the BFI and BIFFEX prices. The forecasts from our proposed model are compared to forecasts generated from VAR, ARIMA and random-walk models, over several steps ahead, and their performance is assessed using both tests of directional predictability as well as the statistical test of Diebold and Mariano (1995).

Finally, section 8 presents our conclusions and some suggestions for fruitful future research which, due to space constraints, are not covered in this thesis.

Chapters 3 to 7 are based on five research papers co-authored with my supervisor, Dr Manolis Kavussanos. More specifically, based on Chapter 3, a paper titled “*The Forward Pricing Function of the Shipping Freight Futures Market*” was presented at the International Association of Maritime Economists (IAME) Conference, 22 – 24 September 1997, London, UK and has appeared in the May 1999 issue of the Journal of Futures Markets. Chapter 4 and chapter 7 are part of a paper titled “*Price Discovery, Causality and Forecasting in the Freight Futures Market*” which was presented at the City University Business School, Research Workshop in Finance on 9 November 1999 and is currently being reviewed by a refereed journal. Chapter 5 is based on two papers titled “*Constant vs. Time-Varying Hedge Ratios*

and Hedging Effectiveness in the BIFFEX Market” and *“Short-Run Deviations, Hedging and Volatility in the Freight Futures Market”*; the former was presented at the 8th World Conference on Transport Research, 12 - 17 July 1998, Antwerp, Belgium and both papers are currently under review by refereed journals. Finally, chapter 6 is part of a paper titled *“Futures Hedging Effectiveness when the Composition of the Underlying Asset Changes; the Case of the BIFFEX Market”*, which is also under review by a refereed journal.

1.5.1 Data and Estimation Periods

Our empirical analysis is undertaken using BFI, BFI routes and BIFFEX price data for the period 29 July 1988 to 30 April 1998. The dataset used in each study is different, depending on the nature of the investigated hypotheses.

The unbiasedness hypothesis, in chapter 3, is examined using BIFFEX prices one, two and three months from maturity and BIFFEX settlement prices on the maturity day of the contract, for the period 29 July 1988 to 30 April 1997. The choice of this dataset is dictated by the delivery cycle of the BIFFEX contract. Since there is a futures contract maturing every month in the market, the smallest feasible frequency for such a study is monthly data.

The causal relationship between contemporaneous BFI and BIFFEX prices and the impact of the arrival of daily "news" in the market on these prices is examined in chapter 4. Our dataset for this study consists of daily BFI and BIFFEX prices, over the period August 1988 to December 1997. The same dataset, is also employed to investigate the temporal variability of the price discovery function of the market, in chapter 6.

The hedging performance of the market, in chapter 5, is investigated using weekly BIFFEX and BFI routes prices, for the period October 1992 to October 1997. The starting observation for this study is different so as to account for changes in the composition of the BFI. A weekly hedging horizon is preferred, in line with other empirical studies in the hedging literature such as Kroner and Sultan (1993) and Gagnon and Lypny (1995), (1997). Weekly BIFFEX and BFI routes prices, for the period August 1988 to October 1997 are also employed to investigate the hedging effectiveness of the contract across sub-periods, in

chapter 6.

Finally, the forecasting model of BFI and BIFFEX prices, in chapter 7, is estimated using daily BFI and BIFFEX prices over the period August 1988 to December 1997. The out-of-sample forecasting performance of the model is evaluated over the period January 1998 to April 1998. The choice of a daily dataset for this study is dictated by two factors. First, the proposed model is based on our empirical model in chapter 4, which is estimated using daily BFI and BIFFEX prices. Second, the objective of this chapter is to propose a short-term model for forecasting BFI and BIFFEX prices; from that respect, the choice of daily data is also necessary.

Price data for the BFI and the BFI routes are from LIFFE. For the period August 1988 to December 1989, BIFFEX prices are from Knight Ridder, Simpson, Spencer and Young Limited (SSY) and the Financial Times; BIFFEX prices for the period January 1990 to April 1998, are collected from LIFFE.

Chapter 2 : A Review of the Time-Series Methods for the Analysis of Non-Stationary Processes

2.1 Introduction

The aim of this chapter is to illustrate the time-series techniques relevant to the empirical analysis undertaken in this thesis. The traditional methodology for investigating relationships between variables was based largely on the recommendations of the Cowles Commission. That is, economic theory provided guidelines for the underlying structure of the econometric relationship. Time-series or cross-sectional data were collected, and inferences were made on the estimated regression relationships with variables in levels. The underlying assumptions regarding the specification of the model, such as linearity, parameter stability, no serial correlation, homoskedasticity and normality, were often checked and models were selected according to their goodness of fit, as judged by their respective R^2 's (see Charemza and Deadman, 1992).

However, it was recognised that when time-series data are used in running such regressions, the results may falsely indicate the existence of a causal relationship between the variables of interest when, in fact, none is present. This problem was described by Granger and Newbold (1974) as the problem of “spurious regressions” and arises because the regression variables are non-stationary. As a result, it became important to investigate the univariate properties of the regression variables, in terms of unit roots (stationarity), and a new methodology for investigating causal relationships between such variables, emerged.

This methodology is presented in this chapter. We start with a discussion on the underlying properties of stationary and non-stationary (or unit root) processes and then we proceed to the tests that are employed to investigate the presence of unit roots in the time series. We present two of the most “popular” unit root tests, developed by Dickey and Fuller (1979 and 1981) and Phillips and Perron (1988), and discuss their properties.

The cointegration methodology, which enables investigation of equilibrium relationships between non-stationary series is discussed next. We present two alternative tests for cointegration. The first, is the two-step estimator of Engle and Granger (1987); this procedure amounts to estimating a static OLS regression in order to obtain a measure of the equilibrium relationship between the non-stationary variables and, in the second step, estimating a short-run model in order to identify the speed with which the variables respond to deviations from this equilibrium relationship. The second testing procedure, developed by Johansen (1988), involves modelling the non-stationary series as a vector autoregressive (VAR) model. As will be shown in section 2.4, this test is more powerful than the Engle and Granger (1987) test and, in addition, it provides us with 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 use of impulse response analysis for investigating the dynamic relationship between the variables in a VAR model is also discussed in this chapter. We present Sims’ (1980) approach for “orthogonalising” the innovations in the VAR model and then constructing “orthogonalised” impulse responses. However, these impulses are not unique and depend on the ordering of the variables in the VAR model. To circumvent these problems, Pesaran and Shin (1997) propose the use of “generalised” impulse responses. The application of orthogonalised and generalised impulse responses in a cointegrating VAR model is also discussed.

The structure of this chapter is as follows. The next section presents the general properties of stationary and non-stationary time-series. Unit root and cointegration tests are discussed in sections 3 and 4, respectively. Section 5 presents the use of impulse response functions in VAR and cointegrating VAR models and finally, section 6 concludes this chapter.

2.2 Unit Root Processes

A stochastic process, S_t , is stationary (also termed *weakly stationary* or *covariance stationary*) if its mean and variance remain constant over time and its autocovariances depend only on the distance between two observation points. These conditions can be written in mathematical form as follows:

1. $E(S_t) = \mu, \forall t$
2. $E[(S_t - \mu)^2] = \text{Var}(S_t) = \sigma^2, \forall t$
3. $E[(S_t - \mu)(S_{t-k} - \mu)] = \text{Cov}(S_t, S_{t-k}) = \gamma_k, \forall t$

This implies that a stationary series fluctuates around a constant mean within a more or less constant range (since its variance is constant) and the covariance between two observations, S_t and S_{t-k} , depends only on the distance between the observations, k , and not the time at which the covariance is calculated. Whether a series is stationary or not depends on whether its AR representation contains a unit root. Assume for instance that S_t is generated by the following AR(1) process

$$S_t = \rho S_{t-1} + u_t ; u_t \sim IN(0, \sigma^2) \quad (2.1)$$

where u_t are normally distributed error terms with zero mean and variance σ^2 . The time series S_t will be stationary if $|\rho| < 1$. On the other hand, if $\rho = 1$ then S_t will be non-stationary¹. To illustrate this, the solution of the difference equation (2.1) when $\rho = 1$, given some initial condition S_0 , is (see e.g. Enders, 1985)

$$S_t = S_0 + \sum_{i=1}^t u_i \quad (2.2)$$

It can be seen that the behaviour of S_t is governed by its initial value, S_0 , and all the

¹ If $|\rho| > 1$ then the series will be explosive i.e. it will tend to either $\pm \infty$.

disturbance terms accruing between period 1 and t . These accumulated disturbances, imply that a u_t shock has a permanent effect on the conditional mean of the S_t . In fact, S_t does not converge to its mean value since, if at some point in time $S_t = c$ then the expected time until S_t again returns to c is infinite.

Moreover, $\text{Var}(S_t) = t\sigma^2$, is not constant and increases to become infinitely large as $t \rightarrow \infty$.

Finally, $\text{Cov}(S_t, S_{t-k}) = (t-k)\sigma^2$ which also increases as t increases. Thus, the correlation coefficient between S_t and S_{t-k} becomes

$$\rho_k = \frac{\text{Cov}(S_t, S_{t-k})}{\sqrt{\text{Var}(S_t)\text{Var}(S_{t-k})}} = \frac{(t-k)\sigma^2}{\sqrt{t\sigma^2(t-k)\sigma^2}} = \sqrt{\frac{t-k}{t}} \quad (2.3)$$

If t is large relative to k then all ρ_k will be approximately unity which implies that 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; that is the series drifts upwards or downwards, as a result of the cumulative effects of the disturbance terms, but does not return to its long run mean of zero. This stochastic trend is eliminated by taking the first difference of the series. Taking for instance the first difference of S_t yields

$$\Delta S_t = u_t$$

which is a stationary process since $E(\Delta S_t) = 0$, $\text{Var}(\Delta S_t) = \sigma^2$ and $\text{Cov}(\Delta S_t, \Delta S_{t-k}) = 0$. Since the first difference of S_t is stationary, then S_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 $I(d)$.

The existence of a unit root has important consequences for the econometric modelling of univariate and multivariate time series. First, ARMA modelling using Box-Jenkins (1970) techniques, can only be applied to stationary time series.

Second, using standard regression techniques to investigate the relationship between non-stationary series may result in what Granger and Newbold (1974) call a “spurious regression” whereby the regression results falsely indicate the existence of a causal relationship between the price series. They show that this problem arises because the OLS estimates in this case are inconsistent and the t- and F-statistics do not follow the standard distributions generated by stationary series.

It is important therefore, to test the order of integration of each variable in a model, before any further econometric analysis is undertaken. This is carried out using unit root tests, which are described in the following section.

2.3 Unit Root Tests

A property of non-stationary series is that the effect of a shock is persistent. As a result there is a high degree of dependence between successive observations and the autocorrelation function of the series, in (2.3), decays very slowly. Hence, failure of the ACF to die down quickly is an indication of non-stationarity. Although visual inspection of the ACF is a useful tool for detecting the presence of unit roots, this method is imprecise and subjective since what appears as a unit root to one observer may appear as a stationary process to another. This problem arises because the ACF of a near unit root process (when ρ in (2.1) takes values close to 1), will exhibit the slowly decaying pattern indicative of a non-stationary process thus, forcing the researcher to conclude that a series is non-stationary when in fact it is not (Enders, 1995).

A more formal procedure to test for unit roots is the Dickey-Fuller (DF) test (Dickey and Fuller, 1979). By subtracting S_{t-1} from both sides of (2.1) 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 (2.1), respectively

$$\Delta S_t = \gamma S_{t-1} + u_t \quad (2.4)$$

$$\Delta S_t = \mu + \gamma S_{t-1} + u_t \quad (2.5)$$

$$\Delta S_t = \mu + \delta t + \gamma S_{t-1} + u_t \quad (2.6)$$

where $\gamma = \rho - 1$, μ is an intercept term and δt is a linear trend term. The DF test involves estimating one of the equations (2.4) to (2.6) 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 $\rho < 1$). 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. Critical values for these tests are tabulated by DF; these depend on the sample size as well as the deterministic regressors contained in the model and are denoted as, τ for model (2.4), τ_μ

for model (2.5) and τ_t for model (2.6). Therefore, one cannot reject the null hypothesis of a unit root when the computed statistics are less, in absolute value, than the appropriate DF critical values.

The issue that arises is which model, in (2.4) to (2.6), one should choose in order to test for a unit root, since each of these models implies a different alternative hypothesis for the data generating process (dgp) of the underlying series. Equation (2.4) tests the null hypothesis of a unit root against the alternative that the S_t series is stationary around a zero mean; the alternative hypothesis tested through equation (2.5) is that the series is stationary around a non-zero mean; finally, the alternative hypothesis implied by equation (2.6) is that the series is stationary around a linear deterministic trend. Moreover, since $\tau_t < \tau_\mu < \tau < 0$, adding a constant and a 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.

Perron (1988) suggests a sequential testing procedure, to decide which model to use for unit roots testing; this procedure is summarised in Table 2.1. In the first step, we start with the least restrictive of the plausible DF models (which will generally be model (2.6)). If we cannot reject the null of a unit root using the τ_t 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 DF (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_t statistic to be asymptotically normal (see West, 1988). In this case, we proceed to step 2A and test the null hypothesis of a unit root, $H_0: \gamma = 0$ in (2.6), using the standard-normal critical values. On the other hand, 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 model (2.5) 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 DF (1981). Rejection of the null hypothesis using the Φ_1 statistic, implies that the constant term in (2.5) is significant under the null hypothesis of a unit root and asymptotic normality for the τ_t statistic follows; thus, the standard-normal critical values are used to test the null hypothesis $H_0: \gamma = 0$ in (2.5), as described in step 4A. On the other hand, if the null hypothesis $\gamma = \mu = 0$ cannot be rejected

then, we proceed to step 5 where we estimate (2.4) 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	$\Delta S_t = \gamma S_{t-1} + \mu + \delta t + u_t$	$\gamma = 0$	τ_τ	-3.45
2	$\Delta S_t = \gamma S_{t-1} + \mu + \delta t + u_t$	$\gamma = \delta = 0$	Φ_3	6.49
2A	$\Delta S_t = \gamma S_{t-1} + \mu + \delta t + u_t$	$\gamma = 0$	Standard Normal	-1.96
3	$\Delta S_t = \gamma S_{t-1} + \mu + u_t$	$\gamma = 0$	τ_μ	-2.89
4	$\Delta S_t = \gamma S_{t-1} + \mu + u_t$	$\gamma = \mu = 0$	Φ_1	4.71
4A	$\Delta S_t = \gamma S_{t-1} + \mu + u_t$	$\gamma = 0$	Standard Normal	-1.96
5	$\Delta S_t = \gamma S_{t-1} + u_t$	$\gamma = 0$	τ	-1.95

Notes:

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

Therefore, in the procedure suggested by Perron (1988), we start with the most general model specification and the testing continues down to more restrictive alternatives. The testing stops as soon as we are able to reject the null hypothesis of a unit root; If we cannot reject the null at any of the stages then we conclude that the series has a unit root. Steps 2A and 4A are undertaken only if we are able to reject the joint hypotheses in steps 2 and 4, respectively. However, even when asymptotic normality holds for the τ_τ and τ_μ statistics, Banerjee et al. (1993) suggest that the DF distribution provides a better approximation than the standard normal in finite samples. Harris (1995), also suggests 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. Similar concerns are raised by Enders (1995) who suggests that, rather than applying the aforementioned testing strategy in a mechanical fashion, the deterministic regressors in the ADF tests should be determined using the information provided by the series. For instance, the plots of spot and futures prices in the previous chapter, 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 ADF test, as in (2.5).

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 is based on the assumption that u_t is white noise. These tests are called Augmented Dickey Fuller tests (ADF) (Dickey and Fuller, 1981). The appropriate regressions are

$$\Delta S_t = \gamma S_{t-1} + \sum_{i=1}^p \psi_i \Delta S_{t-i} + u_t \quad (2.7)$$

$$\Delta S_t = \mu + \gamma S_{t-1} + \sum_{i=1}^p \psi_i \Delta S_{t-i} + u_t \quad (2.8)$$

$$\Delta S_t = \mu + \delta t + \gamma S_{t-1} + \sum_{i=1}^p \psi_i \Delta S_{t-i} + u_t \quad (2.9)$$

To test the null hypothesis of a unit root, $H_0: \gamma = 0$, the same critical values as in the DF test are used (i.e. τ , τ_μ , τ_τ for models (2.7), (2.8) and (2.9), respectively). In performing the ADF 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) (see Harris, 1995). 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 Schwarz Bayesian Information Criterion (SBIC) (Schwarz, 1978)

$$AIC = -2 (LL - K) \quad (2.10)$$

$$SBIC = -2 (LL - 0.5K \ln T) \quad (2.11)$$

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 scores the lowest value of the AIC or SBIC. Usually, the SBIC is preferred over the AIC because it is strongly consistent and always determines the true model asymptotically, whereas for the AIC an overparameterised model will always emerge (see Mills, 1993).

2.3.1 Phillips-Perron (1988) tests

The ADF test includes higher order lagged terms to account for the fact that the underlying dgp of the series may be more complicated than a simple AR(1) process. The additional lags of the dependent variable are used to “whiten” the error term in the ADF regression, since autocorrelated errors invalidate the use of the DF distribution. An alternative approach is that suggested by Phillips (1987) and Phillips and Perron (PP) (1988). Rather than using a parametric correction for autocorrelation (through the additional lagged terms), a non-parametric correction to the t-statistic is undertaken to account for the residual autocorrelation that may be present when the underlying process is not AR(1). Thus, DF type equations (i.e. (2.4) - (2.6)) are estimated and then the t-statistic is amended to take account of any bias due to autocorrelation in the error term. For instance, an asymptotically valid test that $\gamma = 0$ in (2.5), when the underlying process is not necessarily AR(1), is given by the $Z(\tau_\mu)$ test

$$Z(\tau_\mu) = (S_u/S_{T\partial})\tau_\mu - 1/2(S^2_{T\partial} - S^2_u) \left\{ S_{T\partial} \left[T^2 \sum_{t=2}^T (S_{t-1} - \bar{S}_{-1})^2 \right]^{1/2} \right\}^{-1} \quad (2.12)$$

where

τ_μ is the t-statistic for testing the null hypothesis $\gamma = 0$ in (2.5)

S^2_u is a consistent estimator of the true population variance in (2.5) given by

$$S^2_u = T^{-1} \sum_{t=1}^T (\hat{u}_t^2)$$

$S_{T\partial}$ is a consistent estimator of the variance of the residuals in (2.5) given by

$$S_{T\partial} = T^{-1} \sum_{t=1}^T (\hat{u}_t^2) + 2T^{-1} \sum_{j=1}^{\partial} (1-j(\partial+1)^{-1}) \sum_{t=j+1}^T (\hat{u}_t \hat{u}_{t-j})$$

∂ is the lag truncation parameter which is used to ensure that the autocorrelation of the residuals in (2.5) is fully captured, and

\bar{S}_{-1} is the mean value of the S_t series for the first $T - 1$ observations.

PP propose similar modifications for the remaining DF statistics, namely τ_τ , τ , Φ_1 and Φ_3 statistics; these are denoted as $Z(\tau_\tau)$, $Z(\tau)$, $Z(\Phi_1)$ and $Z(\Phi_3)$, respectively. For instance, $Z(\tau_\tau)$ is

a non-parametric corrections of the τ_τ statistics and tests the null that $\gamma = 0$ in (2.6). The critical values for these tests are the same as for the ADF tests.

The PP test is based on a weaker set of assumptions regarding the error process than the ADF test, and can be validly used to test for unit roots when the underlying dgp of the series is quite general. Moreover, the PP test has higher power than the ADF test in rejecting a false null hypothesis. However, Schwert (1989) indicates that the PP test has poor size properties (i.e. the tendency to over-reject the null when it is true) when the underlying dgp has large negative moving average components. Since the true dgp is not known in practice, Enders (1995) suggests using both PP and ADF tests and examine if they reinforce each other.

2.4 Testing For Cointegration

If a stochastic series S_t contains one unit root, then it must be differenced once in order to become stationary; the resulting series can then be analysed using univariate Box-Jenkins (1970) techniques. Generalising this to the multivariate framework, suggests that all the non-stationary series must be differenced, and a regression model must be estimated using the first-differenced series. However, in many situations, this procedure is incorrect because it ignores the information which is contained in the long-run relationship between the variables. In fact, Engle and Granger (1987) recognise that there may be a linear combination of integrated variables that is stationary.

Consider for instance two $I(1)$ time series S_t and F_t . In general, any linear combination among the two series will also be $I(1)$; for example, the residuals ϵ_t obtained from regressing F_t on S_t will also be $I(1)$. However, there may be a number β such that $S_t - \beta F_t = \epsilon_t$ is stationary. In this case, Engle and Granger (1987) define the series S_t and F_t as cointegrated of order (1,1) (denoted as $CI(1,1)$). Therefore, if S_t and F_t stand in a long-run relationship then, even though the series themselves are non-stationary, they will move closely together over time and the difference between them will be stationary. In other words, the concept of cointegration mimics the existence of a long run equilibrium relationship to which an economic system converges over time, and ϵ_t defined above can be interpreted as the disequilibrium error, i.e. the distance that the system is away from equilibrium at time t .

In this section we discuss the two major approaches for identifying cointegrating relationships; the Engle and Granger (1987) two-step estimator and the Johansen (1988) maximum likelihood estimator.

2.4.1 The Engle-Granger (1987) test

Engle and Granger (EG) (1987) propose the following two-step approach for cointegration tests of two non-stationary series. The first step involves estimating the residuals, ε_t , from the following regression, called the cointegrating or equilibrium regression

$$S_t = \beta_1 + \beta_2 F_t + \varepsilon_t \quad (2.13)$$

If S_t and F_t are cointegrated, then the estimated residual series (denoted by $\hat{\varepsilon}_t$) must be stationary. The $\hat{\varepsilon}_t$ series represents the deviations of S_t and F_t from their long run relationship; for the two series to be cointegrated then these deviations must be stationary. To investigate this, EG propose the following ADF test on the estimated residual series $\hat{\varepsilon}_t$

$$\Delta \hat{\varepsilon}_t = \psi \hat{\varepsilon}_{t-1} + \sum_{i=1}^{p-1} \psi_i \Delta \hat{\varepsilon}_{t-i} + \omega_t; \quad \omega_t \sim IN(0, \sigma_\omega^2) \quad (2.14)$$

where lagged values of $\Delta \hat{\varepsilon}_{t-i}$ are entered into the equation so as to “whiten” the errors. The inclusion of a trend term, δ , and/or a constant, μ , in (2.14) depends on whether a constant or a trend appears in the cointegrating regression since deterministic components can appear in (2.13) or in (2.14); if deterministic terms appear in both (2.13) and (2.14) then, the cointegrating test is misspecified. As with ordinary ADF tests, the null hypothesis of no cointegration, or of the existence of a unit root, in the estimated residual series, $H_0: \psi = 0$, is based on a t-test with a non-normal distribution. The DF critical values are not applicable in this case because the $\hat{\varepsilon}_t$ series is estimated from a regression; the OLS estimator “selects” the residuals in (2.13) to have the smallest sample variance, thus making $\hat{\varepsilon}_t$ to appear stationary, even if S_t and F_t are not cointegrated. Therefore, use of the standard DF distribution would tend to over-reject the null. Appropriate critical values for this test are provided by MacKinnon (1991).

Having established that $\hat{\varepsilon}_t \sim I(0)$ the next step in the EG procedure is to identify an error correction model (ECM) of the joint process, using the estimates of last period's disequilibrium $\hat{\varepsilon}_{t-1} = S_{t-1} - \beta_1 - \beta_2 F_{t-1}$ to obtain information on the speed of adjustment to equilibrium, as in equation (2.15)

$$\Delta S_t = -\alpha_1 \hat{\varepsilon}_{t-1} + \gamma_1 \Delta F_t + \sum_{j=1}^m \theta_j \Delta F_{t-j} + \sum_{j=1}^k \varphi_j \Delta S_{t-j} + v_t \quad ; v_t \sim IN(0, \sigma_v^2) \quad (2.15)$$

where α_1 is the speed of adjustment coefficient and lagged values of ΔS_t and ΔF_t are included in the model in order to capture the autocorrelation in the residuals. All the terms in (2.15) are $I(0)$ and hence, statistical inference using standard t- and F-tests is applicable.

The existence of an ECM for a set of cointegrated $I(1)$ variables, as in equation (2.15), is guaranteed as shown by the Granger Representation Theorem (Engle and Granger 1987). This states that if a set of $I(1)$ variables are cointegrated then an ECM can be estimated, and conversely, if a set of $I(1)$ variables can be modelled as an ECM then, these variables are cointegrated.

The ECM specification incorporates both short- and long-run reaction of ΔS_t to changes in the RHS variables. The short-run adjustment is captured by current and past values of ΔF_t as well as lagged values of ΔS_t . The long-run effects are incorporated into the model through the Error Correction Term (ECT), $\hat{\varepsilon}_{t-1}$, which measures the distance the system is away from equilibrium. If equilibrium holds then $\hat{\varepsilon}_{t-1} = 0$. On the other hand, during periods of disequilibrium, this term is different than zero. Therefore, the α_1 coefficient provides information on the speed of adjustment, that is how the spot price responds to departures from the long run equilibrium relationship. Suppose for instance that S_t starts falling more rapidly than is consistent with (2.13); this results in $\hat{\varepsilon}_{t-1} < 0$. Since the α_1 coefficient in (2.15) has a negative sign, the net result is an increase in ΔS_t , thereby forcing S_t back towards its long-run path. This represents a principal feature of cointegrated variables; their time paths must be influenced by the extent of any deviation from their long-run equilibrium.

The EG (1987) approach, is very easily implemented since one can estimate the residual series from the cointegrating regression (2.13), by placing one variable on the left hand side (either S_t or F_t) and use the other as a regressor, and then use these estimates of disequilibrium to specify an ECM. Asymptotically, tests for unit roots in either of the residual series, should give the same results. However, Harris (1995) points out that the finite sample estimates of the long run relationship are potentially biased and using a different normalisation, that is reversing the order of the variables in the cointegrating regression, may yield totally different results. Another drawback 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 (2.13); Phillips and Durlauf (1986) derive the asymptotic distributions of the OLS estimators, β_1 and β_2 , and their associated standard errors in (2.13) and show these to be highly non-normal thus invalidating standard inference. Finally, the ECM of (2.15) imposes the restriction that F_t is weakly exogenous to S_t (i.e. the current value of F_t is not affected by the current value of S_t) and, as a result, the F_t series appears only on the right-hand-side of equation (2.15). As indicated by Harris (1995), this leads to inefficient estimates, since the model does not take into account all the information that the variables have to offer.

The Johansen (1988) procedure circumvents the use of the two-step estimator and the small sample biases associated with the EG approach by directly testing for cointegrating relationships in a multivariate vector autoregressive (VAR) framework. 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; as a result, this test is more powerful than the EG test. Furthermore, it provides us with a test statistic which has an exact limiting distribution and enables us to perform hypothesis tests for restricted versions of the cointegrating relationships. This procedure is described next.

2.4.2 The Johansen (1988) tests for Cointegration

2.4.2.1 VAR and Vector Error Correction Models

The Johansen (1988) cointegration test can be considered as a multivariate extension of the DF test. To illustrate this, consider a set of two $I(1)$ variables, (S_t, F_t) , which are generated by the following bivariate system

$$S_t = \sum_{i=1}^p A_{11}(i)S_{t-i} + \sum_{i=1}^p A_{12}(i)F_{t-i} + \varepsilon_{S,t}$$

$$F_t = \sum_{i=1}^p A_{21}(i)S_{t-i} + \sum_{i=1}^p A_{22}(i)F_{t-i} + \varepsilon_{F,t}$$

where $A_{kj}(i)$ ($k, j = 1, 2$, $i = 1, 2, \dots, p$) are coefficients and $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$ are uncorrelated white noise disturbances. In matrix form this system can be written as

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + \dots + A_p X_{t-p} + \varepsilon_t \quad ; \varepsilon_t \sim IN(0, \Sigma) \quad (2.16)$$

where X_t is the 2×1 vector of variables $(S_t, F_t)'$; ε_t is the 2×1 vector of residuals $(\varepsilon_{S,t}, \varepsilon_{F,t})'$ which are normally distributed with mean zero and variance / covariance matrix Σ ; and A_i , ($i = 1, 2, \dots, p$) are 2×2 matrices of coefficients shown below

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

The system of equations in (2.16) is called a p th order vector autoregression (VAR) model. The VAR can be reparameterised by subtracting X_{t-1} from each side of (2.16) to obtain

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

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

$$\Delta X_t = (A_1 - I_2) \Delta X_{t-1} + (A_2 + A_1 - I_2)X_{t-2} + A_3X_{t-3} + \dots + A_pX_{t-p} + \varepsilon_t$$

Next add and subtract $(A_2 + A_1 - I_2)X_{t-3}$ from the RHS to obtain

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

Continuing in this fashion we obtain

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad (2.17)$$

where $\Pi = -(I_2 - \sum_{i=1}^p A_i)$ and $\Gamma_i = -(I_2 - \sum_{j=1}^i A_j)$. Equation (2.17) is called a Vector Error Correction Model (VECM) ². 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.

The crucial parameter for cointegration between S_t and F_t is the rank of matrix Π ³. If $\text{rank}(\Pi)=0$, then Π is the 2x2 zero matrix implying that there are no any cointegrating relationships between S_t and F_t ; in this case, (2.17) is reduced to a VAR model in first differences. If Π has a full rank, that is $\text{rank}(\Pi)=2$, then all the variables in X_{t-1} are $I(0)$ and the appropriate modelling strategy is to estimate a VAR model in levels as in equation (2.16). If Π has a reduced rank, that is $\text{rank}(\Pi)=1$, 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 error correction term. Since the rank of Π is equal to the number of its characteristic roots (or eigenvalues) which are different from zero, the number of distinct cointegrating vectors can be obtained by estimating how many of these eigenvalues are significantly different from

² This formulation of the VECM can be shown to be equivalent to $\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-p} + \varepsilon_t$; it makes no

difference whether X_{t-1} enters the error correction term with a lag of $t-1$ or $t-p$ (see Harris, 1995).

³ The rank of a square $n \times n$ matrix is the number of its linearly independent rows, or columns.

zero⁴. Johansen (1988) proposes the following two statistics to test for the significance of the estimated eigenvalues.

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i) \quad (2.18)$$

$$\lambda_{\text{max}}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \quad (2.19)$$

where $\hat{\lambda}_i$ are the eigenvalues obtained from the estimate of the Π matrix and T is the number of usable observations. 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 . 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 distribution of these statistics depends upon the number of non-stationary relationships under the null and on the deterministic components that are included in the VECM.

Having identified, with the use of the λ_{trace} and λ_{max} statistics, that $\text{rank}(\Pi)=1$, Π can be factored into two separate vectors α and β , both of dimensions 2×1 , where 1 represents the rank of Π . The properties of α and β are such that

$$\Pi = \alpha\beta'$$

where β represents the vector of cointegrating parameters, and α is the vector of the speed of adjustment parameters. Consider for instance the system of equations in (2.17) which can be expressed in terms of specific equations for each ΔX_t sequence as follows;

$$\begin{pmatrix} \Delta S_t \\ \Delta F_t \end{pmatrix} = \sum_{i=1}^{p-1} \Gamma_i \begin{pmatrix} \Delta S_{t-i} \\ \Delta F_{t-i} \end{pmatrix} + \begin{pmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{pmatrix} \begin{pmatrix} S_{t-1} \\ F_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix}$$

⁴ The characteristic roots (or eigenvalues) of a square $n \times n$ matrix Π , are the values of λ that satisfy the following equation $|\Pi - \lambda I_n| = 0$, where I_n is an $n \times n$ identity matrix.

Since $\text{rank}(\Pi)=1$, the rows of Π are linear multiples of each other and differ by a scalar, s_2

$$\begin{pmatrix} \Delta S_t \\ \Delta F_t \end{pmatrix} = \sum_{i=1}^{p-1} \Gamma_i \begin{pmatrix} \Delta S_{t-i} \\ \Delta F_{t-i} \end{pmatrix} + \begin{pmatrix} \pi_{11} & \pi_{12} \\ s_2 \pi_{11} & s_2 \pi_{12} \end{pmatrix} \begin{pmatrix} S_{t-1} \\ F_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix}$$

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

$$\begin{aligned} \begin{pmatrix} \Delta S_t \\ \Delta F_t \end{pmatrix} &= \sum_{i=1}^{p-1} \Gamma_i \begin{pmatrix} \Delta S_{t-i} \\ \Delta F_{t-i} \end{pmatrix} + \begin{pmatrix} \alpha_1 & \alpha_1 \beta_2 \\ \alpha_2 & \alpha_2 \beta_2 \end{pmatrix} \begin{pmatrix} S_{t-1} \\ F_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \\ &= \sum_{i=1}^{p-1} \Gamma_i \begin{pmatrix} \Delta S_{t-i} \\ \Delta F_{t-i} \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} (\beta_1 \quad \beta_2) \begin{pmatrix} S_{t-1} \\ F_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \end{aligned}$$

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

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \beta' X_{t-1} + \varepsilon_t \quad (2.20)$$

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

2.4.2.2 Maximum Likelihood Estimation of the Cointegrating Vectors

The maximum likelihood estimates of the cointegrating vector, β in (2.20), are obtained using the reduced rank regressions procedure ⁵. This is carried out by regressing ΔX_t and X_{t-1} on ΔX_{t-i} ($i = 1, 2, \dots, p-1$) as follows

$$\begin{aligned}\Delta X_t &= P_1 \Delta X_{t-1} + P_2 \Delta X_{t-2} + \dots + P_p \Delta X_{t-p} + R_{0,t} \\ X_{t-1} &= K_1 \Delta X_{t-1} + K_2 \Delta X_{t-2} + \dots + K_p \Delta X_{t-p} + R_{k,t}\end{aligned}$$

The residuals from these regressions, $R_{0,t}$ and $R_{k,t}$, are then used to form the residuals product moment matrices, S_{ij} $i, j = 0, k$ as follows

$$S_{ij} = T^{-1} \sum_{t=1}^T R_{it} R_{jt}' \quad i, j = 0, k$$

Johansen (1988) shows that the maximum likelihood estimates of β are the eigenvectors corresponding to the r largest eigenvalues from solving the following characteristic equation

$$\left| \lambda S_{KK} - S_{K0} S_{00}^{-1} S_{0K} \right| = 0 \quad (2.21)$$

This gives the n eigenvalues, ordered in descending order, $\hat{\lambda}_1 > \hat{\lambda}_2 > \dots > \hat{\lambda}_n$, and their corresponding eigenvectors $\hat{v} = (\hat{v}_1, \hat{v}_2, \dots, \hat{v}_n)$ ⁶.

The estimated eigenvalues from (2.21) are then used for the computation of the λ_{\max} and λ_{trace} statistics of equations (2.18) and (2.19), respectively. The r largest eigenvectors, corresponding to the r largest eigenvalues, represent the cointegrating vectors i.e. $\beta =$

⁵ The estimates obtained using the reduced rank regressions are identical to those obtained using standard MLE techniques; see as well Johansen (1995).

⁶ Given the characteristic matrix of Π , $(\Pi - \lambda I_n)$, the eigenvector of Π is the vector, $V \neq 0$, that satisfies the following equation: $(\Pi - \lambda I_n)V = 0$.

$(\hat{v}_1, \hat{v}_2, \dots, \hat{v}_r)$. This is because these largest eigenvalues represent the largest correlations between the “levels” residuals, $R_{0,t}$, and the “first difference” residuals, $R_{K,t}$. That is, we obtain estimates of all the distinct $\hat{v}_i'X_t$ ($i = 1, 2, \dots, r$) combinations of the $I(1)$ levels of X_t which produce high correlations with the stationary $\Delta X_t \sim I(0)$ variables. Such combinations are the cointegrating vectors by virtue of the fact that they must themselves be $I(0)$ to achieve a high correlation. Therefore, the magnitude of $\hat{\lambda}_i$ is a measure of how strongly the cointegrating relations, $\hat{v}_i'X_t = \beta'X_t$, are correlated with the stationary part of the model.

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 (2.20) 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 equations in (2.20) contain different sets of regressors (i.e. either different variables or different lag structures for each variable) and the VECM should be estimated as a system of seemingly unrelated regressions (SUR) (Zellner, 1962). This is because, this method yields more efficient estimates than OLS when the equations in the system contain different regressors ⁷.

⁷ Zellner (1962), also shows that when the equations in the system contain identical regressors, then SUR estimation is equivalent to OLS estimation.

2.4.2.3 Model Specification

Implementation of the Johansen (1988) procedure requires that several decisions be made before estimating the long run relationships in the VECM. First, the lag length, p , of the VECM must be determined. The usual practice is to estimate the unrestricted VAR model of equation (2.16), using the longest lag length deemed reasonable for the data set ⁸, and then use a model selection criterion, such as the AIC (1978) or the SBIC (1978) of equations (2.10) and (2.11), respectively to arrive at the most parsimonious model.

Second, the deterministic components that should be included in the formulation of the model should be clearly identified. This step is important since the asymptotic distributions of the cointegration test statistics are dependent upon the presence of trends and/or constants in the model. Johansen and Juselius (1990) and Osterwald-Lenum (1992) expand the VECM to accommodate the different types of deterministic terms (such as an intercept, a linear trend or both); they consider 5 different model specifications;

Model 1: Linear trend and intercept in the short-run model ⁹

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha\beta'X_{t-1} + \mu + \delta t + \varepsilon_t \quad (2.22)$$

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 (see Johansen and Juselius, 1990). However, the existence of quadratic trends in the levels series implies an ever-increasing (or decreasing) rate of growth for these series, which, as Harris (1995) points out “*is difficult to be justified on economic grounds*”.

⁸ For instance, 4, 12 and 21 lags can be chosen for quarterly, monthly and daily data, respectively.

⁹ 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 2: Trend term in the long-run model and intercept term in the short run model

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \begin{pmatrix} \beta \\ \delta \end{pmatrix}' (X'_{t-1} \quad t)' + \mu + \varepsilon_t \quad (2.23)$$

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 3: Intercept term in the short run model

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \beta' X_{t-1} + \mu + \varepsilon_t \quad (2.24)$$

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

Model 4: Intercept term in the long-run model

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \begin{pmatrix} \beta \\ \mu \end{pmatrix}' (X'_{t-1} \quad 1)' + \varepsilon_t \quad (2.25)$$

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 5: No deterministic components in the short run model or in the cointegrating relations

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \alpha \beta' X_{t-1} + \varepsilon_t \quad (2.26)$$

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

The choice of the deterministic components that should be included in the VECM is not easily answered apriori and, usually, some economic argument is needed in order to arrive at the best model specification. For instance, in this thesis we investigate the relationship

between spot and future prices; therefore, the implied long-run relationship is the spot-futures differential. Due to the convergence of futures and spot prices at the maturity day of the contract, we do not expect the presence of linear trend term in the cointegrating vector; hence we do not consider model 2. Similarly, the graphs of spot and futures prices, in chapter 1, do not indicate the presence of a quadratic trend in the series which would justify the use of model 1. Finally, we do not consider model 5 since an intercept term, either in the short or in the long-run model, is needed to account for the units of measurement of the variables. Therefore, we are left with two competing specifications; model 3 and model 4.

To determine whether the intercept term should be included in the cointegrating vector, as in (2.25), or in the short-run model as in (2.24) we employ Johansen's (1991) test for the appropriateness of including an intercept term in the cointegrating vector (H_0) against the alternative that there are linear trends in the level of the series (H_1)

$$-T [\ln(1 - \hat{\lambda}_2^*) - \ln(1 - \hat{\lambda}_2)] \sim \chi^2(1) \quad (2.27)$$

where $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ represent the smallest eigenvalues of the model that includes an intercept term in the cointegrating vector (model 4) and an intercept term in the short-run model (model 3) respectively. For the null hypothesis to be true, the values of $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ should be equivalent. Therefore, acceptance of the null hypothesis indicates that the VECM in equation (2.17) should be estimated with an intercept term in the cointegrating vector i.e. that the preferred specification is model 4.

The intuition behind this test is that the likelihood of finding a cointegrating relationship is greater with the intercept term in the cointegrating vector than if the intercept is absent from the cointegrating vector; this follows from the fact that the critical values of the λ_{\max} and λ_{trace} tests are larger in the former case (see Osterwald-Lenum, 1992). Therefore, a large value of $\hat{\lambda}_2^*$, relative to $\hat{\lambda}_2$, implies that the restriction artificially inflates the number of cointegrating vectors; in other words, the indicated number of cointegrating vectors is 2, instead of 1. Thus, as proven by Johansen (1991), if the test statistic is large, it is possible to reject the null hypothesis of an intercept term in the cointegrating vector and conclude that there is a linear

trend in the variables i.e. that the preferred specification is model 2 ¹⁰.

2.4.2.4 Testing parameter Restrictions on the Cointegrating Relationship

One of the advantages of the Johansen procedure, over the EG approach, is that it provides us with a test statistic which has an exact limiting distribution and enables tests of parameter restrictions in the cointegrating relationship. This suggests that Johansen's (1988) tests are particularly useful in cases where hypotheses tests must be carried out to identify whether the variables follow a particular long-run relationship which is dictated by economic theory. For instance, the unbiasedness hypothesis suggests that futures prices before maturity must be equal to the realised spot prices i.e. that the cointegrating relationship between the series is $z_t = (1, -1)(S_t F_{t;t-n})'$, or alternatively that the cointegrating vector is $(1, -1)$.

The test statistic, proposed by Johansen and Juselius (1990), involves comparing the number of cointegrating relationships under the null and alternative hypotheses. Since the number of cointegrating relationships depends on the number of the largest eigenvalues of the Π matrix, in (2.17), that are significantly different from zero, this test compares the largest eigenvalues of the restricted and the unrestricted models as follows.

Let $\hat{\lambda}_1$ denote the largest eigenvalue of the unrestricted model and $\hat{\lambda}_1^*$ denote the largest eigenvalue of the model with the imposed restrictions on the cointegrating vector. Then, the following likelihood ratio (LR) statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the number of restrictions (n) placed on β' :

¹⁰ Another approach for identifying the deterministic components in a VECM, is to test the hypothesis of both the rank order and the deterministic components jointly, based on the so called Pantula (1989) principle. All plausible models, out of the five cases previously outlined, are presented from the most restrictive to the least restrictive alternative. The procedure is then to move through from the most restrictive model and at each stage to compare the λ_{trace} or the λ_{max} test statistic to its critical value and only stop the first time the null hypothesis cannot be rejected. For an application of this procedure see Harris (1995), p. 96.

$$T [\ln(1 - \hat{\lambda}_1^*) - \ln(1 - \hat{\lambda}_1)] \sim \chi^2(n) \quad (2.28)$$

Small values of $\hat{\lambda}_1^*$ relative to $\hat{\lambda}_1$ indicate a reduced number of cointegrating vectors and a larger value for the LR 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.

In addition to providing a framework for valid inferences in the presence of $I(1)$ variables, modelling the series using the Johansen (1988) procedure has several advantages. Gonzalo (1994) shows that this procedure provides more efficient estimates of the cointegrating relationship than the EG estimator. Moreover, these tests are shown to be fairly robust to the presence of non-normality (Cheung and Lai, 1993) and heteroskedastic disturbances (Lee and Tse, 1996) in the error terms of the VECM. Therefore, given their superior properties, Johansen (1988) tests are employed in the ensuing empirical analysis to investigate the long-run relationship between spot and futures prices in the BIFFEX market.

2.5 Impulse Response Analysis

The impulse response function measures the response of the endogenous variables in the VAR model to shocks in the model. In order to trace the time path of the various shocks on the variables contained in the VAR system we construct the vector moving average (VMA) representation of the VAR model. Just as an autoregression has an MA representation, a VAR can be expressed as the infinite sum of the current and past values of shocks in ε_t . Consider the VAR of equation (2.16), repeated here for convenience

$$X_t = \sum_{i=1}^p A_i X_{t-i} + \varepsilon_t = A_1 X_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + \dots + A_p X_{t-p} + \varepsilon_t \quad ; \varepsilon_t \sim IN(0, \Sigma)$$

Substituting X_{t-1} into the RHS of the VAR model we get

$$\begin{aligned} X_t &= A_1(A_1 X_{t-2} + A_2 X_{t-3} + A_3 X_{t-4} + \dots + A_p X_{t-p-1} + \varepsilon_{t-1}) + A_2 X_{t-2} + A_3 X_{t-3} + \dots + A_p X_{t-p} + \varepsilon_t \\ &= A_1^2 X_{t-2} + A_1 A_2 X_{t-3} + A_1 A_3 X_{t-4} + \dots + A_1 A_p X_{t-p-1} + A_1 \varepsilon_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + \dots + A_p X_{t-p} + \varepsilon_t \end{aligned}$$

Continuing in this fashion (i.e. substituting X_{t-2} into the RHS, etc.), we obtain the VMA representation of the X_t vector (see Sims, 1980)

$$X_t = \sum_{i=1}^{\infty} \Phi_i \varepsilon_{t-i} \quad (2.29)$$

where the 2x2 matrices Φ_i are computed using the recursive relations

$$\Phi_i = A_1 \Phi_{i-1} + A_2 \Phi_{i-2} + \dots + A_p \Phi_{i-p}, \quad i=1,2,\dots$$

with $\Phi_0 = I_2$, and $\Phi_i = 0$ for $i < 0$. Equation (2.29) can be written in matrix form as follows

$$\begin{pmatrix} S_t \\ F_t \end{pmatrix} = \sum_{i=0}^{\infty} \begin{pmatrix} \varphi_{11}(i) & \varphi_{12}(i) \\ \varphi_{21}(i) & \varphi_{22}(i) \end{pmatrix} \begin{pmatrix} \varepsilon_{S,t-i} \\ \varepsilon_{F,t-i} \end{pmatrix} \quad (2.30)$$

The $\varphi_{kj}(i)$ coefficients measure the impact of a shock in the error terms on the endogenous variables of the model. For example, the coefficient $\varphi_{12}(0)$ is the instantaneous impact of a one-unit change in $\varepsilon_{F,t}$ on S_t with all the other variables held constant i.e. $\partial S_t / \partial \varepsilon_{F,t} = \varphi_{12}(0)$, where ∂ is the partial differentiation operator. Similarly, $\varphi_{12}(n)$ represents the response of S_{t+n} following a one-unit change in $\varepsilon_{F,t}$ with all the other variables held constant i.e. $\partial S_{t+n} / \partial \varepsilon_{F,t} = \varphi_{12}(n)$, etc. The four sets of coefficients $\varphi_{11}(i)$, $\varphi_{12}(i)$, $\varphi_{21}(i)$ and $\varphi_{22}(i)$ in (2.30) are called the impulse response functions. Plotting the impulse response functions (i.e. plotting the $\varphi_{kj}(i)$ coefficients against i) is a practical way to visually represent the behaviour of the X_t series in response to various shocks.

