Market Conditions and the Functioning of Metal Futures Markets

by

Haiying JIA

A Thesis Submitted for the Degree of PhD in Finance

Cass Business School, City University, London

30 June 2006

Table of Contents

LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller Test
ARCH	Autoregressive Conditional Heteroscedasticity
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BAS	Bid-Ask Spread
BVAR	Bivariate Vector Autoregressive
CBOT	Chicago Board Of Trade
COMEX	New York Commodities Exchange
DF	Dickey-Fuller Test
ECM	Error Correction Model
ECT	Error Correction Term
EMH	Efficient Market Hypothesis
ERS	Elliot, Rothenberg; Stock Point Optimal Unit Root Test
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GIVE	General Instrumental Variable Estimation
GLS	Generalized Least Square
GMM	Generalized Method of Moments
i.i.d.	Identically and Independently Distributed
IPE	International Petroleum Exchange
KPSS	Kwiatkowski, Phillips, Schmidt and Shin Stationarity Test
LHS	Left Hand Side
LME	London Metal Exchange
MA	Moving Average
MDH	Mixture of Distribution Hypothesis
MRS	Markov Regime Switching
NYMEX	New York Mercantile Exchange
OHR	Optimal Hedge Ratio
OLS	Ordinary Least Square
OSE	Osaka Securities Exchange
RHS	Right Hand Side
RMSE	Root Mean Squared Error
RW	Random Walk
SHME	Shanghai Metals Exchange
SIF	Sequential Information Flow
SIMEX	Singapore International Monetary Exchange
TAPOs	Traded Average Price Options
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedasticity
TV	Trading Volume
UH	Unbiasedness Hypothesis
UNTCAD	United Nations Conference On Trade And Development
VAR	Vector Autoregressive
VECM	Vector Error Correction Model

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I thank my always-smiling supervisors, Dr. Amir Alizadeh and Dr. Michael Tamvakis, for their great guidance and assistance. The door to Dr. Amir Alizadeh's office was always open whenever I ran into a trouble spot or had a question about my research.

I would like to thank Mr. Edward Shi from REFCO for providing me with a practitioner's point of view and the access to various market reports. Also I thank the London Metal Exchange for kindly providing the data for this thesis.

I would also like to thank friends and fellow Ph.D. students at Cass, particularly X. Fu, S. Sivaprasad, R. Ramyar, for their friendship and encouragement during this challenging period for all of us. Their company made my life as a researcher more colourful and enjoyable. Also the heated badminton matches with Xia which I enjoyed every week lightened the stress very much.

My greatest thanks go to my husband, Roar Ådland, for his limitless support and understanding during these years. I'd like to thank all he is, and all he has done for me.

Last but not least, my great thanks go to my mother for her continuous love and inspirations throughout my life.

Haiying Jia

30 June 2006

DECLARATION

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ABSTRACT

With the growth of alternative investment vehicles such as hedge funds and the resulting search for "new" asset classes, the interest in the commodity market has been growing within the financial sector. The commodity futures markets have been successfully providing a platform for investors and industrial participants as an alternative investment vehicle and a tool for risk management.

The storable commodity futures markets are characterised by two distinct market conditions: backwardation and contango, which are directly linked to market fundamentals such as inventory levels and thus influence the price dynamics and functioning of the commodity futures market. While there exists a large body of research in the area of commodity derivatives, research on the linkage between market dynamics and the market conditions as determined by fundamentals is very limited. Accordingly, this thesis aims to investigate the different market dynamics of metal futures markets under these two conditions. The issues under examination include the futures price discovery function, the forecasting performance of the futures price, the long-run cost-of-carry equilibrium and short-run time-varying adjustment, and the price volatility and its relationship with inventory levels and trading volume.

The empirical findings suggest, for the first time, that the price discovery function depends on the state of the storable commodity markets: futures prices are found to be upward biased predictors of the future spot prices when the market is in contango and are downward biased when the market is in backwardation. Nonparametric bootstrap simulations confirm that the forecast errors are negative in a backwardation market and are positive in a contango market, and moreover the forecast errors are larger under the former market condition than the latter. The empirical results also show that the price volatility is higher in a backwardation market than in a contango market as indicated by the negative relationship between price volatility and inventory levels. We also show that the spot volatility is generally higher than the futures price volatility and the difference is greater when the inventory level is low. Moreover, the impact of trading volume on the futures price volatility is found to be stronger when the market is in backwardation in some of the markets.

In short, the empirical findings in this thesis suggest that the functioning of the metal spot and futures market is dependent on market conditions of which the inventory level is an important indictor as implied by the theory of storage. The empirical findings have strong implications for practitioners (particularly, trading houses, funds and banks) who could potentially form different trading strategies based on the distinct market behaviour under the two market conditions.