The impulse response functions measure the impact of a shock in one variable assuming that everything else in the system is held constant. However, the components in $\varepsilon_t = (\varepsilon_{S,t}, \varepsilon_{F,t})'$ may be contemporaneously correlated in which case $E(\varepsilon_t, \varepsilon_t') = \Sigma$ is non-diagonal. If $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$ are correlated, then simulation of a shock to say $\varepsilon_{F,t}$ while assuming that $\varepsilon_{S,t}$ is held constant will lead to misleading results. This ambiguity in interpreting impulse responses arises from the fact that if the errors are correlated, they have a common component which cannot be identified with any specific variable. To overcome this problem, Sims(1980) employs the following Cholesky decomposition of Σ

$$\Sigma = TT'$$

where T is a 2×2 lower triangular matrix. Sims then rewrites the VMA of (2.29) as

$$X_t = \sum_{i=1}^{\infty} (\Phi_i T)(T^{-1} \varepsilon_{t-i}) = \sum_{i=1}^{\infty} \Phi_i^* u_{t-i} \quad (2.31)$$

where $\Phi_i^* = \Phi_i T$ and $u_t = T^{-1} \varepsilon_t$. It can now be seen that

$$E(u_t, u_t') = T^{-1} E(\varepsilon_t, \varepsilon_t') T'^{-1} = T^{-1} \Sigma T'^{-1} = I_2$$

and the new errors, u_t , obtained using the transformation matrix, T , are contemporaneously

uncorrelated and have unit standard errors. In other words, the shocks in u_t are orthogonal to each other and hence, impulse responses can be constructed using these “orthogonalised” errors. For instance, the “orthogonalised” impulse response (OIR) function of a “unit shock” (equal to one standard error) at time t to the orthogonalised error of the spot equation on the futures equation at time $t+n$ is

$$OI_{S,F,t+n} = e_2' \Phi_n T e_1 \quad (2.32)$$

where e_1 and e_2 are selection vectors such as $e_2 = (0 \ 1)'$, $e_1 = (1 \ 0)'$. Similarly, the OIR of the spot equation at time $t+n$, following a unit shock to the futures equation at time t is given by

$$OI_{F,S,t+n} = e_1' \Phi_n T e_2$$

An important disadvantage in Sims' (1980) methodology is that the transformation matrix T is not unique; if we change the order of the variables in X_t (e.g. $X_t = (F_t, S_t)'$ rather than $X_t = (S_t, F_t)'$) then a new transformation matrix will emerge and as a result the OIR will be different. Therefore, different orderings of the variables in the VAR result in different impulse responses. For this reason, orthogonalising the innovations in the VAR using the Cholesky decomposition is said to imply an “ordering” of the variables (see e.g. Lütkepohl, 1991). The importance of this ordering depends upon the magnitude of the correlation coefficient between $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$. The larger the correlation coefficient, the larger the impact of changes in the order of the variable. At the other extreme, when $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$ are uncorrelated (i.e. Σ is diagonal) then the orthogonalised responses are invariant to the ordering of the variables.

2.5.1 Generalised Impulse Responses

The main idea behind the generalised impulse response (GIR) function, proposed by Pesaran and Shin (1997), is to circumvent the problems associated with the dependence of the OIR on the ordering of the variables in the VAR. In the context of the VAR model of equation (2.16), the GIR of the futures equation at time $t+n$ following a shock, at time t , to the error of the spot equation, $\varepsilon_{s,t} = \delta_1$, is given by

$$GI_F(n, \delta_1, \Omega_{t-1}) = E(F_{t+n} | \varepsilon_{s,t} = \delta_1, \Omega_{t-1}) - E(F_{t+n} | \Omega_{t-1}) \quad (2.33)$$

where $E(.|.)$ is the mathematical expectation operator and Ω_{t-1} is the information set available to market agents at time $t-1$. Therefore, the GIR is the difference between the expected time profile of F_{t+n} , following a shock, δ_1 , at time t and the expected time profile of F_{t+n} when the system is not shocked, given the information set available at time $t-1$. The computation of the conditional expectations in (2.33) depends on the nature of the multivariate distribution assumed for the vector of disturbances, ε_t . If ε_t follows a bivariate normal distribution, and assuming that the shock is equal to one standard deviation of the error term in the spot equation i.e. $\delta_1 = \sqrt{\sigma_{ss}}$, then Pesaran and Shin (1997) show that

$$GI_F(n, \delta_1 = \sqrt{\sigma_{ss}}, \Omega_{t-1}) = GI_{S,F,t+n} = \frac{e_2' \Phi_n \Sigma e_1}{\sigma_{ss}} \quad (2.34)$$

where e_1 and e_2 are the selection vectors defined in (2.32) and Φ_n is computed from the VMA of equation (2.29). Similarly, the generalised impulse response function of the spot equation at time $t+n$, following a unit shock to the futures equation at time t is given by

$$GI_{F,S,t+n} = \frac{e_1' \Phi_n \Sigma e_2}{\sigma_{FF}}$$

Unlike the OIR, the GIR are invariant to the ordering of the variables in the VAR and take account of the historical patterns of correlations observed amongst the different shocks. For

the first variable in a VAR, the OIR and the GIR are identical; for the remaining variables they are identical only if Σ is diagonal.

2.5.2 Impulse Response Analysis in a VECM

Impulse response analysis for the VECM of equation (2.17) can be carried out along the lines set out in the previous section. It is important, however, to take into account the fact that the underlying variables are difference stationary and as a result the effect of shocks on these variables will be persistent. Pesaran and Shin (1997) show that, for the VECM of (2.17), the OIR and the GIR of the futures price at time $t+n$, following a unit shock to the spot equation at time t are

$$OI_{S,F,t+n} = e'_2 \Phi_n T e_1 \quad (2.35)$$

$$GI_{S,F,t+n} = \frac{e'_2 \Phi_n \Sigma e_1}{\sigma_{ss}} \quad (2.36)$$

which are the same as the OIR and GIR for the VAR model in (2.32) and (2.34), respectively. Therefore, impulse responses for a VECM can be computed in exactly the same way as in the case of a standard VAR model. The major difference is that in the case of a VAR model $\lim_{i \rightarrow \infty} \Phi_i = 0$ while, for the VECM $\lim_{i \rightarrow \infty} \Phi_i = C(1)$ where $C(1)$ is a non-zero 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 a shock in the variables eventually vanishes while, when the variables are difference stationary, this effect will be persistent and the variables will adjust to a new long-run level once shocked.

2.6 Conclusions

In this chapter, we presented the currently used time-series techniques for investigating equilibrium relationships involving non-stationary price series. We discussed the properties of stationary and non-stationary processes and presented the Dickey and Fuller (1979 and 1981) and Phillips and Perron (1988) unit root tests. We also presented the cointegration methodology and described the Engle and Granger (1987) and Johansen (1988) testing procedures. The latter procedure is more powerful than the Engle and Granger (1987) test and provides us with 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 use of “orthogonalised” and “generalised” impulse response analysis for investigating the dynamic relationship between the variables in a VECM was also discussed. These techniques, are employed to investigate the unbiasedness hypothesis of futures prices, in the following chapter.

Chapter 3 : The Unbiasedness Hypothesis of Futures Prices in the BIFFEX Market

3.1 Introduction

The relationship between futures prices before maturity and expected spot prices on the maturity day of the contract has attracted considerable interest and prompted much discussion in different futures and forward markets. In particular, the extent to which the price of a futures contract reflects unbiased expectations of the spot price on delivery date is of importance to market participants: First, the existence of a bias in futures prices increases the cost of hedging. Second, if futures prices are not unbiased forecasts then, they may not perform their price discovery function efficiently, since they do not represent accurate predictors of expected spot prices.

Several studies in the past have examined the unbiasedness hypothesis. Lai and Lai (1991) find evidence against the unbiasedness hypothesis for the one-month forward British Pound, German Mark, Swiss Franc, Canadian Dollar and Japanese Yen exchange rates. Similar conclusions are drawn by Chowdhury (1991) in the examination of the quarterly lead, tin, zinc and copper forward prices at the London Metal Exchange (LME). Crowder and Hamed (1993) investigate the unbiased expectations hypothesis on the oil futures market; they find that oil futures prices one month prior to maturity are unbiased forecasts of the realised spot prices. Krehbiel and Adkins (1994) examine the quarterly Treasury bill, Eurodollar and

Treasury bond futures prices; their results indicate rejection of the unbiasedness hypothesis. A common feature of the above studies is the use of cointegration techniques due to the non-stationary properties of the spot and futures price series.

Antoniou and Holmes (1996), provide another dimension to the literature by examining the unbiased expectations hypothesis on the FTSE-100 stock index futures market for contracts of different maturities. They find that futures prices 1, 2, 4 and 5 months prior to maturity are unbiased forecasts of the realised spot prices. On the other hand, the unbiasedness hypothesis is rejected for futures prices 3 and 6 months before maturity. They argue that this is due to the increased trading activity associated with these maturities. Contracts in the FTSE market mature at three month intervals; therefore, dates three and six months prior to the maturity of a futures contract are maturity dates for earlier contracts. As one contract matures, investors who are pursuing rolling hedge strategies, will move out of this contract and into the contract which is three or six months prior to maturity. This increased movement between contracts of differing maturities, at the time of contract expiration, may lead to biased futures prices.

Despite this plethora of studies in various commodities and financial markets, the empirical evidence available in the BIFFEX market is scarce. The exception to that are the studies of Chang (1991) and Chang and Chang (1996) who employ conventional statistical techniques to investigate relationships between variables which may be non-stationary. This indicates that their results may be subject to the problem of spurious regressions, the consequences of which were discussed in chapter 2, and emphasises the need for new empirical evidence on the unbiasedness hypothesis using an appropriate econometric framework.

This study then, by investigating the unbiasedness hypothesis in the freight futures market, contributes to the existing literature in many respects. Tests of the unbiasedness hypothesis are extended, using the appropriate econometric methodology, to a futures market whose underlying asset is a service and is characterised by thin trading. Given that all the studies so far examine highly liquid markets, it is of interest to investigate whether thin trading in the market induces the presence of biases. Second, examination of futures contracts with different times to maturity sheds some light to the temporal changes on the relationship between futures prices and realised spot prices as the time to maturity of a futures contract changes.

The short run dynamic properties of spot and futures prices are also investigated, using generalised impulse response analysis (Pesaran and Shin, 1997) so as to identify the speed with which spot and futures prices respond to deviations from their long run relationship. Finally, in this chapter, we also explore the predictive power of futures prices and compare the accuracy of the forecasts implied by the futures prices with forecasts generated from error correction, ARIMA, exponential smoothing and random walk models. After all, if futures prices are unbiased forecasts of the realised spot prices, they should provide the most accurate forecasts of these prices.

The structure of this chapter is as follows: Section 2 sets the theoretical foundations of the unbiased expectations hypothesis. Tests of the unbiasedness hypothesis using the cointegration methodology are discussed in section 3. Section 4 describes the properties of the data series and the unit root tests. Tests of the unbiasedness hypothesis are presented in Section 5 and Section 6 examines the forecasting performance of futures prices. Finally, Section 7 provides our summary and conclusions.

3.2 Unbiased Expectations Hypothesis in Futures Markets

As discussed in chapter 1, the unbiased expectations hypothesis posits parameter restrictions on the relationship between futures prices before maturity and realised spot prices. Two suppositions form this hypothesis: the price of a futures contract before maturity equals the expected spot price on the maturity day of the contract; and the expectation of the spot price is formed rationally. This relationship is described in equation (1.5), repeated here for convenience

$$S_t = F_{t,t-n} + u_t \quad ; \quad u_t \sim \text{iid}(0, \sigma^2) \quad (3.1)$$

Empirically, the unbiasedness hypothesis can be examined by testing the parameter restrictions $(\beta_1, \beta_2) = (0, 1)$ in equation (3.2)

$$S_t = \beta_1 + \beta_2 F_{t,t-n} + u_t \quad ; \quad u_t \sim \text{iid}(0, \sigma^2) \quad (3.2)$$

These restrictions are based on a definition of market efficiency which argues that price changes from one period to the next should be unpredictable given the current information set. If the futures price, $F_{t,t-n}$, 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 predictor of the future spot price. Longworth (1981) for instance, estimates equation (3.2) using OLS and tests the unbiasedness hypothesis for the 1-month forward Canadian Dollar exchange rates. Using an ordinary F-test for the joint restriction $(\beta_1, \beta_2) = (0, 1)$, he concludes that the forward exchange rate is an unbiased predictor of the future spot rate for the period 1970 to 1978.

Given the empirical evidence in different futures markets, that spot and futures prices are non-stationary series, tests of the unbiasedness hypothesis based on equation (3.2) may be suspect due to the problem of spurious regressions, described in chapter 2. Many researchers have tried to accommodate this problem by employing alternative testing methods for the unbiasedness hypothesis. Consider the following transformation of (3.1), by subtracting S_{t-n} from both sides of the equation

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

By regressing the rate of change of the realised spot rate ($S_t - S_{t-n}$) on the basis ($F_{t,t-n} - S_{t-n}$), the unbiasedness hypothesis can then be examined by testing the parameter restrictions $(\beta_1, \beta_2) = (0, 1)$ in the following equation

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

This model is applied for instance, by Bilson (1981) and Froot and Frankel (1989) in the foreign exchange market. We can notice that, subject to certain conditions, tests based on equation (3.4) avoid the problem of non-stationary price series. More specifically, if S_t and $F_{t,t-n}$ are $I(1)$ series, then the LHS of equation (3.4) is $I(0)$. Moreover, if S_{t-n} and $F_{t,t-n}$ are cointegrated with a cointegrating vector $(1, -1)$ (i.e. if the basis is stationary) then the RHS of equation (3.4) is also $I(0)$. This implies that all the parameters in (3.4) are $I(0)$ and hence, standard inference using t- and F-statistics is applicable. In addition, if the null hypothesis in equation (3.4) is true, then

$$(S_t - S_{t-n}) - (F_{t,t-n} - S_{t-n}) = u_t \Rightarrow S_t - F_{t,t-n} = u_t \sim I(0) \quad (3.5)$$

which also implies that futures prices and realised spot prices are cointegrated with a cointegrating vector of $(1, -1)$.

As indicated by Hakkio and Rush (1989), when spot and futures prices follow unit root processes, cointegration is a necessary condition for the unbiasedness hypothesis to hold. If spot and futures prices are not cointegrated then they will tend to drift apart over time in which case, futures prices cannot be unbiased predictors of the realised spot prices. However, cointegration, while being a necessary condition for the unbiasedness hypothesis, is not a sufficient condition. In particular, the unbiasedness hypothesis also implies restrictions on the cointegrating vector of futures prices and realised spot prices, as indicated in equation (3.5).

Therefore, tests of the unbiasedness hypothesis can also be carried out by performing hypothesis tests on the cointegrating relationship. Two procedures may be employed to perform such tests. First, the Phillips and Hansen (1990) fully modified least squares (FM-LS) estimator. This procedure amounts to estimating the cointegrating regression of equation (3.2) using OLS and applying non-parametric corrections to the coefficient estimates, β_1 and β_2 , and their associated standard errors to take account of any bias due to the presence of serial correlation in the residuals of the estimated regression. Within this framework, tests for cointegration are conducted by performing unit root tests on the estimated residuals. Once the existence of a long-run relationship between spot and futures prices has been established, the unbiasedness hypothesis may be examined by testing the restriction $(\beta_1, \beta_2) = (0, 1)$ in equation (3.2) using Wald tests, along the lines proposed by Phillips and Hansen (1990).

The second test involves estimating the cointegrating relationship using the Johansen (1988) procedure. In this case, the joint distribution of spot and futures returns is modelled using the following VECM

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

where X_t is the 2×1 vector $(S_t \ F_{t,t-n})'$; μ is a 2×1 vector of deterministic components which may include an intercept term, a linear trend term or both; ε_t is the 2×1 vector of residuals $(\varepsilon_{S,t}, \varepsilon_{F,t})'$ and Σ is a 2×2 variance/covariance matrix.

The existence of a cointegrating relationship between S_t and $F_{t,t-n}$ is investigated through the λ_{\max} and λ_{trace} statistics of equations (2.18) and (2.19) (Johansen, 1988) which test for the rank of Π . It has been shown in chapter 2 that, if $\text{rank}(\Pi)=1$, then Π can be factored 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. In order to determine whether the intercept term, μ , should be included in the short-run model or in the cointegrating vector, we use Johansen's (1991) LR test of equation (2.27). If the intercept term is restricted to lie on the cointegrating space then the vector series becomes $X_{t-1} = (S_{t-1} \ 1 \ F_{t-1,t-n-1})'$ with a cointegrating vector $\beta' = (1 \ \beta_1 \ \beta_2)$, where the coefficient of S_{t-1} is

normalised to be unity, β_1 is the intercept term and β_2 is the coefficient on $F_{t-1;t-n-1}$.

The cointegrating relationship, $\beta'X_{t-1}$, represents the previous period's (stationary) equilibrium error; similarly, $\beta'X_t$, corresponds to the current period's equilibrium error. By performing hypothesis tests on the cointegrating vector, we can then identify whether the long-run equilibrium relationship, $\beta'X_t = (1 \ \beta_1 \ \beta_2)(S_t \ 1 \ F_{t;t-n})'$, takes a particular form which is dictated by economic theory. For instance, tests of the unbiasedness hypothesis can be constructed by testing the restrictions $\beta_1 = 0$ and $\beta_2 = -1$ in the cointegrating relationship. If these restrictions hold, then the price of a futures contract is an unbiased predictor of the realised spot price, i.e. the equilibrium relationship is given by $S_t = F_{t;t-n}$. Johansen and Juselius (1990) propose the following LR statistic to test these restrictions:

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

where $\hat{\lambda}_1^*$ and $\hat{\lambda}_1$ denote the largest eigenvalues from the restricted and the unrestricted model, respectively and T is the number of usable observations.

Finally, it should be mentioned that tests based on any of the model specifications described above examine the joint hypothesis of risk neutrality (or no risk premium) and rationality of expectations. Violation of either hypothesis can lead to rejection of the joint hypothesis (see Fama, 1991); furthermore, these hypotheses cannot be separated without further assumptions regarding the formation of expectations or the risk preferences of market agents.

3.3 Description and Properties of the Data

The data for this study match the delivery date settlement price with the futures contract price measured one, two and three months prior to the delivery date. The time span of the data is different for each maturity to allow for changes in the trading patterns in the freight futures market, such as the introduction of the “spot” and “prompt” month contracts in July 88 and October 91, respectively. We consider three different sets of observations. The first set consists of closing prices of the futures contract 1 month before maturity, $F_{t,t-1}$, and the corresponding settlement prices at maturity, S_t , which we call monthly prices. Futures prices are sampled at the last trading day of the month preceding the delivery month and the corresponding settlement price is calculated as the average of the BFI over the last five trading days of the contract month or the last five trading days prior to 20 December for the December contract ¹. The first observation covers the futures contract that expires on 29 July 1988 and the last observation is for the futures contract that expires on 30 April 1997 ². In total, this gives us a sample of 106 monthly non-overlapping observations for the period 1988:07 to 1997:04. The second set comprises closing prices of the futures contract two months from maturity, $F_{t,t-2}$, and the corresponding settlement prices at maturity. The first observation coincides with the introduction of the second “prompt” month contract in October 1991 and covers the price of the December 91 contract, two months from maturity. Futures prices two months ahead are sampled every month and this gives us a sample of 65 overlapping observations for the period 1991:12 to 1997:04 ³. The third set consists of closing prices of the futures contract 3 months before maturity, $F_{t,t-3}$, and the corresponding settlement prices at maturity (quarterly prices), representing a pair of 36 non-overlapping observations over the period July 88 to April 97.

¹ The use of the settlement price of the futures contract (i.e. the average of the BFI over the last five trading days of the contract), rather than the BFI price on the maturity day, is chosen because this is the actual price at which the futures contract converges at maturity. Our results remain qualitatively the same when we consider the BFI prices instead.

² The first observation coincides with the introduction of the “spot” and “prompt” month contracts. Thus, futures forecasts one month ahead are sampled every month.

³ In contrast, for the period prior to October 1991, futures forecasts two months ahead are available every three months and hence, the frequency of the observations is different (three-months instead of one month).

Spot price data are from LIFFE. Futures price data for the period July 1988 to December 1989 are from SSY Limited and the Financial Times. Futures price data for the period January 1990 to April 1997 are from LIFFE. All the observations are transformed into natural logarithms.

Table 3.1 presents summary statistics on the first differences of the logarithmic price series. The unconditional means of the spot and futures returns series are statistically insignificant in all the cases. The standard deviations of the two return series seem to be almost the same for the monthly data, compared to the 2 and 3-months series, where the standard deviation of the spot returns are higher than the futures returns, in all the cases. Tests for the significance of the coefficients of skewness and kurtosis indicate the presence of excess skewness on the 3-months futures return. Finally, Jarque-Berra (1980) tests indicate that, with the exception of the 3-months futures series, the return series follow normal distributions.

Since spot and futures prices are sampled at monthly and quarterly intervals, it is prudent to test for seasonal as well as for ordinary unit roots; for instance, seasonalities in commodity markets may be transmitted in the freight market and appear as stochastic seasonal unit roots in the BFI and BIFFEX prices. Hylleberg et al. (1990) propose a methodology for such tests for quarterly data which is extended to monthly data by Franses (1991). Applying these tests to our series indicates that there are no seasonal unit roots in the data even though there is a unit root at zero frequency, in all the cases. The Hylleberg et al. (1990) methodology along with our test results are presented in Appendix A to this chapter. Supplementary augmented Dickey - Fuller (1981) and Phillips-Perron (1988) tests on the levels and 1st differences of the series, presented in Table 3.1, also indicate that the spot and futures prices are first-difference stationary.

Table 3.1

Descriptive statistics on the logarithmic differences of monthly (1988:07 - 1997:04), 2-months (1991:12 - 1997:04) and 3-months (1988:03-1997:02) spot and futures prices.

Panel A: 1-Month Price Series												
	N	Mean	STD	Max	Min	Skew	Kurt	J-B	ADF (lags) in levels	PP (12) in levels	ADF (lags) in 1 st diffs	PP (12) in 1 st diffs
Spot	105	0.001 (0.008)	0.083	0.253	-0.220	-0.106 [0.66]	0.270 [0.59]	0.516 [0.77]	-2.496 (0)	-2.741	-8.899 (0)	-8.748
Futures	105	0.003 (0.008)	0.079	0.196	-0.191	-0.283 [0.24]	-0.064 [0.90]	1.416 [0.49]	-2.449 (0)	-2.809	-8.925 (0)	-8.796
Panel B: 2-Months Price Series												
	N	Mean	STD	Max	Min	Skew	Kurt	J-B	ADF (lags) in levels	PP (12) in levels	ADF (lags) in 1 st diffs	PP (12) in 1 st diffs
Spot	64	-0.003 (0.011)	0.089	0.253	-0.220	0.039 [0.90]	0.136 [0.83]	0.066 [0.97]	-1.702 (0)	-2.017	-6.680 (0)	-6.449
Futures	64	-0.002 (0.009)	0.072	0.177	-0.197	-0.201 [0.52]	0.010 [0.98]	0.429 [0.81]	-1.672 (0)	-2.185	-6.521 (0)	-6.646
Panel C: 3-Months Price Series												
	N	Mean	STD	Max	Min	Skew	Kurt	J-B	ADF (lags) in levels	PP (4) in levels	ADF (lags) in 1 st diffs	PP (4) in 1 st diffs
Spot	35	0.002 (0.024)	0.144	0.263	-0.307	-0.245 [0.57]	-0.911 [0.32]	1.559 [0.46]	-2.644 (0)	-2.732	-5.215 (0)	-5.075
Futures	35	0.005 (0.023)	0.133	0.226	-0.389	-1.041 [0.02]	1.352 [0.14]	8.988 [0.01]	-2.627 (3)	-2.796	-5.466 (2)	-4.569

Notes:

- All series are measured in logarithmic first differences. N is the number of observations.
- Mean and STD are the sample mean and standard deviation of the series. Standard errors of the sample mean are in parentheses (.).
- Max and Min are the maximum and minimum values of the series. 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 $\chi^2(2)$. Significance levels are reported in brackets [.]
- ADF is the Augmented Dickey Fuller (Dickey and 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) unit root test; the truncation lag for the test is in parentheses. 5% critical value for the ADF and PP tests is -2.88.

The graphs of the forecast errors for the monthly ($S_t - F_{t,t-1}$), 2-months ($S_t - F_{t,t-2}$) and quarterly ($S_t - F_{t,t-3}$) data are presented in Figure 3.1 A to Figure 3.1 C, respectively; their summary statistics are presented in Table 3.2. Two points can be mentioned here. First, the forecast errors for all maturities fluctuate around zero and their means are statistically insignificant in all the cases. This suggests that market agents are, on average, correct in their assessment of expected BFI prices and there is no constant bias in the formation of their expectations. However, it is still possible that there may be some non-constant systematic bias in futures prices which forces them to be biased predictors of the realised spot prices. Whether this is the case is investigated in the following section where we present more formal tests of the unbiasedness hypothesis using cointegration techniques.

Second, the variance of the forecast errors increases as the forecast horizon increases from one to three months. Hypothesis tests for the equality of variances indicate that the variances of the 2 and 3-months forecast errors are significantly higher than the variance of the 1-month forecasts. This is expected since the latter forecast is made when the contract is closer to maturity and, hence, there is less uncertainty regarding the outcome of expected BFI prices, compared to longer maturities.

Table 3.2

Statistics on Forecast Errors

	N	Mean	Variance (S^2)	Hypothesis Test for Equal Variances	
1-Month	106	15.561 (1.621)	9768.2	$F = S_2^2 / S_1^2 \sim F(65,105)$	3.1241 [.00]
2-Months	65	28.622 (1.321)	30516.9	$F = S_3^2 / S_1^2 \sim F(35,105)$	4.0488 [.00]
3-Months	36	26.622 (0.803)	39549.8	$F = S_3^2 / S_2^2 \sim F(35,65)$	1.2960 [.18]

Notes:

- Mean and Variance are the sample mean and variance of the series, respectively.
- The t-statistics for the null hypothesis that the mean is zero are in parentheses (.).
- $F = S_2^2 / S_1^2$ is the test statistic for the null hypothesis of the equality of variances. The statistic is distributed as $F(n_2-1, n_1-1)$. Significance levels for the test are in square brackets [.]

Figure 3.1 A

1-Month Forecast Error ($S_t - F_{t,t+1}$) for the Period July 88 to April 97

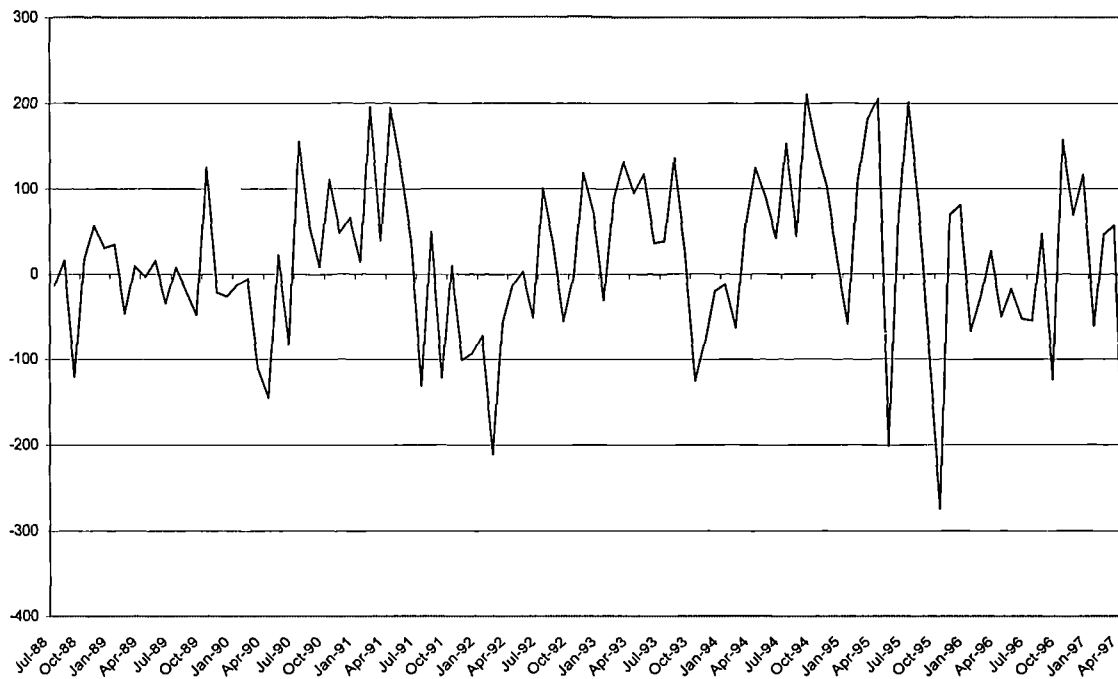


Figure 3.1 B

2-Months Forecast Error ($S_t - F_{t,t+2}$) for the Period December 91 to April 97

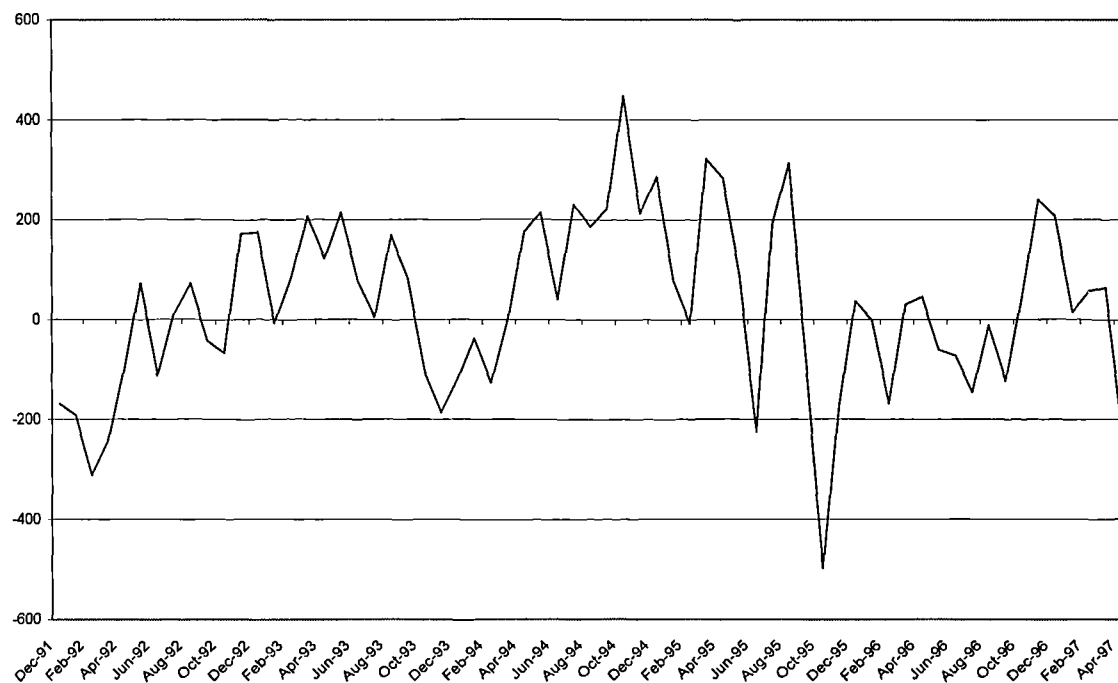
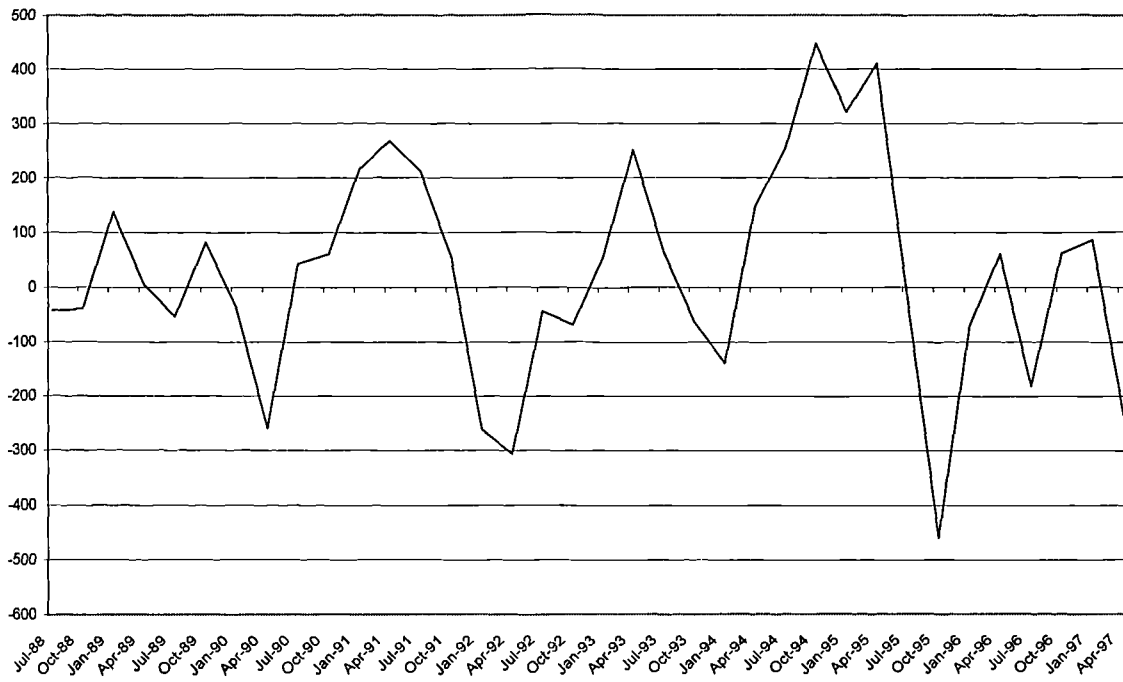


Figure 3.1 C

3-Months Forecast Error ($S_t - F_{t;t-3}$) for the Period July 88 to April 97



3.4 Empirical Results

Having identified that spot and futures prices are $I(1)$ variables, cointegration techniques are used next to test the unbiased expectations hypothesis. We consider three different methods for investigating this hypothesis in the cointegrating framework. First, a regression of the change in the realised spot rate ($S_t - S_{t-n}$) on the basis ($F_{t,t-n} - S_{t-n}$), as in equation (3.4); second, the FM-LS estimation procedure of Phillips and Hansen (1990); and, third the Johansen (1988) procedure. Consider each procedure next.

Table 3.3

Unbiasedness Hypothesis tests using equation (3.4)

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

Unit Root Tests on ($F_{t,t-n} - S_{t-n}$)		Coefficient Estimates		Hypothesis Tests	Diagnostics
ADF (lags)	PP(lags)	β_1	β_2	$H_0: (\beta_1 = 0, \beta_2 = 1)$ $\sim F(2, n-2)$	Q(12)
Panel A: Monthly Data					
-7.467 (0)	-7.214 (12)	0.009 (0.007)	0.895 (0.120)	1.579 [0.21]	18.239
Panel B: 2-Months Data					
-5.141 (0)	-4.964 (12)	0.599 (0.553)	0.920 (0.076)	1.198 [0.31]	11.381
Panel C: Quarterly Data					
-1.698 (3)	-1.896 (4)	-	-	-	-

Notes:

- ADF is the Augmented Dickey Fuller (Dickey and Fuller, 1981) test for the null hypothesis that the spot-futures differential ($F_{t,t-n} - S_{t-n}$) is stationary. 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) unit root test; the truncation lag for the test is in parentheses. 5% critical value for the ADF and PP tests is -2.88 .
- Standard errors for the estimated coefficients are in parentheses. Hypotheses tests for the null hypothesis ($\beta_1 = 0, \beta_2 = 1$) are carried out using an F-test. The statistic is $F(2, n-2)$ distributed where n is the number of observations in Table 3.1. Significance levels for the tests are in brackets.
- Q(12) is the Ljung-Box (1978) Q statistics on the first 12 lags of the sample autocorrelation function of the estimated residuals; the statistic is $\chi^2(12)$ distributed with 5% critical value of 21.03.

The unbiasedness tests using equation (3.4) are presented in Table 3.3. We can see that for the one and two-months prices, the spot-futures differential is stationary. Hence, for these maturities, estimation of equation (3.4) using standard regression techniques is valid. Parameter restriction tests on the estimated coefficients of the model, $H_0: (\beta_1 = 0, \beta_2 = 1)$,

indicate that futures prices one and two months from maturity are unbiased forecasts of the realised spot prices. For the three-months prices, however, unit root tests indicate that the spot-futures differential is non-stationary ⁴; as a result, standard statistical inference in equation (3.4) is not valid since we have a regression of a stationary variable on a non-stationary one. This also implies that for the three-months prices, futures prices and realised spot prices (i.e. $F_{t,t-n}$ and S_t , respectively) are not cointegrated with a cointegrating vector (1, -1) and as a result, the unbiasedness hypothesis is rejected (see as well Liu and Maddala, 1992 for evidence on this).

Additional tests of the unbiasedness hypothesis are carried out using the Phillips and Hansen (1990) FM-LS estimator ⁵. Our results are presented in Table 3.4. Unit root tests on the estimated residuals indicate that futures prices one and two-months from maturity and realised spot prices are cointegrated. Parameter restriction tests on the estimated coefficients indicate that for these maturities futures prices are unbiased forecasts of the realised spot prices. In contrast, futures prices three months from maturity are not cointegrated with the realised spot prices; therefore, the unbiasedness hypothesis is rejected for the three-months futures.

⁴ The order of integration of the spot-futures differential ($F_{t,t-n} - S_{t-n}$) is also investigated using the Johansen procedure. These results indicate that $F_{t,t-n}$ and S_{t-n} are cointegrated across all maturities. Subsequent parameter restriction tests on the cointegrating relationship indicate that for the one and two-months futures, the cointegrating vector is (1, -1). This is rejected, however, for the three-months futures, thus indicating that the spot-futures differential for that maturity is non-stationary.

⁵ The use of this method is also motivated by the overlapping observations problem, present in the two-months price series (Hansen and Hodrick, 1980). This problem arises when the sampling time interval of the futures contract is finer than the futures forecast horizon; for example when using monthly data for the two-months ahead futures forecasts. Such “overlapping observations” induce moving average errors in equation (3.2). In the presence of serial correlation induced by the overlapping futures forecasts, Moore and Cullen (1995) assert that use of the FM-LS estimator is more appropriate than cointegration tests based on Johansen’s procedure.

Table 3.4

Estimating the cointegrating regression $S_t = \beta_1 + \beta_2 F_{t,t-n}$ [equation (3.2)] using the Phillips - Hansen (1990) Fully Modified Estimator

Cointegration Tests		Coefficient Estimates		Hypothesis Tests		
τ (lags)	Z(lags)	β_1	β_2	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 1$	$H_0: \beta_1 = 0 \text{ and } \beta_2 = 1$
Panel A: Monthly Data						
-7.806 (0)	-8.235 (12)	0.367 (0.273)	0.951 (0.038)	1.807 [0.18]	1.715 [0.19]	3.886 [0.14]
Panel B: 2-Month Data						
-4.179 (0)	-4.063 (10)	0.526 (0.585)	0.930 (0.081)	0.809 [0.37]	0.753 [0.39]	2.334 [0.31]
Panel C: Quarterly Data						
-3.164 (0)	-2.775 (9)	-	-	-	-	-

Notes:

- The estimator employed is the Phillips and Hansen (1990) fully modified OLS estimator. Estimation is carried out using Parzen weights; the truncation lag is set equal to 2, 1 and 3 for the one, two and three-months futures, respectively.
- τ is the Dickey and Fuller (1981) test for cointegration on the estimated residuals; the lag length of the regression is determined by minimising the SBIC.
- Z is the Phillips and Perron (1988) test for cointegration; the truncation lag for the test is computed using the formula suggested by Schwert (1989) i.e. $\text{int}[12(N/100)^{0.25}]$.
- The 5% critical value for the null hypothesis of no cointegration is -3.395, -3.433 and -3.516 for the one, two and three-months prices, respectively (MacKinnon, 1991).
- Asymptotic standard errors are in parentheses. Hypotheses tests on the coefficient estimates are carried out using a Wald test. The statistic is χ^2 distributed with degrees of freedom equal to the number of restrictions. Significance levels are in brackets.

The unbiasedness hypothesis is investigated next using the Johansen (1988) procedure. Three steps may be distinguished in this process. First, a well specified VECM with the appropriate deterministic components and a robust lag structure, so as to capture any residual autocorrelation is arrived at. Second, the existence of a cointegrating vector, describing the long-run relationship between spot and futures prices, is investigated in this well specified VECM using the maximum and trace tests proposed by Johansen (1988). Third, once the necessary condition for unbiasedness, that of the existence of a cointegrating relationship, has been identified, the unbiasedness hypothesis is investigated by testing parameter restrictions on the cointegrating vector using the LR statistic of equation (3.7) .

Regarding the first step, we use the SBIC (1978) and the LR test of (2.27) to determine the lag length and the specification of the deterministic components in the VECM. Lag lengths of 2, 1 and 3 are selected for the one-, two- and three-months data, respectively ⁶ and the deterministic components include an intercept in the cointegrating vector in all cases.

Table 3.5
Johansen (1988) tests for the number of cointegrating vectors between spot and futures prices. Monthly, 2-months and quarterly spot and futures prices.

Hypothesis		Test Statistic		Hypothesis		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}
Panel A: Monthly Data									
r = 0	r = 1	26.08	25.08	r = 0	r > 0	33.61	32.32	15.67	19.96
r = 1	r = 2	7.53	7.24	r = 1	r > 1	7.53	7.24	9.24	9.24
Panel B: 2-Month Data									
r = 0	r = 1	48.58	47.06	r = 0	r > 0	51.92	50.29	15.67	19.96
r = 1	r = 2	3.33	3.23	r = 1	r > 1	3.33	3.23	9.24	9.24
Panel C: Quarterly Data									
r = 0	r = 1	21.01	17.19	r = 0	r > 0	28.59	23.39	15.67	19.96
r = 1	r = 2	7.58	6.20	r = 1	r > 1	7.58	6.20	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 $\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$ where $\hat{\lambda}_i$ are the estimated eigenvalues of the Π matrix in equation (3.6).
- $\lambda^*_{\max} = (T - kp)/T \lambda_{\max}$ and $\lambda^*_{\text{trace}} = (T - kp)/T \lambda_{\text{trace}}$, where k is the number of variables in the VECM, are degrees-of-freedom adjusted cointegrating rank tests (Reimers, 1992).
- Critical values are from Osterwald-Lenum (1992), Table 1*.

The second step in testing the unbiasedness hypothesis involves determining the existence of a cointegrating relationship between spot and futures prices using the maximum and trace tests. The estimated statistics in Table 3.5, indicate that spot and futures prices are

⁶ This refers to the lag length of an unrestricted VAR in levels as follows; $X_t = \sum_{i=1}^p A_i X_{t-i} + \varepsilon_t$. 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.

cointegrated. However, Johansen's tests are biased towards finding cointegration too often in small samples. In particular, Cheung and Lai (1993) find that the finite-sample bias of Johansen's tests is a positive function of $T/(T - kp)$ where k is the number of variables in the VECM. Reimers (1992) suggests a small-sample correction of the test statistics for the cointegrating rank. This correction is found to improve the properties of the cointegration tests, particularly in moderately sized samples, and consists of using the factor $(T - kp)$ instead of T in the computation of the λ_{\max} and λ_{trace} tests. Use of the adjusted statistics, denoted as λ_{\max}^* and λ_{trace}^* , confirms that spot and futures prices one, two and three months prior to maturity are cointegrated ⁷.

The unbiasedness hypothesis is examined next by testing the restrictions $\beta_1 = 0$ and $\beta_2 = -1$ in the cointegrating relationship $\beta'X_{t-1} = (1 \ \beta_1 \ \beta_2)(S_{t-1} \ 1 \ F_{t-1;t-n-1})'$, using equation (3.7). If these restrictions hold, then the price of a futures contract is an unbiased predictor of the realised spot price. The estimated coefficients of the cointegrating vectors, along with the residual diagnostics for the models, are presented in Table 3.6, Table 3.7 and Table 3.8 for the monthly, two-months and quarterly data respectively.

⁷ Notice that, in contrast to the Johansen (1988) tests, results from the FM-LS estimator indicate that futures prices three months from maturity and realised spot prices are not cointegrated. This discrepancy in our results may be attributed to the low power of residual-based cointegration tests compared to the Johansen tests (see e.g. Harris, 1995).

Table 3.6

Likelihood ratio tests of parameter restrictions on the normalised cointegrating vector of monthly spot and futures prices. Estimation period: 1988:07 - 1997:04.

Panel A: Model Specification

$$\begin{pmatrix} \Delta S_t \\ \Delta F_{t,t-1} \end{pmatrix} = \Gamma_1 \begin{pmatrix} \Delta S_{t-1} \\ \Delta F_{t-1,t-2} \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} (1 \quad \beta_1 \quad \beta_2) \begin{pmatrix} S_{t-1} \\ 1 \\ F_{t-1,t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix}; \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \sim IN(0, \Sigma)$$

Coefficient Estimates			Hypothesis Tests on β'		
α_1	α_2	$\beta' = (1 \quad \beta_1 \quad \beta_2)$	$H_0: \beta_1 = 0$	$H_0: \beta_2 = -1$	$H_0: \beta_1 = 0 \text{ and } \beta_2 = -1$
0.014 (0.066)	0.565 (4.385)	1.000 0.179 -1.026	0.23 [0.63]	0.25 [0.62]	1.85 [0.40]

Notes:

- α_1 and α_2 are the error correction coefficient estimates 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 S_t .
- The statistic for 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 χ^2 distributed with degrees of freedom equal to the number of restrictions placed on the cointegrating vector. Significance levels are in brackets.

Panel B: Residual Diagnostics

	LM(1)	Q(12)	Normality	ARCH(4)	Normality*	LM(1)*
$\varepsilon_{S,t}$	0.06	8.79	1.73	2.87	9.01	5.24
$\varepsilon_{F,t}$	0.01	16.41	4.32	4.77		
5% c.v.	3.84	21.03	5.99	9.49	9.49	9.49

Notes:

- $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$ are the estimated residuals from each equation in the VECM.
- LM(1) is the Godfrey (1978) Lagrange Multiplier test for serial correlation of order 1; the statistic is asymptotically distributed as $\chi^2(1)$.
- Q(12) is the Ljung-Box (1978) Q statistic on the first 12 lags of the sample autocorrelation function distributed as $\chi^2(12)$.
- Normality is the Jarque - Bera (1980) test for normality, distributed as $\chi^2(2)$.
- ARCH(4) is the Engle(1982) test for ARCH effects; the statistic is $\chi^2(4)$ distributed.
- Normality* and LM(1)* are the bivariate tests for normality (Doornik and Hansen, 1994) and serial correlation distributed as $\chi^2(4)$.

Table 3.7

Likelihood ratio tests of parameter restrictions on the normalised cointegrating vector of 2-months spot and futures prices. Estimation period: 1991:12 - 1997:04.

Panel A: Model Specification

$$\begin{pmatrix} \Delta S_t \\ \Delta F_{t,t-2} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \begin{pmatrix} 1 & \beta_1 & \beta_2 \end{pmatrix} \begin{pmatrix} S_{t-1} \\ 1 \\ F_{t-1,t-3} \end{pmatrix} + \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix}; \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \sim IN(0, \Sigma)$$

Coefficient Estimates

α_1

α_2

$\beta' = (1 \ \beta_1 \ \beta_2)$

H₀:
 $\beta_1 = 0$

H₀:
 $\beta_2 = -1$

H₀:
 $\beta_1 = 0 \text{ and } \beta_2 = -1$

0.006
(0.065)

0.454
(8.506)

1.000 0.638 -1.091

1.31
[0.25]

1.41
[0.24]

4.09
[0.13]

See Notes in Table 3.6, Panel A.

Panel B: Residual Diagnostics

LM(1)

Q(12)

Normality

ARCH(4)

Normality*

LM(1)*

$\varepsilon_{S,t}$

$\varepsilon_{F,t}$

1.68

10.16

0.57

2.06

1.89

5.25

0.01

13.79

2.25

0.85

5% c.v.

3.84

21.03

5.99

9.49

9.49

9.49

See Notes in Table 3.6 Panel B.

For the one and two-months futures prices, the null hypothesis of unbiasedness cannot be rejected at conventional levels of significance. However, for the quarterly futures prices, the restriction is rejected at the 5% level. In order to check whether the rejection of the joint hypothesis in the quarterly series is driven by the presence of a significant intercept term or from the coefficient of the futures price being significantly different from one we test individually for the null hypotheses $\beta_1 = 0$ and $\beta_2 = -1$, using equation (3.7); our results indicate that β_1 and β_2 are individually significantly different from 0 and 1, respectively.

Table 3.8

Likelihood ratio tests of parameter restrictions on the normalised cointegrating vector of quarterly spot and futures prices. Estimation period: 1988:03 - 1997:02.

Panel A: Model Specification

$$\begin{pmatrix} \Delta S_t \\ \Delta F_{t-3} \end{pmatrix} = \sum_{i=1}^2 \Gamma_i \begin{pmatrix} \Delta S_{t-i} \\ \Delta F_{t-i;t-3-i} \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \begin{pmatrix} 1 & \beta_1 & \beta_2 \end{pmatrix} \begin{pmatrix} S_{t-1} \\ 1 \\ F_{t-1;t-4} \end{pmatrix} + \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix}; \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \sim IN(0, \Sigma)$$

Coefficient Estimates			Hypothesis Tests on β'		
α_1	α_2	$\beta' = (1 \ \beta_1 \ \beta_2)$	$H_0: \beta_1 = 0$	$H_0: \beta_2 = -1$	$H_0: \beta_1 = 0 \text{ and } \beta_2 = -1$
0.880 (3.793)	0.834 (4.854)	1.000 3.761 -1.521	6.30 [0.01]	6.23 [0.01]	8.34 [0.02]

See Notes in Table 3.6, Panel A.

Panel B: Residual Diagnostics

	LM(1)	Q(4)	Normality	ARCH(4)	Normality*	LM(1)*
$\varepsilon_{S,t}$	1.35	0.89	0.65	0.62	4.49	8.37
$\varepsilon_{F,t}$	1.62	5.76	5.11	6.02		
5% c.v.	3.84	9.49	5.99	9.49	9.49	9.49

See Notes in Table 3.6, Panel B.

Our conclusions remain the same when we adjust the LR statistic of equation (3.7) for degrees-of-freedom. As in the case of the trace and max eigenvalues tests, the LR tests for linear parameter restrictions on the cointegrating relationship tends to over-reject a true null hypothesis in small samples; thus, the rejection of the unbiasedness hypothesis in the quarterly prices may be attributed to the small number of usable observations employed in the analysis ($T=33$). Psaradakis, (1994) suggests correcting the LR test of equation (3.7) 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 $\Pi = \alpha\beta'$. For the quarterly prices test, where $m = 12$ and $k = 2$, this correction yields a $\chi^2(2)$ statistic of 6.82, with a 95% critical value of 5.99, which still rejects the null hypothesis of unbiasedness.

Overall we conclude that futures prices one and two months prior to maturity are unbiased expectations forecasts of the realised spot prices. On the other hand, futures prices three

months from maturity provide biased forecasts of the realised spot prices. Moreover, these findings are robust to the different testing procedures that are employed to investigate the unbiasedness hypothesis.

The issue that arises is to pinpoint what could possibly create biases on futures prices three months from maturity. As already emphasised, the market is characterised by low trading volume and most of the trading concentrates in the one and two months contracts, which are near to maturity. Gilbert (1986) argues that thin trading in a futures market creates worries about execution of trading orders since attempts to trade at quoted prices may change these prices; this may generally result in some forward market bias. Hence, it seems that limited liquidity divorces futures prices from being unbiased forecasts of the realised spot prices 3 months from maturity. On the other hand, as the contract approaches its maturity day, trading activity in the market increases; this forces futures prices one and two months from maturity to reflect more accurately, compared to three months prices, the expected spot prices on the maturity day of the contract. This finding is in contrast to the findings of Antoniou and Holmes (1996), in the examination of the FTSE-100 contract, who argue that increased trading activity in the market creates price biases in futures prices. It seems that the opposite is true for the freight futures market.

Another possibility is that the bias in futures prices three months prior to maturity reflects imbalances between long and short hedging demand in the market. BIFFEX trades the expected value of a service, which is essentially a non-storable commodity. Pricing biases seem to be more prevalent for the markets of non-storable commodities. Empirical studies by Kolb (1992) and Deaves and Krinsky (1995) indicate the existence of significant positive returns in the futures prices of three non-storable commodities (feeder cattle, live cattle and live hogs); moreover, these returns increase as the time to maturity of a futures contract increases. Conditional on the assumption of rational expectations, these findings are consistent with the theory of normal backwardation, advanced by Keynes (1930), which hypothesises that hedging pressures create a differential between futures prices and expected spot prices at contract expiration (i.e. a risk premium). The significance of the hedging forces as a factor linking futures and spot prices for non-storable commodities is also emphasised by Gray and Tomek (1970) who argue that for these markets, futures prices are linked to

expected spot prices through the balance of hedging forces; if these forces represent only one type of futures market position (either net long or short) then a price bias may result.

3.4.1 Analysis of Short-Run Properties of Spot and Futures Prices

To investigate the effect that this bias has on the short run properties of spot and futures prices we examine the estimated error correction coefficients, α_1 and α_2 , presented in Table 3.6, Table 3.7 and Table 3.8. For the monthly and two-months price series, the estimated error correction coefficients on the futures prices, α_2 , are positive and statistically significant, while the coefficients on the spot prices, α_1 , are statistically insignificant. The sign of the coefficients on the futures prices is in accordance with convergence towards a long-run equilibrium relationship; that is, in response to a positive forecast error at period $t-1$ (i.e. $S_{t-1} > F_{t-1,t-2}$), the price of the futures in the next period will increase in value thus restoring the long-run equilibrium. This finding is consistent with the hypothesis that past forecast errors affect the current forecasts of the realised spot prices, i.e. the futures prices, but not the spot prices themselves. Therefore, only the futures price responds to the previous period's deviations from the long run equilibrium relationship and does all the correction to eliminate this disequilibrium.

Turning into the quarterly price series, we can see that both α_1 and α_2 are positive and significant at the 5% level. This is consistent with our empirical findings regarding the presence of a bias in the quarterly futures prices. If futures prices provide unbiased forecasts of realised spot prices, then they should contain all the information which is relevant in forecasting future spot prices. The existence of a systematic bias, on the other hand, implies that past forecast errors affect the realised spot prices. The positive signs of both error correction coefficients indicate that a positive forecast error at period $t-1$, will force both the futures and the spot prices to increase. Hence, any disequilibrium at period $t-1$ is also carried forward to period t as would be expected by the existence of a bias in futures prices.

This pattern can also be verified by plotting the generalised impulse response (GIR) functions (Pesaran and Shin, 1997) of (2.36), which provide us with a visual representation of the behaviour of spot and futures prices in response to shocks to the equations in the VECM. The

time profiles of the GIR of the spot and futures prices, with respect to one standard error shocks in the equations of the VECM, are presented in Figure 3.2.A and B for the monthly data, Figure 3.3.A and B for the 2-months data and Figure 3.4.A and B for the quarterly data. For the one and two-months prices, we can note that spot and futures prices converge to the same long run level after the effect of the initial shock in either equation has vanished; moreover, this convergence takes place within a period of 1-3 months for the one-month contracts and 4-5 months for the two-months contracts and is driven primarily by the futures price. On the other hand, quarterly spot and futures prices do not converge and remain apart, once shocked, as expected by the signs of the error correction coefficients.

Figure 3.2.A

GIR to one S.E. shock in the equation of Spot; 1-Month Prices (88:07 - 97:04)

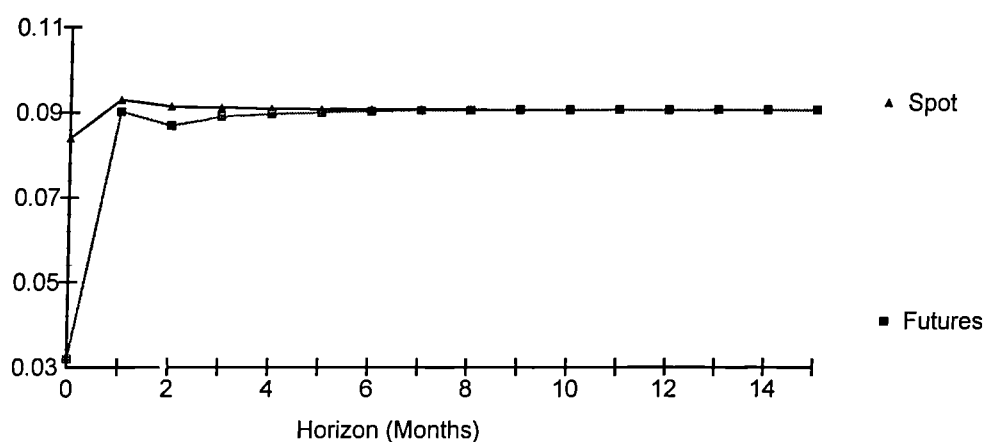


Figure 3.2.B

GIR to one S.E. shock in the equation of Futures; 1-Month Prices (88:07 - 97:04)

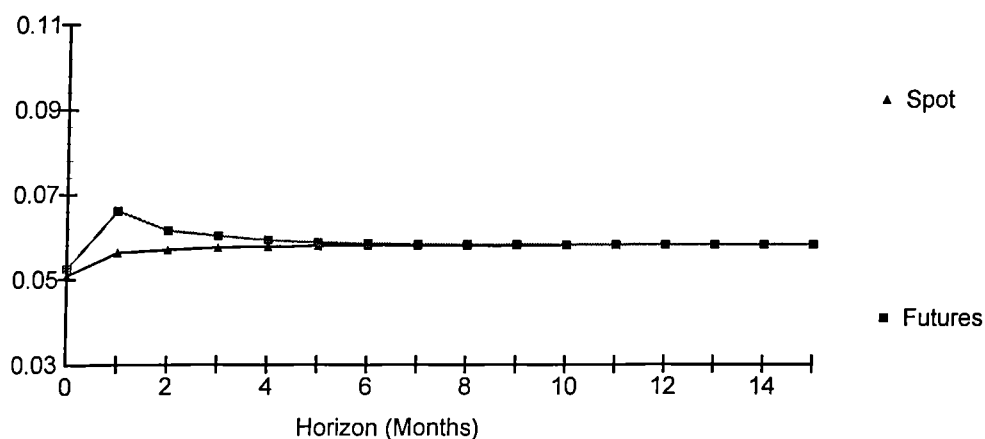


Figure 3.3.A

GIR to one S.E. shock in the equation of Spot; 2-Months Prices (91:12 - 97:04)

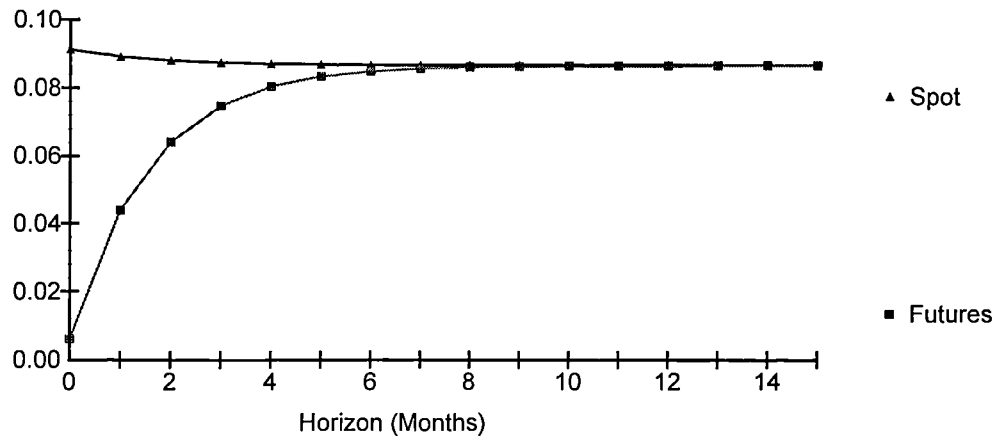


Figure 3.3.B

GIR to one S.E. shock in the equation of Futures; 2-Months Prices (91:12 - 97:04)

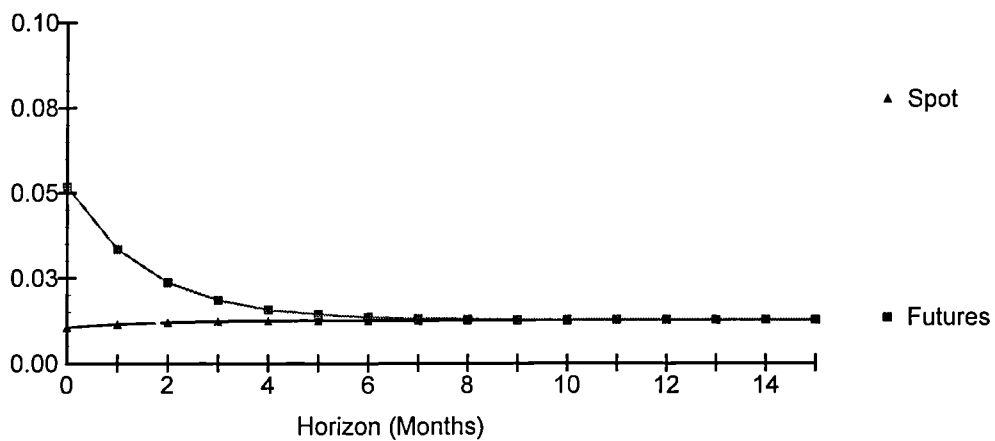


Figure 3.4.A

GIR to one S.E. shock in the equation of Spot; 3-Months Prices (88:03 - 97:02)

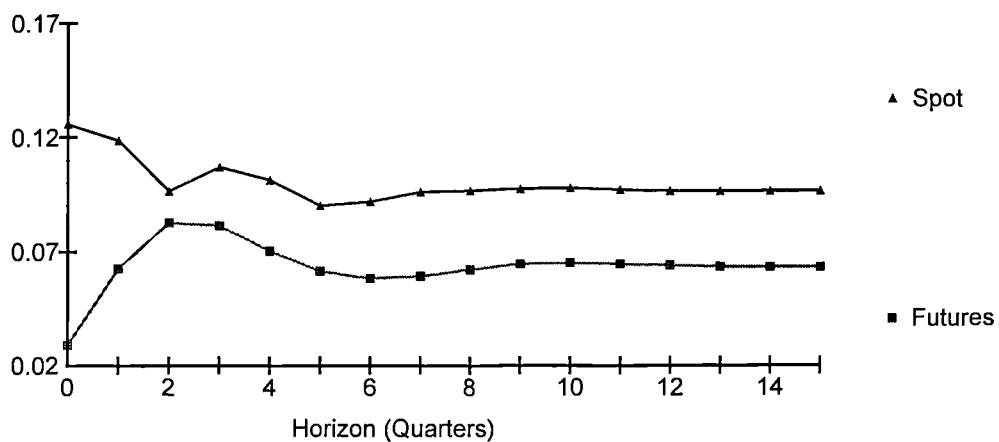
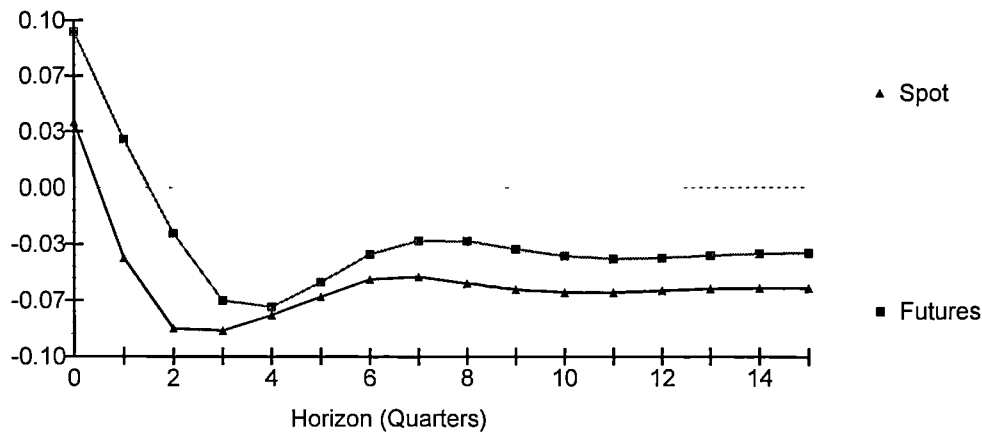


Figure 3.4.B

GIR to one S.E. shock in the equation of Futures; 3-Months Prices (88:03 - 97:02)

The issue that arises is whether the bias on the quarterly futures prices represents a (possibly time varying) risk premium, conditional on the assumption of rational expectations. A common method of characterising time varying risk premia, in different futures and forward markets is through the family of Autoregressive Conditional Heteroskedasticity (ARCH) models⁸; for instance, Domowitz and Hakkio (1985) model the risk premia in the foreign exchange market using the ARCH in mean model, while Hall and Taylor (1989) investigate the existence of risk premia in the tin, lead, copper and zinc contracts at the LME using the GARCH in mean model. However, use of this methodology to the 3-months BIFFEX forecast error did not yield any significant results.

Table 3.9

Modelling the price bias in the 3 months forecast error

$$S_t - F_{t,t-3} = \theta_1 v_{t-1} + v_t; v_t \sim iid(0, \sigma^2)$$

θ_1	Q(8)	Q ² (8)	ARCH(1)	J-B
0.632	9.687	7.646	1.247	1.509
(4.817)	[0.29]	[0.47]	[0.26]	[0.47]

Notes:

- The t-statistic for the null hypothesis $\theta_1 = 0$ is in parentheses (.).
- Q(8) and Q²(8) are the Ljung-Box (1978) Q statistics on the first 8 lags of the sample autocorrelation function of the raw residuals and of the squared residuals; the statistic is $\chi^2(8)$ distributed.
- ARCH(1) is the Engle (1982) tests for ARCH effects of orders 1; the statistic is $\chi^2(1)$ distributed.
- J-B is the Jarque - Bera (1980) test for normality. Significance levels are in brackets.

⁸ For an overview of developments in the formulation of ARCH models and a survey on their empirical applications in finance see Bollerslev et al. (1994).

In order to identify the behaviour of the bias in the BIFFEX prices 3 months from maturity, we specify the conditional mean of the 3 month forecast error (i.e. $S_t - F_{t,t-3}$) using Box-Jenkins (1970) techniques. Our results, presented in Table 3.9, indicate that the forecast error follows a Moving Average (MA) process of order 1. Therefore, we conclude that the bias in futures prices 3 months from maturity is a function of the previous period's error term. This can be interpreted either as evidence for the existence of a risk premium which follows an MA(1) process or as the result of market irrationality since the market fails to embody in the current futures prices a systematic time series component of the forecast error (see as well Copeland, 1991). Unfortunately, we cannot distinguish between these two alternatives since, any test of the unbiasedness hypothesis is a joint test that there is no risk premium and that market agents are endowed with rational expectations (Fama, 1991). Therefore, failure to accept the unbiasedness hypothesis can be attributed to failure of any of these two reasons. Nevertheless, we can still investigate whether the existence of a systematic bias in futures prices, which implies that futures prices do not represent accurate predictors of the realised spot prices, affects the price discovery function of the market. This is addressed in the following section.

3.5 Forecasting Performance of Futures Prices

This section investigates the ability of end of month futures prices to predict the realised spot prices on the maturity day of the contract. The forecasting performance of futures prices is an issue which has been investigated in the literature for different futures markets. For instance, Ma (1989) and Kumar (1992) compare the forecasting accuracy of oil futures prices to forecasts generated from time-series and random walk models, while Hafer et al. (1992) compare the forecasting performance of Treasury-Bill futures prices to that of forward prices and survey data. Broadly speaking, it is found that futures prices provide superior forecasts of the realised spot prices than forecasts generated from alternative models, although their forecasting performance diminishes as the forecast horizon increases.

The purpose of this 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 than using the readily available information provided by futures prices. Futures price forecasts are compared to forecasts generated by bivariate VECM and univariate ARIMA and Holt - Winters (Holt, 1957 and Winters, 1960) exponential smoothing models (see Appendix 3B). The performance of the two latter models, in forecasting the BFI, has been investigated by Cullinane (1992) who finds that ARIMA models provide the most accurate forecasts of the BFI for a forecast horizon up to 7 days, while, for greater lead times, the Holt-Winters model provides superior forecasts. For comparison purposes, we also consider a benchmark random walk model. This model assumes that BFI prices at time $t-n$ are the most accurate predictors of settlement prices at time t , S_t ; therefore, it uses information from the historical spot prices to generate forecasts of the future settlement prices and requires no estimation.

In order to compare the forecasting performance of futures prices with that of time-series models, care must be taken to ensure that forecasts from the latter correspond precisely to the forecasts implied by the futures prices. BIFFEX prices converge to the settlement price at the maturity day of the contract and hence, the futures price n months from maturity provides a forecast of the settlement price for this particular day. Since the settlement price of the futures

contract is calculated as the average of the BFI over the last five trading days of the contract, time-series models should be estimated in such a way so that forecasts for these particular days can be obtained. This requirement, in turn, implies that the time-series models should be estimated using daily price data.

Therefore, a VECM is estimated using the most recent 300 daily spot and futures prices of the contract which is closer to maturity⁹. Over the period 1988:04 to 1997:03, 107 different VECM models are identified and estimated along the lines described in section 5 of this chapter. For instance, the first model is estimated using 300 daily observations of spot and futures prices up to 29 April 1988 which is the last trading day of the July 1988 contract three-months before expiry. Our estimation procedure is as follows; Dickey-Fuller (1981) and Phillips-Perron (1988) tests are performed on the spot and futures prices to identify their order of integration and subsequently, the existence of a stationary relationship between them is investigated using the Johansen (1988) tests. The resulting VECM produces forecasts of the BFI prices for the last five trading days of the July 1988 contract. The arithmetic average of these forecasts yields the forecasted value of the settlement price. This estimation procedure is repeated for the subsequent periods, utilising at any given point in time the most recent 300 daily spot and futures observations. Along the same lines, ARIMA models are estimated for each forecast period utilising at any given point the most recent 300 daily BFI observations. The most parsimonious ARIMA model is identified using Box-Jenkins (1970) techniques and the five general model specifications estimated for each forecast period, are presented in Table 3.10.

For instance, over the period April 1988 to September 1989, the model that provides the best fit for the BFI series is a first difference model with autoregressive terms at lags 1 and 3. Finally, using the same set of observations as in the ARIMA modelling procedure, the Holt-Winters model is estimated to generate forecasts for the settlement prices 1, 2 and 3 months ahead.

⁹ In line with our analysis, Ma (1989) and Kumar (1992) also estimate models from daily data using a rolling regressions procedure.

Table 3.10

ARIMA(p,d,q) model specifications for forecasting one and three month ahead realised spot (BFI) prices

Selected Model		Estimation Period
$\Delta S_t = \phi_1 \Delta S_{t-1} + \phi_3 \Delta S_{t-3} + v_t$	$; v_t \sim \text{iid}(0, \sigma^2)$	88:04, 88:06 - 89:09, 94:10 – 95:07
$\Delta S_t = \phi_1 \Delta S_{t-1} + \phi_2 \Delta S_{t-2} + \phi_3 \Delta S_{t-3} + v_t$	$; v_t \sim \text{iid}(0, \sigma^2)$	89:10 - 90:05
$\Delta S_t = \phi_1 \Delta S_{t-1} + \theta_1 v_{t-1} + v_t$	$; v_t \sim \text{iid}(0, \sigma^2)$	90:06 - 92:06, 94:01 - 94:09
$\Delta S_t = \phi_1 \Delta S_{t-1} + \phi_2 \Delta S_{t-2} + v_t$	$; v_t \sim \text{iid}(0, \sigma^2)$	92:07 - 93:12, 95:08 - 96:04
$\Delta S_t = \phi_1 \Delta S_{t-1} + v_t$	$; v_t \sim \text{iid}(0, \sigma^2)$	96:05 - 97:03

Notes:

- Estimation Period refers to the last trading day of the month over which an ARIMA model is estimated. In total 107 models are identified and estimated over the period 1988:04 and 1988:06 to 1997:03. Each model is estimated using the most recent 300 daily BFI observations up to the last trading day of each month and generates forecasts of the settlement price 1, 2 and 3 months ahead.

The forecasting accuracy of each method is assessed using the following criteria. Mean Absolute Error (MAE), which measures the absolute deviation of the predicted value from the realised value; Root Mean Square Error (RMSE) which attaches a higher weight to larger forecast errors and finally, Theil's (1966) Inequality Coefficient, which takes into account the ability of each method to forecast trends and changes ¹⁰. These are calculated as follows

$$\text{MAE} = \frac{1}{N} \sum_{t=1}^N |S_t - Z_t| \quad (3.8)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{t=1}^N (S_t - Z_t)^2} \quad (3.9)$$

$$\text{Theil's} = \sqrt{\frac{1}{N} \sum_{t=1}^N (S_t - Z_t)^2} / \left(\sqrt{\frac{1}{N} \sum_{t=1}^N (S_t)^2} + \sqrt{\frac{1}{N} \sum_{t=1}^N (Z_t)^2} \right) \quad (3.10)$$

where;

S_t are the realised values of the BFI settlement prices

¹⁰ When these criteria give conflicting indications regarding the forecasting performance of alternative models, our decisions are based on the RMSE, which is considered as being the most reliable criterion (see as well, Pindyck and Rubinfeld, 1991).

Z_t are the forecasted values of the BFI settlement prices

N is the number of forecasts

Table 3.11

Comparison of forecast statistics for alternative sources of forecasts

Forecast Source	N	MAE	RMSE	Theil's
Panel A: 1-month ahead forecasts				
Futures	106	0.0529	0.0669	3.077×10^{-4}
VECM	106	0.0526	0.0668	3.055×10^{-4}
ARIMA	106	0.0601	0.0760	3.964×10^{-4}
Random Walk	106	0.0616	0.0776	4.134×10^{-4}
Holt-Winters	106	0.0807	0.1078	7.991×10^{-4}
Panel B: 2-month ahead forecasts				
Futures	65	0.0941	0.1140	8.942×10^{-4}
VECM	65	0.0993	0.1189	9.722×10^{-4}
ARIMA	65	0.1020	0.1283	0.0011
Random Walk	65	0.1037	0.1285	0.0011
Holt-Winters	65	0.1896	0.2382	0.0039
Panel C: 3-month ahead forecasts				
Futures	36	0.1032	0.1277	0.0011
VECM	36	0.1200	0.1378	0.0013
ARIMA	36	0.1277	0.1468	0.0015
Random Walk	36	0.1219	0.1418	0.0014
Holt-Winters	36	0.2881	0.3634	0.0091

Notes:

- N is the number of forecasts; MAE is the Mean Absolute Error of (3.8); RMSE is the Root Mean Square Error of (3.9); Theil's is Theil's (1966) Inequality Coefficient of (3.10).
- 1-month ahead forecasts are for the period 1988:07 to 1997:04.
- 2-months ahead forecasts are for the period 1991:12 - 1997:4.
- 3-months ahead forecasts are for the period July 1988 to April 1997.

The results in Table 3.11 indicate that, apart from the one-month horizon where the VECM provides marginally better forecasts than the futures prices, for the remaining horizons futures prices outperform the other models considered. Given the additional time and effort incurred to estimate the VECM, in comparison to the futures forecasts which are readily available in the market, the results for the one-month horizon do not provide reliable evidence to undermine the apparently better forecasting ability of futures prices. We can also note that the forecasting performance of futures prices diminishes as the forecast horizon increases; this is consistent with the findings of Ma (1989) and Kumar (1992) and reflects that more

information, regarding the future course of spot prices, is available to market participants when the forecasts are made for a shorter horizon. However, while futures prices display this forecasting weakness, they still provide the best forecasts.

Regarding the other forecasting methods, the VECM outperforms the remaining time-series models for all the forecast horizons; ARIMA models outperform the random walk model for the one and two-months forecasts although this is reversed for the three-months. On the other hand, the Holt-Winters model has the worst forecasting accuracy over all forecast horizons. This poor performance can be attributed to the stochastic properties of the BFI series. Harisson (1967) shows the Holt-Winters model to be equivalent to an ARIMA(0,2,2) model specification; if the underlying series can be identified by a different class of ARIMA models, as is the case in our analysis, then forecasts generated by the Holt-Winters model will be far from accurate (see as well Harisson, 1967, and Granger and Newbold, 1986). These results indicate that users of the BIFFEX market receive accurate signals from the futures prices regarding the future course of cash prices.

3.6 Conclusions

The unbiased expectations hypothesis suggests that the price of a futures contract before maturity should be an unbiased predictor of the spot price on the maturity day of the contract. Several studies have investigated this hypothesis in different futures and forward markets with mixed evidence. In this chapter, we extend the empirical evidence on this by investigating the same question in the freight futures market. Parameter restriction tests on the cointegrating relationship between spot and futures prices, indicate 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.

The latter, is thought to be a result of thin trading in the three-months contract and of the possible imbalance between short and long hedging demand for this contract, compared to shorter maturities. The bias in futures prices 3 months from maturity is modelled as an MA(1) process which indicates either the existence of a risk premium which follows such a process or may reflect market irrationality since the market fails to embody in the current futures prices a systematic time series component of the forecast error.

However, despite the existence of a bias in the three-months contract, futures prices across all maturities provide more accurate forecasts of the realised spot prices than forecasts generated from VECM, random walk, ARIMA and the Holt-Winters models. This finding, emphasises the significance of the freight futures market as a price discovery centre where information about future supply and demand conditions is assimilated and interpreted in an efficient manner. Therefore, market participants receive accurate signals from BIFFEX prices and can use these prices as indicators of the future course of BFI prices. Whether futures prices also help discover information regarding current spot prices – which represents the second dimension of the price discovery role of futures markets – is investigated in the next chapter.

Appendix 3.A: Seasonal Unit Root tests on the One- and Three-Months Spot and Futures Prices

Hylleberg et al. (1990) (HEGY) suggest that testing for unit roots, in the presence of seasonal time series, such as with monthly or quarterly data, should be done in a seasonal setting. They argue that economic variables may exhibit strong seasonal patterns which account for a major part of their total variation and are significant in the model specification process. Such patterns may first of all result from stationary seasonal processes, which are conventionally modelled using seasonal dummies and allow for some variation but no persistent change in the seasonal patterns over time. Alternatively, seasonal processes may be non stationary if there is a varying and changing seasonal pattern over time. Such processes, called seasonally integrated processes, cannot be captured using deterministic dummies since the seasonal components drift substantially over time.

The properties of seasonally integrated series are quite similar to the properties of ordinary integrated series. In particular, they have “long memory” so that shocks to the series last forever and may in fact alter permanently the seasonal patterns so that the series of observations corresponding to each month or each quarter may evolve in different ways. Moreover, the first difference of a seasonally integrated process will not be stationary; the series need to be seasonally differenced to achieve stationarity. For instance, the appropriate transformation for stationarity may not be $S_t - S_{t-1}$, but $S_t - S_{t-12}$ for monthly data, or $S_t - S_{t-4}$ for quarterly data, as proposed by Box and Jenkins (1970). However, this procedure blindly assumes that unit roots exist at all the seasonal frequencies; it does not allow for the existence of unit roots at some, but not all, frequencies.

3.A.1 Testing for Seasonal Unit Roots in Quarterly Series

HEGY (1990) propose a procedure, which is an extension of the DF methodology, that tests for the existence of a unit root at zero frequency (i.e. an ordinary unit root) as well as at each one of the seasonal frequencies, on quarterly time series. Consider the seasonal difference operator $\Delta_4 S_t = (1 - L^4)S_t = S_t - S_{t-4}$ which can be factorised as follows:

$$(1 - L^4) = (1 - L)(1 + L + L^2 + L^3) = (1 - L)(1 + L)(1 - iL)(1 + iL) \quad (3.11)$$

where i is the complex number that $i^2 = -1$ and, L^n is the lag operator such that $(1 - L^n)S_t = S_t - S_{t-n}$. Equation has four roots on the unit circle. The first root $(1 - L)$ is the standard unit root, we have considered so far, at zero frequency. The remaining unit roots are obtained from the seasonal filter $S(L) = (1 + L + L^2 + L^3)$, and these correspond to the two quarter (half yearly) frequency $(1 + L)$ and a pair of complex conjugate roots at the four quarter (annual) frequency, $(1 \pm iL)$ ¹¹.

By expanding the polynomial $(1-L^4)S_t$ and recognising that there may be some deterministic components (such as a constant (μ), a deterministic trend term (t), deterministic seasonals ($D_{i,t}$) or some combination of these) in the series, and also allowing enough lags of the dependent variable on the right hand side of the equation so as to make the error term white noise, the following auxiliary regression is derived

$$\Delta_4 S_t = \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-1} + \pi_4 y_{3,t-2} + \sum_{i=1}^m \Delta_4 S_{t-i} + \mu + \delta t + \sum_{i=1}^3 q_i D_{i,t} + u_t \quad (3.12)$$

where

$$y_{1,t-1} = (1 + L + L^2 + L^3) S_{t-1}$$

$$y_{2,t-1} = -(1 - L + L^2 - L^3) S_{t-1}$$

$$y_{3,t-1} = -(1 - L^2) S_{t-1}$$

Applying OLS to (3.12) gives estimates of all the π_i . In case there are seasonal unit roots the corresponding π_i , $i = 2, 3, 4$ are zero. There will be no seasonal unit roots if π_2, π_3, π_4 are different from zero. If $\pi_1 = 0$, then the presence of a unit root at zero frequency cannot be

¹¹ Banerjee et al. (1993) relate these roots to frequencies in an intuitive way. For instance, consider the deterministic process $(1 + L)S_t = 0 \Rightarrow S_t + S_{t-1} = 0$ or $S_t = -S_{t-1}$; it follows that $S_{t+1} = -S_t$ and $S_{t+2} = -S_{t+1}$ or $S_{t+2} = S_t$ which means that the process returns to its original value on a cycle with a period of 2 i.e. it has a frequency of π ; similarly, $(1 - iL)S_t$ can be expressed as $S_{t+4} = S_t$ which means that the process returns to its original value on a cycle with a period of 4 i.e. it has a frequency of $\pm\pi/2$.

rejected. These hypotheses are tested with one sided t-tests for $\pi_1 = 0$ and $\pi_2 = 0$, against the alternative that $\pi_1 < 0$ and $\pi_2 < 0$, and the joint F-test for $\{\pi_3, \pi_4\} = 0$, since the complex roots $\pm i$ are indistinguishable.

3.A.2 Testing for Seasonal Unit Roots in Monthly Series

The HEGY (1990) approach of identifying seasonal unit roots is extended to monthly data by Franses (1991) and Beaulieu and Mirron (1993). Consider the seasonal difference operator $\Delta_{12} = (1 - L^{12})$ which can be factorised as

$$\begin{aligned} (1 - L^{12}) &= (1 - L)(1 + L)(1 - iL)(1 + iL)[1 + (\sqrt{3} + i)L/2][1 + (\sqrt{3} - i)L/2] \\ &[1 - (\sqrt{3} + i)L/2][1 - (\sqrt{3} - i)L/2][1 + (i\sqrt{3} + 1)L/2][1 - (i\sqrt{3} - 1)L/2] \\ &[1 - (i\sqrt{3} + 1)L/2][1 + (i\sqrt{3} - 1)L/2] \end{aligned} \quad (3.13)$$

where all terms other than $(1 - L)$ represent seasonal unit roots. Analytically, the roots of this equation are

$$1, -1, \pm i, -\frac{1}{2}(\sqrt{3} \pm i), \frac{1}{2}(\sqrt{3} \pm i), \frac{1}{2}(i\sqrt{3} \pm i), -\frac{1}{2}(i\sqrt{3} \pm i)$$

with each root corresponding to the following frequencies; $0, \pi, \pm \pi/2, \mp 5\pi/6, \pm \pi/6, \mp 2\pi/3, \pm \pi/3$. Franses (1991) expands the polynomial in (3.13) and derives the following auxiliary regression.

$$\begin{aligned} \Delta_{12}S_t &= \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-1} + \pi_4 y_{3,t-2} + \pi_5 y_{4,t-1} + \pi_6 y_{4,t-2} + \pi_7 y_{5,t-1} + \pi_8 y_{5,t-2} \\ &+ \pi_9 y_{6,t-1} + \pi_{10} y_{6,t-2} + \pi_{11} y_{7,t-1} + \pi_{12} y_{7,t-2} + \sum_{i=1}^m \Delta_{12}S_{t-i} + \mu + \delta t + \sum_{i=1}^{11} q_i D_{i,t} + u_t \end{aligned} \quad (3.14)$$

where

$$\begin{aligned} y_{1,t-1} &= (1 + L)(1 + L^2)(1 + L^4 + L^8) S_{t-1} \\ y_{2,t-1} &= -(1 - L)(1 + L^2)(1 + L^4 + L^8) S_{t-1} \\ y_{3,t-1} &= -(1 - L^2)(1 + L^4 + L^8) S_{t-1} \\ y_{4,t-1} &= -(1 - L^4)(1 - \sqrt{3}L + L^2)(1 + L^2 + L^4) S_{t-1} \end{aligned}$$

$$y_{5,t-1} = -(1 - L^4)(1 + \sqrt{3}L + L^2)(1 + L^2 + L^4) S_{t-1}$$

$$y_{6,t-1} = -(1 - L^4)(1 - L^2 + L^4)(1 - L + L^2) S_{t-1}$$

$$y_{7,t-1} = -(1 - L^4)(1 - L^2 + L^4)(1 + L + L^2) S_{t-1}$$

Applying OLS to (3.14) gives estimates of all the π_i . If there are seasonal unit roots the corresponding π_i , $i = 2, \dots, 12$ are zero. There will be no seasonal unit roots if π_2 through π_{12} are significantly different from zero. If $\pi_1 = 0$, then the presence of a unit root at zero frequency cannot be rejected. When $\{\pi_1, \pi_2, \dots, \pi_{12}\} = 0$ the model has 1 non-seasonal and 11 seasonal unit roots and it is appropriate to apply the $(1 - L^{12})$ filter. These hypotheses are tested with one sided t-tests for $\pi_1 = 0$ and $\pi_2 = 0$, against the alternative that $\pi_1 < 0$ and $\pi_2 < 0$, and F-tests for $\{\pi_3, \pi_4\} = 0$, $\{\pi_5, \pi_6\} = 0$, $\{\pi_7, \pi_8\} = 0$, $\{\pi_9, \pi_{10}\} = 0$ and $\{\pi_{11}, \pi_{12}\} = 0$, against the alternative that these pairs are jointly significantly different from zero.

3.A.3 Results on Seasonal Unit Roots

Stopford (1997) argues that seasonal variations in commodity demand and production affect the level of ocean freight rates, a conjecture that is verified in Kavussanos and Alizadeh (1998). These seasonal patterns may also be reflected on the BFI and BIFFEX prices. Whether these patterns are stochastic is a matter that is analysed empirically by testing for the existence of seasonal unit roots. We estimate the auxiliary regressions (3.14) and (3.12), for the one- and three-months spot and futures prices, respectively. The lag length and the deterministic components to be included in each regression are determined using the SBIC. The lag length is zero in all cases and the deterministic components include an intercept term for the monthly spot and futures prices and an intercept term and three seasonal dummies for the quarterly spot and futures prices.

The selected models are presented in Table 3.12 and Table 3.13¹². For the monthly spot and futures prices, the hypothesis for the existence of seasonal unit roots is examined through the t-tests on π_2 and the F-tests on the pairs of complex roots, i.e. F_1 through F_5 ; these reject the

¹² Due to the transformations in the auxiliary regressions, the sample consists of 94 usable observations for the monthly series and 32 observations for the quarterly series.

null hypothesis at the 5% level of significance. The results are similarly conclusive for the quarterly spot and futures prices. That is, there is no evidence for the existence of unit roots at any seasonal frequency. Non-stationary stochastic seasonality does not seem to be an important feature of the freight futures market, as the examination of the monthly and quarterly futures and spot prices suggests.

Table 3.12

**HEGY Tests for Seasonal Unit Roots in the Logarithms of Monthly (1988:07 - 1997:04)
Spot and Futures Prices**

$$\Delta_{12}S_t = \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-1} + \pi_4 y_{3,t-2} + \pi_5 y_{4,t-1} + \pi_6 y_{4,t-2} + \pi_7 y_{5,t-1} + \pi_8 y_{5,t-2} + \pi_9 y_{6,t-1} \\ + \pi_{10} y_{6,t-2} + \pi_{11} y_{7,t-1} + \pi_{12} y_{7,t-2} + \mu + u_t$$

t and F Statistics				Critical Values	
Frequency	Null Hypothesis	Futures	Spot	2.5%	5%
0	$t : \pi_1 = 0$	-2.769	-2.791	-2.99	-2.72
π	$t : \pi_2 = 0$	-3.996	-4.659	-2.13	-1.84
$\pm \pi/2$	$F_1 : \{\pi_3, \pi_4\} = 0$	6.848	6.804	3.70	3.01
$\mp 5\pi/6$	$F_2 : \{\pi_5, \pi_6\} = 0$	7.406	9.814	3.66	2.97
$\pm \pi/6$	$F_3 : \{\pi_7, \pi_8\} = 0$	7.947	5.263	3.66	3.00
$\mp 2\pi/3$	$F_4 : \{\pi_9, \pi_{10}\} = 0$	10.925	6.760	3.77	2.98
$\pm \pi/3$	$F_5 : \{\pi_{11}, \pi_{12}\} = 0$	5.3510	5.809	3.71	3.03

Residual Diagnostics		
Lags of Dependent Variable	0	0
Observations	94	94
Q(12)	1.882 [0.99]	0.543 [0.99]
J-B	0.876 [0.65]	1.024 [0.59]
SBIC	-8.107	0.674

Notes:

- $y_{n,t-1}$, $n = 1, 2, \dots, 7$ are polynomials of y_t described in (3.14).
- The auxiliary regressions include a constant only as determined by the SBIC. Lags is the number of lagged terms of the dependent variable that are included in the auxiliary regression as regressors.
- Q(12) is the Ljung-Box (1978) Q statistic on the first 12 lags of the sample autocorrelation function.
- J-B is the Jarque-Bera(1980) test for normality. Significance levels are in brackets.
- Critical Values for 120 observations are from Franses and Hobijn (1997), Tables 1, 2, 3, 5, 6, 7.