1 CHAPTER ONE

INTRODUCTION

1.1 Introduction

The first recorded case of organised futures trading occurred in Japan during the 1600's (Tweles and Jone 1998). Wealthy landowners and feudal lords of Imperial Japan found themselves squeezed between an expanding money economy in the cities and their primarily agrarian-based resources. The rents that they collected from feudal tenants were paid in the form of a share of each year's rice harvest. This income was irregular and subject to uncontrollable factors such as weather and other seasonal characteristics. Because the money economy required that the nobility have ready cash on hand at all times, income instability stimulated the practice of shipping surplus rice to the principal cities of Osaka and Edo, where it could be stored and sold as needed. In an effort to raise cash quickly, landlords soon began selling tickets (warehouse receipts) against goods stored in rural or urban warehouses. Merchants generally bought these tickets in anticipation of their projected needs (they also suffered under uncertain harvests). Eventually, the warehouse "rice tickets" became a generally acceptable form of currency to facilitate the transaction of business and later on developed into the original concept of futures trading.

Futures trading started booming as the economy in the United States expanded in the first half of the nineteenth century, as commodity exchanges evolved from club-style associations into formalised exchange trading, the first of which was the Chicago Board of Trade (CBOT), established in 1848. It was on the CBOT on 13 March, 1851, that the first futures contract was recorded. This contract authorised the delivery of 3000 bushels of corn to be made in June at a price of one cent per bushel below the 13 March price (Irwin, 1954). Till the 1960s most of the futures trading was in agricultural products, such as corn and soybeans, and mostly in the United States. At present, a variety of futures contracts have been developed for a large number of commodities and financial assets. Generally, commodities are classified into "soft" commodities, such as agriculture (grain, cocoa, etc.), oil and gas etc., or "hard" commodities, such as minerals, timber and other "hard-form" commodities. Table 1.1 contains different commodities on which futures contracts are written (www.csidata.com Commodity System Inc.).

Table 1.1 Commodities underlying futures contracts

Agricultural products	Barley, bean, butter, cocoa, coffee, corn, cotton, dried cocoon, egg, cotton seed, feeder cattle, hogs, live cattle, lumber, milk, oats, orange juice, peas, pork belly, potato, rape seed, raw silk, raw sugar, red beans, rice, rubber, shrimp, soybean, soybean meal, soybean oil, sunflower seed, wheat, and white sugar.
Energy products	Crude oil, crude palm oil, electricity, gasoline, heating oil, kerosene, and natural gas.
Metals	Aluminium, aluminium alloy, copper, gold, lead, nickel, platinum, silver, tin, and zinc.

The primary reason for the successful trading in commodity futures markets is that futures markets provide platforms for risk management and price discovery. This thesis attempts to further document the intricate dynamics of the commodity futures markets, where the focus is on the functioning of the industrial metals futures markets in terms of the price discovery role of the futures prices, the presence of distinct market behaviour under different market conditions in terms of volatility, sensitivity to the arrival of news, as well as the speed of adjustment towards a long-run equilibrium described by the cost-of-carry relationship. The introduction of a link between market conditions and market dynamics can potentially accommodate the apparently contradictory empirical findings in the literature, in particular with regard to price discovery, and has a sound basis in economic theory.

1.2 The Economic Functions of Futures Markets

The first and most important social benefit of futures markets is that they provide a risk management platform for the market participants through hedging. Considering the original idea of futures trading, the Japanese landowners were able to secure rice prices against uncertainties in the harvest by selling the "warehouse rice tickets" well in advance, i.e. when the rice was still growing in the farm. Market agents, such as suppliers and consumers of crude oil, metals and other assets, sell (or buy) futures contracts in order to secure a known future price for the commodity or asset. The price risks that suppliers and consumers face in the physical world can be offset by taking the appropriate position in futures markets.

Price discovery is the second social benefit that futures markets provide. Price discovery is the ability of futures price to provide information about the price of the underlying commodity at some point in the future. The price discovery function of the futures market has been a popular research topic in the financial economics literature. Agents who sell futures contracts set the price on the basis of their anticipation of the price at the future point, just as do the buyers. Hence, if the market fully reflects the available information when the futures contract is written, that price should be the expectation of the agents regarding the physical price at maturity, subject to a possible non-zero risk premium.

The third social benefit, which is sometimes ignored by economists, is that a futures market facilitates speculation and trading. According to the Chambers Dictionary, "speculation" is a more or less risky investment of money for the sake of unusually large profits. Historically futures and forward markets met the need of market participants to secure the price of an underlying asset at any point in time to the delivery in the future. Nowadays only very few of the contracts are settled in a formal physical delivery. Most traders choose to close out their positions (settling) prior to the delivery time specified in the contract (maturity), implying that the cash settlement invites investors with no physical interest in the underlying asset to participate in the futures markets if they see any profit making opportunities.

Other than the aforementioned social benefits, the futures (and options) markets are claimed to have some other advantages that make these markets successful. The ability to redistribute risks means that no investors need to accept an uncomfortable level of risk. Therefore investors may be willing to supply more funds to the market. Futures markets, particularly the commodity futures market, provide more liquidity than the physical markets. The greater liquidity lowers the transaction costs. Futures markets also provide leverage. For instance, it is far cheaper to buy a Eurodollar futures contract (about $800USD margin) than to buy the underlying Eurodollar position ($1 million USD).