Regarding the presence of a zero frequency unit root, the null hypothesis that $\pi_1 = 0$, against the alternative that $\pi_1 < 0$, cannot be rejected at the 2.5% level. Therefore, these results reinforce our conclusions from the DF and PP tests, in Table 3.1, that monthly and quarterly spot and futures price series are $I(1)$. For the 2-months spot and futures prices, however, we

cannot obtain reliable inference from seasonal unit roots tests, since critical values for these tests are available for a sample size of 120, whereas our sample size consists only of 65 observations. Given these limitations, we use ordinary DF and PP unit root tests instead, in Table 3.1, which indicate that the series are $I(1)$.

Table 3.13

HEGY Tests for Seasonal Unit Roots in the Logarithms of Quarterly (1988:03 - 1997:02) Spot and Futures Prices

$$\Delta_4 S_t = \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-1} + \pi_4 y_{3,t-2} + \mu + \sum_{i=1}^3 q_i D_{i,t} + u_t ; u_t \sim \text{iid}(0, \sigma_u^2)$$

t and F Statistics				Critical Values	
Frequency	Null Hypothesis	Futures	Spot	2.5%	5%
0	$t : \pi_1 = 0$	-3.004	-3.039	-3.06	-2.77
π	$t : \pi_2 = 0$	-3.555	-4.457	-3.07	-2.77
$\pm \pi/2$	$F_1 : \{\pi_3, \pi_4\} = 0$	9.730	9.061	7.80	6.63
Residual Diagnostics					
Lags of the Dependent Variable	0	0			
Observations	32	32			
Q(4)	0.856 [0.93]	4.129 [0.39]			
J-B	0.034 [0.98]	0.677 [0.71]			
SBIC	-19.876	-9.7254			

Notes:

- $y_{n,t-1}$, $n = 1, 2, 3$ are polynomials of y_t described in (3.12).
- The auxiliary regressions include a constant and three seasonal dummies as determined by the SBIC. Lags is the number of lagged terms of the dependent variable that are included in the auxiliary regression as regressors.
- Q(4) is the Ljung-Box (1978) Q statistic on the first 4 lags of the sample autocorrelation function.
- J-B is the Jarque-Bera (1980) test for normality. Significance levels are in brackets.
- Critical Values for 48 observations are from Franses and Hobijn (1997), Tables 1, 2, 3.
- $D_{i,t}$ are deterministic seasonal dummies taking the value of 1 in the i^{th} quarter and zero otherwise.

The conclusions, regarding the presence of seasonal unit roots, are consistent with the findings of similar studies in other markets; HEGY (1990), Beaulieu and Mirron (1993) and Franses (1991) find that for seasonal (monthly and quarterly) macroeconomic time series in the UK, the US and the Netherlands respectively, there are, in general, no unit roots at seasonal frequencies. Similar conclusions are drawn by Clare et al. (1995) in the examination of the monthly prices of the FTSE Index.

The results presented here are also consistent with other studies in the shipping markets. Kavussanos (1997) examines the monthly second-hand prices of different size dry cargo vessels and concludes, that all the price series have a unit root at zero frequency but none of them have a unit root at any of the seasonal frequencies. Similar conclusions are drawn by Kavussanos and Alizadeh (1998) in examining dry-bulk spot and time-charter freight rates across different classes of vessels.

Appendix 3.B: Holt - Winters Exponential Smoothing Model

Assume that the series, S_t , is generated by the following linear trend process

$$S_t = b_0 + b_1 t + \varepsilon_t \quad ; \varepsilon_t \sim \text{iid}(0, \sigma^2)$$

Holt (1957) and Winters (1960) propose the following generalisation of exponential smoothing for the level and the trend of the S_t series.

$$\bar{S}_t = \bar{S}_{t-1} + T_{t-1} + \beta e_t$$

$$T_t = T_{t-1} + \gamma \beta e_t$$

where: \bar{S}_t is the estimated level of the smoothed S_t series at time t

T_t is the estimate of the trend at time t

$$e_t = (S_t - \bar{S}_{t-1} - T_{t-1}),$$

Given the initial conditions $\bar{S}_2 = S_2$ and $T_2 = S_2 - S_1$, estimates for the smoothing parameters β

and γ are obtained by minimising the function $\sum_{i=2}^n e_i^2$. Then, the h -step ahead forecast of the S_t

series is given by

$$S_{t+h} = \bar{S}_t + hT_t$$

Thus the h -step ahead forecast takes the most recent value of the smoothed series \bar{S}_t and adds in an expected increase hT_t based on the smoothed long run trend. For a review of different classes of exponential smoothing models see Gardner (1985).

Chapter 4 : The Causal Relationship between Spot and Futures Prices in the BIFFEX Market

4.1 Introduction

In the previous chapter we investigated the relationship between futures prices and expected spot prices in the BIFFEX market. We found that BIFFEX prices one and two months from maturity provide unbiased forecasts of the realised spot prices, whereas, futures prices three months from maturity are biased estimates of these prices. However, despite the existence of a bias in the latter prices, futures prices for all maturities provide more accurate forecasts of the realised spot prices than forecasts generated from alternative models thus, emphasising the importance of the BIFFEX market as a price discovery centre.

In addition to providing a mechanism for market agents to form expectations regarding spot prices that will prevail in the future, futures markets also help discover information regarding current spot prices; this represents the second dimension of the price discovery role of futures markets (see as well, the discussion in Chapter 1 of this thesis). For futures markets to provide an efficient pricing mechanism, they must respond to new market information in the same way as the underlying spot prices and must lead the changes in these prices.

In this chapter, we investigate the causal linkage between contemporaneous spot and futures prices in the BIFFEX market. A considerable amount of empirical research has been directed

towards examining this relationship in different commodity and financial futures markets. In particular, the focus of attention has been on the lead-lag relationship between futures returns and the underlying spot returns; for the futures prices to fulfil their price discovery role they must lead the underlying spot prices. Stoll and Whaley (1990) report the existence of a two-way feedback relationship between futures returns and stock index returns in the S&P-500 and the Major Market Index ¹contracts with the lead from futures to spot being stronger. Similar conclusions are drawn by Wahab and Lashgari (1993) and Hung and Zhang (1995) in the examination of stock index futures (FTSE-100 and S&P-500) and interest rate futures, respectively. Finally, Tse (1995) finds that futures returns lead the spot price returns in the Nikkei Stock Index contract. Overall, the findings of these studies indicate that causality between spot and futures prices can run in one (futures to spot) or both (futures / spot feedback) directions, depending on the market under investigation, and in all the cases futures prices contribute to the discovery of new information regarding the current level of spot prices.

Despite this plethora of studies in various commodities and financial futures markets, there is no evidence on the causal relationship between spot and futures prices for the BIFFEX market. Investigation of this issue not only provides, for the first time, empirical evidence on the price discovery function of the BIFFEX contract but also contributes to the existing financial literature in two respects. First, BIFFEX trades the expected value of the service of seaborne transportation. The non-storable nature of the market implies that spot and futures prices are not linked by a cost-of-carry relationship, as in the case of the financial and agricultural futures. Investigation of the price discovery role of the BIFFEX market can thus provide answers as to whether futures prices in this market contribute to the discovery of new information to the extent evidenced in the markets of storable commodities. Second, the trading activity in the market is low. Fortenbery and Zapata (1997) find that in the thinly traded market of cheddar cheese in the US, futures contracts price new information independently from the underlying spot market and consequently do not contribute to the discovery of new information regarding the current spot prices. Whether the same is true for

¹ The Major Market Index (MMI) is a price-weighted stock index, consisting of 20 stocks traded on the American Stock Exchange. The MMI futures contract is traded on the Chicago Mercantile Exchange. See Kolb (1997) for more information on this.

the BIFFEX market, is an issue which is investigated empirically in this chapter.

The structure of this chapter is as follows. The next section defines the concept of Granger causality (Granger, 1969) and links it with that of cointegration. Section 3 discusses the properties of the data; section 4 offers empirical results on the causality tests and impulse response analysis. Finally, section 5 concludes this chapter.

4.2 Granger Causality and Cointegration

The causal relationship between spot and futures prices in the BIFFEX market is investigated using the following Vector Error Correction model (VECM) (Johansen, 1988)

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \sim IN(0, \Sigma) \quad (4.1)$$

where $X_t = (S_t, F_t)'$ is the vector of spot and futures prices, each being $I(1)$ such that the first differenced series are $I(0)$; Δ denotes the first difference operator; Γ_i and Π are 2×2 coefficient matrices measuring the short- and long-run adjustment of the system to changes in X_t , and ε_t is a 2×1 vector of white noise error terms.

The following steps are involved in our analysis. First, the existence of a stationary relationship between spot and futures prices is investigated in the VECM of equation (4.1) through the λ_{\max} and λ_{trace} statistics (Johansen, 1988) which amount to testing for the rank of Π . If $\text{rank}(\Pi)=1$ then there exists a single cointegrating vector and Π can be factored as $\Pi = \alpha\beta'$, where α and β' are 2×1 vectors. Using this factorisation, 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.

Second, if spot and futures prices are cointegrated, then causality must exist in at least one direction (Granger, 1986). To test causality formally, the following expanded VECM may be estimated using OLS in each equation

$$\begin{aligned} \Delta S_t &= \sum_{i=1}^{p-1} a_{S,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i} \Delta F_{t-i} + \alpha_S Z_{t-1} + \varepsilon_{S,t} \\ \Delta F_t &= \sum_{i=1}^{p-1} a_{F,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i} \Delta F_{t-i} + \alpha_F Z_{t-1} + \varepsilon_{F,t} \end{aligned} \quad (4.2)$$

where $a_{s,i}$, $b_{s,i}$, $a_{f,i}$, $b_{f,i}$ are the short-run coefficients and $z_{t-1} = \beta'X_{t-1}$ is the error correction term from equation (4.1).

A time series, F_t , is said to Granger cause another time series, S_t , if the present values of S_t can be predicted more accurately by using past values of F_t than by not doing so, considering also other relevant information including past values of S_t (Granger, 1969). Therefore, Granger's criterion for causality is whether or not the variance of the predictive error is reduced when past F_t values are included in the prediction of S_t .

More formally, F_t is said to Granger cause S_t if

$$\sigma^2(S_t | S) > \sigma^2(S_t | S, F) \quad (4.3)$$

where $S = \{S_{t-1}, S_{t-2}, \dots, S_{t-p}\}$

$F = \{F_{t-1}, F_{t-2}, \dots, F_{t-p}\}$

$\sigma^2(S_t | S)$ and $\sigma^2(S_t | S, F)$ is the variance of the minimum prediction error of S_t , obtained by regressing S_t on S and S and F , respectively.

In terms of the VECM of equation (4.2), F_t Granger causes S_t if some of the $b_{s,i}$ coefficients, $i = 1, 2, \dots, p-1$ are not zero and/or α_s , the error correction coefficient in the equation for spot prices, is significant at conventional levels. Similarly, S_t Granger causes F_t if some of the $a_{f,i}$ coefficients, $i = 1, 2, \dots, p-1$ are not zero and/or α_f is significant at conventional levels. These hypotheses can be tested using t-tests for the significance of the error correction coefficients and F-tests on the joint significance of the lagged estimated coefficients. If both S_t and F_t Granger cause each other then there is a two-way feedback relationship between the two markets. In sum, the error correction coefficients, α_s and α_f serve two purposes: to identify the direction of causality between spot and futures prices and to measure the speed with which deviations from the long-run relationship are corrected by changes in the spot and futures prices.

The VECM of equation (4.2) provides a framework for valid inference in the presence of $I(1)$ variables. Moreover, this procedure is particularly suited for tests of Granger causality since,

in contrast to the Engle and Granger (1987) procedure, inference on the model does not depend on the ordering of the variables in the cointegrating regression. For instance, Wahab and Lashgari (1993) and Hung and Zhang (1995), using the two-step estimator of Engle and Granger (1987), have had to investigate two different forms of the cointegrating regression (one with the spot price as the dependent variable and the other with the futures price) and subsequently estimate four separate error correction equations - two for each error correction term - to ensure that their results were not affected by the ordering of the variables.

4.3 Properties of the Data Series

To test Granger causality, we use a dataset which consists of daily spot and futures prices from 1 August 1988 to 31 December 1997 (2380 observations)². Spot price data are from LIFFE. Futures prices for the period August 1988 to December 1989 are from Knight Ridder and the Financial Times; for the period January 1990 to December 1997, futures price data are collected from LIFFE. All the observations are transformed into natural logarithms.

The futures prices are of 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. Combining information from futures contracts with different times to maturity may create structural breaks in the series at the date of the futures rollover since, futures 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 bias the results. To address this issue, we introduce in the equations of the VECM a dummy variable which controls for the possible effects of the futures contract rollover; the dummy takes the value of one on the futures contract rollover date and zero otherwise. Cointegration and Granger causality tests with the dummy variables are qualitatively the same to the ones without the dummy variables, reported in the following section. This is because the dummies are found to be jointly insignificant, the $\chi^2(2)$ Wald test for their joint significance is 2.82 with a 5% critical value of 5.99, thus indicating that the effect of combining price information from contracts with different times to maturity is not statistically significant, and consequently are excluded from the ensuing analysis.

To provide additional evidence that the effect of the futures contract rollover is not significant, we also investigate the causal relationship between BFI and BIFFEX prices using a “perpetual” futures contract (Pelletier, 1983). A “perpetual” futures contract is calculated as a weighted average of a near and distant futures contracts, weighted according to their respective number of days from maturity; this procedure generates a series of futures prices

² The first observation in our sample corresponds to the introduction of new delivery months in the BIFFEX market.

with constant maturity and avoids the problem of price-jumps caused by the expiration of a particular futures contract (see Herbst et al., 1989). For our analysis, a perpetual BIFFEX contract is calculated for a 22-days horizon, which corresponds to the average number of trading days in a month, by taking a weighted average of the rates of BIFFEX 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 BIFFEX contracts (see chapter 1), with $S \leq 22 \leq P$; the price of 22-days perpetual BIFFEX contract is calculated as follows:

$$F_{22} = F_S [(P - 22)/(P - S)] + F_P [(22 - S)/(P - S)]$$

where F_S and F_P denote the prices of the spot and prompt month BIFFEX contracts, respectively. Use of a 22-days perpetual BIFFEX contract yields empirical results which are qualitatively the same to the ones reported in the following sections thus providing further evidence that the effect of the futures contract rollover is not significant. A disadvantage of this procedure is that in order to create a “perpetual” futures contract, market agents must establish long positions in the “spot” and “prompt” BIFFEX contracts and rebalance these positions on a daily basis as the time to expiry of a futures contract changes³. As a result, implementation of a “perpetual” futures position is more difficult and costly than a position in a single futures contract. Consequently, our results in the following sections are based on the price of a single BIFFEX contract.

³ For instance on 7 October 1997 the prices of the “spot” (October 97) and “prompt” (November 97) BIFFEX contracts are as follows (days to expiration in parentheses); Oct-97: 1400 (19), Nov-97: 1490 (39). The price of the 22-days “perpetual” futures contract is calculated as follows:

$$F_{22} = 1400 [(39 - 22)/(39 - 19)] + 1490 [(22 - 19)/(39 - 19)] = 1400*0.85 + 1490*0.15 = 1413.5$$

The following day, 8 October 97, the following prices are observed in the market; Oct-97: 1420 (18), Nov-97: 1515 (38). The new price is now $F_{22} = 1420 (16/20) + 1515(4/20) = 1420*0.8 + 1515*0.2 = 1439$. We can see that the weights of the two contracts change, as the time to expiry of each contract changes.

Table 4.1

**Summary Statistics of Logarithmic First Differences in Spot and Futures Prices;
Sample period 1/8/88 to 31/12/97**

	<i>T</i>	Skew	Kurt	J-B	Q(36)	Q ² (36)	ADF (lags)		PP (12)	
							levels	diffs.	levels	diffs.
Spot	2380	-0.05 [.37]	7.58 [.00]	5697	463.3	292.1	-2.98 (7)	-11.85 (6)	-2.31	-21.10
Futures	2380	-1.04 [.00]	14.27 [.00]	20614	97.4	42.8	-2.51 (1)	-42.75 (0)	-2.59	-42.94
1% critical value				9.21	58.11	58.11	-3.46	-3.46	-3.46	-3.46
5% critical value				5.99	51.48	51.48	-2.88	-2.88	-2.88	-2.88

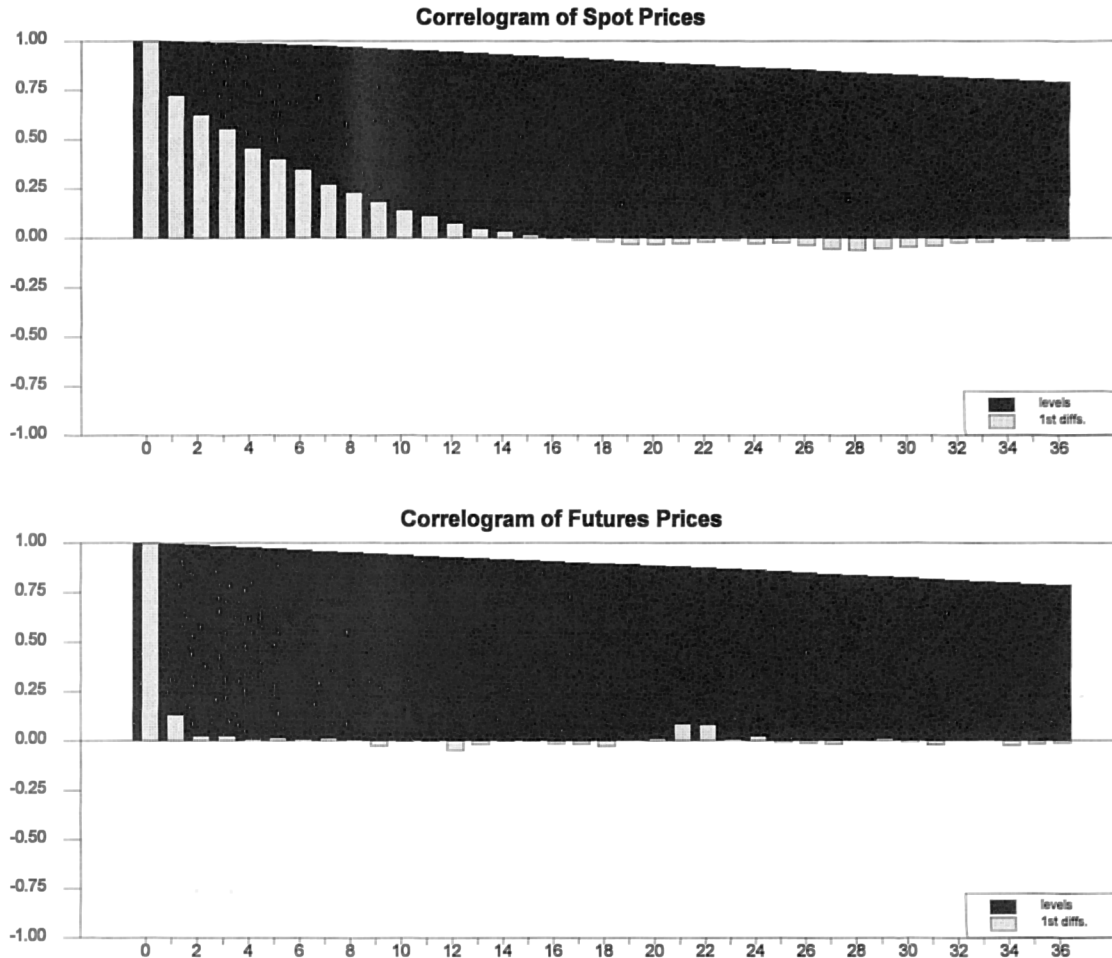
Notes:

- *T* is the number of observations. The statistics are based on logarithmic first differences.
- 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 $\sqrt{T} (\hat{\alpha}_4 - 3) \sim N(0,24)$. Values in square brackets are p-values.
- J-B is the Jarque - Bera (1980) test for normality; the statistic is $\chi^2(2)$ distributed.
- Q(36) and Q²(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 $\chi^2(36)$.
- ADF is the Augmented Dickey Fuller (Dickey and 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) unit root test on the levels of the series; the truncation lag for the test is set equal to 12.

Summary statistics of logarithmic first differences of daily spot and futures prices are presented in Table 4.1. There is evidence of excess skewness in the futures returns and of excess kurtosis in both series which is in line with other studies investigating high frequency financial data. As a consequence, the Jarque-Bera (1980) tests indicate significant departures from normality for the spot and futures returns series. The Ljung-Box Q statistic (Ljung and Box, 1978) on the first 36 lags of the sample autocorrelation function is significant indicating that serial correlation is present in the spot and futures returns. The existence of autocorrelation seems to be more acute for the spot price data. This may be explained by the fact that the BFI is calculated through the rates supplied by the shipbroking companies. These rates are based either on actual reported fixtures, or in the absence of an actual fixture, reflect the shipbroker's expert view of what the rate would be if a fixture had been concluded. It is likely that in the absence of an actual fixture, the shipbrokers submit an assessment which is a mark-up over the previous day's rate which, in turn, induces autocorrelation in the BFI returns. Finally, the Q² statistics, indicate the existence of heteroskedasticity in the spot but not in the futures returns.

Figure 4.1

Correlograms of Spot and Futures Prices; Daily Prices from 1/08/88 to 31/12/97



The order of integration of the spot and futures prices is investigated using the ADF and PP tests on the levels and first-differences of the series. These tests indicate that futures prices follow a unit root process. For the spot prices, the ADF test rejects the null hypothesis of a unit root at the 5% level (but not at the 1%) while the PP test indicates that the series has a unit root. Visual inspection of the correlograms of spot and futures prices, in Figure 4.1, also indicates that the price series follow unit root processes; the correlograms of the series in levels exhibit persistence, whereas, the correlograms for the first-differenced series die-out fairly quickly. Given the additional supporting evidence from the PP test and from the autocorrelation function of the series, we conclude that BFI and BIFFEX are $I(1)$ variables.

4.4 Estimation Results

4.4.1 Results on Vector Error Correction Models (VECM)

Having identified that spot and futures prices are $I(1)$ variables, cointegration techniques are used next to examine the existence of a long-run relationship between these series. The lag length ($p = 4$) in the VECM of equation (4.1) is chosen on the basis of SBIC (1978). Johansen's (1991) LR test, of equation (2.27), in Table 4.2, indicates that an intercept term should be included in the long-run relationship. The estimated λ_{\max} and λ_{trace} statistics, in the same table, show that the BFI and BIFFEX prices stand in a long-run relationship between them, thus justifying the use of a VECM.

The empirical long-run relationship implied by the resulting cointegrating vector is $z_t = \beta'X_t = S_t + 0.1683 - 1.0231F_t$. Further insight into the causal interactions between spot and futures prices can be gained by restricting the cointegrating vector to be the spot futures differential, i.e. the basis. Due to spot futures convergence at the maturity of a futures contract, the current level of the basis can provide an indication of the likely future direction of spot prices in the market. For instance, Fama and French (1987) find that the lagged basis has power in predicting spot price changes for 15 commodities markets in the US. Similar conclusions are drawn by Viswanath (1993) in the examination of corn, wheat and soybeans futures. The null hypothesis that the cointegrating vector, $\beta' = (1, 0, -1)$, that is that the equilibrium relationship is the lagged basis, $z_{t-1} = S_{t-1} - F_{t-1}$, is examined using the test statistic of equation (2.28). The estimated statistic, in Table 4.2, shows that the null hypothesis cannot be rejected at conventional levels of significance and, therefore, in the ensuing analysis the cointegrating vector is restricted to be the basis $z_{t-1} = S_{t-1} - F_{t-1}$.

Table 4.2

Johansen (1988) tests for cointegration; BFI and BIFFEX prices from 1/8/88 to 31/12/97

Lags	LR	Null	Cointegrating Vector		Hypothesis Test	
			$\lambda_{\max}(r, r+1)$	$\lambda_{\text{trace}}(r)$	$\beta' = (1, \beta_1, \beta_2)$	$\beta' = (1, 0, -1)$
4	0.02	r=0	141.50	149.44	1, 0.1683, -1.0231	2.54
		r=1	7.94	7.94		
5% c.v.	2.71	r=0	15.67	19.96		5.99
		r=1	9.24	9.24		

Notes:

- Lags is the lag length of the VECM model in equation (4.1); the lag length is determined using the SBIC.
- LR is Johansen's (1991) test for the null hypothesis that there are no linear trends in the levels of the data
 $LR = -T [\ln(1 - \hat{\lambda}_2^*) - \ln(1 - \hat{\lambda}_2)] \sim \chi^2(1)$ where $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ represent the smallest eigenvalues of the model that includes an intercept term in the cointegrating vector and an intercept term in the short run model, respectively. Acceptance of the null hypothesis indicates that the VECM in equation (4.1) should be estimated with an intercept term in the cointegrating vector.
- $\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$ tests the null hypothesis of r cointegrating vectors against the alternative of r+1.
- $\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$ tests the null that there are at most r cointegrating vectors against the alternative that the number of cointegrating vectors is greater than r. 95% critical values are from Osterwald-Lenum(1992), Table 1*.
- $\beta' = (1 \ \beta_1 \ \beta_2)$ are the coefficient estimates of the cointegrating vector where the coefficient of S_{t-1} is normalised to be unity, β_1 is the intercept term and β_2 is the coefficient on F_{t-1} .
- The null hypothesis that the cointegrating vector is the lagged basis, $\beta' X_{t-1} = (1, 0, -1)$ $X_{t-1} = S_{t-1} - F_{t-1}$ is examined using the test statistic $-T [\ln(1 - \hat{\lambda}_1^*) - \ln(1 - \hat{\lambda}_1)] \sim \chi^2(2)$ where $\hat{\lambda}_1^*$ and $\hat{\lambda}_1$ denote the largest eigenvalues associated with the restricted and the unrestricted model, respectively.

The VECM estimation results are presented in Table 4.3, Panel A. To correct for heteroskedasticity, White's (1980) heteroskedasticity consistent standard errors are estimated. Since F-tests rely on the assumption of homoskedasticity, χ^2 distributed Wald test statistics, in Panel B, are employed to test for Granger causality (see Greene, 1997 p. 548). Residual diagnostics for serial correlation, presented in the same table, do not indicate any misspecification.

Table 4.3

OLS Estimates of the Error Correction Model and Granger Causality Tests; Sample period 1/8/88 to 31/12/97

$$\Delta S_t = \sum_{i=1}^{p-1} a_{S,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i} \Delta F_{t-i} + \alpha_S Z_{t-1} + \varepsilon_{S,t}$$

$$\Delta F_t = \sum_{i=1}^{p-1} a_{F,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i} \Delta F_{t-i} + \alpha_F Z_{t-1} + \varepsilon_{F,t}$$

Equation (4.2)

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \sim IN(0, \Sigma)$$

PANEL A: OLS Model Estimates

Explanatory Variable	Dependent Variable					
	ΔS_t		ΔF_t			
	Coefficients	t-stat.	Coefficients	t-stat.		
$z_{t-1} = S_{t-1} - F_{t-1}$	α_S	-0.0289 ^a	-8.563	α_F	0.0290 ^a	3.173
ΔS_{t-1}	$a_{S,1}$	0.4131 ^a	10.357	$a_{F,1}$	0.4081 ^a	5.099
ΔS_{t-2}	$a_{S,2}$	0.1221 ^a	2.625	$a_{F,2}$	-0.1056	-1.236
ΔS_{t-3}	$a_{S,3}$	0.1250 ^a	4.091	$a_{F,3}$	-0.0321	-0.369
ΔF_{t-1}	$b_{S,1}$	0.0455 ^a	6.596	$b_{F,1}$	0.1154 ^a	4.976
ΔF_{t-2}	$b_{S,2}$	0.0194 ^a	3.266	$b_{F,2}$	-0.0052	-0.262
ΔF_{t-3}	$b_{S,3}$	0.0111 ^a	1.751	$b_{F,3}$	0.0119	0.610

Residual Diagnostics

\bar{R}^2	0.601	0.029
System LL	16434	
System AIC	-16420	
System SBIC	-16380	
Q(36)	44.66 [.15]	45.56 [.13]
Q ² (36)	86.73 [.00]	46.40 [.12]
Heteroskedasticity $\sim \chi^2(1)$	51.48 [.00]	66.62 [.00]

PANEL B: Wald Tests for Granger Causality

$H_0: b_{S,i} = 0, i=1, \dots, 3 \sim \chi^2(3)$	55.00	[.00]	-	
$H_0: a_{F,i} = 0, i=1, \dots, 3 \sim \chi^2(3)$	-		29.68	[.00]

Notes:

- a, b and c denote significance at the 1%, 5% and 10% level respectively.
- t-statistics and Wald tests are calculated using White's (1980) heteroskedasticity consistent covariance matrix.
- The cointegrating vector $z_{t-1} = \beta' X_{t-1} = S_{t-1} - F_{t-1}$ is restricted to be the basis.
- LL is the maximum value of the log-likelihood function.
- Heteroskedasticity is a LM test based on the regression of the squared residuals on the squared fitted values of the models; the test statistic is $\chi^2(1)$. Significance levels are in brackets.
- See the notes in Table 4.1 for the definitions of the remaining diagnostics.

Examination of the speed of adjustment coefficients (α_s and α_f) provides insight into the adjustment process of spot and futures prices towards equilibrium. The coefficients are statistically significant and their signs imply direct convergence to the long-run relationship; in response to a positive deviation from their equilibrium relationship at period $t-1$, i.e. $S_{t-1} > F_{t-1}$, the spot price in the next period will decrease in value while the futures price will increase thus eliminating any disequilibrium. Therefore, both spot and futures prices adjust to eliminate any deviations from their long-run relationship, although this adjustment process is expected to be rather slow as manifested by the magnitude of the estimated coefficients; the percentage of the disequilibrium that is eliminated each day, i.e. $\alpha_f - \alpha_s$, is 5.79%.

Turning now into the coefficients for the lagged own-returns and lagged cross-market returns, we can see that three lags of each variable are significant in the spot returns equation, while only the first lag of both is significant in the futures returns equation. Wald tests, for the joint significance of the lagged cross-market returns in the equations for spot and futures, indicate the existence of a two-way feedback relationship between the two markets and the magnitude of the statistics indicates that the causality from futures to spot returns runs stronger than the other way. Comparing the \bar{R}^2 values we can see that the ECM explains 60.1% of the variation in the spot equation while, only 2.9% of the variation in the futures returns is explained by the model. This suggests that most of the variability in futures returns represents “news” arriving in the market and indicates that futures prices play a leading role in incorporating new information.

4.4.2 Impulse Response Analysis

A more detailed insight on the causal relationship between spot and futures prices is obtained by analysing the generalised impulse response (GIR) functions (Pesaran and Shin, 1997), of (2.36), which measure the reaction of BFI and BIFFEX prices to shocks in the equations of the VECM. The point estimates of the GIR of the spot and futures prices with respect to one standard error shocks to the equations of the VECM are presented in Table 4.4, and their time profiles are plotted in Figure 4.2 and Figure 4.3.

Table 4.4

Generalised Impulse Responses of Spot and Futures Prices to one Standard Error Shock in the equations for Spot and Futures Prices; Sample period 1/8/88 to 31/12/97					
Horizon (days)	Shock in the equation for Spot		Shock in the equation for Futures		
	Response of		Response of		
	Spot	Futures	Spot	Futures	
0	0.00406	0.00528	0.00139	0.01545	
1	0.00601	0.00751	0.00307	0.01739	
2	0.00756	0.00806	0.00474	0.01765	
3	0.00909	0.00846	0.00639	0.01794	
4	0.01019	0.00894	0.00787	0.01810	
5	0.01102	0.00928	0.00920	0.01821	
10	0.01282	0.01030	0.01409	0.01862	
15	0.01269	0.01065	0.01678	0.01891	
20	0.01211	0.01076	0.01816	0.01909	
30	0.01120	0.01077	0.01913	0.01926	
40	0.01084	0.01074	0.01930	0.01929	
50	0.01074	0.01072	0.01931	0.01930	

Notes:

- GIR of spot and futures prices to one standard error shock to the equations of the VECM are constructed using equation (2.36).

We observe that the instantaneous impact (i.e. at period 0) of a shock in either equation is larger on futures than on spot prices. This suggests that futures prices react more rapidly to “news” arriving in the market and hence play a leading role in incorporating new information. At the same time, spot prices seem to adjust more slowly to a new level following a shock. Consider for instance the responses of spot and futures prices to innovations in the spot

returns, presented in Figure 4.2. The effect of the shock on futures tends to die out after about 10 to 15 days. In contrast, after overshooting over a protracted period of time, spot prices adjust to a new long-run level after a period of 35 to 40 days. A similar pattern is observed following an innovation in futures returns, in Figure 4.3. Futures prices adjust to a new long-run level after a period of 5 – 10 days while, around 25 days are needed for spot prices to adjust; this is expected given the superior information role of futures prices.

Figure 4.2

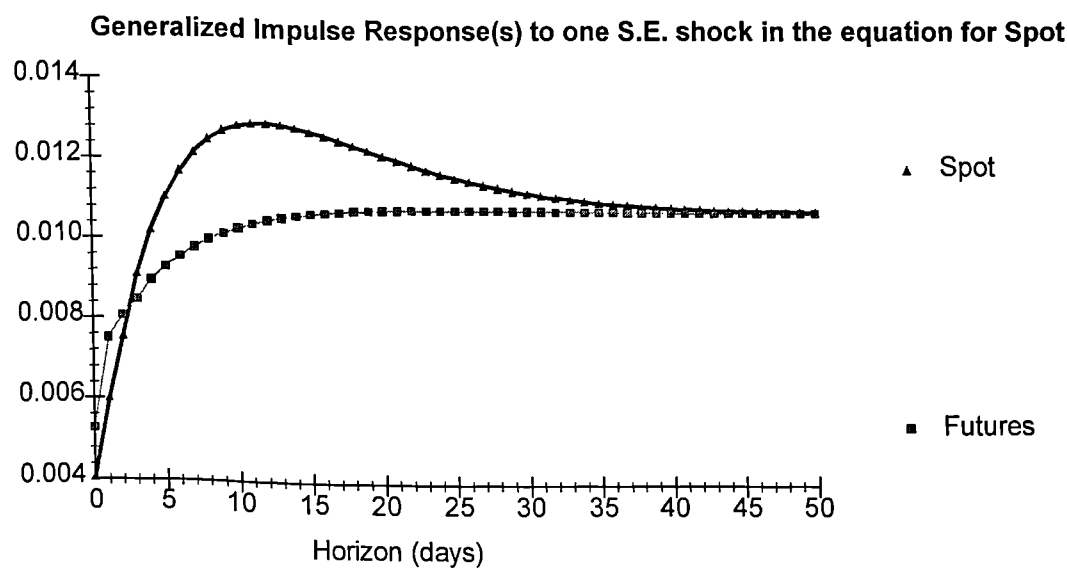
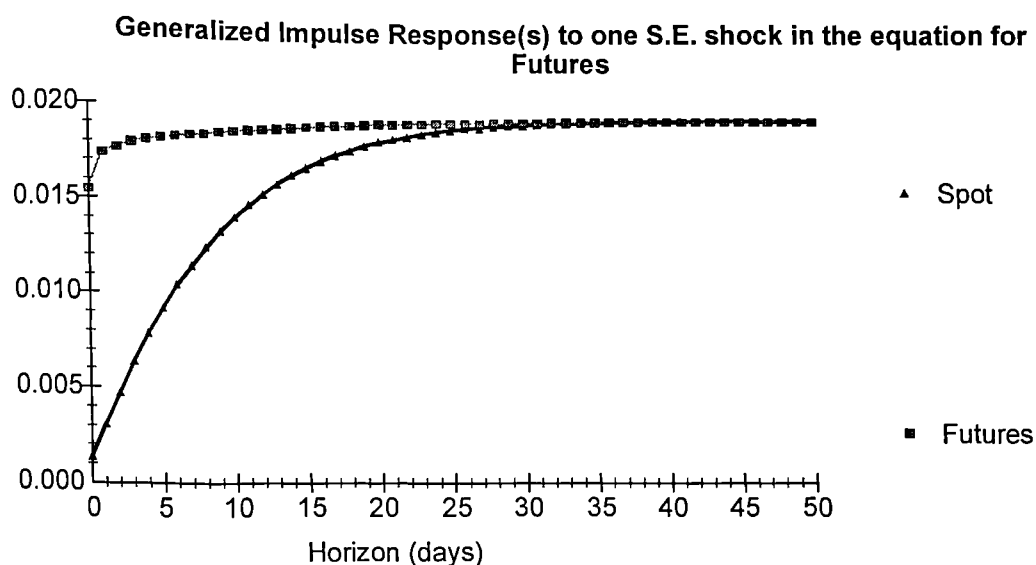


Figure 4.3



This indicates that futures prices respond to new information and reach the long-run equilibrium level more rapidly than their corresponding spot prices. In a world with non-differential transaction costs across markets and no restrictions on borrowing or short selling, we would expect the spot and futures markets to be equally accessible to all traders. Investors who have collected and analysed new information, regarding the expected level of spot and futures prices, would 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. In other words, prices in one market may “lead” prices in the other market. The lower costs of transacting in the futures market may be the reason that futures markets seem to be informationally more efficient than their corresponding spot markets. While a short position in futures contracts may be entered into as easily as a long position, the same may not be necessarily true for the spot market. This problem is accentuated when the underlying spot market trades a service, as in the BIFFEX market, in which case it is not possible to establish a short position in the spot market.

Moreover, futures markets provide 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. Finally, another point is that BFI is calculated based on the shipbrokers’ assessments of the market. In the absence of an actual fixture in the market, these assessments reflect merely the shipbroker’s expert view of what the rate would be if a fixture had been concluded and hence do not convey “new” information in the market. The above characteristics of the shipping freight futures market can explain why futures prices in the BIFFEX market should price new information more rapidly compared to their underlying spot prices.

4.5 Conclusions

In this chapter, we investigated the causal linkage between contemporaneous spot and futures prices in the BIFFEX market, using daily data. Our major findings can be summarised as follows. Spot and futures prices stand in a long-run relationship between them. The resulting VECM is used to investigate the short-run dynamics and the price movements in the two markets. Causality tests and impulse response analysis indicate that futures prices tend to discover new information more rapidly than spot prices. This pattern is thought to reflect the fundamentals of the underlying commodity since, due to the impossibility of short-selling the underlying spot index, investors who have collected and analysed new information would prefer to trade in the futures rather than in the spot market.

The findings in this chapter complement our result from chapter 3 and indicate that, despite the non-storable nature of the market and the thin trading, futures prices in the BIFFEX market contribute to the discovery of new information regarding both current and expected BFI prices and, as a result, the market performs its price discovery function efficiently. Moreover, the existence of a VECM describing the dynamics of BFI and BIFFEX prices, indicates that the predictability of these prices can be improved by incorporating the information provided by the cointegrating relationship; the forecasting performance of the estimated model is investigated in chapter 7. Before that, in the following chapter, we investigate whether the market also performs its hedging function efficiently.

Chapter 5 : The Hedging Effectiveness of the BIFFEX Contract; Constant vs. Time-Varying Hedge Ratios.

5.1 Introduction

Our empirical results in chapters 3 and 4, indicate that the BIFFEX market performs its price discovery function efficiently since, futures prices contribute to the discovery of new information regarding both expected and current BFI prices. In this chapter, we investigate whether the market also fulfils, to the same extent, its hedging function and, in particular, we assess the effectiveness of futures contracts in controlling freight rate risk in the routes that constitute the BFI.

The objective of hedging is to control the risk of adverse price changes in the spot market. To achieve this, the hedger determines a hedge ratio i.e. the number of futures contracts to buy or sell for each unit of spot commodity on which he bears price risk. In chapter 1, we presented the minimum variance hedge ratio methodology of Johnson (1960), Stein (1961) and Ederington (1979). 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 cash and futures price changes to the variance of futures price changes; this is equivalent to the slope coefficient, γ^* , in the following regression

$$\Delta S_t = \gamma_0 + \gamma^* \Delta F_t + u_t ; u_t \sim \text{iid}(0, \sigma^2) \quad (5.1)$$

Within this specification, the higher the R^2 of equation (5.1) the greater the effectiveness of the minimum-variance hedge. Minimum risk hedge ratios and measures of hedging effectiveness are estimated for T-bill futures by Ederington (1979) and Franckle (1980); for the oil futures by Chen, Sears and Tzang (1987); for stock indices by Figlewski (1984) and Lindahl (1992); for currencies by Grammatikos and Saunders (1983) and by Malliaris and Urrutia (1991) and for the freight futures market by Thuong and Visscher (1990) and Haralambides (1992). The major conclusion of these studies is that commodity and financial futures contracts perform well as hedging vehicles with R^2 's ranging from 80% to 99%. In contrast, for the freight futures market, the R^2 's vary from 32% to less than 1% across the different BFI routes. This poor hedging performance of the BIFFEX contract is thought to reflect the heterogeneous composition of the BFI which consists of dissimilar shipping routes, in terms of vessel sizes and transported commodities.

However, this method of calculating hedge ratios is demonstrated by Myers and Thompson (1989) and Kroner and Sultan (1993) to be lacking in several respects. The first objection is related to the implicit assumption in equation (5.1) that the risk in spot and futures markets is constant over time. This assumption contrasts sharply with the fact that many asset prices are characterised by time-varying distributions which implies that optimal, risk-minimising hedge ratios should be time-varying. A second problem is that equation (5.1) is potentially misspecified because it ignores the existence of a long-run cointegrating relationship between spot and futures prices (Engle and Granger, 1987). These issues raise concerns regarding the risk reduction properties of hedge ratios generated from equation (5.1).

In this chapter, we investigate the effectiveness of time-varying hedge ratios in the freight futures market. While this issue has been investigated in numerous commodity and financial futures markets there is no empirical evidence for the BIFFEX market. Unlike other futures markets, in which futures contracts are used as a hedge against price fluctuations in the underlying asset, in the BIFFEX market futures contracts are employed as a cross-hedge against freight rate fluctuations on the individual shipping routes which constitute the BFI.

Examination of the cross-sectional variability of hedge ratios and measures of hedging effectiveness across the different shipping routes is of considerable interest to those involved in trading and regulating the BIFFEX market. Market agents (shipowners or charterers) whose physical operations concentrate on BFI constituent routes can benefit from using optimal hedge ratios that minimise their freight rate risk. Regulators, also have an interest in setting an underlying index which promotes the proper functioning of the market. Cross-hedging freight rate risk using an index-based futures contract is only successful when the freight rate and the futures price behave similarly. The strength of this relationship is dependent upon the composition of the underlying index. Routes which are similar in terms of vessel sizes and cargo flows, are likely to be more strongly related to futures prices than routes which are not; this is actually the major argument in favour of the introduction of the BPI as the underlying asset of the futures contract, from November 1999. Therefore, by investigating the hedging effectiveness of the BIFFEX contract, we can shed some light to these important issues.

The model that we use in this study is a vector error correction model (VECM) (Johansen, 1988) with a GARCH error structure (Bollerslev, 1986). The VECM models the long-run relationship between spot and futures prices and the GARCH error structure permits the second moments of their joint distribution to change over time; the time-varying hedge ratios are then calculated from the estimated covariance matrix of the model. This study also extends previous research in other futures markets by including the squared lagged error correction term (ECT) of the cointegrated spot and futures prices in the specification of the conditional variance in what is termed the GARCH-X model (Lee, 1994).

The structure of this chapter is as follows; The next section presents the derivation of the conditional, time-varying hedge ratios; Section 3 illustrates the empirical model that is used in this study; Section 4 discusses the properties of the data series; Section 5 offers empirical results and section 6 evaluates the in and out-of-sample hedging effectiveness of the proposed strategies. Finally, section 7 concludes this chapter.

5.2 Hedging and Time-Varying Hedge Ratios

Market participants in futures 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 freight futures market. The return on the shipowner's hedged portfolio of spot and futures positions, ΔP_t , is given by equation (1.7), repeated here for convenience

$$\Delta P_t = \Delta S_t - \gamma_t \Delta F_t \quad (5.2)$$

where, $\Delta S_t = S_t - S_{t-1}$ is the change in the spot position between $t-1$ and t ; $\Delta F_t = F_t - F_{t-1}$ is the change in the futures position between $t-1$ and t ; and γ_t is the hedge ratio at time t . If the joint distribution of spot and futures returns is time-varying, then the variance of the hedged portfolio will change as new information arrives in the market; therefore, 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

$$\text{Var}(\Delta P_t | \Omega_{t-1}) = \text{Var}(\Delta S_t | \Omega_{t-1}) - 2\gamma_t \text{Cov}(\Delta S_t, \Delta F_t | \Omega_{t-1}) + \gamma_t^2 \text{Var}(\Delta F_t | \Omega_{t-1}) \quad (5.3)$$

where $\text{Var}(\Delta S_t | \Omega_{t-1})$, $\text{Var}(\Delta F_t | \Omega_{t-1})$ and $\text{Cov}(\Delta S_t, \Delta F_t | \Omega_{t-1})$ are, respectively, the conditional variances and covariance of the spot and futures returns. The optimal time-varying hedge ratio is then defined as the value of γ_t which minimises the conditional variance of the hedged portfolio returns i.e. $\min_{\gamma_t} [\text{Var}(\Delta P_t | \Omega_{t-1})]$. Taking the partial derivative of equation (5.3) with respect to γ_t , setting it equal to zero and solving for γ_t , yields the optimal hedge ratio conditional on the information set available at $t-1$, as follows

$$\gamma_t^* | \Omega_{t-1} = \frac{\text{Cov}(\Delta S_t, \Delta F_t | \Omega_{t-1})}{\text{Var}(\Delta F_t | \Omega_{t-1})} \quad (5.4)$$

The *conditional* minimum-variance hedge ratio of equation (5.4) is the ratio of the

conditional covariance of spot and futures price changes over the conditional variance of futures 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. Moreover, the conditional hedge ratio nests the *conventional* hedge ratio, γ^* in equation (5.1), by restricting the conditional moments of spot and futures prices in equation (5.4) to be constant.

5.3 Time-Varying Hedge Ratios and ARCH Models

To estimate γ_t^* in equation (5.4), the conditional second moments of spot and futures 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 futures returns with a GARCH error structure. The error correction part of the model is necessary because spot and futures prices share a common stochastic trend, and the GARCH error structure permits the variances and the covariance of the price series to be time-varying. Therefore, the conditional means of spot and futures returns are specified using the following VECM

$$\Delta X_t = \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} | \Omega_{t-1} \sim \text{distr}(0, H_t) \quad (5.5)$$

where $X_t = (S_t \ F_t)'$ is the vector of spot and futures prices, Γ_i and Π are 2x2 coefficient matrices measuring the short- and long-run adjustment of the system to changes in X_t and ε_t is the vector of residuals $(\varepsilon_{S,t} \ \varepsilon_{F,t})'$ which follow an as-yet-unspecified conditional distribution with mean zero and time-varying covariance matrix, H_t . The significance of incorporating the cointegrating relationship into the statistical modelling of spot and futures prices is emphasised in studies such as Kroner and Sultan (1993), Ghosh (1993b), Chou et al. (1996) and Lien (1996); hedge ratios and measures of hedging performance may change sharply when this relationship is unduly ignored from the model specification.

The conditional second moments of spot and futures returns are specified as a GARCH(1,1) model (Bollerslev, 1986) using the following augmented Baba et al. (BEKK) representation (see Engle and Kroner, 1995)

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'W_{t-1}D \quad (5.6)$$

where C is a 2x2 lower triangular matrix, A and B are 2x2 diagonal coefficient matrices, with $\alpha_{ii}^2 + \beta_{ii}^2 < 1$, $i=1,2$ for stationarity, W_{t-1} represents additional explanatory variables which

belong to Ω_{t-1} and influence H_t and D is a 1×2 vector of coefficients ¹. In this diagonal representation, the conditional variances are a function of their own lagged values and their own lagged error terms, while the conditional covariance is a function of lagged covariances and lagged cross products of the ε_t 's. Moreover, this formulation guarantees H_t to be positive definite almost surely for all t and, in contrast to the constant correlation model of Bollerslev (1990), it allows the conditional covariance of spot and futures returns to change signs over time ².

Additional explanatory variables may be incorporated in H_t through the W_{t-1} term. Lee (1994) for instance, in the examination of spot and forward exchange rates, includes the square of the lagged error correction term (ECT). A similar specification is adopted by Choudhry (1997) in examining spot and futures stock indices returns. By including the squared lagged ECT term, $z_{t-1}^2 = (\beta'X_{t-1})^2$, in the conditional variance equation, one can examine the temporal relationship between disequilibrium, as proxied by the magnitude of the ECT, and uncertainty, which is measured by the time varying variances. If spot and futures prices deviate from their long-run relationship then they may become more volatile as they respond to eliminate these deviations. If this is the case, then the inclusion of the error correction term in the conditional variance may be appropriate.

Preliminary evidence on our data set with the conditional normal distribution reveals substantial excess kurtosis in the estimated standardised residuals even after accounting for second moment dependencies. As demonstrated in Bollerslev and Wooldridge (1992), this invalidates traditional inference procedures. Following Bollerslev (1987), the conditional Student- t distribution is used as the density function of the error term, ε_t , and the degrees of

¹ Estimation of the full BEKK model on our dataset does not yield convergent results, despite trying different initial values for the estimated parameters. Hence, the A and B matrices are restricted to be diagonal; as indicated in Bollerslev et al. (1994), this restriction results in a more parsimonious representation of the conditional variance, compared to the full BEKK model. 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 futures prices; see Kroner and Sultan (1993), Gagnon and Lypny (1995, 1997), Tong (1996) and Bera et al. (1997) for evidence on this.

² For a 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).

freedom, ν , is treated as another parameter to be estimated; this distribution has been found successful in characterising the conditional distributions of spot and futures prices in different markets (see for instance, Gagnon and Lypny, 1995 and 1997, and Hogan et al., 1997). The general form of the likelihood function becomes

$$L(H_t, \varepsilon_t, \theta) = \frac{\Gamma[(2 + \nu)/2]}{\Gamma(\nu/2)(\pi(\nu - 2))} |H(\theta)_t|^{-1/2} \left[1 + \frac{1}{\nu - 2} \varepsilon(\theta)'_t H(\theta)_t^{-1} \varepsilon(\theta)_t \right]^{-[(2 + \nu)/2]} \quad (5.7)$$

$, (\nu > 2)$

where θ is the vector of parameters to be estimated, $\Gamma(\cdot)$ is the gamma function and ν denotes the degrees of freedom³. This distribution converges to the multivariate normal as $\nu \rightarrow \infty$ although, in empirical applications, the two likelihood functions give similar results for values of ν above 20. Baillie and Bollerslev (1995) show that for $\nu < 4$, the above distribution has an undefined or infinite degree of kurtosis⁴. In such case, they suggest using the Bollerslev and Wooldridge (1992) quasi-maximum likelihood estimation (QMLE) procedure⁵.

³ The gamma function interpolates the factorials in the sense that $\Gamma(\nu+1) = \nu!$ for $\nu > 0$; see Feller (1966).

⁴ The theoretical kurtosis of a t-distribution is computed as $3(\nu-2)(\nu-4)^{-1}$, $\nu > 4$; see Bollerslev (1987).

⁵ Consider the conditional bivariate normal log-likelihood function $L(H_t, \varepsilon_t, \theta) = -\log 2\pi - \frac{1}{2} \log |H(\theta)_t| - \frac{1}{2} \varepsilon(\theta)'_t H(\theta)_t^{-1} \varepsilon(\theta)_t$, which is maximised with respect to the unknown parameters, θ . Using standard MLE, the variance-covariance matrix of the estimated coefficients is given by $\text{var}(\hat{\theta}) = J^{-1}$ where J is the information matrix, i.e.

$J = -E(\partial^2 L / \partial \theta \partial \theta')$. Under QMLE, $\text{var}(\hat{\theta}) = J^{-1} K J^{-1}$ where K is the outer product of the first-order derivatives, $K = \sum_{t=1}^T (\partial L / \partial \theta)(\partial L / \partial \theta)'$.

5.4 Description of the Market and Properties of the Data

Our data set consists of weekly ⁶ futures and spot prices for each route in BFI, from 23 September 1992 to 31 October 1997 (10 February 1993 to 31 October 1997 for route 9). The spot price data are Wednesday closing prices of all the BFI constituent routes and the futures prices are Wednesday closing prices of the futures contract which is nearest to maturity; when a holiday occurs on Wednesday, Tuesday's observation is used in its place. In order to avoid the problems associated with thin markets and expiration effects, it is assumed that a hedger rolls over to the next nearest contract one week prior to the expiration of the current contract. Notice, that due to revisions in the composition of the BFI, the weights of these routes in the BFI are not the same over the period investigated by this study (see Table 1.2); however, during the out-of-sample period, which runs from April 1996 to October 1997, there are no changes in the specifications of these routes.

Summary statistics of logarithmic spot and futures price differences are presented in Table 5.1. Based on the coefficients of excess kurtosis, spot and futures price series appear to be leptokurtic. Jarque-Bera (1980) tests indicate significant departures from normality for all the series. The Ljung-Box Q statistic (Ljung and Box, 1978) on the first 24 lags of the sample autocorrelation function is significant for the spot price data indicating that serial correlation is present in the spot returns. Engle's (1982) ARCH tests and the Q^2 statistic, generally indicate the existence of heteroskedasticity in the spot price returns. Finally, ADF and PP tests on the levels and first differences indicate that the series are difference stationary.

⁶ Weekly data are preferred in this study 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 and implies that hedgers in the market rebalance their futures position on a weekly basis. Second, weekly data provide us with an adequate number of observations ($N=267$) to investigate the in- and out-of-sample performance of GARCH based hedge ratios, compared to other frequencies (i.e. 2 or 4 weeks). Finally, the choice of a weekly hedging horizon is also in line with the empirical studies in other futures markets; see as well Kroner and Sultan (1993) and Gagnon and Lypny (1995), (1997).

Table 5.1

Summary Statistics; Sample Period 23/09/92 to 31/10/97 (10/02/ 93 to 31/10/ 97 for route 9)

	N	Skew	Kurt	J-B	Q(24)	Q ² (24)	ARCH (1)	ARCH (5)	ADF (lags) in levels	PP (4) in levels	ADF (lags) in 1 st diffs	PP (4) in 1 st diffs
Route 1	267	0.82 [.00]	2.81 [.00]	117.36	160.61	28.63	14.43	18.04	-3.41 (2)	-2.73	-8.65 (0)	-8.67
Route 1A	267	0.82 [.00]	2.32 [.00]	89.33	184.39	32.38	10.29	14.02	-2.84 (2)	-2.38	-8.53 (1)	-8.05
Route 2	267	0.24 [.47]	1.19 [.00]	18.43	72.79	19.03	0.01	5.18	-2.43 (2)	-2.36	-11.87 (1)	-11.49
Route 2A	267	0.84 [.00]	2.55 [.00]	103.75	102.14	8.76	1.48	1.55	-2.34 (2)	-2.23	-10.31 (1)	-9.57
Route 3	267	-0.11 [.47]	3.69 [.00]	152.68	116.13	48.01	7.75	10.15	-2.55 (2)	-2.25	-9.30 (1)	-9.74
Route 3A	267	0.25 [.10]	1.15 [.00]	17.49	125.05	128.55	61.44	64.85	-2.54 (2)	-2.41	-8.99 (1)	-8.64
Route 6	267	0.25 [.10]	3.31 [.00]	124.14	174.79	63.20	28.33	29.72	-1.99 (1)	-1.96	-8.30 (0)	-8.50
Route 7	267	0.33 [.03]	2.98 [.00]	103.90	132.57	20.40	3.31	4.29	-2.79 (2)	-2.68	-9.44 (0)	-9.36
Route 8	267	1.03 [.00]	6.49 [.00]	516.02	138.32	29.15	6.26	6.44	-2.22 (1)	-1.95	-9.04 (0)	-9.07
Route 9	247	1.24 [.00]	7.60 [.00]	658.56	157.58	126.64	59.33	60.87	-2.06 (2)	-1.65	-8.67 (1)	-7.98
Route 10	267	0.61 [.00]	2.31 [.00]	75.24	190.38	46.29	25.14	25.31	-2.62 (1)	-2.29	-8.37 (0)	-8.38
Futures	267	-0.34 [.02]	0.90 [.00]	14.20	36.67	14.11	0.01	3.89	-2.06 (1)	-2.17	-15.94 (0)	-15.97
1% c.v.				9.21	42.98	42.98	6.63	15.09	-3.46	-3.46		-3.46
5% c.v.				5.99	36.42	36.42	3.84	11.07	-2.88	-2.88		-2.88

Notes:

- The data are weekly, log-differenced prices covering the period from 23 September 1992 to 31 October 1997 (10 February 93 to 31 October 97 for route 9)
- 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; the statistic is $\chi^2(2)$ distributed.
- Q(24) and Q²(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; these tests are distributed as $\chi^2(24)$.
- ARCH (1) and (5) are the Engle (1982) tests for ARCH effects; the statistic is χ^2 distributed with 1 and 5 degrees of freedom respectively.
- ADF is the Augmented Dickey Fuller (Dickey and 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) unit root test; the truncation lag for the test is set to 4.

5.5 Empirical Results

Having identified that all spot and futures prices are $I(1)$ variables, cointegration techniques are used next to examine the existence of a long-run relationship between each spot series and the BIFFEX prices. The lag length (p) in the VECM of equation (5.5), chosen on the basis of the SBIC (1978), is presented in Table 5.2. The same table, also presents Johansen's (1991) LR test of (2.27) for the appropriateness of including an intercept term in the cointegrating vector. Tests results indicate that restricting the intercept term to lie on the cointegrating vector is appropriate for all the routes. The estimated λ_{\max} and λ_{trace} statistics indicate that with the exception of Route 9, the BFI routes stand in a long-run relationship with the futures price, i.e. are cointegrated, thus justifying the use of VECM. For route 9, the λ_{\max} and λ_{trace} statistics suggest that $\text{rank}(\Pi) = 0$ in equation (5.5), implying that a VAR model in first differences is appropriate.

The normalised coefficient estimates of the cointegrating vector, i.e. $\beta'X_{t-1}$ from equation (5.5), for each route, are presented in Table 5.2. These estimates, representing the long-run relationship between spot routes and futures prices, are used in the joint estimation of the conditional mean and the conditional variance, of equations (5.5) and (5.6)⁷. This takes place using the Berndt et al (1974) algorithm to maximise the log-likelihood function of equation (5.7). The Student-t distribution is used as the density function of the error term for routes 1, 1A, 2, 2A, 3, 3A and 9 while, the models for routes 6, 7, 8 and 10, for which the estimated degrees-of-freedom parameter was $\nu < 4$, are estimated using QMLE (Bollerslev and Wooldridge, 1992).

⁷ Notice that the estimates of the cointegrating vector are not restricted to be (1 -1 0). This restriction implies that the cointegrating vector reflects the lagged basis and follows from the convergence of spot and futures prices at the maturity of the futures contract, as in our analysis in chapter 4. However, in this study, we consider the shipping routes which form part of the underlying asset and not the underlying asset itself. Although BIFFEX prices converge to the BFI at maturity, this does not necessarily imply that BIFFEX prices should also converge to the shipping routes which constitute the BFI.

Table 5.2

Johansen (1988) tests for cointegration between Spot Routes and BIFFEX

	Lags	LR	Null	λ_{\max}	λ_{trace}	Cointegrating Vector (1 β_1 β_2)
Route 1	3	0.21	r=0	29.019	33.282	1, -1.4097, -0.8096
			r=1	4.263	4.263	
Route 1A	3	0.32	r=0	23.003	27.813	1, 1.5825, -1.2251
			r=1	4.810	4.810	
Route 2	3	0.15	r=0	27.026	31.523	1, -1.6847, -0.7949
			r=1	4.497	4.497	
Route 2A	3	0.29	r=0	22.544	27.657	1, 0.4536, -1.0948
			r=1	5.113	5.113	
Route 3	3	0.10	r=0	26.069	30.562	1, -1.4405, -0.8100
			r=1	4.492	4.492	
Route 3A	3	0.13	r=0	19.908	24.337	1, 1.3762, -1.1914
			r=1	4.429	4.429	
Route 6	2	0.41	r=0	15.890	20.949	1, 0.0419, -0.9868
			r=1	5.059	5.059	
Route 7	3	0.27	r=0	15.850	22.053	1, -0.7311, -0.8719
			r=1	6.203	6.203	
Route 8	2	0.13	r=0	22.294	26.439	1, -0.4527, -0.8695
			r=1	4.145	4.145	
Route 9	3	0.09	r=0	6.989	10.217	
			r=1	3.229	3.229	
Route 10	3	0.25	r=0	16.938	22.425	1, 0.2207, -0.9948
			r=1	5.487	5.487	
5% c.v.		2.71	r=0	15.670	19.960	
			r=1	9.240	9.240	

Notes:

- The data are weekly, log-differenced prices covering the period from 23 September 1992 to 31 October 1997 (10 February 93 to 31 October 97 for route 9).
- Lags is the lag length of the VECM in (5.5); the lag length is determined by means of the SBIC.
- LR is Johansen's (1991) test for the null hypothesis that there are no linear trends in the levels of the data
 $LR = -T [\ln(1 - \hat{\lambda}_2^*) - \ln(1 - \hat{\lambda}_2)] \sim \chi^2(1)$ where $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ represent the smallest eigenvalues of the model that includes an intercept term in the cointegrating vector and an intercept term in the short run model, respectively. Acceptance of the null hypothesis indicates that the VECM in equation (5.5) should be estimated with an intercept term in the cointegrating vector.
- $\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$ tests the null hypothesis of r cointegrating vectors against the alternative of $r+1$.
- $\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$ tests the null that there are at most r cointegrating vectors against the alternative that the number of cointegrating vectors is greater than r . 95% critical values are from Osterwald-Lenum (1992), Table 1*.
- $\beta' = (1 \ \beta_1 \ \beta_2)$ are the coefficient estimates of the cointegrating vector where the coefficient of S_{t-1} is normalised to be unity, β_1 is the intercept term and β_2 is the coefficient on F_{t-1} .

Table 5.3 Panel A

Maximum Likelihood Estimates of the VECM-GARCH models; Sample Period 23/09/92 to 31/10/97 (10/02/93 to 31/10/97 for route 9)

$$\Delta S_t = \sum_{i=1}^{p-1} a_{S,t} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,t} \Delta F_{t-i} + \alpha_{S,t} \Delta F_{t-1} + \varepsilon_{S,t}$$

$$\Delta F_t = \sum_{i=1}^{p-1} a_{F,t} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,t} \Delta F_{t-i} + \alpha_{F,t} \Delta F_{t-1} + \varepsilon_{F,t}, \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} | \Omega_{t-1} \sim \text{distr}(0, H_t)$$

$$H_t = \begin{pmatrix} h_{SS,t} & h_{SF,t} \\ h_{SF,t} & h_{FF,t} \end{pmatrix} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix} \begin{pmatrix} \alpha_{11} & 0 \\ 0 & \alpha_{22} \end{pmatrix} \varepsilon_{t-1} \varepsilon'_{t-1} + \begin{pmatrix} \beta_{11} & 0 \\ 0 & \beta_{22} \end{pmatrix} H_{t-1} \begin{pmatrix} \beta_{11} & 0 \\ 0 & \beta_{22} \end{pmatrix} + \begin{pmatrix} d_{11} & 0 \\ 0 & d_{22} \end{pmatrix} z'_{t-1} (d_{11} \ d_{22})$$

	Route 1	Route 1A	Route 3	Route 3A	Route 6	Route 7	Route 8	Route 9	Route 10
	GARCH-X	GARCH-X	GARCH-X	GARCH	GARCH	ARCH-X	GARCH	GARCH	GARCH
α_S	-0.082 (0.023) a	-0.082 (0.025) a	-0.092 (0.024) a	-0.102 (0.020) a	-0.026 (0.009) a	-0.049 (0.016) a	-0.054 (0.013) a	-	-0.028 (0.013) b
$a_{S,1}$	0.467 (0.050) a	0.531 (0.043) a	0.361 (0.047) a	0.413 (0.041) a	0.567 (0.044) a	0.497 (0.052) a	0.547 (0.057) a	0.417 (0.047) a	0.608 (0.059) a
$a_{S,2}$	-	-	-	-	-	-	-	-	-
$b_{S,1}$	0.214 (0.042) a	0.286 (0.051) a	0.119 (0.031) a	0.195 (0.044) a	0.058 (0.022) a	0.114 (0.034) a	-	0.241 (0.040) a	0.054 (0.030) c
$b_{S,2}$	-	-	-	-	-	0.092 (0.033) a	-	-	-
α_F	-	-	-	-	0.046 (0.022) b	-	0.092 (0.026) a	-	0.052 (0.023) b
$a_{F,1}$	0.180 (0.073) b	0.178 (0.061) a	-	-	-	-	-	-	0.247 (0.092) a
$a_{F,2}$	-	-	-	-	-	-	-	-	-
$b_{F,1}$	-	-	-	-	-	-0.101 (0.061) b	-	-	-
$b_{F,2}$	-0.155 (0.059) a	-0.178 (0.060) a	-0.089 (0.054) c	-0.105 (0.057) c	-	0.165 (0.085) b	-	-0.153 (0.056) a	-0.126 (0.056) b
Conditional Variance Equations									
c_{11}	0.012 (0.003) a	0.013 (0.003) a	0.015 (0.002) a	0.008 (0.004) b	0.014 (0.002) a	0.019 (0.002) a	0.005 (0.002) a	0.005 (0.001) a	0.015 (0.002) a
c_{12}	0.010 (0.016)	0.010 (0.004) a	0.017 (0.013)	0.011 (0.016)	0.014 (0.005) a	0.015 (0.003) a	0.036 (0.006) a	0.005 (0.005)	0.012 (0.004) a
c_{22}	0.013 (0.041)	7*10e-5 (1.451)	2*10e-6 (34.41)	0.014 (0.014)	0.015 (0.008) c	0.037 (0.002) a	2*10e-6 (0.003)	0.005 (0.013)	0.036 (0.003) a
α_{11}	0.329 (0.094) a	0.357 (0.094) a	0.462 (0.128) a	0.283 (0.101) a	0.385 (0.073) a	0.329 (0.087) a	0.319 (0.099) a	0.283 (0.053) a	0.452 (0.106) a
α_{22}	0.030 (0.142)	0.103 (0.106)	0.047 (0.178)	0.119 (0.116)	0.177 (0.116)	-0.088 (0.133)	0.141 (0.079) c	0.090 (0.071)	-0.206 (0.102) b
β_{11}	0.806 (0.100) a	0.772 (0.078) a	0.111 (0.609)	0.919 (0.061) a	0.357 (0.238)	-	-0.910 (0.026) a	0.947 (0.022) a	0.515 (0.130) a
β_{22}	0.908 (0.479) b	0.966 (0.086) a	0.903 (0.147) a	0.889 (0.275) a	-0.832 (0.081) a	-	0.394 (0.282)	0.980 (0.060) a	-0.208 (0.298)
d_{11}	0.114 (0.040) a	0.138 (0.032) a	0.219 (0.045) a	-	-	0.139 (0.033) a	-	-	-
d_{22}	0.043 (0.068)	0.019 (0.029)	0.125 (0.080)	-	-	-0.009 (0.047)	-	-	-
v	6.238 (2.424) a	5.297 (1.666) a	4.260 (1.101) a	9.073 (4.426) b	-	-	-	6.259 (2.245) a	-
LL	1106.45	1081.28	1188.91	1083.14	1707.11	1603.97	1663.464	1001.55	1639.42
LR (D = 0)	5.14 ~ $\chi^2(2)$	14.20 ~ $\chi^2(2)$	8.88 ~ $\chi^2(2)$	4.01 ~ $\chi^2(2)$	3.34 ~ $\chi^2(2)$	16.12 ~ $\chi^2(2)$	1.63 ~ $\chi^2(2)$	-	2.68 ~ $\chi^2(2)$
LR (VECM)	15.77 ~ $\chi^2(4)$	14.73 ~ $\chi^2(4)$	11.06 ~ $\chi^2(4)$	10.79 ~ $\chi^2(4)$	14.17 ~ $\chi^2(4)$	9.22 ~ $\chi^2(2)$	21.47 ~ $\chi^2(4)$	36.80 ~ $\chi^2(4)$	15.37 ~ $\chi^2(4)$
AIC	-2182.90	-2132.56	-2349.82	-2142.28	-3392.22	-3181.60	-3306.92	-1981.10	-3252.84
SBIC	-2129.09	-2078.75	-2299.61	-2099.24	-3352.76	-3134.97	-3271.06	-1942.49	-3206.21

Notes:

- Estimation period is from 23 September 1992 to 31 October 1997 (N=267) and 10 February 93 to 31 October 97 for route 9 (N = 247).
- a, b and c denote significance at the 1%, 5% and 10% level respectively.

- Models for routes 1, 1A, 2, 2A, 3, 3A and 9 are estimated using the conditional t-distribution; for these routes numbers in parentheses are asymptotic standard errors and ν is the estimate of degrees of freedom from the t-distribution. Routes 6, 7, 8 and 10 are estimated using QML techniques; for these routes, asymptotic robust standard errors are reported.
- LL is the maximum value of the log-likelihood function.
- LR ($D=0$) is the likelihood ratio statistics for the restriction $D = 0$. LR (VECM) is the LR test for the restriction $A = B = 0$ in the simple GARCH model.

Table 5.3 Panel B

Residual diagnostics on the estimated models

	Route 1		Route 1A		Route 3		Route 3A		Route 6		Route 7		Route 8		Route 9		Route 10	
	Spot	Fut	Spot	Fut	Spot	Fut	Spot	Fut	Spot	Fut	Spot	Fut	Spot	Fut	Spot	Fut	Spot	Fut
Kurtosis*	5.681		7.626		26.049		4.182								5.656			
Kurtosis	4.025	3.934	5.062	3.844	6.033	3.877	3.316	3.867	6.324	3.742	5.995	3.921	9.622	3.885	4.698	3.885	5.693	3.860
Skewness	0.372	-0.276	0.686	-0.277	0.375	-0.356	0.106	-0.376	0.865	-0.425	-0.252	-0.404	1.062	-0.475	0.227	-0.389	0.453	-0.444
$\alpha_{ii}^2 + \beta_{ii}^2$ (i=1,2)	0.758	0.826	0.724	0.944	0.226	0.818	0.926	0.805	0.276	0.724	-	-	0.930	0.175	0.977	0.969	0.470	0.086
Half-Life	3.499	4.645	3.150	13.05	1.465	4.451	10.04	4.186	1.537	3.147	-	-	10.584	1.397	30.997	23.262	1.918	1.283
$\alpha_{ii}^2 + \beta_{ii}^2$ (i=1,2)	0.840	0.830	0.728	0.954	0.904	0.834	-	-	-	-	-	-	-	-	-	-	-	-
(GARCH)																		
Half-Life	4.981	4.721	3.183	15.69	7.870	4.816	-	-	-	-	-	-	-	-	-	-	-	-
(GARCH)																		
Q(24)	22.59	31.12	18.01	31.41	30.22	33.62	26.89	32.99	14.61	35.85	17.05	31.88	29.55	33.14	26.58	34.94	25.67	33.04
Q ² (24)	23.86	16.79	16.69	16.72	31.21	16.67	23.27	14.94	13.84	11.79	14.04	15.14	10.78	11.84	13.26	14.44	19.32	11.48
ARCH(1)	0.027	0.330	0.008	0.431	0.317	0.189	0.184	0.123	0.085	0.366	0.008	0.086	0.153	.006	1.334	0.031	0.006	0.307
ARCH(5)	4.576	3.959	0.640	4.202	9.286	2.846	2.755	5.971	2.091	2.688	2.182	2.187	1.087	2.551	1.618	1.618	1.042	1.741
Sign Bias	[.387]	[.047]	[.885]	[.039]	[.586]	[.123]	[.276]	[.131]	[.987]	[.122]	[.531]	[.117]	[.201]	[.328]	[.946]	[.202]	[.946]	[.102]
- ve Size Bias	[.422]	[.046]	[.933]	[.167]	[.977]	[.124]	[.055]	[.119]	[.953]	[.140]	[.726]	[.142]	[.425]	[.467]	[.135]	[.196]	[.955]	[.090]
+ ve Size Bias	[.129]	[.096]	[.662]	[.052]	[.849]	[.087]	[.117]	[.084]	[.619]	[.069]	[.921]	[.111]	[.222]	[.312]	[.211]	[.156]	[.936]	[.052]
Joint Test	[.332]	[.084]	[.896]	[.091]	[.763]	[.327]	[.221]	[.348]	[.829]	[.257]	[.823]	[.381]	[.544]	[.178]	[.083]	[.533]	[.973]	[.216]

Notes:

- See the notes in Table 2 for the definitions of the statistics.
- Kurtosis* is the theoretical kurtosis of the t-distribution; it is computed as $3(v-2)/(v-4)^{-1}$ where v is the estimated degrees of freedom of the model.
- Significance levels for the Engle and Ng (1993) tests are in brackets [.] (See footnote 12)
- Half-life measures the period of time (number of weeks) over which a shock to volatility reduces to half its original size and is given by $1 - [\log(2)/\log(\alpha_{ii}^2 + \beta_{ii}^2)]$, $i=1,2$ (see Chowdhury, 1997). The closer to unity is the value of the persistence measure, $\alpha_{ii}^2 + \beta_{ii}^2$, the slower is the decay rate and the longer is the half life.
- Half-Life (GARCH) and $\alpha_{ii}^2 + \beta_{ii}^2$ (GARCH) are, respectively the half-life and measure of volatility persistence for the simple GARCH(1,1) model.

The preferred GARCH or GARCH-X models, selected on the basis of LR tests, for each route are presented in Table 5.3, Panel A ⁸. In most cases the GARCH(1,1) specification provides a good description of the joint distribution of spot and futures price returns, with the exception of route 7, where an ARCH(1) model is found superior and routes 2 and 2A where all the coefficients in the conditional variance equations were found to be insignificant.

Several observations merit attention. First, the speed of adjustment of spot and futures prices to their long-run relationship, measured by the α_s and α_f estimated coefficients respectively, seems to vary across the different routes. For the panamax routes (routes 1, 1A, 3 and 3A) and the capesize route 7, the error correction coefficients in the equation for the spot prices are negative while, in the futures equation they are insignificant. This implies that in response to a positive deviation from their long-run relationship at period $t-1$, i.e. $S_{t-1} > F_{t-1}$, the spot price in the next period will decrease in value while the futures price will remain unresponsive and suggests that for these routes, spot prices react more swiftly to return to their long-run relationship. Turning now into the remaining capesize routes (i.e. Routes 6, 8 and 10), the error correction coefficients in the spot equation are negative while, in the futures equation they are significantly positive. This suggests that for these routes both spot and futures prices respond to deviations from their long-run relationship.

Consider next the conditional variance part of the equations. LR statistics, testing the GARCH-X models against a GARCH (denoted LR(D=0)) and a simple VECM model with constant variances (denoted as LR(VECM)) indicate that the GARCH-X model is superior to alternative specifications for routes 1, 1A, 3 and 7 ⁹. For these routes, the coefficients of the squared error correction terms in the spot variance equations, d_{11} , are significant, while the coefficients in the futures equation, d_{22} , are insignificant. Short-run deviations from the long-run relationship between spot and futures prices affect primarily the volatility of spot price changes since, as the analysis of the ECT coefficients in the conditional mean equations suggests, spot prices are more responsive to deviations from the long-run relationship.

⁸ 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.

⁹ The GARCH-X model is not estimated for route 9, since route 9 and BIFFEX prices are not cointegrated.

For the routes which are estimated with the conditional t-distribution, the term ν is the estimate of the degrees of freedom. For large values of ν , (around 20), the t-distribution approaches the normal. In all cases, the estimated value of ν , suggests that the choice of the t-distribution is appropriate. The theoretical kurtosis implied by a t distribution is presented in Table 5.3 Panel B. Consider for instance route 1A. In this model, $\nu = 5.297$ which implies a theoretical kurtosis of 7.626 (see footnote 4). The actual kurtoses of the standardised residuals are 5.06 and 3.84 for the spot and futures equations, respectively. This suggests that, although both spot and futures returns exhibit a significant degree of leptokurtosis, the theoretical kurtosis implied by the model is slightly higher.

The degree of persistence in variance for each route is measured by the estimated sum $\alpha_{11}^2 + \beta_{11}^2$ ¹⁰. These measures, also presented in Table 5.3 Panel B, indicate a varying degree of persistence across the different routes, although in all cases the sum is less than unity implying that the GARCH system is covariance stationary. Similar conclusions emerge when we consider the half-life of shocks to volatility¹¹.

Table 5.3 Panel B also presents measures of volatility persistence from the estimated GARCH models for routes 1, 1A and 3. We can see that the inclusion of the ECT in the variance equation, for routes 1, 1A and 3, reduces the persistence of spot and futures returns volatility over the simple GARCH specifications. This is consistent with the empirical evidence in other markets which indicates that the introduction of additional explanatory variables in the conditional variance equations either reduces or eliminates the degree of persistence in the GARCH model; see Hogan et al. (1997), Kavussanos et al. (1996), Kavussanos (1997) and Lamoureux and Lastrapes (1990) for evidence on this.

¹⁰ The degree of persistence in variance, measures whether shocks to volatility are persistent or not. For instance, as the sum of the $\alpha_{ii}^2 + \beta_{ii}^2$, $i=1,2$ coefficients tends to 1, the degree of persistence in variance increases and as a result, shocks have a permanent effect on volatility.

¹¹ Half-life measures the period of time (number of weeks) over which a shock to volatility reduces to half its original size and is estimated as $1 - [\log(2)/\log(\alpha_{ii}^2 + \beta_{ii}^2)]$, $i=1,2$ (see Chowdhury, 1997). The closer to unity is the value of the persistence measure, $\alpha_{ii}^2 + \beta_{ii}^2$, the slower is the decay rate and the longer is the half life.

Finally, diagnostic tests on the standardised ARCH residuals, $\varepsilon_t/\sqrt{h_t}$, and standardised squared ARCH residuals, ε_t^2/h_t , indicate that the selected models are well specified. In addition, sign and size bias tests (Engle and Ng, 1993) suggest that 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 ¹².

¹² The test statistic for the Engle and Ng (1993) tests is the t-ratio of b in the regressions; $u_t^2 = a + b S_{t-1}^- + \beta' z_{0t} + e_t$ (sign bias test); $u_t^2 = a + b S_{t-1}^- \varepsilon_{t-1} + \beta' z_{0t} + e_t$ (negative size bias test); $u_t^2 = a + b S_{t-1}^+ \varepsilon_{t-1} + \beta' z_{0t} + e_t$ (positive size bias test) where u_t^2 are the squared standardised residuals, ε_t^2/h_t , S_{t-1}^- is a dummy variable taking the value of one when ε_{t-1} is negative and zero otherwise, $S_{t-1}^+ = 1 - S_{t-1}^-$, 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, $z_{0t} = (h_{t-1}, \varepsilon_{t-1}^2)$. The joint test is based on the regression $u_t^2 = a + b_1 S_{t-1}^- + b_2 S_{t-1}^- \varepsilon_{t-1} + b_3 S_{t-1}^+ \varepsilon_{t-1} + \beta' z_{0t} + e_t$. The test statistic for the joint test $H_0: b_1 = b_2 = b_3 = 0$, is an LM statistic distributed as $\chi^2(3)$ with 95% critical value of 7.81.

5.6 Time Varying Hedge Ratios and Hedging Effectiveness

Following estimation of the GARCH models, measures of the time-varying variances and covariances are extracted and used to compute the time-varying hedge ratios of equation (5.4). Figure 5.1 to Figure 5.9 present the conditional hedge ratios, obtained from the selected GARCH or GARCH-X models, together with the conventional hedge ratio obtained from the OLS model of equation (5.1). It can be seen that the conditional hedge ratios are clearly changing as new information arrives in the market.