1.3 Market Conditions in Commodity Futures Markets

1.3.1 The Theory of Storage

In markets for storable commodities such as metals, stock levels play an important role in price formation. The production and consumption of commodities need not be matched in every period, which give rise to changes in inventory. Stocks are used to reduce costs of changing production in response to fluctuating demand and to avoid stockouts. In the commodity literature the theory of storage developed by Kaldor (1939), Working (1948, 1949), Telser (1958) and Brennan (1958) is to date the dominant theory which relates commodity spot and futures prices. According to this theory, the difference between futures and spot price equals to the cost of storage and an implicit benefit that producers and consumers receive by holding inventories of a commodity till maturity. This benefit is referred to as the convenience yield and theory suggests that it accrues to the inventory holder due to the flexibility in meeting unexpected demand and supply shocks.

An alternative interpretation of this original literature is to explain convenience yield in terms of an embedded timing option. In particular, the holder of a storable commodity (e.g. copper, aluminium) can decide when to consume it. If it is optimal to store a commodity for future consumption, then it is priced like an asset, but if it is optimal to consume it immediately, then the commodity is priced as a consumption good. Thus, a commodity's spot price is the maximum of its current consumption and asset values. In contrast, futures prices derive solely from the asset value of the deferred right to consume after delivery (Routledge, Seppi and Spatt, RSS, 2000). Inventory decisions are important also in this context because inventory levels influence the relative current and future scarcity of a commodity and, hence, link current consumption and expected future prices (RSS, 2000).

On the basis of the original theory of storage, the structural models of commodity prices focus on the implications of possible stockouts, which affects the no-arbitrage valuation because of the impossibility of carrying negative inventories (Wright and Williams, 1982, 1989; Williams and Wright, 1991; Scheinkman and Schechtman, 1983; Deaton and Laroque, 1992; Bailey and Chambers, 1996; and Bobenrieth, Bobenrieth and Wright, 2002). These papers argue that in the presence of possible stockouts, spot prices may rise above expected future spot prices net of cost of carry. The implications of possible stockouts on futures prices have been studied in RSS (2000).

One of the main implications of the theory of storage is that the convenience yield is expected to depend upon the level of inventory in a marginal and possible nonlinear form. Kaldor (1939, p.4) states that:

> "... *The amount of stock which can thus be useful is, in given circumstances, strictly limited; their marginal yield falls sharply with an increase in the stock above requirements, and may rise very sharply with a reduction in stocks below requirement* ..."

This forms the basis for one of the main hypotheses in this thesis, namely that market behaviour can be traced back to two separate market states that are proxies for the market conditions (backwardation and contango) and are believed to be closely related to inventory levels.

1.3.2 Backwardation and Contango

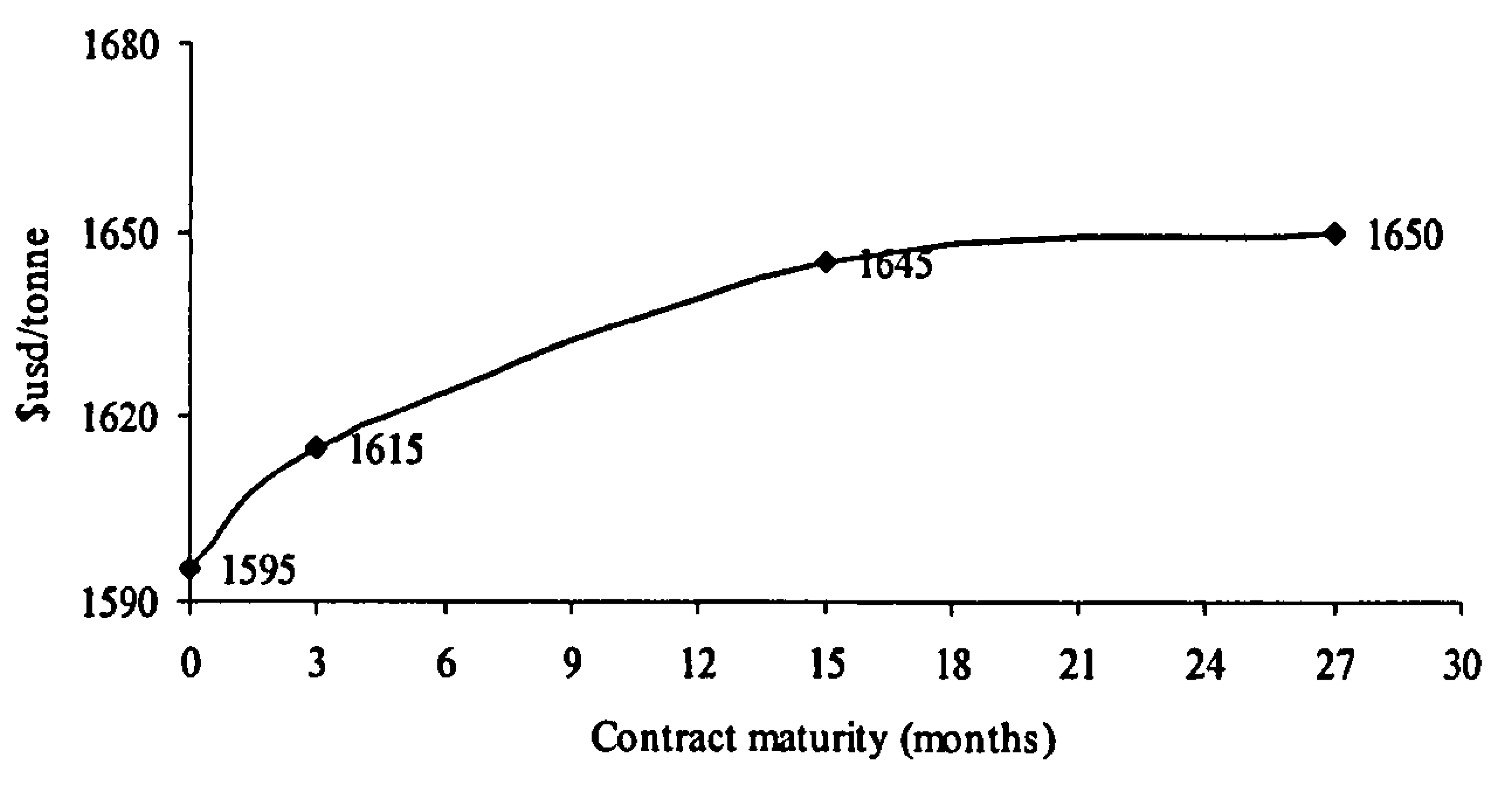
The theory of storage suggests that the link between the spot and futures price consists of two elements – cost-of-carry and convenience yield. The futures price ($F_{t,t+n}$), at time t, for delivery at time $t+n$ equals the price of the underlying asset (S_t) at time t plus the total costs associated with purchasing and holding the underlying asset from time t to $t+n$ and the convenience yield from holding the asset. 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 (for instance, wastage for perishable commodities and transportation costs related to delivery). Mathematically the general price relationship between the spot and futures can be expressed as:

$$F_{t,t+n} = S_t + coc_{t,t+n} - cy_{t,t+n} \tag{1.1}$$

where $coc_{t,t+n}$ represents the cost of carry (carrying costs) necessary to carry the commodity forward from time t to the delivery date of the futures contract, at time $t+n$, and $cy_{t,t+n}$ represents the convenience yield of holding the asset between t and $t+n$.

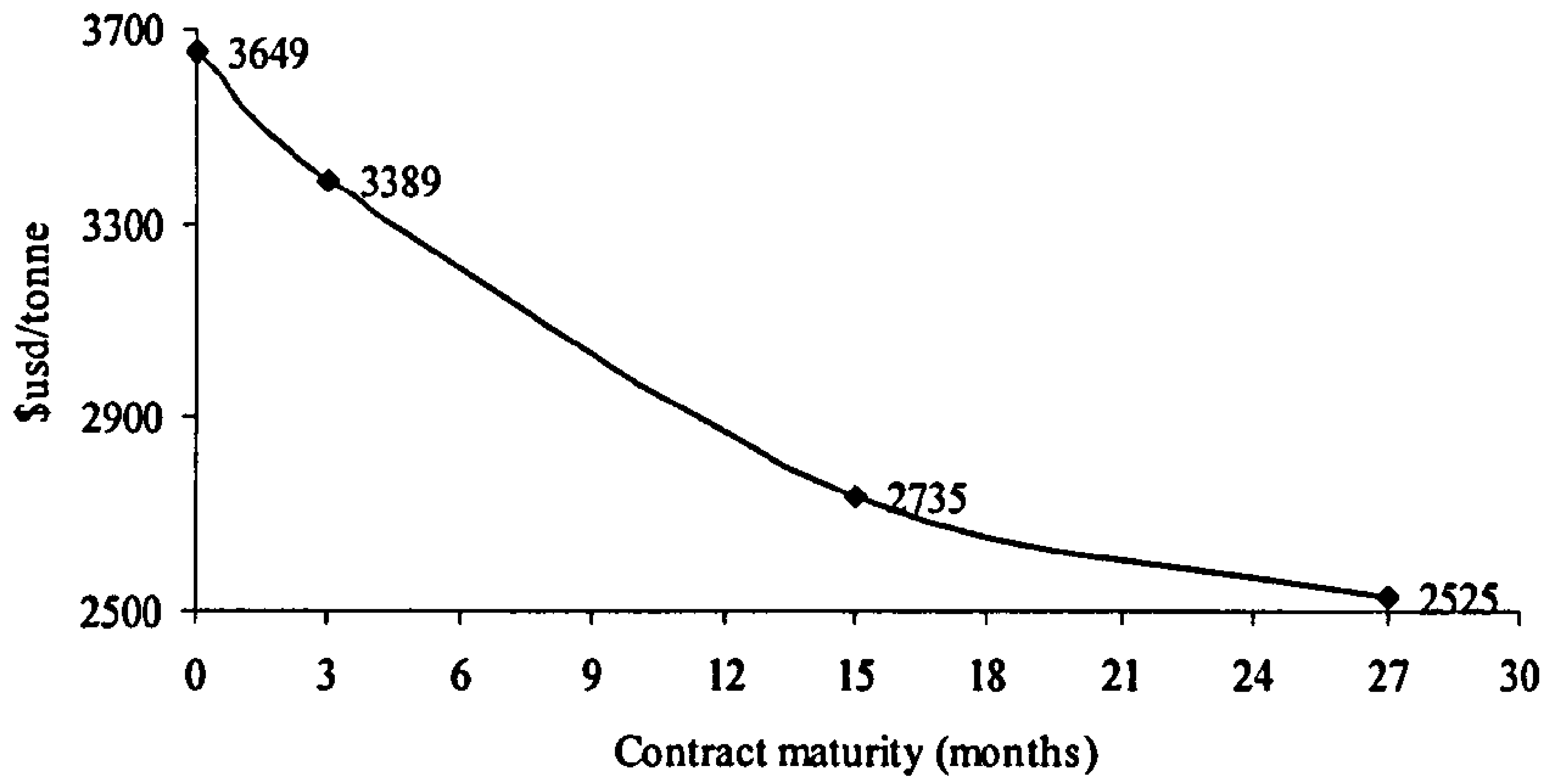
When the cost-of-carry element dominates the spot and futures price relationship, the futures price should always be above the spot price, in which case the market is referred to as being in "contango". Theoretically, any deviations from this equilibrium will be eliminated by riskless "cash-and-carry arbitrage" trades. For example, if the futures price is above the cost-of-carry price then traders in the market can derive arbitrage profits by buying the underlying commodity and selling the futures contracts in what is known as "cash-and-carry" arbitrage. At the maturity of the futures contract, the investor can then deliver the physical commodity against the agreed futures price at a profit. Figure 1.1 plots the prices of the spot, 3-month, 15-month and 27-month futures contracts of aluminium alloy traded on the London Metal Exchange (LME). The upward slope of the forward price curve suggests the market is in contango. On 18 July 2005 the cash buyer price of LME aluminium alloy was 1595 \$/tonne and the 3-month futures price was 1615 \$/tonne. We can assume that the 20 \$/tonne difference between the spot and 3-month futures prices is the total carrying cost during the three month period from 18 July to 17 October 2005. If the 3-month futures price were 1645 \$/tonne on 18 July, one would buy the cash at 1595 \$/tonne and simultaneously short sell a 1645 \$/tonne futures contract and store the metal over three month at the cost of 20 \$/tonne. On 17 October with total spending of 1615 \$/tonne (1595 \$/tonne + 20 \$/tonne) the trader would clear his short position in the futures contract by making delivery at a price of 1645 \$/tonne. Thus he would be able to make a 30 \$/tonne (1645 \$/tonne - 1615 \$/tonne) riskless arbitrage profit.

Figure 1.1 LME aluminium alloy prices on 18 July 2005



In contrast, if the convenience yield element dominates the relationship, the futures price may be below the spot price (or more accurately, below the full-carry futures price indicated by the cost-of-carry) and the market is referred to as being in "backwardation". Under such market conditions, for instance, if there is a shortage in the physical market, market participants will not be willing to lend or sell the physical assets that they have, implying the existence of a convenience yield by holding the assets. The fact that futures prices are below the full carry price in this case, does not necessarily imply an opportunity for reverse cash-and-carry arbitrage. Figure 1.2 graphs the spot, 3-month, 15-month and 27-month futures prices of the copper contracts on the LME on 18 July 2005. The downward slope of the curve suggests that the copper market was in backwardation on that day.

Figure 1.2 LME copper prices on 18 July 2005



1.3.3 Convenience Yield

In the structural models of Working (1949), Brennan (1958), Deatonne and Laroque (1992), RSS (2000), convenience yields arise endogenously as a result of the interaction between supply, demand and storage decisions. In particular, RSS (2000) show that, in a competitive rational expectations model of storage, when stock levels for a commodity in the economy is driven to its lower bound, e.g. in periods of relative scarcity of the commodity available for trading, convenience yields are high. It is worth noting that the existing theoretical models of commodity prices based on the theory of storage (such as RSS 2000) assume risk-neutrality, and thus make no prediction about risk-premia.

Another branch of the literature, also referred to as the no-arbitrage based theory of commodity pricing, models the convenience yield as an exogenous stochastic process (see, for instance, Brennan, 1991; Gibson and Schwartz, 1990; Amin, Ng, and Pirrong, 1995; Schwartz, 1997; and Nielsen and Schwartz, 2004). Spot prices and convenience yields are modelled as separate stochastic processes with a constant correlation. However RSS (2000) point out that the correlation between the spot prices and convenience yields is unlikely to be constant due to its dependence on inventory level. These reduced-form models follow standard contingent claim pricing techniques and have become very popular both in academic research and in commercial applications as they typically allow for closed form solutions. However, reduced-form models are by nature mathematical and make no predictions about what are the appropriate specifications of the joint dynamics of spot and convenience yield. The choices are mostly dictated by analytical convenience and data. Moreover, with the exception of Nielsen and Schwartz (2004), these models do not allow the volatility of spot prices to depend on the convenience yield, as postulated by the theory of storage and empirically confirmed by Fama and French (1988).