Figure 5.1

Route 1 Time-Varying and Conventional Hedge Ratios

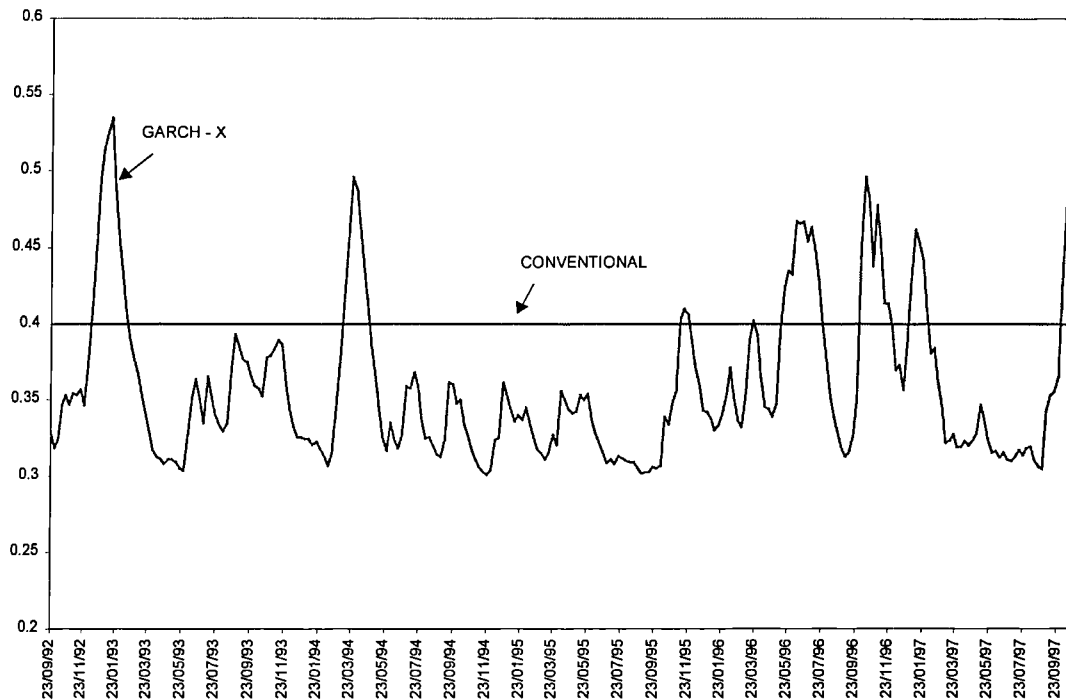


Figure 5.2

Route 1A Time-Varying and Conventional Hedge Ratios

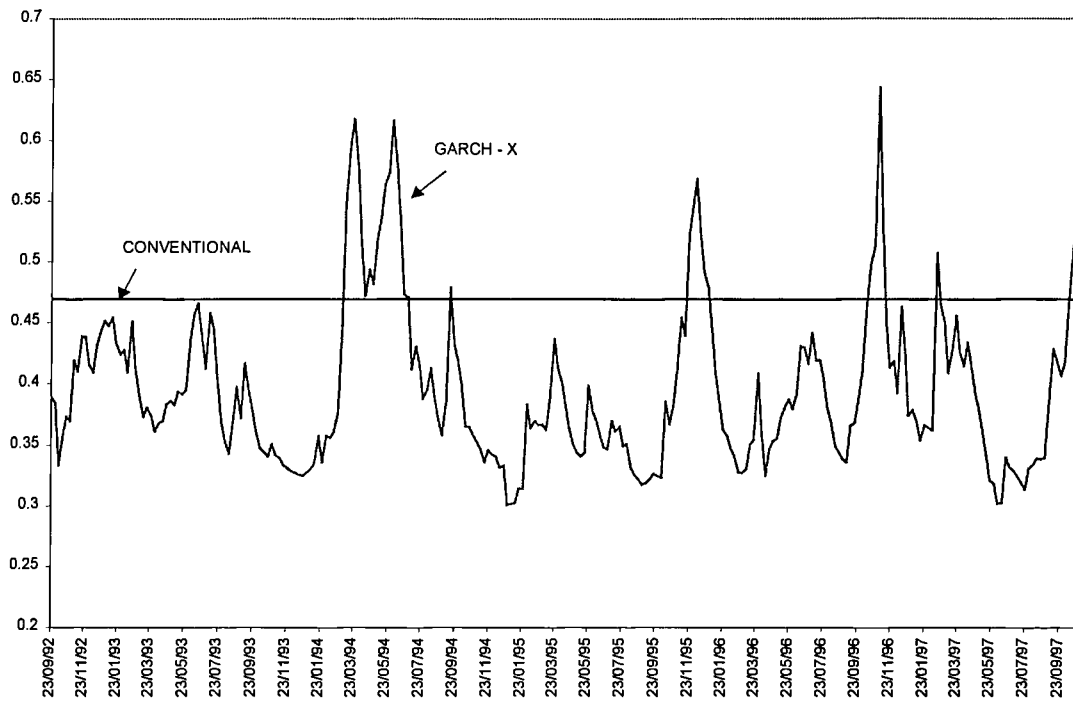


Figure 5.3

Route 3 Time-Varying and Conventional Hedge Ratios

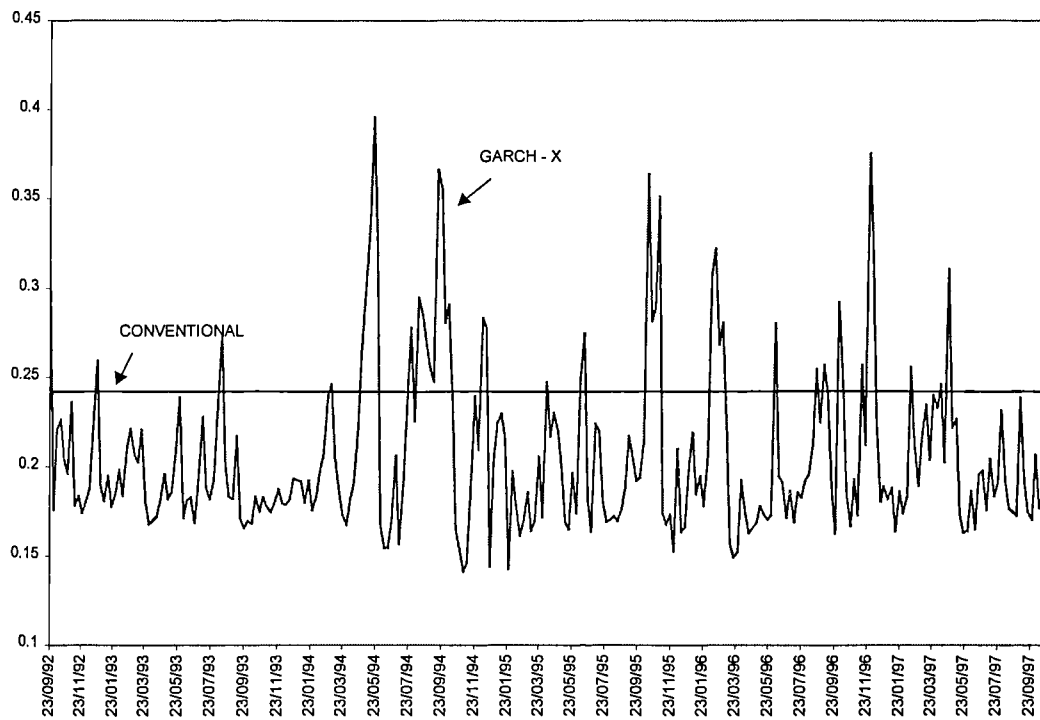


Figure 5.4

Route 3A Time-Varying and Conventional Hedge Ratios

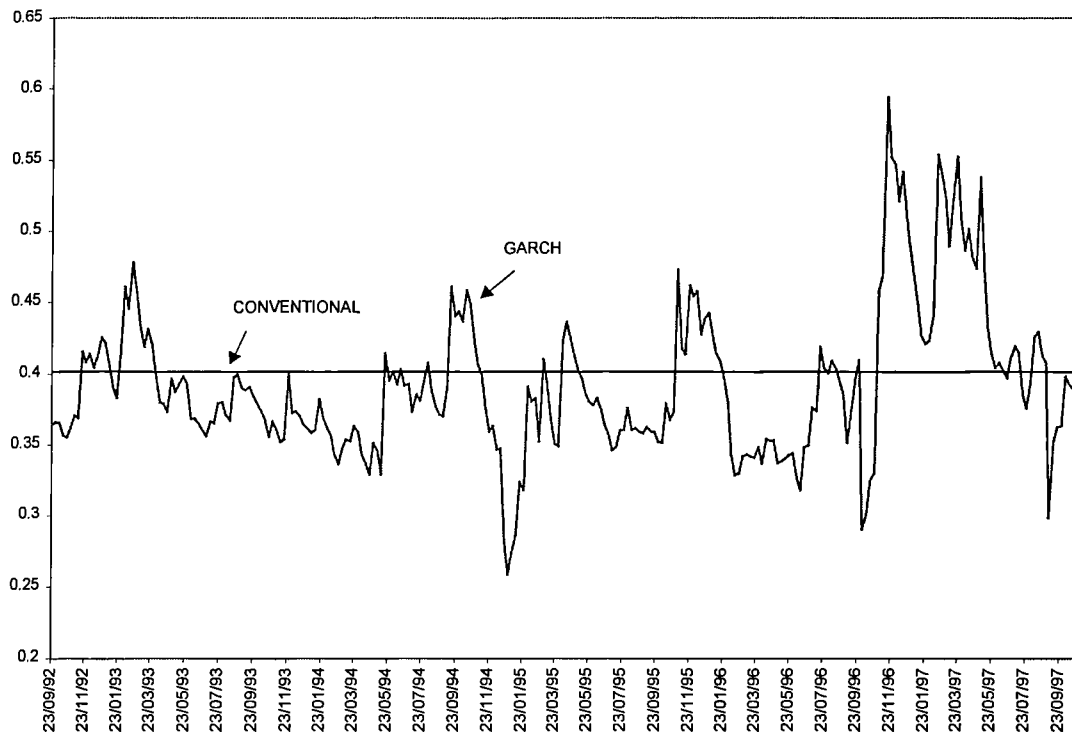


Figure 5.5

Route 6 Time-Varying and Conventional Hedge Ratios

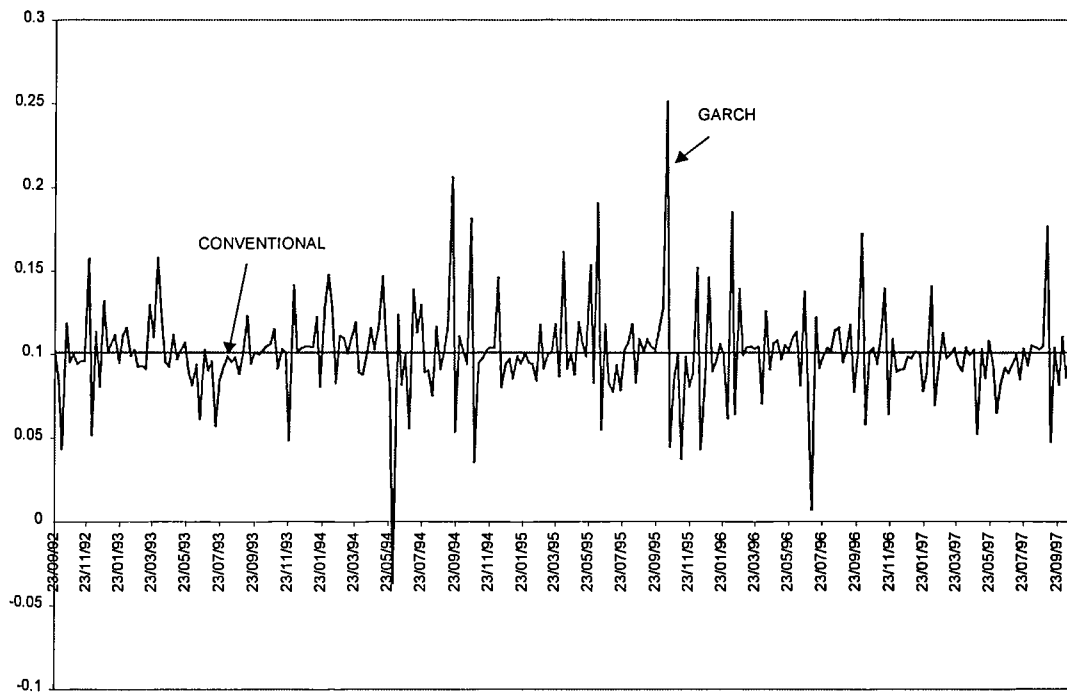


Figure 5.6

Route 7 Time-Varying and Conventional Hedge Ratios

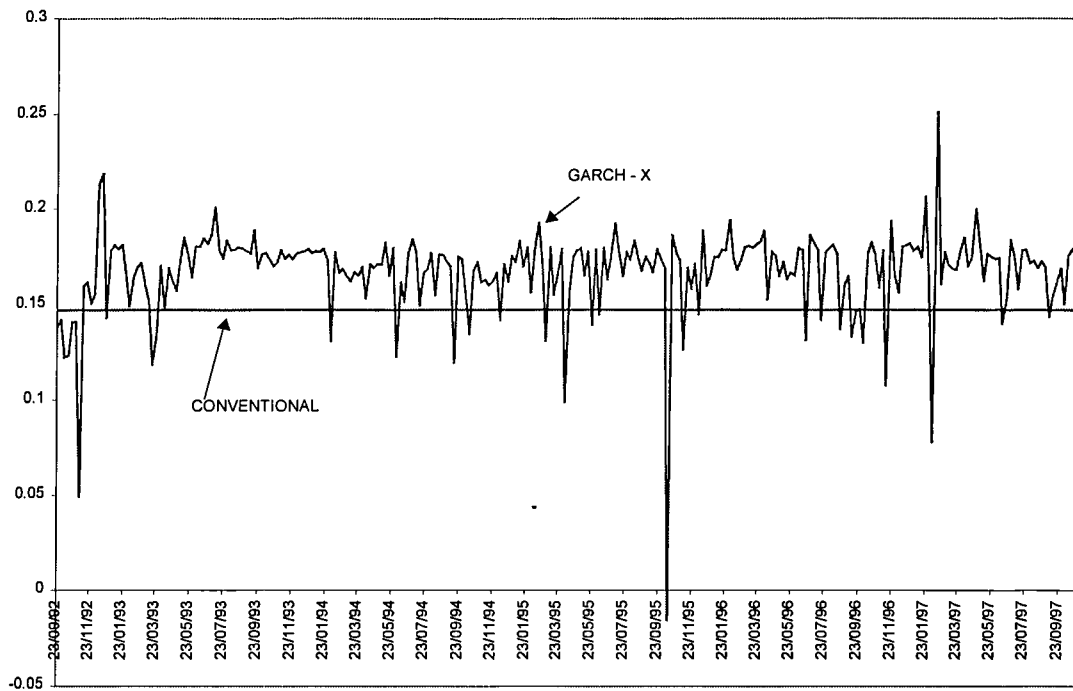


Figure 5.7

Route 8 Time-Varying and Conventional Hedge Ratios

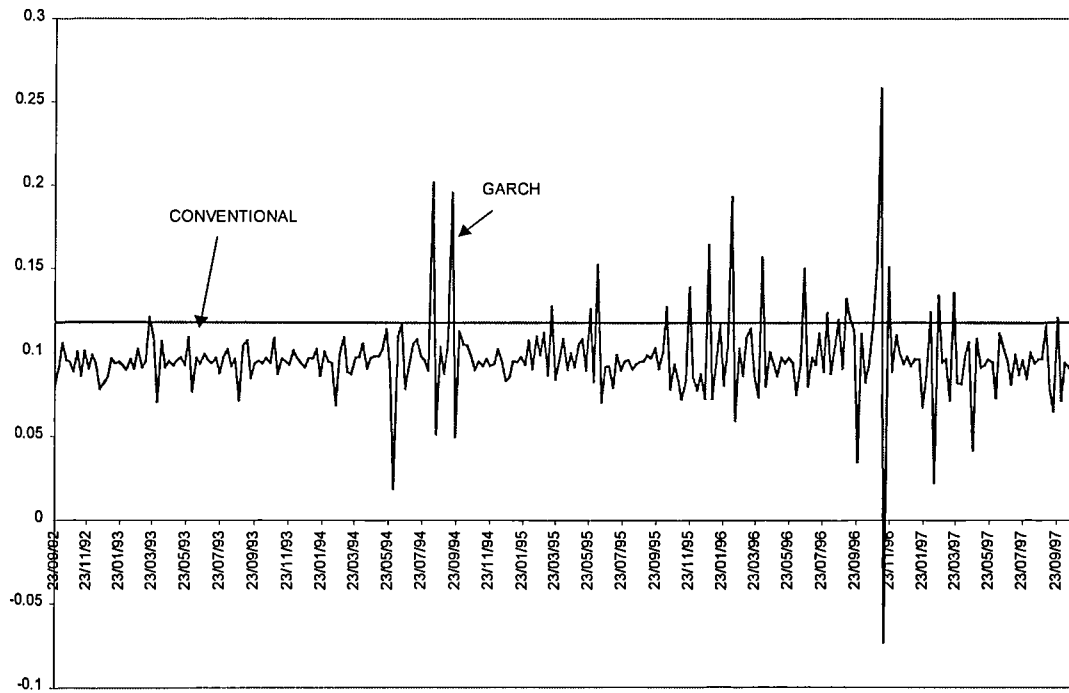


Figure 5.8

Route 9 Time-Varying and Conventional Hedge Ratios

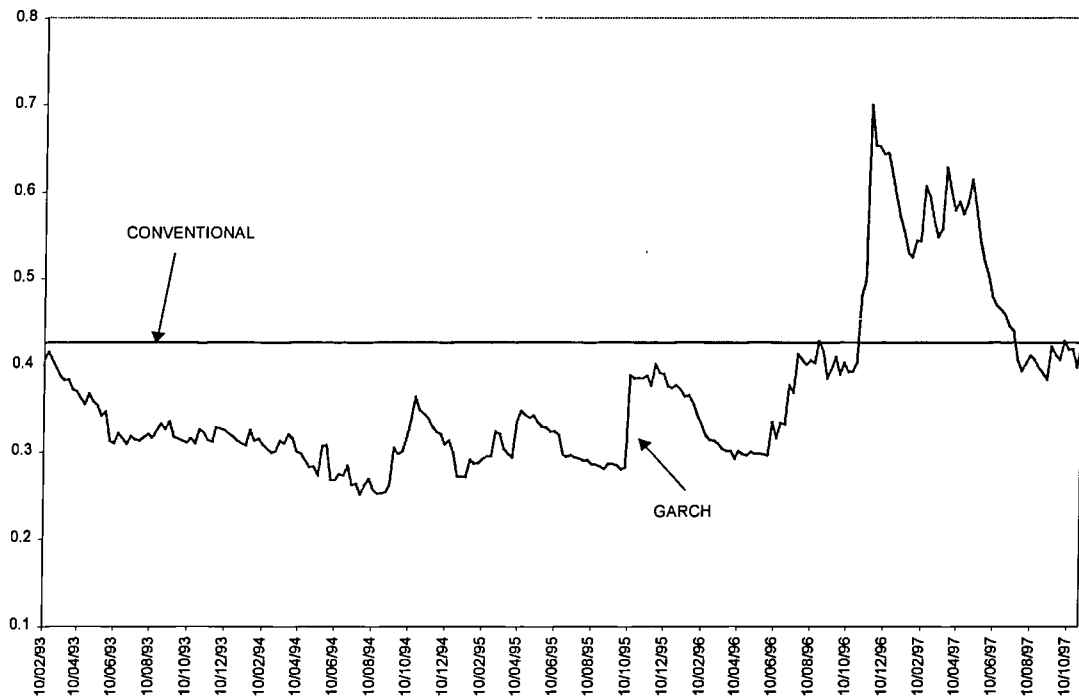


Figure 5.9

Route 10 Time-Varying and Conventional Hedge Ratios

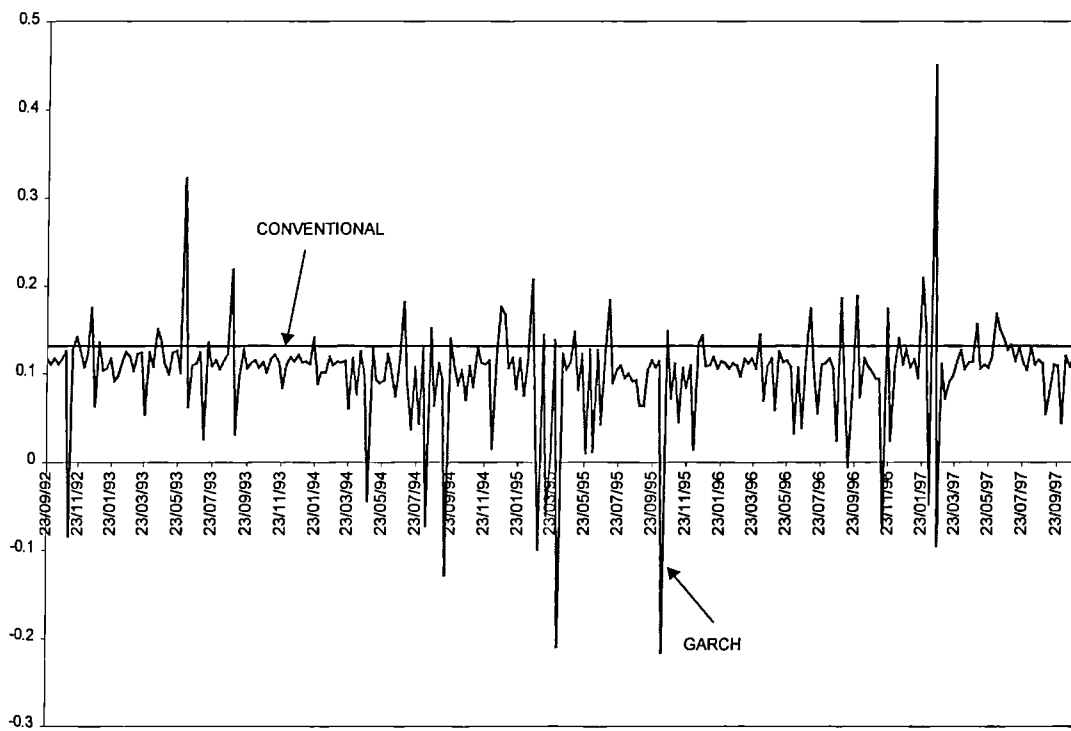


Table 5.4 presents the means and standard deviations of the constant and time-varying hedge ratios across the 11 BFI constituent routes. The conventional hedge ratios have a larger average value than their conditional counterparts in 7 routes. Unit root tests reveal that, with the exception of route 9, 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 5.4

Summary Statistics of the Time-Varying Hedge Ratios

		Mean	STD	ADF(lags)
Route 1	VECM-GARCH-X	0.359	0.051	-5.338(1)
	Conventional	0.400	-	-
Route 1A	VECM-GARCH-X	0.395	0.065	-3.939 (1)
	Conventional	0.469	-	-
Route 2	Conventional	0.397	-	-
Route 2A	Conventional	0.435	-	-
Route 3	VECM-GARCH-X	0.205	0.046	-8.846 (0)
	Conventional	0.242	-	-
Route 3A	VECM-GARCH	0.392	0.052	-4.342 (0)
	Conventional	0.402	-	-
Route 6	VECM-GARCH	0.101	0.028	-20.761 (0)
	Conventional	0.101	-	-
Route 7	VECM-GARCH-X	0.167	0.022	-15.554 (0)
	Conventional	0.147	-	-
Route 8	VECM-GARCH	0.097	0.025	-15.588 (1)
	Conventional	0.118	-	-
Route 9	VECM-GARCH	0.366	0.095	- 1.771 (0)
	Conventional	0.426	-	-
Route 10	VECM-GARCH	0.101	0.060	-21.013 (0)
	Conventional	0.132	-	-

Notes:

- Mean and STD is the mean and standard deviation of the series.
- ADF is the Augmented Dickey Fuller test (Dickey and Fuller (1981)) on the level of the series; 5% critical value is -2.88. The ADF regressions include an intercept term; the lag length of the ADF test (in parentheses) is determined by minimising the SBIC.

5.6.1 Tests of In-Sample Hedging Effectiveness

To formally compare the performance of each type of hedge, we construct portfolios implied by the computed hedge ratios each week and calculate the variance of the returns to these portfolios over the sample, i.e., we evaluate the variance of equation (5.2) as follows

$$\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t) \quad (5.8)$$

where γ_t^* are the computed hedge ratios. The variance of the hedged portfolios is then compared to the variance of the unhedged position, i.e. $\text{Var}(\Delta S_t)$, and the variance reduction achieved through hedging is calculated as follows

$$1 - \frac{\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t)}{\text{Var}(\Delta S_t)} \quad (5.9)$$

The larger the reduction in the unhedged variance, the higher the degree of hedging effectiveness. When γ_t^* in equation (5.9) is the OLS hedge ratio of equation (5.1) then this measure of hedging effectiveness is the same as the R^2 of equation (5.1) (see Appendix 5.A). For each route, we consider 5 different hedge ratios; the hedge ratios from the VECM-GARCH and VECM-GARCH-X specifications, the OLS hedge of equation (5.1), the hedge ratio generated from a VECM with constant variances, which is estimated as a SUR system (Zellner, 1962)¹³, and a naive hedge which involves taking a futures position which exactly offsets the spot position (i.e. setting $\gamma_t^* = 1$).

¹³ The VECM is estimated as a system of seemingly unrelated regressions (SUR) since this method yields more efficient estimates than the OLS when the equations in the system contain different regressors (see Zellner, 1962).

Table 5.5

**In Sample Hedging Effectiveness for the Period September 92 to October 97 (N = 267) and
February 93 to October 97 for Route 9 (N = 247)**

Portfolio Variance											
	Route 1	Route 1A	Route 2	Route 2A	Route 3	Route 3A	Route 6	Route 7	Route 8	Route 9	Route 10
Unhedged	0.001478	0.002275	0.001332	0.001914	0.000739	0.001673	0.000425	0.000924	0.000560	0.002001	0.000734
Naïve	0.001805	0.002377	0.001668	0.002125	0.001569	0.001993	0.001717	0.002072	0.001800	0.002249	0.001932
Conventional	0.001219	0.001918	0.001076	0.001606	0.000642	0.001411	0.000408	0.000889	0.000538	0.001700	0.000705
VECM	0.001225	0.001925	0.001078	0.001609	0.000642	0.001411	0.000408	0.000889	0.000538	0.001701	0.000706
VECM-GARCH	0.001219	0.001925	-	-	0.000654	0.001416	0.000403	0.000888	0.000532	0.001674	0.000734
VECM-GARCH-X	0.001198	0.001892	-	-	0.000648	0.001389	0.000404	0.000887	0.000534	-	0.000703
Variance Reduction											
Naïve	-22.06%	-4.47%	-25.22%	-11.02%	-112.4%	-19.16%	-304.1%	-124.2%	-221.3%	-12.39%	-163.3%
Conventional	17.56%	15.70%	19.20% *	16.08% *	13.15% *	15.66%	4.02%	3.80%	4.08%	15.03%	3.83%
VECM	17.12%	15.38%	19.04%	15.94%	13.12%	15.64%	4.00%	3.79%	4.08%	15.00%	3.77%
VECM-GARCH	17.52%	15.39%	-	-	11.47%	15.32%	5.07% *	3.92%	5.02% *	16.34% *	3.01%
VECM-GARCH-X	18.96% *	16.85% *	-	-	12.31%	16.92% *	4.81%	4.00% *	4.64%	-	4.21% *

Notes:

- This table presents in-sample comparisons of portfolio performance under alternative model specifications for the period September 92 to October 97 (267 observations) and from February 93 to October 97 for route 9 (247 observations).
- An asterisk (*) denotes the model with the largest variance reduction.
- Portfolio Variance is the variance of the portfolio in equation (5.8).
- Variance reduction is the variance reduction from the unhedged position from the use of the alternative models in equation (5.9).

Our results are presented in Table 5.5. The GARCH-X model provides greater variance reduction of the returns of the hedged portfolio than the alternative models in five routes (Routes 1, 1A, 3A, 7 and 10). In Route 3 however, the simple OLS model outperforms both GARCH specifications despite the “superior” statistical properties of the latter models. We can also note that, the naive hedge is the worst hedging strategy since, using a hedge ratio of 1, increases the portfolio variance compared to the unhedged position, in all cases. Finally, another feature of the in-sample results is that, on average, the variance reduction for the panamax routes (Routes 1, 1A, 2, 2A, 3, 3A and 9) is higher than that for the capesize routes; this is not surprising since the former routes represent 70% of the total BFI composition.

5.6.2 Tests of Out-of-Sample Hedging Effectiveness

The in-sample performance of the alternative hedging strategies gives an indication of their historical performance. However, as indicated in Chapter 1, investors are more concerned with how well they can do in the future using alternative hedging strategies. So, out-of-sample performance is a more realistic way to evaluate the effectiveness of the conditional hedge ratios. For that, we withhold 80 observations of the sample (that is, after 17 April 1996, representing a period of one and a half years) 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;

$$E(h_{SF,t+1} | \Omega_t) = c_{11}c_{12} + \alpha_{11}\alpha_{22}\varepsilon_{S,t}\varepsilon_{F,t} + \beta_{11}\beta_{22}h_{SF,t} + d_{11}d_{22}z_t^2$$

$$E(h_{FF,t+1} | \Omega_t) = c_{12}^2 + c_{22}^2 + \alpha_{22}^2\varepsilon_{F,t}^2 + \beta_{22}^2h_{FF,t} + d_{22}^2z_t^2$$

The one step ahead forecast of the hedge ratio is computed as

$$E(\gamma_{t+1}^* | \Omega_t) = E(h_{SF,t+1} | \Omega_t) / E(h_{FF,t+1} | \Omega_t)$$

The following week, (24 April 1996) 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 ¹⁴. The out-of-sample results are presented in Table 5.6.

¹⁴ In practice, an actual hedger will perform the modelling procedure described in Section 5.5 for each new observation in the out-of sample tests i.e. he will model the conditional mean of the series so as to obtain the estimates of the cointegrating vector and then estimate jointly the conditional mean and the conditional variance given these estimates of the cointegrating relationship. However, use of this procedure in our case, would make the estimation of the out-of-sample tests computationally cumbersome. In order to overcome this problem, we update the estimates of the cointegrating vector every twenty observations. Hence, for the first out-of-sample tests, we estimate the coefficients of the cointegrating vector using the data up to 17 April 1996. Then, for the next 20 observations the VECM-GARCH system is re-estimated using these estimates of the cointegrating vector and so on.

The VECM-GARCH-X model outperforms the alternative hedging strategies for routes 1 and 1A; in route 1A for instance, the variance reduction achieved by the VECM-GARCH-X relative to the OLS model is 5.7% ¹⁵. This suggests that for these routes, the inclusion of the squared ECT in the conditional variance equation, has important implications for the determination of the hedge ratios and thus for the issue of 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. Regarding the other routes, the simple GARCH model provides superior variance reduction, compared to the alternative strategies, for routes 3A and 8.

For routes 7 and 10, however, hedging increases the portfolio variance compared to the unhedged position. Therefore, for these routes, market participants are better-off if they leave their positions unhedged. Another striking feature of the out-of-sample results, is the superior performance of the naive hedge in route 9. This result is clearly surprising given the poor in- and out-of-sample performance of the naive hedge for the other routes. Also note that, in line with the in-sample results, the variance reduction for the panamax routes is higher than that for the capesize routes. The highest variance reduction is evidenced in route 1A (23.25%) and the lowest in route 3 (13.81%). In contrast, for the capesize routes the greatest variance reduction is for route 8 (7.76%) while the lowest is in route 7 (-9.56%).

Finally, for routes 3 and 6 the OLS hedge performs better, compared to the GARCH model, in reducing the variability of the returns of the hedged portfolio. Myers (1991) and Garcia et al (1995) also find that there are no gains in variance reduction by using time-varying hedge ratios, in the wheat and soybean futures markets, respectively. This suggests that the additional complexity of specifying and estimating GARCH models may be justified for some commodities but not for others.

¹⁵ This is calculated, using the results in Table 5.6, as follows; $1 - \text{Var}(\text{GARCH-X})/\text{Var}(\text{Conv})$
 $= 1 - 0.001611/0.001708 = 0.057$.

Table 5.6

Out-of-Sample Hedging Effectiveness for the Period November 95 to October 97 (N = 80 observations)

	Portfolio Variance										
	Route 1	Route 1A	Route 2	Route 2A	Route 3	Route 3A	Route 6	Route 7	Route 8	Route 9	Route 10
Unhedged	0.001934	0.002099	0.001293	0.002384	0.001264	0.002689	0.000178	0.000994	0.000809	0.004539	0.000605
Naïve	0.002317	0.002316	0.001747	0.002413	0.001965	0.002563	0.001878	0.003014	0.002222	0.003623	0.002603
Conventional	0.001611	0.001708	0.000998	0.001919	0.001089	0.002212	0.000172	0.001113	0.000771	0.003964	0.000694
VECM	0.001617	0.001707	0.000999	0.001939	0.001093	0.002220	0.000171	0.001102	0.000768	0.003948	0.000669
VECM-GARCH	0.001607	0.001707	-	-	0.001109	0.002202	0.000175	0.001089	0.000746	0.003797	0.000642
VECM-GARCH-X	0.001604	0.001611	-	-	0.001099	0.002205	0.000176	0.001105	0.000764	-	0.000624
	Variance Reduction										
Naïve	-19.81%	-10.33%	-35.10%	-1.21%	-55.53	4.67%	-955.5%	-203.2%	-174.6%	20.18% *	-330.6%
Conventional	16.69%	18.62%	22.77% *	19.50% *	13.81% *	17.74%	3.26%	-11.97%	4.67%	12.67%	-14.86%
VECM	16.39%	18.66%	22.76%	18.67%	13.47%	17.44%	3.75% *	-10.87%	5.03%	13.01%	-10.72%
VECM-GARCH	16.91%	18.67%	-	-	12.27%	18.10% *	1.91%	-9.56% *	7.76% *	16.34%	-3.15% *
VECM-GARCH-X	17.04% *	23.25% *	-	-	13.03%	18.01%	1.30%	-11.19%	5.55%	-	-6.26%

Notes:

- This table presents out-of-sample comparisons of portfolio performance under alternative model specifications for the period November 95 to October 97 (80 observations).
- An asterisk (*) denotes the model with the largest variance reduction.
- Portfolio Variance is the variance of the portfolio in equation (5.8).
- Variance reduction is the variance reduction from the unhedged position from the use of the alternative models in equation (5.9).

The reduction in the out-of-sample portfolio variances achieved by the GARCH specifications relative to the OLS hedges ranges from 5.7% ($= 1 - 0.001611/0.001708$) in route 1A to 0.43% ($= 1 - 0.001604/0.001611$) in route 1; this compares favourably with the findings in other futures markets. Kroner and Sultan (1993) report percentage variance improvements of GARCH hedges, relative to the OLS, ranging between 4.64% and -0.95% for 5 currencies; Gagnon and Lypny (1995), (1997) report 1.87% variance reduction for the Canadian interest rate futures and 0.70% variance reduction for the Canadian stock index futures; Bera et al (1997) estimate 2.74% and 5.70% variance reductions for the corn and soybean futures. However, none of these studies considers the GARCH-X model that we propose above.

Despite the mixed evidence provided in favour of the GARCH based hedge ratios in the freight futures market, all the proposed hedging strategies fail to eliminate a large proportion of the variability of the unhedged portfolio; the greatest variance reduction is 23.25% in route 1A. This is well below the variance reduction over the unhedged position evidenced in other markets, (57.06% for the Canadian Interest rate futures (Gagnon and Lypny, 1995), 69.61% and 85.69% for the corn and soybean futures (Bera et al., 1997) and 97.91% and 77.47% for the SP500 and the Canadian Stock Index futures contract (Park and Switzer, 1995)), and reflects the fact that futures prices do not capture accurately the fluctuations on the individual routes as a result of the heterogeneous composition of the underlying index.

5.7 Conclusions

In this chapter, we examined the hedging effectiveness of the BIFFEX contract and investigated alternative methods for computing more efficient hedge ratios. In- and out-of-sample tests indicate that time-varying hedge ratios outperform alternative specifications in reducing market risk, in 4 shipping routes. Market agents can benefit from this framework by computing superior hedge ratios and thus controlling more efficiently their freight rate risk. This risk reduction, however, is lower than that evidenced in other commodity and financial futures markets in the literature. This is thought to be the result of the heterogeneous composition of the BFI, in terms of vessel sizes and cargo routes, and suggests that the hedging effectiveness of the futures contract may be improved by restructuring the BFI so as to reflect more homogeneous trade flows. The results from this chapter indicate that futures prices follow more closely the fluctuations on the panamax routes than the capesize routes. Therefore, it seems that the introduction of the BPI, as the underlying asset of the futures contract, may have a beneficial impact on the hedging performance of the market. From that respect, it is also interesting to investigate the effect of previous revisions to the index on the hedging effectiveness of the BIFFEX contract. This way, we can provide some preliminary evidence regarding the possible impact of this imminent restructuring on the hedging performance of the market. This is analysed in the following chapter.

Appendix 5.A: Derivation of the In-Sample Hedging Effectiveness Evaluation Formula

Consider the measure of hedging effectiveness of equation (5.9), repeated here for convenience

$$1 - \frac{\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t)}{\text{Var}(\Delta S_t)} \quad (5.10)$$

Ederington (1979) shows that when γ_t^* , above, is the OLS hedge ratio of equation (5.1), γ^* , then equation (5.10) is the same as the R^2 of equation (5.1). To illustrate this, consider the OLS hedge ratio

$$\gamma^* = \frac{\text{Cov}(\Delta S_t, \Delta F_t)}{\text{Var}(\Delta F_t)} \quad (5.11)$$

Since $\gamma_t^* = \gamma^*$, $\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t)$ in (5.10), can be written as follows

$$\begin{aligned} \text{Var}(\Delta S_t - \gamma_t^* \Delta F_t) &= \text{Var}(\Delta S_t - \gamma^* \Delta F_t) \\ &= \text{Var}(\Delta S_t) - 2\gamma^* \text{Cov}(\Delta S_t, \Delta F_t) + (\gamma^*)^2 \text{Var}(\Delta F_t) \end{aligned} \quad (5.12)$$

Substituting (5.11) into (5.12), we get

$$\begin{aligned} &\text{Var}(\Delta S_t) - 2 \frac{\text{Cov}(\Delta S_t, \Delta F_t)}{\text{Var}(\Delta F_t)} \text{Cov}(\Delta S_t, \Delta F_t) + \frac{\text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)^2} \text{Var}(\Delta F_t) \\ &= \text{Var}(\Delta S_t) - 2 \frac{\text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)} + \frac{\text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)} \\ &\Rightarrow \text{Var}(\Delta S_t - \gamma^* \Delta F_t) = \text{Var}(\Delta S_t) - \frac{\text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)} \end{aligned} \quad (5.13)$$

Substituting $\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t)$ with equation (5.13), into (5.10) we get

$$\begin{aligned}
 1 - \frac{\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t)}{\text{Var}(\Delta S_t)} &= 1 - \frac{\text{Var}(\Delta S_t) - \frac{\text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)}}{\text{Var}(\Delta S_t)} \\
 &= 1 - \frac{\frac{\text{Var}(\Delta S_t)\text{Var}(\Delta F_t) - \text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)}}{\text{Var}(\Delta S_t)} = 1 - \frac{\text{Var}(\Delta S_t)\text{Var}(\Delta F_t) - \text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)\text{Var}(\Delta S_t)} \\
 &= 1 - 1 + \frac{\text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)\text{Var}(\Delta S_t)} = \frac{\text{Cov}(\Delta S_t, \Delta F_t)^2}{\text{Var}(\Delta F_t)\text{Var}(\Delta S_t)} = R^2
 \end{aligned}$$

which is the R^2 of equation (5.1).

Chapter 6 : The Effect of Revisions in the BFI to the Price Discovery and Risk Management Functions of the Market

6.1 Introduction

Our results in the previous chapter, indicate that the hedging effectiveness of the futures contract varies substantially across the different shipping routes which constitute the BFI. Hedging freight rate risk using BIFFEX contracts is more effective for the panamax routes compared to capesize routes, and this is thought to be the result of the heavier composition of the BFI towards panamax vessels. However, futures contracts are not so effective in eliminating spot market risk to the extent evidenced in other commodity and financial futures markets. This poor hedging performance is thought to be caused by the diverse nature, in terms of vessel sizes, types of fixtures and transported commodities, of the underlying shipping routes which constitute the BFI.

In this chapter, we extend the empirical evidence on the performance of the market by investigating the impact of the revisions in the composition of the BFI to the price discovery and risk management functions of the BIFFEX market. The motivation for this study derives from two interesting policy issues surrounding the composition of the BFI. First, all the major

revisions in the BFI - such as the introduction of time-charter routes or the exclusion of the handysize routes (see as well Table 1.2 and Figure 1.2) - are driven by the intention to generate an underlying index which promotes the more effective functioning of the BIFFEX contract; from that respect, it is therefore interesting to investigate the impact of these revisions on the two major functions of the BIFFEX contract and thus identify whether they have achieved their intended objective. The second issue has to do with the exclusion of the capesize routes from the BFI, which will take place in November 1999, and the introduction of the BPI as the underlying asset of the BIFFEX contract. By investigating the effect of previous revisions in the composition of the BFI on the performance of the BIFFEX contract, we can thus provide some preliminary evidence regarding the possible impact of this new restructuring of the index. Finally, investigation of the price discovery and hedging effectiveness functions of the market over different sub-periods, provides additional supporting evidence to our results from the analysis of the entire sample and enables us to discount the possibility that these results are sensitive to the period of time examined.

To address these issues, causality tests, along the lines set out in chapter 4, are performed over sub-periods so as to investigate whether the causal relationship between spot and futures prices has strengthened as a result of the more homogeneous composition of the index in recent years. Moreover, the effectiveness of constant and dynamic hedging strategies across different sub-periods is also examined so as to identify whether previous revisions in the composition of the BFI had an impact on the effectiveness of the futures contract as a hedging instrument.

The structure of this chapter is as follows. The next section describes our empirical results on the causal relationship between contemporaneous spot and futures prices in the BIFFEX market. Section 3 investigates the hedging effectiveness of the BIFFEX contract. Finally, Section 4 concludes this chapter.

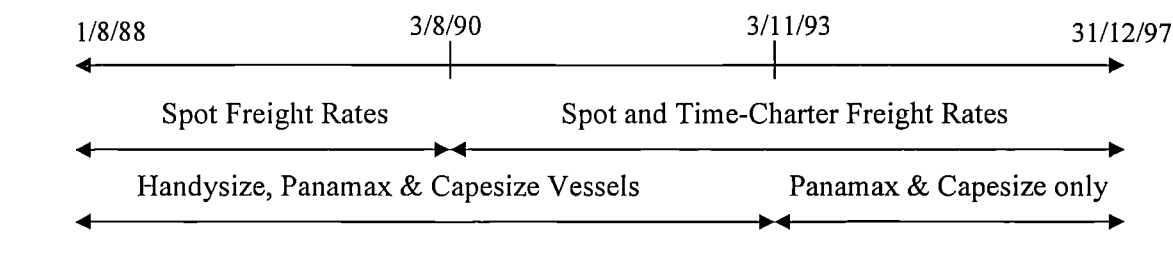
6.2 The Effect of Revisions in the Index to the Causal Relationship between BFI and BIFFEX prices

Our empirical results in chapter 4 indicate that futures prices in the BIFFEX market lead the underlying BFI prices to the discovery of new information. New information arriving in the market tends to be revealed first in the BIFFEX prices and is then transmitted to the underlying spot prices. In this section we investigate whether this pattern in the information role of futures prices has altered, following major revisions in the composition of the BFI.

To address this issue, the whole sample of daily BFI and BIFFEX prices, from 1 August 1988 to 31 December 1997, is divided into three sub-periods, corresponding to differing compositions of the BFI¹. The first covers the period from 1 August 1988 to 3 August 1990; within this period the BFI consisted of handysize, panamax and capesize, spot freight rates only. The second covers the period after the introduction of the time-charter routes and before the exclusion of the handysize routes i.e. from 6 August 1990 to 2 November 1993. The third period runs from 3 November 1993 to 31 December 1997 when the handysize routes were dropped from the composition of the index. The different compositions of the BFI over these sub-periods are presented in Figure 6.1. Causality tests are then carried out for each sub-period along the lines described in chapter 4.

Figure 6.1

Major revisions of the BFI



¹ The futures prices are of 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. Summary statistics for the spot and futures prices over the entire sample period are presented in Table 4.1. In line with our analysis in chapter 4, we also consider a 22-days "perpetual" BIFFEX contract. This is to discount the possibility that our results are biased by price jumps in the futures prices at contract expiration. Our results are qualitatively the same to the ones reported here.

Table 6.1

**Summary Statistics of Logarithmic First Differences of BFI and BIFFEX Prices over
Different Sub-periods**

	<i>T</i>	Skew	Kurt	J-B	Q(36)	Q ² (36)	ADF (lags)		PP (12)	
							levels	Diff	levels	diffs
1st Period : 01/08/88 - 03/08/90 (Spot Routes Only, All Size Ships)										
Spot	509	-1.85 [.00]	20.69 [.00]	9368	754.3	30.5	-1.99 (3)	-6.13 (2)	-1.45	-14.68
Futures	509	-1.44 [.00]	22.77 [.00]	11167	62.1	15.7	-1.51 (1)	-19.38 (0)	-1.64	-19.72
2nd Period : 06/08/90 – 02/11/93 (Spot and T/C Routes, All Size Ships)										
Spot	819	-0.44 [.00]	4.61 [.00]	752	1303.6	97.9	-2.02 (2)	-9.46 (1)	-1.66	-21.10
Futures	819	-1.54 [.00]	17.98 [.00]	11352	40.7	17.9	-1.87 (0)	-26.31 (0)	-1.85	-26.25
3rd Period : 03/11/93 - 31/12/97 (Spot and T/C Routes, Panamax and Capesize Vessels)										
Spot	1052	-0.63 [.00]	1.88 [.00]	224	2858.7	1122.2	-1.59 (1)	-8.19 (0)	-1.27	-9.13
Futures	1052	-0.56 [.00]	9.22 [.00]	3782	74.81	25.69	-1.39 (1)	-27.59 (0)	-1.44	-27.79
1% critical value				9.21	58.11	58.11	-3.46	-3.46	-3.46	-3.46
5% critical value				5.99	51.48	51.48	-2.88	-2.88	-2.88	-2.88

Notes:

- *T* is the number of observations. The statistics are based on logarithmic first differences.
- 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 $\sqrt{T} (\hat{\alpha}_4 - 3) \sim N(0,24)$. Values in square brackets are p-values.
- J-B is the Jarque - Bera (1980) test for normality; the statistic is $\chi^2(2)$ distributed.
- Q(36) and Q²(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 $\chi^2(36)$.
- ADF is the Augmented Dickey Fuller (Dickey and 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) unit root test; the truncation lag for the test is set equal to 12.

Summary statistics of logarithmic first differences of spot and futures prices for each sub-period are presented in Table 6.1. There is evidence of negative excess skewness. Also, excess kurtosis is present in both series, a finding which is in line with other studies investigating high frequency financial data. As a consequence, Jarque-Bera (1980) tests indicate significant departures from normality for the spot and futures returns series. The Ljung-Box Q statistics (Ljung and Box, 1978) on the first 36 lags of the sample

autocorrelation function indicate that serial correlation is present in the spot and futures returns with the exception of the futures returns in the second period. The Q^2 statistics indicate the existence of heteroskedasticity in the spot but not in the futures returns. Finally, ADF and PP tests on the levels and first differences indicate that both price series are first-difference stationary.

Table 6.2

Johansen (1988) tests for cointegration; BFI and BIFFEX prices

Lags	LR	Null	Cointegrating Vector		Hypothesis Test	
			$\lambda_{\max}(\mathbf{r}, \mathbf{r}+1)$	$\lambda_{\text{trace}}(\mathbf{r})$	$\beta' = (1, \beta_1, \beta_2)$	$\beta' = (1, -1, 0)$
1 st Period: 01/08/88 - 03/08/90 (Spot Routes Only, All Size Ships)						
4	0.01	r=0	46.96	52.32	1, -0.1718, -0.9758	2.32
		r=1	5.36	5.36		
2 nd Period : 06/08/90 – 02/11/93 (Spot and T/C Routes, All Size Ships)						
3	0.02	r=0	48.88	52.20	1, 0.3571, -1.0496	2.09
		r=1	3.32	3.32		
3 rd Period : 03/11/93 - 31/12/97 (Spot and T/C Routes, Panamax and Capesize Vessels)						
4	0.07	r=0	64.35	66.92	1, 0.1789, -1.0246	2.01
		r=1	2.57	2.57		
5% c.v.						
	2.71	r=0	15.87	20.18		5.99
		r=1	9.16	9.16		

Notes:

- Lags is the lag length of the VECM model in equation 4.1; the lag length is determined using the SBIC.
- LR is Johansen's (1991) test for the null hypothesis that there are no linear trends in the levels of the data

$$LR = -T [\ln(1 - \hat{\lambda}_2^*) - \ln(1 - \hat{\lambda}_2)] \sim \chi^2(1)$$
where $\hat{\lambda}_2^*$ and $\hat{\lambda}_2$ represent the smallest eigenvalues of the model that includes an intercept term in the cointegrating vector and an intercept term in the short run model, respectively. Acceptance of the null hypothesis indicates that the VECM in equation (1) should be estimated with an intercept term in the cointegrating vector.
- $\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$ tests the null hypothesis of r cointegrating vectors against the alternative of r+1.

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$$
 tests the null that there are at most r cointegrating vectors against the alternative that the number of cointegrating vectors is greater than r. 95% critical values are from Osterwald-Lenum(1992), Table 1*.

- $\beta' = (1 \ \beta_1 \ \beta_2)$ are the coefficient estimates of the cointegrating vector where the coefficient of S_{t-1} is normalised to be unity, β_1 is the intercept term and β_2 is the coefficient on F_{t-1} .
- The null hypothesis that the cointegrating vector is the lagged basis, $\beta' X_{t-1} = (1, 0, -1) X_{t-1} = S_{t-1} - F_{t-1}$ is examined using the test statistic $-T [\ln(1 - \hat{\lambda}_1^*) - \ln(1 - \hat{\lambda}_1)] \sim \chi^2(2)$ where $\hat{\lambda}_1^*$ and $\hat{\lambda}_1$ denote the largest eigenvalues associated with the restricted and the unrestricted model, respectively.

Having identified that spot and futures prices are $I(1)$ variables, the VECM of equation 4.1 is used to investigate the existence of a long-run relationship between these series. Table 6.2 presents the lag length of the VECM, chosen on the basis of the SBIC (1978), and Johansen's (1991) LR test for the appropriateness of including an intercept term in the long-run relationship of equation (2.27); the latter tests indicate that the intercept term should be included in the cointegrating vector in all the cases. The estimated λ_{\max} and λ_{trace} statistics of equations (2.18) and (2.19), in the same table, show that the BFI and BIFFEX prices stand in a long-run relationship between them in all the sub-periods, thus justifying the use of a VECM. Finally, parameter restriction tests on the normalised cointegrating vectors, $z_t = \beta'X_t$, indicate that the long-run relationship between BFI and BIFFEX prices is the basis i.e. $z_{t-1} = \beta'X_{t-1} = (1, 0, -1) X_{t-1} = S_{t-1} - F_{t-1}$. Therefore, in the ensuing analysis the cointegrating vector is restricted to be the basis.

Table 6.3 presents the error correction coefficients, the \bar{R}^2 and the Wald tests for Granger causality for each sub-period for the VECM of equation 4.1. Consider first the periods before and after the introduction of the time-charter routes (Periods 1 and 2, respectively). In both cases, the spot error correction coefficients are significant while the futures error correction coefficients are insignificant; this indicates that the adjustment process when a disequilibrium occurs, is made through the spot price while the futures price remains unresponsive. The spot coefficient for the first period is larger in magnitude than in the second period, which implies that for the period before the introduction of the time-charter routes spot prices are more responsive to deviations from the long-run relationship. Turning now to the Wald tests for causality, during the period August 88 to August 90, the lagged coefficients of futures in the equation of spot are jointly insignificant; therefore, for this period the flow of information from futures to spot is driven only by the lagged basis. The opposite takes place in the second period where the lagged coefficients of futures are jointly significant, thus suggesting that the information discovery role of futures prices has strengthened for the period after the introduction of the time-charter routes. This may be because time-charter rates in shipping freight markets reflect the expectations of market agents regarding the future level of spot rates. As a result, the price discovery role of futures prices, which also reflect the expectations of the market regarding future BFI prices, has increased.

Table 6.3

Granger Causality tests for Sub-periods Corresponding to Major Revisions in the Composition of the BFI

Dependent Variable	ΔS_t		ΔF_t	
1st Period: 01/08/88 - 03/08/90 (Spot Routes Only, All Size Ships)				
	(4 lags in the VECM)			
	Coefficient	t-statistic	Coefficient	t-statistic
Z_{t-1}	-0.0538 ^a	-4.8416	0.0205	1.1972
\overline{R}^2	0.440		0.039	
Granger Causality Tests				
$H_0: b_{S,i} = 0, i=1, 2, 3 \sim \chi^2(3)$	2.616	[.45]	-	
$H_0: a_{F,i} = 0, i=1, 2, 3 \sim \chi^2(3)$	-		14.750	[.00]
2nd Period: 06/08/90 – 02/11/93 (Spot and T/C Routes, All Size Ships)				
	(3 lags in the VECM)			
	Coefficient	t-statistic	Coefficient	t-statistic
Z_{t-1}	-0.0273 ^a	-5.599	0.0202	1.4673
\overline{R}^2	0.532		0.012	
Granger Causality Tests				
$H_0: b_{S,i} = 0, i=1, 2 \sim \chi^2(2)$	19.716	[.00]	-	
$H_0: a_{F,i} = 0, i=1, 2 \sim \chi^2(2)$	-		6.579	[.04]
3rd Period: 03/11/93 – 31/12/97 (Spot and T/C Routes, Panamax and Capesize Vessels)				
	(4 lags in the VECM)			
	Coefficient	t-statistic	Coefficient	t-statistic
Z_{t-1}	-0.0202 ^a	-5.5814	0.0457 ^a	3.0897
\overline{R}^2	0.763		0.042	
Granger Causality Tests				
$H_0: b_{S,i} = 0, i=1, 2, 3 \sim \chi^2(3)$	22.891	[.00]	-	
$H_0: a_{F,i} = 0, i=1, 2, 3 \sim \chi^2(3)$	-		27.125	[.00]

Notes:

- The lag length of the VECM is determined by means of the SBIC.
- t-statistics and Wald tests are calculated using White's heteroskedasticity consistent covariance matrix.
- a, b and c denote significance at the 1%, 5% and 10% level, respectively.

Consider next the period after the exclusion of the handysize routes from the index (period 3). The Wald tests indicate the existence of a two-way feedback relationship. When compared to the previous period, the error correction coefficient in the spot equation decreases in

magnitude and the corresponding coefficient in the futures equation becomes statistically significant; moreover, the error correction coefficient in the futures equation is more than twice as large as the coefficient in the spot equation. Therefore, in contrast to the previous periods, the process of adjusting towards any disequilibrium is made now primarily through the futures prices which indicates that the information discovery role of futures prices has strengthened even further for the period after November 1993.

This increase in the price discovery role of futures prices may be attributed to the exclusion of the handysize routes from the composition of the index. Due to the impossibility of short-selling the underlying shipping routes in the BIFFEX market, investors who possess superior information regarding the expected level of freight rates can only benefit from this information by trading in the futures market. However, it is much more difficult to form correct expectations of the future price of an index when it consists of a number of diverse components; even if the expectations of the investors for a particular shipping route are realised, this does not guarantee a corresponding change in the average index, to which the futures contract converges at maturity. The level of freight rates on the routes which compose the BFI may change sharply for reasons such as seasonality, political events, weather conditions etc. The effect of these factors on individual routes depends on their idiosyncratic characteristics; see for instance Kavussanos and Alizadeh (1998) on how seasonal factors affect freight rates across different vessel sizes and contract types (spot and time-charter). By eliminating the handysize routes from the BFI, the composition of the index became more homogeneous and hence the importance of futures prices as a vehicle for information discovery increased.