Commodities differ from stocks, bonds and other conventional financial assets in that they are continuously produced and consumed. In general there are the following differences (RSS, 2000):

- Commodity futures prices are often "backwardated" in that they decline with time-to-delivery. For example, Litzenberger and Rabinowitz (1995) document that nine-month futures prices are below the one-month prices 77 percent of the time for crude oil.
- The price of a commodity and its volatility are positively correlated since both of them are negatively correlated with inventory levels (Geman, 2005 p. 28).
- Commodity prices are strongly heteroskedastic (see, for instance, Duffie and Gray, 1995) and price volatility is positively correlated with the degree of backwardation (see Ng and Pirrong, 1994 and Litzenberger and Rabinowitz, 1995).

- The term structure of commodity forward price volatility typically declines with contract horizon. This is known as the "Samuelson (1965) effect." However, violations of this pattern occur when inventory levels are high (see, Fama and French, 1988).

- Unlike financial assets, many commodities have pronounced seasonalities in both price levels and volatility.

Because of these very characteristics of the commodity futures market, research in this area must necessarily consider different issues compared to research on the equities and fixed income markets. In particular, the impact of market conditions (such as the inventory levels of the physical commodities) and their time-varying relationship with the dynamics of the commodity spot and futures markets need to be taken into account.

1.4 Motivation and Objectives

Based on the theory of storage and the results in the literature, one can argue that inventory levels dictate marginal convenience yield in a nonlinear fashion. Moreover, the level of convenience yield determines whether the market is, broadly speaking, in backwardation or contango. Through the link between inventory levels, convenience yield, and market conditions, several researchers have already shown that the inventory levels are very important in determining the dynamics of commodity spot and futures prices. However, this has thus far been limited to the relationship between spot and futures price volatility and inventory levels (see, for instance, Nielsen and Schwartz, 2004; Pindyck 2001).

There are several other features of the spot and futures market dynamics for storable commodities which can be expected to depend upon market conditions in a similar fashion. The objective of this thesis is to investigate whether such dependence on market conditions also extends to:

- The price discovery function of futures prices;

- The short-term adjustment of spot and futures prices to the long-run cost-of-carry equilibrium;

- The spot and futures price volatility and their relationship with the inventory level;
- The relationship between price volatility and trading volume.

This is motivated, for instance, by the simple observation that the ability of market players to carry out arbitrage trades depends on market conditions. By definition, a backwardated market can only exist because holders of the commodity benefit more from maintaining their position rather than lending the physical commodity. Clearly this "obstacle" could have implications for the flow of information and the speed of adjustment towards the long-run equilibrium in the commodity spot and futures markets.

A better understanding of the market dynamics of these commodities is of particular interest to participants in industries reliant on the production or consumption such as metal merchants, miners, and smelters. Energy providers, banks, investment funds, trading houses are also active participants in the non-ferrous metals markets. At the macroeconomic level, commodity markets play an important role in the economy of many countries, especially the big commodity producers and consumers such as USA, Australia and China. A greater understanding of the commodity prices has important policy implications for commodity dependent nations for key indicators such as interest rates, inflation and economic growth.

1.5 Contributions

The underlying theme of this thesis is the linkage between market conditions (as proxied by backwardation and contango) and the functioning of the futures market, which includes the futures price discovery function, the short-run and long-run price dynamics, the forecasting performance of the futures price, the dynamics of spot and futures price volatility and inventory level; and the relationship between volatility and trading volume.

A general contribution regarding the time series properties of metal price series is that the stationarity tests used in this thesis not only include conventional tests, but also include tests which allow for endogenous break points to account for structural changes. The finding that the prices and inventory levels are nonstationary, even after allowing for structural breaks confronts the commodity price properties that are illustrated by Deatonne and Laroque (1992)[1]. However, as pointed out by Dixit and Pindyck (1994) nonstationarity is more easily rejected for very long time series.

1.5.1 The Price Discovery of Futures Markets

In general, the price discovery function of futures markets is investigated in the form of testing the validity of the Unbiasedness Hypothesis (UH) in the futures price formation. Thus far, the UH has been tested in a linear framework in the literature. We argue that the mixed results found in the literature may be due to the failure in accounting for the dynamic market behaviour under different market conditions. In Chapter 4, we apply a regime dependent model such as the Markov Regime Switching (MRS) model to examine the dependency of the validity of the UH on the market conditions. The results show that the forecast error (the difference between the futures and settlement price) is positive when the market is in contango and is negative when the market is in backwardation. The nonparametric bootstrap resampling method confirms that the distribution of the mean of the forecast error is left skewed in a backwardation market

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[1] Deatonne and Laroque (1992) observe thirteen agricultural commodity prices over the period of 1900 to 1987 and draw the following stylized conclusions about commodity prices:

- Though they do not claim that all of the prices are stationary, it is suggested that the prices tend to revert to their mean or to a deterministic trend;
- The prices are autocorrelated with autocorrelation coefficients in excess of 0.6;
- The commodity prices are volatile and the variability exhibits seasonality;
- Prices exhibit positive skewness and substantial kurtosis.

and right skewed in a contango market. The empirical findings of this study suggest, for the first time, that the price discovery function of the futures prices depends on the state of the markets and contribute to the literature by offering a sound economic explanation for the rejection of the UH often reported in the empirical literature.