We can also note that the \bar{R}^2 for the spot equation increases from the first period to the third and, as a result, the predictability of spot returns using information from lagged spot and futures returns, increases as well. Finally, in line with our results from the analysis of the entire sample, the \bar{R}^2 for the spot equations are substantially higher than the \bar{R}^2 for the futures equations. This reflects the superior performance of futures prices as a price discovery centre.

Therefore, it seems that the price discovery role of the BIFFEX contract has strengthened following revisions in the BFI; the introduction of time-charter routes as well as the exclusion of the handysize routes increased the flow of information from futures to spot prices in the market ². In the case of time-charter routes this reflects the fact that time-charter rates encompass the expectations of market agents regarding the future level of spot rates and hence, are strongly linked with the BIFFEX prices. Regarding the handysize routes, the observed increase in the price discovery function of the market is a result of the more homogeneous composition of the index for the period after their exclusion. This may also imply that the exclusion of the capesize routes from the index, in November 1999, is likely to have a beneficial impact on the market as it will increase the homogeneity of the index which will consist of panamax only trade flows.

² Due to data limitations, we do not consider tests of the unbiasedness hypothesis across sub-periods. More specifically, for the period 1 August 88 to 3 August 90, the available number of observations for the one- and three-months spot and futures prices is 24 and 9, respectively; moreover, 2-months price data are only available for the period after October 91. Reliable inference from such small samples is not feasible, given the small-sample biases in Johansen's tests; this problem is accentuated by the fact that the performance of the small sample corrections, suggested by Riemers (1992) and Psaradakis (1994) – see chapter 3, has not been investigated for samples of less than 25 observations. For these reasons, we do not pursue tests of the unbiasedness hypothesis across sub-periods.

6.3 BFI Revisions and Hedging Effectiveness

6.3.1 Introduction

Our preceding results indicate that the causal relationship between BIFFEX and BFI prices has strengthened following the revisions in the composition of the BFI. In this section, we investigate whether these revisions have also affected the risk management function of the market. Casting the problem in the risk minimisation framework, and thereby measuring the hedging effectiveness by the reduction in the variance of revenues, we investigate the variability of measures of hedging effectiveness across different shipping routes and different time periods, corresponding to differing compositions of the underlying asset. In order to provide robust evidence regarding the hedging potential of the futures contract we consider constant and dynamic hedging strategies so as to identify the strategy that would have provided, on an ex-post basis, the greatest variance reduction across the different shipping routes and time-periods. Finally, we also investigate whether the differences in the degree of hedging effectiveness across the different periods are statistically significant using bootstrapping techniques.

As described in chapter 5, the hedge ratio that minimises the variance of the returns in the hedge portfolio is equivalent to the ratio of the unconditional covariance between cash and futures price changes to the variance of futures price changes; this is equivalent to the slope coefficient, γ^* , in the following regression

$$\Delta S_t = \gamma_0 + \gamma^* \Delta F_t + u_t ; \quad u_t \sim \text{iid}(0, \sigma^2) \quad (6.1)$$

Within this specification, the higher the R^2 of equation (6.1) the greater the effectiveness of the minimum-variance hedge. However, this method of calculating hedge ratios is criticised by Myers and Thompson (1989) and Kroner and Sultan (1993), since hedge ratios are derived based on the implicit assumption that the risk in spot and futures markets is constant over time. This implies that optimal risk-minimising hedge ratios should be time-varying. The

latter are defined as the ratio of the conditional covariance of spot and futures price changes over the conditional variance of futures price changes, as follows

$$\gamma_t^* | \Omega_{t-1} = \frac{\text{Cov}(\Delta S_t, \Delta F_t | \Omega_{t-1})}{\text{Var}(\Delta F_t | \Omega_{t-1})} \quad (6.2)$$

To estimate γ_t^* in equation (6.2), we employ the following bivariate VECM – GARCH model which was described in chapter 5 of the thesis

$$\begin{aligned} \Delta X_t &= \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad ; \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} | \Omega_{t-1} \sim IN(0, H_t) \\ H_t &= \begin{pmatrix} h_{SS,t} & h_{SF,t} \\ h_{SF,t} & h_{FF,t} \end{pmatrix} = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \end{aligned} \quad (6.3)$$

where $X_t = (S_t, F_t)'$ is the vector of spot and futures prices, Γ_i and Π are 2x2 coefficient matrices measuring the short- and long-run adjustment of the system to changes in X_t and ε_t is the vector of residuals $(\varepsilon_{S,t}, \varepsilon_{F,t})'$, which follow a bivariate normal distribution with mean zero and time-varying covariance matrix, H_t . In the specification of the conditional covariance matrix, C is a 2x2 lower triangular matrix, A and B are 2x2 diagonal coefficient matrices, with $\alpha_{ii}^2 + \beta_{ii}^2 < 1$, $i=1,2$ for stationarity³.

Estimation of the model in (6.3) takes place by maximising the bivariate conditional normal log-likelihood function. The standard errors of the estimated coefficients are computed using the Quasi Maximum Likelihood (QML) procedure of Bollerslev and Wooldridge (1992). This yields standard errors which are robust to departures from the maintained assumption of conditional normality.

³ See chapter 5 of the thesis, for a discussion on the properties of this model.

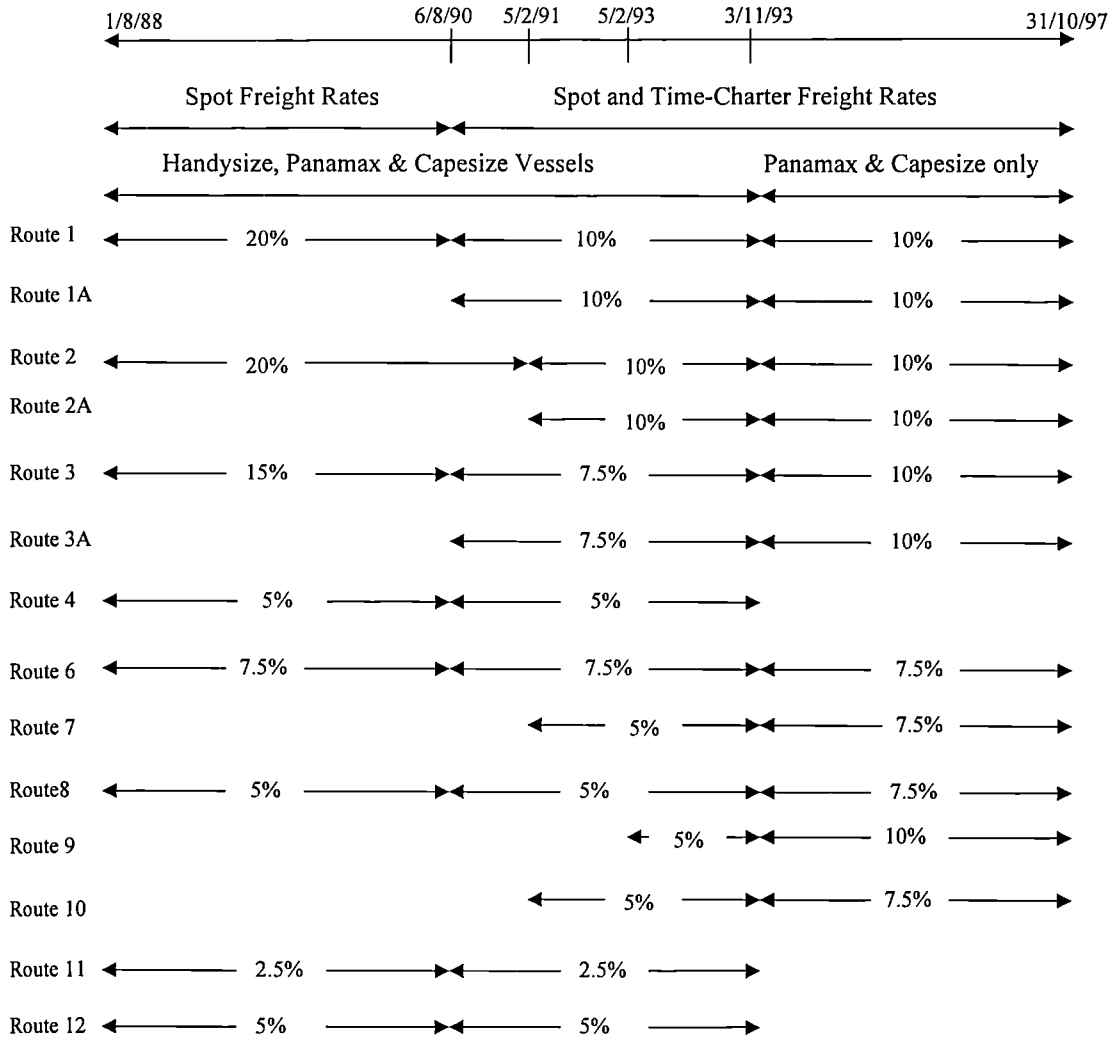
6.3.2 Properties of the Data Series

Our data set consists of weekly spot and futures prices from 1 August 1988 to 31 October 1997. The spot price data are Wednesday closing prices of all the BFI constituent routes and the futures prices are Wednesday closing prices of the futures contract which is nearest to maturity; when a holiday occurs on Wednesday, Tuesday's observation is used in its place. It is assumed that a hedger rolls over to the next nearest contract one week prior to the expiration of the current contract. Spot price data are from LIFFE. Futures prices for the period August 1988 to December 1989 are from Knight Ridder and the Financial Times; for the period January 1990 to December 1997, futures price data are collected from LIFFE.

In order to investigate the effect of BFI revisions to the hedging effectiveness of the futures contract, we consider different estimation intervals for each route; these, along with the contribution of each route to the BFI, are presented in Figure 6.2 (see also Table 1.2 for the revisions of the BFI routes). For routes 1, 2, 3, 6 and 8, estimation is carried out over three periods. The first period runs from 1 August 1988 (from 4 November 1988 for route 6) to 3 August 90 (or to 2 February 91 for route 2) corresponding to the period before the introduction of the time-charter routes. The second period runs from 6 August 90 (or 5 February 91 for route 2) to 2 November 93 and represents the period after the introduction of the time-charter routes in the BFI. The third period runs from 3 November 93 up to 31 October 97, corresponding to the period after the exclusion of the handysize routes from the BFI. Routes 1A, 2A, 3A, 7, 9 and 10, are estimated over two periods. The starting observation for these routes is, in the case of routes 1A, 2A and 3A the day at which the routes were introduced, (6 August 90 or 5 February 91 for route 2A) and in the case of routes 7, 9 and 10 the day at which the routes were revised to their current definitions (5 February 91 or 5 February 93 for route 9). The second estimation period for these routes runs from 3 November 93 up to 31 October 97.

Figure 6.2

Estimation Intervals for the BFI constituent Routes



The handysize routes (routes 4, 11 and 12) are also estimated over two periods; the first period runs from 1 August 1988 (from 4 November 1988 for route 12) to 3 August 90 and the second period is from 6 August 1990 to 2 November 1993, when the handysize routes were eventually excluded from the BFI ⁴.

We can see that the estimation sub-periods are different for each route. Moreover, with the exception of routes 1, 3 and 8, sub-periods 1 and 2 for the BFI routes do not correspond

⁴ Notice that we do not consider the handysize route 5 because it was introduced to the BFI on 6 August 1990.

exactly to the sub-periods before and after the introduction of the time-charter routes that we considered in the investigation of the price discovery function of the market, in the previous section of this chapter. These discrepancies in the definitions of the sub-periods for each route arise because the revisions in the weights of the routes, or the introduction of new routes to the index, take place at different points in time over the estimation period; however, this helps us identify in more detail the factors - such as the revisions in the weights of the routes, the introduction of the time-charter routes, or the exclusion of the handysize routes - that affect the hedging performance of each route.

In Table 6.4, we report summary statistics of the logarithmic spot and futures price differences across the different sub-periods investigated in this study. The Jarque-Bera (1980) tests indicate significant departures from normality for all the return series with the exception of route 3 in the first period, route 9 in the second period and the futures returns in the third period. The Ljung-Box Q statistics (Ljung and Box, 1978) on the first 12 lags of the sample autocorrelation function indicate that serial correlation is present in the spot returns but not in the futures returns. The existence of ARCH effects in the series is investigated through Engle's (1982) ARCH test and the Q^2 statistic; these tests indicate the presence of second-moment dependencies in the spot routes returns for some of the sub-periods with the exception of routes 2, 2A and 11 where there is no evidence of ARCH effects in any of the sub-periods. Finally, ADF and PP tests on the levels and first differences indicate that the series are first-difference stationary.

Table 6.4

Summary Statistics on logarithmic Spot and Futures Price Differences

Route	Period	N	J-B	Q(12)	Q ² (12)	ARCH (1)	ADF (lag)	PP (12)	ADF (lag)	PP (12)
							Levels		1 st diffs	
1	1	106	77.54	42.28	17.42	9.11	-2.44 (1)	-2.56	-6.15 (1)	-4.80
	2	169	39.93	14.41	6.08	1.93	-2.43 (1)	-2.23	-10.74 (0)	-10.68
	3	208	94.24	112.50	19.44	10.53	-2.63 (2)	-2.00	-7.54 (0)	-6.72
1A	2	169	6.65	79.64	15.04	2.26	-2.39 (2)	-1.94	-6.53 (1)	-6.32
	3	208	84.33	120.93	18.24	7.38	-2.50 (1)	-1.64	-7.27 (0)	-6.37
2	1	132	316.99	36.42	4.73	1.11	-2.96 (1)	-2.52	-7.00 (1)	-7.81
	2	143	25.93	26.73	3.19	0.00	-2.75 (1)	-2.20	-8.92 (1)	-9.40
	3	208	16.32	34.11	9.82	0.01	-2.06 (1)	-1.61	-10.34 (1)	-9.82
2A	2	143	13.70	64.05	7.75	2.10	-2.59 (1)	-1.64	-7.05 (1)	-5.80
	3	208	78.23	56.53	3.28	1.10	-2.04 (1)	-1.45	-9.14 (1)	-8.29
3	1	106	1.84	51.22	11.27	2.99	-1.81 (2)	-1.51	-5.35 (1)	-6.18
	2	169	189.65	18.50	10.55	3.81	-2.27 (3)	-2.20	-8.34 (1)	-9.30
	3	208	134.33	80.82	16.84	7.09	-2.03 (1)	-1.69	-8.16 (0)	-7.68
3A	2	169	76.58	74.27	20.41	1.42	-2.43 (1)	-1.92	-7.77 (0)	-7.19
	3	208	14.45	74.21	91.67	49.17	-2.11 (1)	-1.62	-7.83 (0)	-7.19
4	1	106	43.53	36.87	22.55	0.12	-1.49 (0)	-1.18	-6.99 (0)	-7.57
	2	169	176.75	55.87	9.99	3.05	-1.94 (2)	-1.93	-8.16 (1)	-8.66
6	1	92	201.50	42.48	11.13	1.12	-1.07 (2)	-0.85	-4.94 (1)	-5.95
	2	169	276.46	107.51	13.81	1.19	-1.37 (5)	-1.19	-8.10 (0)	-9.17
	3	208	84.33	141.72	38.51	32.17	-1.75 (2)	-1.58	-6.77 (0)	-6.73
7	2	143	337.40	46.06	2.54	0.01	-1.73 (1)	-1.96	-8.14 (0)	-8.63
	3	208	39.42	75.05	26.25	4.94	-2.10 (1)	-1.73	-8.03 (0)	-7.48
8	1	106	153.21	26.06	3.92	0.38	-1.92 (0)	-2.14	-6.85 (0)	-7.14
	2	169	64.66	93.45	15.02	3.67	-1.23 (2)	-1.12	-7.91 (0)	-8.46
	3	208	324.70	84.69	9.32	4.26	-2.00 (2)	-1.83	-8.02 (0)	-8.00
9	2	39	2.43	19.01	8.82	1.45	-1.86 (2)	-1.59	-3.06 (2)	-4.32
	3	203	481.57	94.19	75.29	49.90	-2.04 (1)	-1.53	-7.97 (1)	-6.65
10	2	143	155.38	74.98	26.13	19.12	-1.68 (2)	-1.76	-10.64 (0)	-7.89
	3	208	52.16	129.53	35.09	23.17	-2.21 (1)	-1.68	-7.06 (0)	-6.41
11	1	92	76.15	20.66	2.44	0.01	-0.47 (0)	-0.52	-9.52 (0)	-7.84
	2	169	44.69	20.34	1.76	0.76	-0.79 (0)	-1.33	-9.48 (0)	-9.63
12	1	92	77.35	38.72	19.04	4.01	-0.24 (1)	-0.74	-19.58 (0)	-6.99
	2	169	64.77	10.95	3.69	2.77	-1.26 (1)	-1.34	-10.26 (0)	-10.45
Futures	1	106	102.88	8.96	4.60	0.04	-1.49 (0)	-1.96	-8.40 (0)	-8.45
	2	169	64.60	10.42	7.80	0.36	-1.78 (0)	-1.89	-12.99 (0)	-12.89
	3	208	3.89	12.84	11.32	0.04	-1.48 (0)	-1.60	-13.90 (0)	-13.92
5% c.v.			5.99	21.03	21.03	3.84	-2.88	-2.88	-2.88	-2.88
1% c.v.			9.21	26.22	26.22	6.63	-3.46	-3.46	-3.46	-3.46

Notes:

- See Figure 6.2 for the definition of the different estimation periods. N is the number of observations.
- J-B is the Jarque - Bera (1980) test for normality; the statistic is $\chi^2(2)$ distributed.
- Q(12) and Q²(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 tests are distributed as $\chi^2(12)$.
- ARCH (1) is the Engle (1982) tests for ARCH effects; the statistic is $\chi^2(1)$ distributed.
- ADF is the Augmented Dickey Fuller (Dickey and Fuller, 1981) test. The ADF regressions include an intercept term; the lag length of the test (in parentheses) is determined by minimising the SBIC.
- PP is the Phillips and Perron (1988) unit root test; the truncation lag for the test is set to 12.

6.3.3 Empirical Results

Having identified that spot and futures prices are $I(1)$ variables, cointegration techniques are used next to examine the existence of a long-run relationship between these series. This is investigated in the VECM of equation (6.3), using the λ_{\max} and λ_{trace} statistics which test for the rank of Π . If $\text{rank}(\Pi)=1$ then there is a single cointegrating vector and Π can be factored as $\Pi = \alpha\beta'$, where α and β' are 2×1 vectors. Using this factorisation, 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.

The lag length (p) in the VECM of equation (6.3), chosen on the basis of the SBIC (1978), is presented in Table 6.5. The same table, also presents the estimated λ_{\max} and λ_{trace} statistics. We can see that the panamax routes stand in a long-run relationship with the futures prices across all the sub-periods, with the exception of route 1 in the second period and route 9 for all the periods. On the other hand, the evidence presented for the capesize and the handysize routes is less strong. Capesize routes are cointegrated with BIFFEX prices only in the cases of route 7, route 8 for the third period and route 10. Moreover, with the exception of route 4 in the first period, none of the handysize routes is cointegrated with the BIFFEX prices. The observed discrepancies on the existence of a cointegrating relationship between BFI routes and BIFFEX prices across the different classes of vessels can be attributed to the fact that these routes represent different segments of the dry-bulk shipping markets. Since the panamax routes are more heavily represented on the BFI, compared to the capesize and handysize routes, their association with the BIFFEX prices is more strong than in the case of the other routes. Whether this pattern has also affected significantly the hedging effectiveness on these routes is an issue which is addressed in the following section.

Table 6.5

Johansen (1988) tests for cointegration

Route	Period	Lags	Null	$\lambda_{\max}(r, r+1)$	$\lambda_{\text{trace}}(r)$	Cointegrating Vector $\beta' = (1, \beta_1, \beta_2)$
1	1	2	r=0	19.472	21.207	1, 0.344, -1.043
			r=1	1.734	1.734	
	2	2	r=0	12.130	15.652	
			r=1	3.522	3.522	
	3	2	r=0	26.967	29.796	1, -1.108, -0.850
			r=1	2.829	2.829	
1A	2	2	r=0	25.167	29.408	1, 2.665, -1.381
			r=1	4.242	4.242	
	3	2	r=0	25.117	28.214	1, 2.020, -1.283
			r=1	3.097	3.097	
2	1	2	r=0	19.357	22.933	1, -1.324, -0.839
			r=1	3.576	3.576	
	2	2	r=0	29.037	32.515	1, -1.927, -0.758
			r=1	3.473	3.473	
	3	2	r=0	29.228	32.344	1, -1.533, -0.815
			r=1	3.117	3.117	
2A	2	2	r=0	27.785	31.386	1, 0.610, -1.120
			r=1	3.601	3.601	
	3	2	r=0	24.549	27.935	1, 0.847, -1.147
			r=1	3.386	3.386	
3	1	2	r=0	20.193	23.722	1, 1.916, -1.269
			r=1	3.529	3.529	
	2	2	r=0	20.553	24.255	1, -0.856, -1.077
			r=1	3.702	3.702	
	3	2	r=0	23.498	26.118	1, -0.842, -1.202
			r=1	2.620	2.620	
3A	2	2	r=0	21.153	25.571	1, 3.022, -1.425
			r=1	4.417	4.417	
	3	2	r=0	28.356	30.938	1, 2.007, -1.275
			r=1	2.582	2.582	
4	1	2	r=0	17.873	18.733	1, 3.348, -1.455
			r=1	0.860	0.860	
	2	2	r=0	5.311	7.994	
			r=1	2.682	2.682	
6	1	2	r=0	14.528	15.735	
			r=1	1.207	1.207	
	2	2	r=0	11.626	12.667	
			r=1	1.041	1.041	
	3	2	r=0	15.120	17.424	
			r=1	2.304	2.304	

(continued)

Table 6.5 (continued)

Route	Period	Lags	Null	$\lambda_{\max}(\mathbf{r}, \mathbf{r}+1)$	$\lambda_{\text{trace}}(\mathbf{r})$	Cointegrating Vector $\beta' = (\mathbf{1}, \beta_1, \beta_2)$
7	2	2	r=0	20.022	24.213	1, 2.658, -1.333
			r=1	4.192	4.192	
	3	2	r=0	24.659	27.779	1, -0.542, -0.899
			r=1	3.119	3.119	
8	1	2	r=0	13.871	18.861	1, -0.893, -0.811
			r=1	4.989	4.989	
	2	2	r=0	13.617	15.586	
			r=1	1.970	1.970	
	3	2	r=0	19.187	21.806	
			r=1	2.619	2.619	
9	2	2	r=0	5.002	8.655	
			r=1	3.653	3.653	
	3	2	r=0	10.441	13.203	
			r=1	2.762	2.762	
10	2	2	r=0	25.876	29.519	1, 4.111, -1.529
			r=1	3.643	3.643	
	3	2	r=0	20.479	23.916	1, -0.533, -0.894
			r=1	3.437	3.437	
11	1	2	r=0	5.962	7.573	
			r=1	1.611	1.611	
	2	2	r=0	11.376	15.133	
			r=1	3.757	3.757	
12	1	2	r=0	5.395	6.686	
			r=1	1.291	1.291	
	1	2	r=0	9.325	10.642	
			r=1	1.317	1.317	
95% critical values			r=0	15.67	19.96	
			r=1	9.24	9.24	

Notes:

- See Figure 6.2 for the definition of the different estimation periods.
- Lags is the lag length of the VECM in (6.3); the lag length is determined using the SBIC.
- $\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$ tests the null hypothesis of r cointegrating vectors against the alternative of $r+1$.
- $\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i)$ tests the null that there are at most r cointegrating vectors against the alternative that the number of cointegrating vectors is greater than r . 95% critical values are from Osterwald-Lenum (1992), Table 1*.
- $\beta' = (1 \ \beta_1 \ \beta_2)$ are the coefficient estimates of the cointegrating vector where the coefficient of S_{t-1} is normalised to be unity, β_1 is the intercept term and β_2 is the coefficient on F_{t-1} .

For the routes which are not cointegrated with the BIFFEX prices, the estimated statistics indicate that $\text{rank}(\Pi) = 0$ in (6.3), implying that a VAR model in first differences is

appropriate. For the routes which are cointegrated with the BIFFEX prices, the normalised coefficient estimates of the cointegrating vector, i.e. $\beta'X_{t-1}$ from equation (6.3), for each route are presented in Table 6.5. These estimates, representing the long-run relationship between spot routes and futures prices, are used in the joint estimation of the conditional mean and the conditional variance ⁵. This takes place by maximising the bivariate conditional normal log-likelihood function. The standard errors of the estimated coefficients are computed using the Quasi Maximum Likelihood (QML) procedure of Bollerslev and Wooldridge (1992). This yields standard errors which are robust to departures from the maintained assumption of conditional normality ⁶.

Table 6.6 presents the value of the log-likelihood function, evaluated at the maximum, of the bivariate VECM-GARCH time-varying model in (6.3) and of a VECM with constant conditional variance matrix ⁷. Likelihood ratio tests, show that the time-varying GARCH model is preferred over the constant VECM in 18 out of 32 cases (56.25 %). The selected model, is then used to generate hedge ratios. In the case of the GARCH model, measures of the time-varying variances and covariances are extracted and used to compute the time-varying hedge ratios of equation (6.2). For the constant VECM, hedge ratios are calculated from the estimated residual series of the model, as the ratio of the residual covariance of the spot and futures equations over the variance of the residuals from the futures equation. Finally, the conventional hedge ratio, γ^* in equation (6.1), is also estimated and used for comparison.

⁵ Notice that, as explained on footnote 7 in chapter 5, the estimates of the cointegrating vector are not restricted to be (1,0, -1).

⁶ The estimated models are subjected to diagnostics testing to ensure that they are well specified. The diagnostics we employ are the same as the ones in chapter 5, i.e. Ljung-Box Q tests on the standardised residuals and squared standardised residuals, Engle's tests for ARCH effects and Engle and Ng (1993) tests for asymmetries in the conditional variance equations. These tests do not indicate any misspecification.

⁷ Due to the small number of observations for route 9 in the second period (N = 39), a GARCH model is not estimated for this route.

Table 6.6

Likelihood Ratio Tests of the Estimated VECM-GARCH versus VECM models on BFI Routes and BIFFEX Prices

Route	1			1A			2			2A			3			3A			4	
	1	2	3	2	3		1	2	3	2	3		1	2	3	2	3		1	2
LL (GARCH)	623.1	929.9	1224.7	969.5	1183.3		798.1	821.2	1226.3	834.5	1192.8		640.6	1046.4	1289.7	950.9	1207.4		703.1	1027.7
LL (VECM)	618.9	921.4	1215.8	967.6	1179.1		789.7	820.9	1225.9	834.5	1192.8		640.4	1038.4	1277.9	945.4	1203.3		702.9	1015.6
LR	8.5 ^c	16.9 ^a	17.8 ^a	4.5	8.5 ^c		16.8 ^a	0.6	0.8	0.1	0.1		0.4	16.0 ^a	23.5 ^a	11.1 ^b	8.4 ^c		0.3	24.1 ^a
Route	6			7			8			9			10			11			12	
Period	1	2	3	2	3		1	2	3	2	3		2	3		1	2		1	2
LL (GARCH)	608.9	1096.4	1330.5	819.3	1245.9		703.0	1132.0	1271.4	-	1205.3		915.4	1272.6		602.5	1062.2		586.4	1045.8
LL (VECM)	591.8	1091.3	1320.3	818.6	1240.1		701.9	1119.5	1267.7	237.8	1172.1		909.5	1264.8		600.5	1059.8		585.9	1044.3
LR	34.2 ^a	10.1 ^b	20.3 ^a	1.2	11.5 ^b		2.1	24.9 ^a	7.3	-	66.6 ^a		11.8 ^b	15.5 ^a		4.1	4.8		1.2	2.9

Notes:

- See Figure 6.2 for the definition of the estimation periods across the different routes.
- LL(GARCH) is the maximised value of the log-likelihood function of the GARCH(1,1) model in (6.3).
- LL(VECM) is the maximised value of the log-likelihood function of the model in equation (6.3) with constant conditional covariance matrix.
- LR is the likelihood ratio test for the restriction $A = B = 0$ in the conditional variance specification of the VECM-GARCH model of equation (6.3). It is computed as two times the difference of the log-likelihood of the GARCH and the VECM; the statistic is $\chi^2(4)$ distributed.
- ^a, ^b and ^c denote that the LR statistic is significant at the 1%, 5% and 10% level, respectively.

To compare formally the performance of each type of hedge, we construct portfolios implied by the computed hedge ratios each week and calculate the variance of the returns to these portfolios over the sample, i.e., we evaluate

$$\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t) \quad (6.4)$$

where γ_t^* are the computed hedge ratios. The variance of the hedged portfolios is then compared to the variance of the unhedged position, i.e. $\text{Var}(\Delta S_t)$, and the variance reduction, VR, achieved through hedging is calculated as follows

$$\text{VR} = 1 - \frac{\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t)}{\text{Var}(\Delta S_t)} \quad (6.5)$$

The larger the reduction in the unhedged variance, the higher the degree of hedging effectiveness. When γ_t^* in equation (6.5) is the OLS hedge ratio of equation (6.1), γ^* , then this measure of hedging effectiveness is the same as the R^2 of (6.1) (see Appendix 5.A).

Table 6.7

OLS Hedge Ratios and Measures of Hedging Effectiveness for the OLS and the GARCH Hedges

Route	Period			Route	Period		
	1	2	3		1	2	3
1	γ^* (OLS)	0.8549 a	0.4131 a	6	γ^* (OLS)	0.1622 a	0.1066 a
	VR(OLS)	33.70% *	18.64%		VR(OLS)	7.72%	4.48% *
	VR(VECM or VECM-GARCH)	31.47%	18.69% *		VR(VECM or VECM-GARCH)	10.39% *	6.07% *
1A	γ^* (OLS)	0.4281 a	0.4866 a	7	γ^* (OLS)	0.0813	0.1565 b
	VR(OLS)	13.51% *	16.49%		VR(OLS)	1.01%	4.62%
	VR(VECM or VECM-GARCH)	13.33%	17.30% *		VR(VECM or VECM-GARCH)	1.09% *	5.47% *
2	γ^* (OLS)	0.7040 a	0.3839 a	8	γ^* (OLS)	0.1433 a	0.0414
	VR(OLS)	31.61% *	10.77% *		VR(OLS)	11.20% *	0.88% *
	VR(VECM or VECM-GARCH)	30.70%	19.21%		VR(VECM or VECM-GARCH)	10.86%	0.29%
2A	γ^* (OLS)	0.3804 a	0.4438 a	9	γ^* (OLS)	0.2093 a	0.4571 a
	VR(OLS)	13.05% *	17.37% *		VR(OLS)	8.48% *	16.01%
	VR(VECM or VECM-GARCH)	13.01%	17.02%		VR(VECM or VECM-GARCH)	8.41%	16.38% *
3	γ^* (OLS)	0.3907 a	0.2488 a	10	γ^* (OLS)	0.0965	0.1632 b
	VR(OLS)	16.05% *	13.15% *		VR(OLS)	3.00%	5.65% *
	VR(VECM or VECM-GARCH)	15.64%	11.10%		VR(VECM or VECM-GARCH)	4.71% *	4.24%
3A	γ^* (OLS)	0.5151 a	0.3971 a	11	γ^* (OLS)	0.0084	0.0439
	VR(OLS)	17.38% *	14.71% *		VR(OLS)	0.08% *	0.93% *
	VR(VECM or VECM-GARCH)	16.03%	14.41%		VR(VECM or VECM-GARCH)	0.04%	0.90%
4	γ^* (OLS)	0.0888 a	0.1702 a	12	γ^* (OLS)	0.0626 b	0.0327
	VR(OLS)	3.94% *	6.34% *		VR(OLS)	2.65% *	0.46% *
	VR(VECM or VECM-GARCH)	3.47%	6.10%		VR(VECM or VECM-GARCH)	2.62%	0.45%

Notes:

- See Figure 6.2 for the definition of the estimation periods across the different routes.
- γ^* is the minimum variance hedge ratio of equation (6.1). Standard errors for the significance of the estimated coefficient are calculated using the Newey – West (1987) correction for heteroskedasticity and serial correlation, with a truncation lag of 24.
- ^a, ^b, and ^c denote significance at the 1%, 5% and 10% level, respectively. An Asterisk (*) denotes the model with the larger variance reduction.
- VR(OLS) is the variance reduction of the spot position achieved using the conventional hedge ratio, γ^* . It is equivalent to the R^2 of equation (6.1).
- VR(VECM or VECM-GARCH) is the variance reduction of the spot position of equation (6.5) achieved using the hedge ratio generated by the selected model in Table 6.6.

The estimated OLS hedge ratios, γ^* 's in (6.1), and measures of hedging effectiveness, $VR(OLS)$, are presented in Table 6.7⁸. The same table also presents the degree of hedging effectiveness, VR in equation (6.5), from the selected VECM-GARCH or VECM hedge ratios, in Table 6.6⁹. We can see that the OLS hedge ratios outperform the other hedges in 24 cases, out of 33 (72.73%); for the remaining 9 cases, (27.27%), the VECM-GARCH hedges provide superior variance reduction.

The degree of hedging effectiveness seems to differ substantially across sub-periods and shipping routes. Consider first, the periods before and after the introduction of time-charter routes to the index (periods 1 and 2). The hedging effectiveness decreases in all the cases with the exception of routes 4 and 11, where the hedging effectiveness increases from 3.94% to 6.34% and from 0.08% to 0.93%, respectively. The reduction in hedging effectiveness is more striking for routes 1, 2 and 8. More specifically, for routes 1 and 2 the degree of hedging effectiveness is reduced by almost 3 times (from 33.7% to 7.17% and from 31.61% to 10.77%, respectively), and for route 8, the degree of hedging effectiveness is reduced from 11.20% to 0.88%; notice also that the OLS hedge ratio for route 8 in the second period becomes statistically insignificant which implies that the futures contract has no power in reducing the riskiness of the spot position.

Consider next the period after the exclusion of the handysize routes. The hedging effectiveness increases in all cases, with the exception of route 3A, where the hedging effectiveness decreases from 17.38% to 14.71%. The highest increase is evidenced in routes 1, 2 and 9 where the degree of hedging effectiveness increased almost twofold with respect to period 2; notice that the weight of route 9, increased from 5% to 10% while, the weights of routes 1 and 2 remained the same. Notice also that the hedge ratios for routes 7, 8 and 10 in

⁸ To account for the serial correlation and heteroskedasticity appearing in the spot returns, standard errors are computed using the Newey and West (1987) estimator.

⁹ Our methodology is similar to the one employed in chapter 5. There are some differences, however, which are dictated by the nature of our dataset. First, due to the small number of observations for each route, particularly in the first two sub-periods, out-of-sample tests for hedging effectiveness are not pursued here. Second, due to the fact that BIFFEX prices are not cointegrated with all BFI routes in every sub-period we do not consider the GARCH-X model, described in chapter 5.

the third period become statistically significant when compared to the second period.

Another feature of our results is that, on average, the variance reduction for the panamax routes is higher than that for the handysize and capesize routes. For instance, in the first period the lowest hedging effectiveness for a panamax route is 16.05% in route 3 while the highest hedging effectiveness for a handysize route is 3.94% in route 4 and for a capesize route is 11.20% in route 8. The capesize routes seem to perform better than the handysize routes in the first period, although this is reversed in the second period. On average, however, their performance is poor, compared to that of the panamax routes; this follows from the heavier representation of the panamax routes on the BFI as well as from the fact that these three categories of vessels represent different segments of the dry-bulk market which are weakly correlated with each other.

Finally, and also in line with our results from chapter 5, the futures contract fails to eliminate a large proportion of the variability of the unhedged portfolio, the greatest variance reduction is in route 1 for the first period (33.70%). This is well below the variance reduction over the unhedged position evidenced in other markets, (57.06% for the Canadian Interest rate futures (Gagnon and Lypny, 1995), 69.61% and 85.69% for the corn and soybean futures (Bera et al., 1997) and 97.91% and 77.47% for the SP500 and the Canadian Stock Index futures contract (Park and Switzer, 1995), and is a reflection of the heterogeneous composition of the underlying index.

6.3.4 Comparison of the Hedging Performance across Sub-Periods

The preceding analysis indicates that there are nominal differences in the effectiveness of the hedging mechanism, following the revisions in the composition of the BFI. To address the issue of whether the observed nominal differences in the variance reduction of the spot position across the sub-periods are statistically significant, we construct empirical confidence intervals for the differences in measures of hedging effectiveness across sub-periods, using bootstrapping techniques. Bootstrapping is a data-based simulation method that uses the empirical distribution of the statistic of interest, rather than the theoretical distribution implied by statistical theory, to conduct statistical inference. Bootstrapping is particularly useful in cases where the standard error of the statistic is very difficult to estimate analytically; this is the case when the statistic of interest is the difference in the degree of hedging effectiveness, as indicated by Li and Vukina (1998) ¹⁰.

Our procedure is the following. For each period, we select the model that provides the highest degree of hedging effectiveness (either the GARCH, the VECM or the OLS) and compute the variance reduction achieved through hedging, using equation (6.5). This is denoted as VR_i , $i = 1, 2, 3$ for the different periods. The statistic of interest is the difference of the VR_i across two sub-periods, $VR_i - VR_{i-1}$ (i.e. $VR_2 - VR_1$ and $VR_3 - VR_2$). The selected model for each period along with the value of the observed statistic are presented in Table 6.8. To investigate whether the observed differences are statistically significant, we draw independent bootstrap samples with replacement from the four sample series of interest, namely the returns of the hedged ($\Delta S_t - \gamma_t^* \Delta F_t$, where γ_t^* is the selected hedge ratio) and the unhedged position (i.e. the returns in the spot market, ΔS_t) across two adjacent periods.

¹⁰ The difference between bootstrapping and other simulation methods, most notably Monte Carlo, is that the former is based on the actual empirical data to obtain a description of the sample properties of the empirical estimators. In contrast, Monte Carlo methods are used to identify whether the theoretical properties of estimators, implied by statistical theory, conform to a particular dataset. For an overview of the applications of bootstrapping see Efron and Tibshirani (1993).

Table 6.8

Empirical Confidence Intervals for the Differences in the degree of Hedging Effectiveness across Sub-periods

Route	Selected Model for period				Periods 1 – 2		Periods 2 – 3	
	1	2	3		VR ₂ - VR ₁		VR ₃ – VR ₂	
1	OLS	OLS	GARCH	observed	-0.2653 ^b		0.1152 ^b	
				95% CI	-0.4262	-0.0547	0.0150	0.2082
1A		OLS	GARCH	observed	-		0.0374	
				95% CI			-0.0868	0.1667
2	OLS	OLS	OLS	observed	-0.2084 ^b		0.0877	
				95% CI	-0.3368	-0.0656	-0.0481	0.2104
2A		OLS	OLS	observed	-		0.0432	
				95% CI			-0.1061	0.0395
3	OLS	GARCH	OLS	observed	-0.0345		0.0055	
				95% CI	-0.2104	0.1471	-0.1513	0.1691
3A		OLS	OLS	observed	-		-0.0267	
				95% CI			-0.1862	0.1393
4	OLS	OLS		observed	0.0239		-	
				95% CI	-0.0697	0.1073		
6	GARCH	OLS	GARCH	observed	-0.0604		0.0159	
				95% CI	-0.0524	0.0876	-0.0651	0.0932
7		GARCH	GARCH	observed	-		0.0436	
				95% CI			-0.0360	0.1179
8	OLS	OLS	OLS	observed	-0.1031		0.0476	
				95% CI	-0.2636	0.0906	-0.0230	0.1079
9		OLS	GARCH	observed	-		0.0791	
				95% CI			-0.1062	0.3025
10		GARCH	OLS	observed	-		0.0095	
				95% CI			-0.0862	0.1068
11	OLS	OLS		observed	0.0085		-	
				95% CI	-0.0326	0.0361		
12	OLS	OLS		observed	-0.0220		-	
				95% CI	-0.0891	0.0595		

Notes:

- See Figure 6.2 for the definition of the estimation periods across the different routes.
- The selected model for each period is the model, in Table 6.7, that provides the highest degrees of hedging effectiveness.
- Observed is the observed difference in the degree of hedging effectiveness from the selected models between two adjacent periods.
- 95% CI is the 95% empirical confidence interval for the differences in the degree of hedging effectiveness.
- ^a, ^b, and ^c denote significance at the 1%, 5% and 10% level, respectively.

Based on these bootstrap samples, we calculate the variances of the series and compute the variance reduction from hedging for each sub-period, i.e. VR_i using equation (6.5); these are then used to compute the bootstrap replication statistic $VR_i - VR_{i-1}$. This procedure is repeated 10,000 times and generates a series of 10,000 observations of the bootstrap statistic. The 95% empirical confidence interval is then constructed by eliminating the lowest 250 and the highest 250 observations from the ordered series of the bootstrap statistic; if the value of 0 falls within the limits of the empirical confidence interval, then the difference in the degree of hedging effectiveness across the sub-periods is not significant ¹¹.

Our results are presented in Table 6.8. We can see that the differences in the degree of hedging effectiveness between periods 1 and 2 are significant only for routes 1 and 2. Notice that during the first period, routes 1 and 2 are the most heavily represented routes on the BFI, with a weight of 20% each, and the BIFFEX contract offers the greatest variance reduction for hedges on these routes, as is evidenced in Table 6.7.

This indicates that the reduction in the contribution of the routes to the BFI affects significantly the hedging performance for these routes which are more heavily represented on the index. Two reasons may be put forward in support of this. First, for route 3, whose weight to the BFI in the first period was less than that of routes 1 and 2 (15%, compared to 20%), the reduction in the contribution of this route to 7.5% in the second period did not result in a significant reduction in its hedging performance. Second, the hedging performance of the routes whose weights remained unchanged between periods 1 and 2 (i.e. the handysize routes 4, 11 and 12 and the capesize routes 6 and 8) has not been altered significantly between these periods. This suggests that the introduction of the time-charter routes to the index did not affect the hedging performance of these routes and, as a consequence, does not account for the observed decrease in the hedging performance of routes 1 and 2.

¹¹ Our results remain qualitatively the same when we consider 10% and 1% levels of significance.

Therefore, the decrease in the hedging performance for routes 1 and 2 can be attributed to the reduction of their weights in the BFI. This finding contrasts with the evidence presented by Glen and Rogers (1997) who argue that changing the weights in the composition of the constituent routes in the SSY capesize index does not alter significantly the correlation of these routes with the index. It seems that the opposite is true for the BIFFEX contract since futures prices are more strongly correlated with the shipping routes which have a heavier representation on the underlying index.

Consider next the period after the exclusion of the handysize routes. We can see that there is a nominal increase in the hedging effectiveness for all the routes, with the exception of route 3A. However, this increase is statistically significant only in the case of route 1. Therefore, the exclusion of the handysize routes from the index did not affect the hedging performance across all the BFI routes, as it was anticipated by the regulatory authorities; this may be attributed to the fact that the handysize routes represented a small portion, only 17.5%, of the index.

Despite this, it seems that the hedging performance of the BIFFEX contract will strengthen even further after the forthcoming exclusion of the capesize routes and the introduction of the BPI as the underlying asset of the contract. Three reasons may be put forward for this.

First, the weights of five out of the seven routes of the new index will increase from their current level and the weights of the other two routes will remain unchanged (see Table 1.2). This suggests that the hedging performance, at least for the former routes, will increase since, as our results indicate, freight rate risk can be hedged more effectively for these routes which have a heavier representation on the BFI. A second reason is that the capesize routes currently represent 30% of the index and, as a result, their exclusion from the BFI will have a more beneficial effect on the hedging performance of the market, than the exclusion of the handysize routes, which represented only 17.5% of the index.

Finally, the new index will have a more homogeneous structure than the BFI and will consist of shipping routes which are strongly correlated with each other. The correlation coefficients of the BFI routes, presented in Table 1.4, indicate that the BFI essentially consists of two

distinct groups of underlying shipping routes; panamax and capesize. The within-group correlation is strong in both cases although their correlation with the other group is weak; the average correlation for panamax routes is 53.1%, while the average correlation for the capesize routes is 44.4%. On the other hand, the average correlation between panamax and capesize routes is only 20.9%. Gemmill (1985) indicates that the inclusion in the BFI of routes which are weakly correlated with the remaining routes of the index, such as for instance the capesize routes which are weakly correlated with the panamax routes, will not improve much the performance of hedges on the capesize routes and may actually deteriorate the performance of hedges on the panamax routes. For these reasons, it seems that the introduction of the BPI as the new underlying asset of the BIFFEX contract is likely to have a beneficial impact on the risk management function of the market.

6.4 Conclusions

This chapter examined whether the price discovery and risk management functions of the BIFFEX contract have changed following major revisions in the composition of the BFI. The motivation for this test derives from two interesting policy issues surrounding the revisions of the BFI. First, since all the major revisions of the BFI are driven by the intention to generate an underlying index which promotes the more effective functioning of the BIFFEX contract, it is interesting to investigate whether these revisions have achieved their intended objective. Second, by investigating the effect of past revisions in the composition of the BFI on the two functions of the BIFFEX contract, we can provide preliminary evidence regarding the possible impact of the introduction of the BPI as the new underlying asset of the futures contract from November 1999.

To address these issues we perform causality tests and assess the effectiveness of constant and dynamic hedging strategies across sub-periods, corresponding to revisions in the underlying asset. Our results indicate that the price discovery role of futures prices has strengthened following both the introduction of the time-charter routes and the exclusion of the handysize routes from the BFI.

Regarding the hedging performance, the following can be noted. First, between periods 1 and 2, there is a significant decrease in the hedging performance for routes 1 and 2. This is thought to be the result of the reduction in the weights of these routes to the BFI, from 20% to 10%, and indicates that futures prices are more strongly correlated with those shipping routes that have a heavier representation on the underlying index. For the other routes, there is no significant change in the hedging performance, which also suggests that the introduction of the time-charter routes did not have a significant impact on the risk management function of the market.