1.5.2 Cost-of-Carry Relationship and Market Conditions

The long-run equilibrium between futures and spot prices has been theoretically investigated and well documented (see, for instance, Heaney, 1998 and Pindyck, 2002). However, limited attention has been paid to the potentially time-varying short-run adjustment of prices toward the long-run equilibrium. Chapter 5 attempts to fill this gap in the literature and contributes in several aspects.

Firstly, it investigates the long-run and short-run relationship between the spot and futures prices with the presence of the cost-of-carry elements in all the seven industrial metal futures market, in comparison to Heaney (1998) who focuses only on the lead market. It is important to investigate all the metals traded on the exchange as any findings of (dis)similarity across markets may be explained by market micro-structure effects (e.g. an illiquid market versus a liquid market) and, hence, it provides a broader and better founded understanding of the behaviour and dynamics of the industrial metal futures market as a whole.

Secondly, the empirical evidence in Chapter 5 suggests that spot prices (and to a lesser extent futures prices) decrease in response to a deviation from the equilibrium and that the inventory level restores equilibrium by building up. This finding is intuitive since if the spot price continues to increase or inventory level continues to decrease, the cost-of-carry equilibrium cannot be restored. However, this fact has not been highlighted in the literature. It has important policy implications since if the test results suggest otherwise the futures markets under examination may not be efficient in the sense that the market reactions to any deviation from the equilibrium cannot be restored by the market itself, but rather needs some external force (e.g. regulation control) to equilibrate the market.

1.5.3 Commodity Price Volatility and Inventory Level

French (1986), Fama and French (1987, 1988), Williams and Wright (1991) and Ng and Pirrong (1994) derive the implications of a convex, decreasing relation between convenience yield and inventory level for spot and futures volatility based on the theory of storage. While several studies in the literature have tested this implication based on the spot and futures price volatility, there have been no attempts to directly test the empirical asymmetric relationship between price volatility and inventory level in the storable commodity markets. The contributions of Chapter 6 are twofold. Firstly, it derives a further testable implication of the theory of storage on the price volatility and inventory changes. Secondly, this is the first academic work to directly test the dynamic relationship between spot and futures price volatility and between the volatility and inventory levels.

1.5.4 Commodity Futures Price Volatility and Trading Volume

Recent studies (see, for instance, Lamoureux and Lastrapes, 1990; Najand and Yung, 1991; Bessembinder and Seguin, 1993; Foster, 1995; Watanabe, 2001) examine the relationship between price volatility and market liquidity in a GARCH framework where the (contemporaneous) trading volume is introduced as an explanatory variable in the conditional volatility process. However the contemporaneous volume-volatility relationship is primarily a test of whether the two processes are driven by identical information flow. Also, as pointed out by Foster (1995) the use of contemporaneous volume leaves open the question of simultaneity bias. In Chapter 7, we test the possible asymmetric relationship between the futures price volatility and trading volume in a TGARCH model. The contribution of this study is twofold. Firstly, to date there exist no research that investigates the trading volume – price relationship under different market conditions in commodity markets. Secondly, the literature that the lead-lag relationship between volatility and volume is examined for the first time in the industrial metal futures markets. The findings provide insight into the liquidity – price relationship in the commodity futures markets in terms of asymmetric response to different market conditions.

1.6 Structure of the Thesis

This thesis consists of nine chapters, including this introduction. There are five empirical chapters dealing with the different topics highlighted in the previous section. In each of these chapters, we discuss the relevant theory; propose and explain the hypothesis; describe the methodology and testing procedures; and report the empirical results before the conclusion.

Chapter 2 is devoted to a review of the relevant literature in the futures markets. The research in the areas related to the topics investigated in the thesis is documented in four sections.

Chapter 3 consists of a discussion of time-series techniques that are employed in this study. It starts with the testing procedures for the stationarity of time series such as the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) (1992) test and Elliott, Rothenberg, Stock Point Optimal (ERS) (1996) test. In particular, we apply the Perron (1997) unit root which allows structural breaks in the test. Univariate and multivariate time-series models, such as the ARMA, VAR, VECM, and Generalized Autoregressive Conditional Heteroscedasticity (GARCH), are also introduced and discussed. The Johansen (1991, 1995) cointegration testing method is also described. The Markov Regime Switching (MRS) model of Hamilton (1989, 1992) that can take into account structural changes is presented. We also present the data set and the time series properties in Chapter 3.