Turning next to the period after the exclusion of the handysize routes, we can note that the hedging effectiveness of the futures contract increases significantly only in the case of one route. Therefore, the exclusion of the handysize routes from the index did not improve the

hedging performance across all the BFI routes, as it was anticipated by the regulatory authorities; this may be attributed to the fact that the handysize routes represented a small portion, only 17.5%, of the index.

Overall, our results in this chapter are consistent with our empirical results in chapters 4 and 5 of the thesis. We can see that the market performs its price discovery efficiently, however, its performance regarding risk management is far from perfect. This reflects the fact that hedging freight rate risk on the BIFFEX market is essentially a cross hedge. Unlike other futures markets in which futures contract are used to hedge price risk on the underlying asset, in the BIFFEX market, futures contracts are used to hedge freight rate risk on the constituent routes of the underlying asset. Although there is a strong linkage between BFI and BIFFEX prices, the relationship between BFI routes and BIFFEX prices is less strong, and, as our results in this chapter indicate, dependent upon the general composition of the index. Since the BFI consists of shipping routes which are dissimilar in terms of vessel sizes and transported commodities, futures prices cannot capture accurately the fluctuations on these routes and hence, cannot provide risk reduction to the extent that is observed in other markets.

The issue that arises is whether the introduction of the BPI as the new underlying asset of the futures contract will have a beneficial impact on the market. It seems that this will be the case since, the more homogeneous composition of this new index, compared to the BFI, is likely to increase the correlation between BFI routes and BIFFEX prices and hence, strengthen the risk management functions of the market.

Chapter 7 : A Time-Series Model for Forecasting Spot and Futures Prices in the BIFFEX Market

7.1 Introduction

In this chapter, we investigate the performance of alternative time-series models in generating short-term forecasts of the BFI and BIFFEX prices. The issue of forecasting BFI prices was also considered in chapter 3 where we explored the predictive power of futures prices in the market to forecast the settlement BFI prices at the maturity day of the contract, one, two and three months ahead. We found that futures prices provide more accurate forecasts of the realised settlement prices than forecasts generated from the VECM, random walk, ARIMA and the Holt-Winters models. This indicates that participants in the BIFFEX market receive accurate signals from futures prices and can use the information generated by these prices so as to guide their physical market decisions; therefore, charterers or shipowners can use the futures prices as indicators of the future course of BFI prices one, two and three months ahead.

Market agents, however, can also benefit from having accurate short-term forecasts of the BFI and BIFFEX prices, since availability of such forecasts will enable them to design more efficient trading and speculative 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 use of multivariate specifications is motivated by

our empirical results on the causal relationship between contemporaneous spot and futures prices, in chapter 4. We found that BFI and BIFFEX prices are cointegrated and respond to the magnitude of deviations from their long-run relationship, which is the spot – futures differential; that is, the basis. This suggests that the predictability of BFI and BIFFEX prices can be improved by incorporating the information contained in the cointegrating relationship (Engle and Yoo, 1987). In order to investigate this issue, we compare the forecasting performance of the VECM of chapter 4, to that of ARIMA, VAR and Random Walk models and we employ the statistical test of Diebold and Mariano (1995) to assess whether the forecasts from the competing models are equally accurate.

These models are estimated using BFI and BIFFEX prices from the beginning of our dataset (i.e. 1 August 1988) and from the period after the exclusion of the handysize routes from the BFI (i.e. 3 November 1993). This way, we can examine whether the strengthening of the price discovery role of futures prices for the latter period, which is indicated by our empirical results in chapter 6, can improve the forecasting performance of the estimated models and hence lead to more accurate forecasts of the BFI and BIFFEX prices.

The structure of this chapter is as follows. The next section describes the models that are employed to generate the forecasts. Section 3 evaluates the forecasting performance of the alternative model specifications. Finally, Section 4 concludes this chapter.

7.2 Estimation of Alternative Time-Series Models for Forecasting Spot and Futures in the BIFFEX market

In order to identify the model that provides the most accurate short-term forecasts of spot and futures prices in the market, we consider five alternative models for predicting BFI and BIFFEX prices.

The first model is the VECM, analysed in chapter 4 of this thesis. The model is estimated using daily BFI and BIFFEX prices over the period 1 August 1988 to 31 December 1997 and is presented in Table 7.1 ¹.

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 equations for spot and futures returns, and is thus estimated as a system of seemingly unrelated regressions (SUR) since this method yields more efficient estimates than the OLS (see Zellner, 1962). Using the SBIC (1978) as the model selection criterion, the final estimated model is presented in Table 7.1 under the column SUR-VECM.

The third model is a VAR in first differences; this model is identical to the VECM except that no error-correction term is included in any of the equations. Similar model specifications have been used by Wahab and Lashgari (1993) and Tse (1995) in order to investigate the contribution of the cointegrating error in enhancing prediction accuracy.

Fourth, univariate ARIMA models (Box-Jenkins, 1970), which have been proposed by Cullinane (1992) as tools for forecasting the BFI, are also estimated. The most parsimonious models for the spot and futures returns, are selected using the SBIC and ensuring well specified diagnostics. Table 7.1 presents the estimation results for the VECM, SUR-VECM, VAR and ARIMA models over the period 1 August 1988 to 31 December 1997. These

¹ The futures prices are of 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. Summary statistics for the spot and futures prices are presented in Table 4.1 of chapter 4.

models are then estimated recursively during the out-of-sample period, which runs from 1 January 1998 to 30 April 1998, and generate forecasts of the BFI and BIFFEX prices up to 20 steps (trading days) ahead.

Finally, the random-walk (RW) model is also considered for benchmark comparison; this model postulates that spot (futures) prices at time $t-n$, S_{t-n} (F_{t-n}) are the most accurate predictors of spot (futures) prices at time t , S_t (F_t). Therefore, it uses the current spot or futures prices to generate forecasts of these prices and hence, requires no estimation ².

² Cullinane (1992) also estimates the exponential smoothing model of Holt (1957) and Winters (1960). This model was considered in chapter 3, and described in appendix 3.B. Given its poor forecasting performance, evidenced by our results in that chapter, this model is not estimated here.

Table 7.1

OLS Estimates of the Models for the Out-Of-Sample Forecasts; Estimation Period 1/8/88 to 31/12/97

VECM									
$\Delta S_t = \sum_{i=1}^{p-1} a_{S,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,i} \Delta F_{t-i} + \alpha_S Z_{t-1} + \varepsilon_{S,t}$									
$\Delta F_t = \sum_{i=1}^{p-1} a_{F,i} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,i} \Delta F_{t-i} + \alpha_F Z_{t-1} + \varepsilon_{F,t} \quad ; \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \sim IN(0, \Sigma)$									
VECM					SUR-VECM				
Dependent Variable					VAR				
Explanatory Variable	AS _t		ΔF _t		AS _t		ΔF _t		ARIMA
	coeff.	t-stat.	coeff.	t-stat.	coeff.	t-stat.	coeff.	t-stat.	
Z _{t-1}	-0.029 ^a	-8.563	0.029 ^a	3.173	-0.029 ^a	-10.081	0.031 ^a	3.118	-
ΔS _{t-1}	0.413 ^a	10.357	0.408 ^a	5.099	0.405 ^a	19.832	0.319 ^a	5.525	-
ΔS _{t-2}	0.122 ^a	2.625	-0.106	-1.236	0.132 ^a	6.283	-	-	-
ΔS _{t-3}	0.125 ^a	4.091	-0.032	-0.369	0.128 ^a	6.871	-	-	-
ΔS _{t-7}	-	-	-	-	-	-	-	-	-
ΔF _{t-1}	0.046 ^a	6.596	0.115 ^a	4.976	0.046 ^a	7.655	0.122 ^a	5.502	-
ΔF _{t-2}	0.019 ^a	3.266	-0.005	-0.262	0.020 ^a	3.524	-	-	-
ΔF _{t-3}	0.011 ^a	1.751	0.012	0.610	0.010 ^c	1.820	-	-	-
Residual Diagnostics									
R ²	0.601		0.029		0.601		0.029		0.017
LL		16434				16433			6536
AIC		-16420				-16394			-6535
SBIC		-16380				-16423			-6532
Q(36)	44.66		45.56		44.78		48.32		44.58

Notes:

- a, b and c denote significance at the 1%, 5% and 10% level respectively.
- The cointegrating vector, $z_{t-1} = S_{t-1} - F_{t-1}$, is restricted to be the basis
- LL is the value of the log-likelihood function, evaluated at the maximum.
- Q(36) is the Ljung-Box (1978) Q statistics on the first 36 lags of the sample autocorrelation function of the residuals; the statistic is $\chi^2(36)$ distributed with 5% critical value of 50.99.

7.3 Forecasting Performance of the Time-Series Models

The forecasting performance statistics for each model, across the different forecast horizons, are presented in matrix form in Table 7.2 and Table 7.3 for the spot and futures prices, respectively. Numbers on the principal diagonal are the root mean square errors (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. 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 also 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

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi f_d(0)}{N}}} \sim N(0,1) \quad (7.1)$$

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 (1987). 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 a, b and c - see the table notes) next to the RMSE ratios. Finally, the proportion of forecasts from each model that predict correctly the direction of movements of the realised prices is presented in the same tables. These tests are not applicable for the RW model which assumes that there is no change in the forecasts of the future prices.

Table 7.2

Spot Price Forecasts for the period 1/1/98 to 30/4/98

Horizon (days)	<i>N</i>	RMSEs	VECM	SUR-VECM	VAR	ARIMA	RW
1	82	VECM	0.00544				
		SUR-VECM	0.99718	0.00546			
		VAR	0.96983 ^a	0.97257 ^a	0.00561		
		ARIMA	0.94579	0.94846	0.97521	0.00575	
		RW	0.51057 ^a	0.51201 ^a	0.52645 ^a	0.53983 ^a	0.01066
		Direction	90.24%	90.24%	89.02%	87.81%	-
2	80	VECM	0.01108				
		SUR-VECM	0.99883	0.01109			
		VAR	0.95539 ^a	0.95651 ^a	0.01160		
		ARIMA	0.91232 ^b	0.91339 ^b	0.95491	0.01214	
		RW	0.53628 ^a	0.53691 ^a	0.56132 ^a	0.58782 ^a	0.02066
		Direction	92.59%	93.83%	88.89%	87.65%	-
3	80	VECM	0.01658				
		SUR-VECM	1.00045	0.01657			
		VAR	0.94589 ^a	0.94547 ^a	0.01752		
		ARIMA	0.89550 ^a	0.89510 ^a	0.94673	0.01851	
		RW	0.54843 ^a	0.54818 ^a	0.57980 ^a	0.61243 ^a	0.03022
		Direction	92.50%	92.50%	87.50%	86.25%	-
4	79	VECM	0.02231				
		SUR-VECM	1.00167	0.02228			
		VAR	0.93969 ^a	0.93812 ^a	0.02375		
		ARIMA	0.89275 ^a	0.89126 ^a	0.95005	0.02499	
		RW	0.56443 ^a	0.56349 ^a	0.60066 ^a	0.63224 ^a	0.03953
		Direction	91.14%	91.14%	84.81%	84.81%	-
5	78	VECM	0.02884				
		SUR-VECM	1.00225	0.02878			
		VAR	0.93663 ^a	0.93452 ^a	0.03079		
		ARIMA	0.89725 ^a	0.89523 ^a	0.95796 ^c	0.03215	
		RW	0.59200 ^a	0.59067 ^a	0.63205 ^a	0.65979 ^a	0.04872
		Direction	89.74%	89.74%	82.05%	83.33%	-
10	73	VECM	0.06885				
		SUR-VECM	1.00037	0.06882			
		VAR	0.92965 ^a	0.92930 ^a	0.07406		
		ARIMA	0.90876 ^a	0.90842 ^a	0.97753 ^b	0.07576	
		RW	0.75740 ^a	0.75711 ^a	0.81471 ^a	0.83344 ^b	0.09090
		Direction	89.04%	89.04%	76.71%	76.71%	-
15	68	VECM	0.10654				
		SUR-VECM	0.99566	0.10700			
		VAR	0.93034 ^a	0.93439 ^a	0.11452		
		ARIMA	0.92174 ^a	0.92576 ^a	0.99076 ^b	0.11558	
		RW	0.87659 ^c	0.88041	0.94223	0.95102	0.12154
		Direction	77.94%	77.94%	64.71%	64.71%	-
20	63	VECM	0.13324				
		SUR-VECM	0.98968	0.13463			
		VAR	0.93034 ^a	0.94005 ^b	0.14322		
		ARIMA	0.93071 ^a	0.94041 ^b	1.00039	0.14316	
		RW	0.96685	0.97694	1.03925	1.03884	0.13781
		Direction	66.67%	66.67%	58.73%	58.73%	-

Notes:

- Forecasts are generated by the models in Table 7.1. *N* is the number of forecasts.

- 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 covariance estimator with a truncation lag of 25. Significance levels are for a two-tail test.
- The direction of change is the proportion of forecasts from each model that predict correctly the direction of movements of spot and futures prices.
- a, b and c denote significance at the 1%, 5% and 10% level respectively.

Consider first the spot price forecasts in Table 7.2. The RMSEs of the VECM and the SUR-VECM specifications are almost identical for all the forecast horizons. This is also confirmed by Diebold and Mariano's (1995) test which indicates that the difference between the RMSE from the two models is not significant. The VECM produces forecasts which are significantly more accurate than the RW model for up to 15 days ahead; for the 20-days horizon however, the gain in forecasting accuracy by employing the VECM over the RW model is not statistically significant. This pattern in the forecasting performance of the VECM based forecasts corresponds to the delivery cycle of the futures contract. Futures prices can help improve forecasting performance for an horizon which does not extend beyond the expiry day of the futures contract. Given that there is a contract maturing every month in the market, the maximum effective forecast horizon for futures prices should be the number of trading days in a month, which is about 17 to 22 days depending on the contract month.

Regarding the performance of the VAR and the ARIMA models, they outperform the RW model for up to 10-days ahead. However, with the exception of the 1-day ahead forecasts where the ARIMA is as good as any of the other models, both models produce forecasts which are significantly less accurate than the VECM based forecasts. Therefore, it seems that conditioning spot returns to lagged futures returns and 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-step ahead forecasts is 48.943% (i.e. $1 - 0.51057$). This compares favourably to the findings in other markets; Ghosh (1993a) reports reductions ranging from 15% to 34% for the S&P 500 and the Commodity Research Bureau (CRB) indices respectively; Ghosh and Gilmore (1997) find that the ECM reduces the RMSE of the naive model by 63% and 23% for the British Pound and Deutsche Mark rolling spot contracts while Tse (1995) finds that the ECM outperforms

the naive model by 3% in the Nikkei stock index market. Similar conclusions emerge when we consider the directional predictability of the model. The VECM predicts correctly the direction of the BFI 1-day ahead 90.24% of the time (or alternatively, 74 correct predictions for the 82 days of the out-of-sample period); on the other hand, Tse (1995) finds that the ECM scores 64.3% correct directional predictions. However, these studies use only 1-step ahead forecasts and do not consider hypothesis tests for the equality of the RMSE. Investigation of greater lead times, coupled with hypothesis tests for the RMSE, is important since the VECM appears consistently better across longer forecast horizons, in contrast to the 1-day forecasts in which case it is as good as the ARIMA model.

Turning next to the futures price forecasts in Table 7.3, it can be seen that the VECM generates forecasts which are not significantly more accurate than the forecasts obtained from the other models. Similarly, the number of correct direction predictions of the VECM for the 1-day horizon is 52.44% which is very close to the expected number of successes under pure chance (50 percent). Overall, it can be seen that with the exception of the 4 and 5-step ahead forecasts, in which case the ARIMA model is superior to the RW model, there is little gain in forecasting accuracy by employing time-series models rather than using the readily available information provided by the current futures prices. The forecasting results for the futures prices compare poorly to the results observed in the spot price forecasts and in the study of Ghosh (1993a), who finds that the ECM outperforms the random walk model by 24% and 39% for the S&P 500 and the CRB futures markets, respectively.

The poor performance of the VECM futures price forecasts, compared to the VECM spot price forecasts, suggests that, while conditioning spot returns to lagged futures returns generates more accurate forecasts of the spot prices, conditioning futures returns to lagged spot returns does not enhance the forecasting accuracy of futures prices. This asymmetric pattern in the forecasting performance is in line with our results from the causality tests and impulse response analysis, in chapter 4, and reflects the fact that causality from futures to spot runs stronger than the other way. This is also consistent with the VECM explaining only 2.9% of the variations in the futures equation, in Table 7.1, thus indicating that most of the variability in futures returns represents pure innovations which cannot be modelled and hence cannot be predicted.

Table 7.3

Futures Price Forecasts for the period 1/1/1998 to 30/4/1998

Horizon (days)	N	RMSEs	VECM	SUR-VECM	VAR	ARMA	RW
1	82	VECM	0.01636				
		SUR-VECM	1.00592	0.01627			
		VAR	0.99765	0.99177	0.01640		
		ARMA	0.98945	0.98362	0.99178	0.01654	
		RW	0.95956	0.95391	0.96183	0.96980	0.01705
		Direction	52.44%	51.22%	53.66%	54.88%	-
2	81	VECM	0.02601				
		SUR-VECM	1.00504	0.02588			
		VAR	0.99723	0.99223	0.02609		
		ARMA	0.97089	0.96602	0.97358	0.02679	
		RW	0.94469	0.93995	0.94731	0.97301	0.02754
		Direction	61.73%	59.26%	59.26%	59.26%	-
3	80	VECM	0.03489				
		SUR-VECM	1.00312	0.03478			
		VAR	0.99788	0.99478	0.03496		
		ARMA	0.96135	0.95836	0.96339	0.03629	
		RW	0.93789	0.93498	0.93989	0.97560	0.03720
		Direction	62.50%	57.50%	61.25%	62.50%	-
4	79	VECM	0.04430				
		SUR-VECM	1.00193	0.04421			
		VAR	1.00081	0.99888	0.04426		
		ARMA	0.96693	0.96506	0.96614	0.04581	
		RW	0.94739	0.94556	0.94662	0.97980 ^b	0.04676
		Direction	58.23%	53.17%	58.23%	62.03%	-
5	78	VECM	0.05361				
		SUR-VECM	1.00059	0.05357			
		VAR	1.00239	1.00180	0.05348		
		ARMA	0.97347	0.97289	0.97115	0.05507	
		RW	0.95776	0.95719	0.95548	0.98386 ^b	0.05597
		Direction	58.97%	53.85%	57.69%	60.26%	-
10	73	VECM	0.09302				
		SUR-VECM	0.99402	0.09358			
		VAR	1.00503	1.01108	0.09256		
		ARMA	1.00106	1.00709	0.99605	0.09292	
		RW	0.99423	1.00021	0.98925	0.99318	0.09356
		Direction	54.80%	52.06%	54.80%	57.53%	-
15	68	VECM	0.12111				
		SUR-VECM	0.98708	0.12270			
		VAR	1.00697	1.02015	0.12028		
		ARMA	1.02636	1.03979	1.01925	0.11800	
		RW	1.02531	1.03873	1.01822	0.99898	0.11812
		Direction	48.53%	47.06%	51.47%	47.06%	-
20	63	VECM	0.12957				
		SUR-VECM	0.98298	0.13182			
		VAR	1.00852	1.02599	0.12848		
		ARMA	1.04062	1.05865	1.03183	0.12451	
		RW	1.04289	1.06096	1.03408	1.00218	0.12424
		Direction	44.44%	44.44%	47.62%	47.62%	-

See the notes in Table 7.2 for the definitions of the statistics.

a, b and c denote significance at the 1%, 5% and 10% level respectively.

7.3.1 Forecasting Performance for the Post-handysize Period

Our empirical results on the causal relationship between BFI and BIFFEX prices, in chapter 6, indicate that the price discovery role of futures prices has strengthened for the period after the exclusion of the handysize routes from the BFI, as a result of the more homogeneous composition of the index for that period. This increase in the flow of information from futures to spot returns suggests that, by estimating the models using only data for the period after the exclusion of the handysize routes, one may obtain more accurate forecasts of the spot and futures prices than by estimating the models over the entire sample period.

In order to address this issue, we estimate the models in Table 7.1 using data for the period after the exclusion of the handysize routes from the BFI i.e. after 3 November 1993. The forecast performance statistics for the spot prices are presented in Table 7.4.

The VECM and the SUR-VECM specifications have an almost identical forecasting performance for all the forecast horizons and the VECM produces forecasts which are significantly more accurate than the RW model for up to 15 days ahead. For the 20-days horizon, however, there is no significant difference in the forecasting performance of the VECM and RW models, which is the same as our results from the analysis of the entire sample in Table 7.2. For a forecast horizon up to 10-days, the post-handysize VECM scores a lower RMSE and hence generates more accurate forecasts than the VECM estimated over the entire sample (e.g. 0.00520 instead of 0.00544 for the 1-step ahead forecasts). Similar improvements in the RMSEs are evidenced for the post-handysize VAR and ARIMA models over their counterparts from the entire sample. However, both of these models produce forecasts which are significantly less accurate than the post-handysize VECM forecasts. Moreover, in contrast to the entire sample period, the post-handysize VECM significantly outperforms the ARIMA model for the 1-step ahead forecasts.

Table 7.4
Spot Price Forecasts for the period 1/1/98 to 30/4/98; Post-Handysize Period

Horizon (days)	N	RMSEs	VECM	SUR-VECM	VAR	ARIMA	RW
1	82	VECM	0.00520				
		SUR-VECM	1.00931	0.00515			
		VAR	0.97272 ^a	0.96375 ^b	0.00535		
		ARIMA	0.94159 ^c	0.93291	0.96800	0.00552	
		RW	0.48805 ^a	0.48354 ^a	0.50173 ^a	0.51832 ^a	0.01066
		Direction	86.59%	86.59%	89.02%	86.59%	-
2	80	VECM	0.01093				
		SUR-VECM	1.00454	0.01088			
		VAR	0.95884 ^a	0.95450 ^a	0.01140		
		ARIMA	0.91075 ^b	0.90664 ^c	0.94985	0.01201	
		RW	0.52921 ^a	0.52682 ^a	0.55193 ^a	0.58107 ^a	0.02066
		Direction	91.36%	91.36%	87.65%	86.42%	-
3	80	VECM	0.01653				
		SUR-VECM	1.00121	0.01651			
		VAR	0.94843 ^a	0.94729 ^a	0.01743		
		ARIMA	0.89387 ^b	0.89279 ^b	0.94247	0.01849	
		RW	0.54681 ^a	0.54615 ^a	0.57654 ^a	0.61173 ^a	0.03022
		Direction	91.25%	91.25%	88.75%	87.50%	-
4	79	VECM	0.02208				
		SUR-VECM	0.99950	0.02209			
		VAR	0.94121 ^a	0.94168 ^a	0.02346		
		ARIMA	0.89122 ^b	0.89167 ^b	0.94688	0.02478	
		RW	0.55861 ^a	0.55889 ^a	0.59350 ^a	0.62679 ^a	0.03953
		Direction	89.87%	91.14%	86.08%	86.08%	-
5	78	VECM	0.02830				
		SUR-VECM	0.99942	0.02831			
		VAR	0.93781 ^a	0.93835 ^a	0.03018		
		ARIMA	0.89736 ^a	0.89789 ^a	0.95687	0.03154	
		RW	0.58084 ^a	0.58118 ^a	0.61936 ^a	0.64727 ^a	0.04872
		Direction	88.46%	88.46%	84.62%	85.90%	-
10	73	VECM	0.06825				
		SUR-VECM	1.00124	0.06817			
		VAR	0.93252 ^a	0.93137 ^a	0.07319		
		ARIMA	0.92117 ^a	0.92003 ^a	0.98782	0.07409	
		RW	0.75082 ^a	0.74989 ^a	0.80514 ^a	0.81507 ^a	0.09090
		Direction	86.30%	87.67%	78.08%	80.82%	-
15	68	VECM	0.10714				
		SUR-VECM	1.00200	0.10693			
		VAR	0.93021 ^a	0.92836 ^a	0.11518		
		ARIMA	0.94502 ^b	0.94314 ^b	1.01592	0.11338	
		RW	0.88157 ^c	0.87981	0.94771	0.93286	0.12154
		Direction	76.47%	77.94%	66.18%	69.12%	-
20	63	VECM	0.13523				
		SUR-VECM	1.00212	0.13495			
		VAR	0.92418 ^a	0.92223 ^a	0.14633		
		ARIMA	0.96114	0.95910	1.03998	0.14070	
		RW	0.98129	0.97921	1.06179	1.02097	0.13781
		Direction	66.67%	66.67%	60.32%	61.91%	-

- See the notes in Table 7.2 for the definitions of the statistics.
- ^a, ^b and ^c denote significance at the 1%, 5% and 10% level respectively.

Table.7.5

Futures Price Forecasts for the period 1/1/98 to 30/4/98; Post-Handysize Period

Horizon (days)	N	RMSEs	VECM	SUR-VECM	VAR	ARMA	RW
1	82	VECM	0.01666				
		SUR-VECM	1.00203	0.01663			
		VAR	0.99965	0.99763	0.01667		
		ARMA	1.01197	1.00993	1.01233	0.01647	
		RW	0.97714	0.97516	0.97748	0.96558	0.01705
		Direction	51.22%	52.44%	52.44%	53.66%	-
2	81	VECM	0.02618				
		SUR-VECM	0.99964	0.02619			
		VAR	0.99825	0.99861	0.02623		
		ARMA	0.98274	0.98310	0.98446	0.02664	
		RW	0.95080	0.95115	0.95247	0.96750	0.02754
		Direction	62.96%	61.73%	60.49%	58.03%	-
3	80	VECM	0.03454				
		SUR-VECM	0.99888	0.03458			
		VAR	0.99778	0.99890	0.03462		
		ARMA	0.95747	0.95855	0.95960	0.03607	
		RW	0.92860	0.92964	0.93066	0.96984	0.03720
		Direction	65.00%	62.50%	63.75%	61.25%	-
4	79	VECM	0.04386				
		SUR-VECM	0.99845	0.04393			
		VAR	1.00195	1.00351	0.04377		
		ARMA	0.96228	0.96377	0.96041	0.04558	
		RW	0.93802	0.93948	0.93620	0.97479	0.04676
		Direction	60.76%	59.49%	60.76%	60.76%	-
5	78	VECM	0.05314				
		SUR-VECM	0.99828	0.05323			
		VAR	1.00439	1.00612	0.05291		
		ARMA	0.96895	0.97062	0.96471	0.05484	
		RW	0.94940	0.95103	0.94525	0.97982 ^b	0.05597
		Direction	61.54%	60.26%	62.82%	58.97%	-
10	73	VECM	0.09277				
		SUR-VECM	0.99886	0.09288			
		VAR	1.01152	1.01267	0.09172		
		ARMA	1.00008	1.00122	0.98869	0.09277	
		RW	0.99158	0.99270	0.98028	0.99150 ^b	0.09356
		Direction	54.80%	54.80%	58.90%	56.16%	-
15	68	VECM	0.12197				
		SUR-VECM	0.99944	0.12204			
		VAR	1.02102	1.02159	0.11946		
		ARMA	1.03374	1.03432	1.01246	0.11799	
		RW	1.03256	1.03314	1.01130	0.99886	0.11812
		Direction	48.53%	48.53%	48.53%	45.59%	-
20	63	VECM	0.13144				
		SUR-VECM	1.00046	0.13138			
		VAR	1.02953	1.02906	0.12767		
		ARMA	1.05483	1.05435	1.02457	0.12461	
		RW	1.05791	1.05743	1.02757	1.00292	0.12424
		Direction	44.44%	46.03%	47.62%	46.03%	-

• See the notes in Table 7.2 for the definitions of the statistics.

• ^a, ^b and ^c denote significance at the 1%, 5% and 10% level respectively.

Regarding the directional predictability tests, we can see that the post-handysize VECM is slightly less accurate than the VECM from the entire sample; the post-handysize VECM predicts correctly the direction of the BFI 1-day ahead 86.59% of the time, instead of 90.24% for the VECM estimated over the entire sample (or alternatively, 71 correct predictions, instead of 74, for the 82 days of the out-of-sample period).

Turning next to the futures price forecasts in Table.7.5, we can see that the post-handysize VECM has a lower RMSE, than the VECM estimated over the entire sample, for the 3, 4, 5 and 10-days ahead forecasts. Despite this improvement however, the VECM generates forecasts which are not significantly more accurate than the forecasts obtained from the other models. Overall, our results for the futures prices are qualitatively the same to the results obtained from the analysis of the entire sample and indicate that there is little gain in forecasting accuracy by employing time-series models rather than using the readily available information provided by the current futures prices.

7.4 Conclusions

In this chapter, we investigated the performance of alternative time-series models in generating short-term forecasts of the BFI and BIFFEX prices. Based on our empirical results from chapters 4 and 6, we examine the forecasting performance of a VECM of BFI and BIFFEX prices where the cointegrating vector is restricted to be the basis. The forecasts from this model are compared to forecasts generated by ARIMA, VAR, and the Random Walk models.

We find that the VECM generates significantly more accurate forecasts of BFI prices, compared to the Random Walk model, for a period up to 15 days ahead. This effective forecast horizon corresponds to the delivery cycle of the futures contract and dictates that futures prices can help improve the forecasting performance of spot prices for a period up to the expiry day of the futures contract. For the futures prices however, the increase in forecasting performance achieved by conditioning futures prices on the lagged spot prices and the basis, through the VECM, is insignificant across all the forecast horizons. This reflects that causality from futures to spot runs stronger than the other way and that most of the variability in the futures returns is attributed to pure innovations which cannot be predicted.

When the models are estimated for the period after the exclusion of the handysize routes from the BFI, the VECM generates more accurate forecasts of the spot prices, compared to the model estimated over the entire sample, and outperforms all the other models for a forecast horizon up to 15-days ahead. For the futures forecasts however, the results are qualitatively the same to the ones obtained from the analysis of the entire sample and indicate that there is little gain in the accuracy of BIFFEX prices forecasts by employing time-series models rather than using the readily available information provided by the current futures prices; this again, reflects the increased importance of futures prices as a price discovery centre, particularly for the period after the exclusion of the handysize routes from the index.

Therefore, market agents in the BIFFEX market can benefit by employing the VECM, investigated in this chapter, to generate accurate forecasts of the spot price index and hence design more efficient investment and speculative trading strategies.

Chapter 8 : Conclusions and Further Research

8.1 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 BIFFEX market. These are the most important functions of any futures market and are often presented as the justification for futures trading (see e.g. Garbade and Silber, 1983).

A considerable amount of empirical research has been directed towards examining these hypotheses in different financial and commodity futures markets. There is little evidence however, regarding the BIFFEX contract. It is has been therefore, the objective of this thesis to fill this gap in the literature. Moreover, by addressing these issues we provide, for the first time, empirical evidence from a market which trades the expected value of a service and is characterised by low trading activity.

Another important issue which has been covered by this thesis is the temporal variation in the performance of the price discovery and risk management functions of the market following the revisions in the composition of the BFI. An investigation of this issue is particularly timely given the introduction of the BPI as the new underlying asset of the BIFFEX contract, in November 1999. Finally, in this thesis we also address the issue of forecasting the BFI and BIFFEX prices and propose a model which outperforms all the other models considered so

far in the literature.

The structure of this chapter is as follows. In the following section we report the conclusions for each chapter, while in section 3 we discuss the policy implications of our findings. Finally, section 4 presents some topics for further research, which, due to space and time constraints, are not investigated here.

8.2 Summary of the Findings and Conclusions

In the first chapter, we described the two benefits that futures markets, in general, provide to economic agents – risk management and price discovery; a description of the BFI and BIFFEX markets is also provided in that chapter. 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 Phillips and Perron (1988) unit root tests were presented. We also presented the cointegration methodology and described the Engle and Granger (1987) and Johansen (1988) testing procedures. The latter procedure is more powerful than the Engle and Granger (1987) test and it provides us with 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 use of “orthogonalised” and “generalised” impulse response analysis for investigating the dynamic relationship between variables in a VECM was also discussed.

The empirical analysis of the thesis is presented in chapters 3 through 7. In chapters 3 and 4 we investigated two different aspects of the price discovery function of the market, namely the relationship between current futures prices and expected spot prices – the unbiasedness hypothesis – and the relationship between contemporaneous spot and futures prices. More specifically, in chapter 3, we investigated the unbiased expectations property of the futures prices in the market. Cointegration techniques, employed to examine this hypothesis, indicate that futures prices one and two months before maturity are unbiased forecasts of the realised spot prices, while a bias exists in the three-months futures prices. The latter, is thought to be a result of thin trading in the three-months contract and of the possible imbalance between short and long hedging demand for this contract, compared to shorter maturities.

The short-run dynamics of futures and expected spot prices in the market are further investigated using impulse response analysis. Our results indicate that when the unbiasedness

hypothesis fails, in the three-months futures prices, a shock to the system results in disequilibrium between futures prices and realised spot prices; in contrast, when the unbiasedness hypothesis holds, spot and futures prices return to the same long-run equilibrium level once the effect of the initial shock has vanished.

Finally, in the same chapter we also explore the predictive power of futures prices in the market; we compare the accuracy of the forecasts implied by the futures prices with forecasts generated from error correction, ARIMA, exponential smoothing and random walk models. We find that futures prices for all maturities provide superior forecasts of the realised spot prices than forecasts generated from the other models. We also find that the forecasting performance of futures prices diminishes as the forecast horizon increases; this is consistent with the findings of Ma (1989) and Kumar (1992) and reflects that more information, regarding the future course of spot prices, is available to market participants when the forecasts are made for a shorter horizon. However, while futures prices display this forecasting weakness, they still provide the best forecasts.

In chapter 4, we investigated the causal linkage between contemporaneous spot and futures prices in the BIFFEX market – which represents the second dimension of the price discovery role of futures markets. Our major findings can be summarised as follows. BFI and BIFFEX prices stand in a long-run relationship between them. The resulting VECM is used to investigate the short-run dynamics and the price movements in the two markets. Causality tests and impulse response analysis indicate that futures prices tend to discover new information more rapidly than spot prices. This pattern is thought to reflect the fundamentals of the market. More specifically, market agents who have collected and analysed new information, regarding the expected level of spot and futures prices, will prefer to trade in the futures rather than in the spot market. This is due to the following reasons. First, since the underlying spot market trades a service, it is not possible to establish a short position in this market, in contrast to the futures market where a short position can be entered into as easily as a long position. Therefore, market agents who believe that freight rates will fall, can only benefit through this information by trading in the futures market. Second, futures markets in general provide flexibility to investors since they enable them to speculate on the price movements of the underlying asset without the financial burden of owning the asset itself;

this point is particularly important given the highly capital intensive nature of the shipping industry. The above characteristics of the market can explain why futures prices in the BIFFEX market price new information more rapidly compared to their underlying spot prices.

The risk management function of the market is investigated in chapter 5 where we examine the effectiveness of time-varying hedge ratios in reducing freight rate risk in the BFI routes. In- and out-of-sample tests indicate that time-varying hedge ratios outperform the constant and the naïve hedges, in 4 shipping routes. Two interesting results emerge from this analysis. First, freight rate risk can be hedged more effectively for the panamax routes, compared to the handysize routes; this follows from the fact that futures prices capture more closely the fluctuations on the panamax routes, due to heavier representation of these routes to the BFI. Second, the freight rate risk reduction across all the BFI routes is lower than that evidenced in other commodity and financial futures markets in the literature. This is thought to be the result of the heterogeneous composition of the BFI, in terms of vessel sizes and cargo routes.

The effect of previous revisions in the composition of the BFI to the price discovery and risk management functions of the BIFFEX contract is analysed in chapter 6. Causality tests across sub-periods, corresponding to revisions in the BFI, indicate that the price discovery role of futures prices has strengthened following both the introduction of the time-charter routes and the exclusion of the handysize routes from the BFI. In the case of the time-charter routes, this is attributed to the fact that time-charter rates in the shipping freight markets, reflect the expectations of market agents regarding the future level of spot rates. As a result, they are closely linked with the futures prices, which also reflect the expectations of the market regarding future BFI prices. The increase in the price discovery function of the BIFFEX market, following the exclusion of the handysize routes, is attributed to the more homogeneous composition of the BFI for that period. As suggested by our results in chapter 4, market agents who have superior information regarding the expected level of freight rates can only benefit from this information by trading in the futures market. However, it is much more difficult to form correct expectations of the future price of an index when it consists of a number of diverse components; even if the expectations of the investors for a particular shipping route are realised, this does not guarantee a corresponding change in the average

value of the index, to which the futures contract converges at maturity. By eliminating the handysize routes from the BFI, the composition of the index became more homogeneous and hence the importance of futures prices as a vehicle for information discovery increased.

Regarding the hedging performance, the following can be noted. First, there is a significant decrease in the hedging performance for routes 1 and 2, following the reduction in their contribution to the BFI, from 20% to 10%. This indicates that futures prices are more strongly correlated with those shipping routes that have a heavier representation on the underlying index and that freight rate risk can be hedged more effectively for these routes, compared to other routes with lower weights. Second, for the remaining routes of the BFI there is no significant change on the degree of their hedging performance, following the introduction of the time-charter routes, which indicates that the introduction of these routes to the index did not have a significant impact on the risk management function of the market. Finally, following the exclusion of the handysize routes from the BFI, there is a nominal increase in the hedging effectiveness for all the routes, with the exception of route 3A. However, this increase is statistically significant only in the case of route 1. Therefore, it seems that the exclusion of the handysize routes from the index did not affect the hedging performance across all the BFI routes, as it was anticipated by the regulatory authorities; this may be attributed to the fact that the handysize routes represented a small portion, only 17.5%, of the index.

Finally, in chapter 7 we investigated the performance of different time-series models in generating short-term forecasts of the BFI and BIFFEX prices. More specifically, we examined the forecasting performance of a VECM of BFI and BIFFEX prices where the cointegrating vector is restricted to be the basis. The forecasts from this model were compared to forecasts generated by ARIMA, VAR, and the Random Walk model.

We find that the VECM generates significantly more accurate forecasts of BFI prices, compared to the Random Walk model, for a period up to 15 days ahead. This forecast horizon corresponds to the delivery cycle of the futures contract and dictates that futures prices can help improve the forecasting performance of spot prices for a period up to the expiry day of the futures contract. For the futures prices however, the increase in forecasting performance

achieved by conditioning futures prices on the lagged spot prices and the basis, through the VECM, is insignificant across all the forecast horizons. This reflects the finding that causality from futures to spot runs stronger than the other way and that most of the variability in the futures returns is attributed to pure innovations which cannot be predicted.

When the models are estimated for the period after the exclusion of the handysize routes from the BFI, the VECM generates more accurate forecasts of the spot prices, compared to the model estimated over the entire sample, and outperforms all the other models for a forecast horizon up to 15-days ahead. For the futures forecasts however, the results are qualitatively the same to the ones obtained from the analysis of the entire sample and indicate that there is little gain in the accuracy of BIFFEX prices forecasts by employing time-series models rather than using the readily available information provided by the current futures prices; this again, reflects the increased importance of futures prices as a price discovery centre, particularly for the period after the exclusion of the handysize routes from the index.

Concluding, this thesis examines the performance of the price discovery and risk management functions of the BIFFEX market. These two functions represent the major benefits that futures markets provide to economic agents and are often presented as the justification for futures trading. An additional objective of the thesis is to investigate the temporal variability in the performance of these functions following the revisions in the composition of the underlying index. Investigation of this issue can shed some light on whether these revisions have affected the performance and the functioning of the market, as it was intended by the regulatory authorities, and also enables us to provide some preliminary evidence regarding the possible impact of the exclusion of the capesize routes from the BFI in November 1999. Finally, the thesis also investigates whether the forecastability of spot prices can be improved by incorporating the information contained in the futures prices, thus providing further evidence on the superior informational properties of futures prices in the market.

Our findings can be summarised as follows. The BIFFEX market performs its price discovery function efficiently since futures prices contribute to the discovery of new information regarding both current and expected spot prices. Therefore, despite the thin trading in the

market, futures prices contain information which is superior to that contained in the spot prices; moreover, market agents can use the information generated by these prices so as to guide their decisions in the physical market. The performance of the market regarding risk management, however, is far from perfect. This reflects the fact that hedging freight rate risk on the BIFFEX market is essentially a cross hedge. Unlike other futures markets in which futures contract are used to hedge price risk on the underlying asset, in the BIFFEX market, futures contracts are used to hedge freight rate risk on the constituent routes of the underlying asset. Since the BFI consists of shipping routes which are dissimilar in terms of vessel sizes and transported commodities, futures prices cannot capture accurately the fluctuations on these routes and hence, cannot provide risk reduction to the extent that is observed in other markets.

The results from the sub-period analysis indicate that the performance of the price discovery, and to a lesser extent of the risk management functions, has increased as a result of the more homogeneous composition of the index following its revisions over the recent years; this by itself indicates that the forthcoming exclusion of the capesize routes is likely to have a beneficial impact on the performance of the market. Finally, the results from the forecasting models indicate that by incorporating the information contained in the futures prices, market agents can obtain more accurate forecasts of the BFI prices.

8.3 Policy Implications

As indicated in the introduction to this thesis, the success of a futures 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 futures market which eventually leads to loss of trading interest by the market agents.

Our results indicate that the market performs its price discovery function efficiently. Futures prices contribute to the discovery of new information about current and expected supply and demand conditions. Therefore market agents receive accurate signals from the futures prices, regarding the future course of cash prices, and can use the information generated by these prices so as to guide their decisions in the physical market.

Our findings for the risk management function of the market are less encouraging. The risk reduction in the BFI routes compares very poorly to the risk reduction evidenced in other commodity and financial futures markets; for instance, the greatest variance reduction is 23.25% in route 1A while the variance reductions evidenced in other markets in the literature range from 57.06% to 97.91% (see as well the discussion in chapters 5 and 6 of the thesis). The underlying reason for this poor hedging performance is the composition of the BFI. The index consists of shipping routes which are dissimilar in terms of vessel sizes and transported commodities. As a result, the futures contract cannot capture accurately the fluctuations on these routes and hence cannot provide risk reduction to the extent that is observed in other markets.

The issue that arises is whether the exclusion of the capesize routes from the index and the introduction of the BPI as the underlying asset of the futures contract will have a beneficial effect on the risk management function of the market. The new index will have a more homogeneous structure than the BFI and will consist of shipping routes which are strongly

correlated with each other, as is evidenced by the correlation matrix of the BFI routes, in Table 1.4. As a result, the correlation of the shipping routes with the futures prices will also increase and the effectiveness of hedges will strengthen accordingly.

It also seems that this beneficial effect will be more noticeable than the one evidenced for the period after the exclusion of the handysize routes. This is due to the following reasons. First, the handysize routes accounted for only 17.5% of the total BFI composition; therefore, with the exception of route 1, their exclusion did not alter significantly the relationship between the underlying trade routes and the futures prices. In contrast, capesize routes currently represent 30% of the BFI. Second, the BPI will consist of panamax routes only and, thus will be more homogeneous than the panamax and capesize index that resulted after the exclusion of the handysize routes.

Moreover, the diminishing trading activity in the BIFFEX market may reflect the fact that market users abstain from using the futures contract due to its poor hedging performance. If this is the case, then an increase in the hedging performance of the BIFFEX contract may also have a beneficial impact on the trading activity in the market.

8.4 Suggestions for Further Research

In this thesis we investigated the price discovery and risk management functions of the BIFFEX contract. We also considered how the performance of these functions has been affected following the revisions in the composition of the BFI. The motivation for investigating these issues derives from the fact that these are the most important functions of any futures market and hence the findings of the thesis are of particular importance to those involved in trading and in regulating this market. In this section we present some suggestions for fruitful future research in the BIFFEX market. These represent extensions to the current study which, due to space constraints, are not investigated here.

Regarding the price discovery function of the market, future research should study the relationship between the underlying shipping routes and the BIFFEX prices. The findings of such studies will enable us to identify whether futures prices contribute to the discovery of new information regarding the future prices of the BFI routes and hence will determine whether market agents can use the information contained in the current futures prices to obtain an indication regarding the expected level of the freight rates on the BFI routes.

Turning next into the hedging performance of the market, the current study can be extended to investigate the effectiveness of time-varying hedge ratios in reducing freight rate risk in a portfolio of freight routes, rather than in a single route. The findings of this research will be particularly relevant to a shipowner who operates a fleet of vessels across different shipping routes, or to a charterer who wants to transport his commodity to different parts of the world. Gagnon et al. (1998) for instance, 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 find, however, that by taking the portfolio effects into consideration, the increase in the hedging performance is small, only 1.88%. Whether similar findings will emerge by considering, for instance, a portfolio of time-charter routes, or a portfolio of grain routes is an issue worth investigating.

Future research can also investigate whether the introduction of the BFI as the underlying asset of the BIFFEX contract will strengthen the price discovery and risk management function of the market. Provided that sufficient data will be available, the framework for such a study is presented in chapter 6.

There is also ample scope for further research in the area of forecasting. In particular, it will be interesting to investigate the performance of different time-series models in generating short-term forecasts of the BFI routes. For instance one can compare the forecasting performance of a VECM of BFI routes and BIFFEX prices to forecasts generated by univariate ARIMA models, along the lines described in chapter 7 of the thesis. Market agents can potentially benefit by having accurate forecasts of the BFI routes since they will be able to design more effective investment and speculative strategies. Finally, these BFI routes forecasts can be combined to generate a forecasted value of the BFI; this way we can investigate whether the forecasting performance of the BFI can be increased by forecasting each one of its constituent routes and weighting these forecasts according to the weights of these routes to the BFI, rather than forecasting the BFI on a stand-alone basis.

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