In Chapter 4, we investigate the price discovery function of the metal futures markets in terms of testing the validity of the Unbiasedness Hypothesis. We first apply a linear GMM regression to the whole sample. Subsequent recursive rolling window estimation results suggest strong parameter instability in the UH testing model. Hence we use a testing method which allows for the estimation parameters to be state dependent, specifically the Markov Regime Switching model. Lastly a nonparametric bootstrap resampling technique is used to examine the forecasting performance of futures prices under different market conditions.

Chapter 5 investigates the long-run equilibrium and time varying short-run adjustment of spot and futures prices. The long-run equilibrium is tested using the Johansen (1991,

1995) cointegration technique. A MRS-VECM is applied to capture the regime dependent short-run adjustment from the prices to the long-run equilibrium.

In Chapter 6 the relationships between the spot and futures price volatility and between the volatility and inventory level are examined. As in Chapter 7, the mean process of the spot and futures prices is modelled in a VECM in which in the long-run cost-of-carry relationship is taken into account. A GARCH model is applied to measure the conditional volatility process of the prices. The contemporaneous and lead-lag relationships are investigated in both a linear and nonlinear framework. In particular, the asymmetric relationships as implied by the theory of storage are tested in a Markov Regime Switching model, in which the transition probabilities are determined by the inventory level.

The relationship between the futures price and its volatility and the market liquidity is examined in Chapter 7. The conditional volatility is measured by a GARCH model and we investigate whether the volatility – volume relationship depends on market conditions by introducing dummy variables to account for the backwardation and contango market conditions.

Finally, Chapter 8 summarizes the thesis by outlining the major findings and drawing some conclusions. It also gives suggestions for future research.

2 CHAPTER TWO

A REVIEW OF THE LITERATURE

2.1 Introduction

Given the importance of futures markets in the global financial sector, a large body of academic research has been devoted to examine and explore different aspects and functions of these markets. The aim of this chapter is to present a comprehensive review of previous studies in the functioning of the (commodity) futures markets including: the price discovery of futures prices; price behaviour; market microstructure and hedging in the futures market.

1) The price discovery function of the futures markets has been the subject of many studies especially after Brennan (1958) and Telser (1958) early works on the rational expectation in the futures markets and Fama and French's (1987) notion of the efficient market theory in the futures market. This research area focuses on whether futures price reflect the market participants rational expectation of the future spot price.

2) The second research area investigates the spot and futures price dynamics, such as the contemporaneous spot and futures price relationship, the properties of the returns on futures contracts, and the term structure of commodity futures prices.

3) The third topic covers the futures market microstructure, such as the relationship between prices and trading volume, open interest, and bid ask spread.

4) The fourth research area is in the hedging application, i.e. the optimal hedge ratio between futures and cash contracts.

2.2 Price Discovery and EMH in Commodity Futures Markets

The early literature on the commodity futures market focuses on the relationship between the spot and futures prices, assuming the current futures price reflects the expected spot price (Brennan, 1958; Telser, 1958). The underlying hypothesis is that the futures price is an unbiased predictor of the expected spot price at maturity (the Unbiasedness Hypothesis, UH[2]). Mathematically, the UH can be expressed as: $F_{t,t+n} = E(S_{t+n} \mid I_t)$, where $F_{t,t+n}$ is the futures price at time t with maturity at time $t+n$; S_{t+n} is the spot price at time $t+n$ (settlement price); E is the expectation operator and I_t represents the available information set.

Goss (1981) is among the earliest researchers who test the validity of the UH in the commodity futures markets. He uses monthly (average) prices of the metal contracts traded on the LME (copper, zinc, lead and tin) over the period July 1971 to May 1978 and performs a number of regressions including Ordinary Least Square (OLS) estimation and Hendry's (1976) 'General Instrumental Variable Estimation' method (GIVE), which is a instrument variable estimation method and thus tackles the error autocorrelation problem, to examine the validity of the UH. The findings suggest that the UH cannot be rejected at the conventional significance levels for the case of tin using either the OLS or GIVE estimation method, while the UH is rejected based on the OLS estimates in the copper and zinc markets and is rejected in both cases in the lead market. In a follow-up paper, Goss (1983) tests the semi-strong EMH[3] using the same LME data set and concludes that the futures prices do not fully reflect all public information.

Hsieh and Kulatilaka (1982) test the validity of the UH using three-month forward prices for copper, zinc, lead and tin metals traded on the LME over the period January 1970 to September 1980. They argue that the realised return, which is defined as $r_{t+n} = [F_{t,t+n} - S_{t+n}] / F_{t,t+n}$, should have a zero mean and should not be correlated with

[2] The UH has also been called the 'simple efficiency' hypothesis, 'speculative efficiency' hypothesis and unbiased expectations hypothesis.

[3] Goss (1983) points out that the semi-strong form of the EMH has been tested using two methods: (1) to regress the forecast error ($S_{t+n} - F_{t,t+n}$) for a particular commodity contract upon forecast errors from closely related commodities; (2) to compare the forecast performance of futures prices on spot prices with the forecasts made by some econometric models. Goss (1983) applies the former methodology to test the semi-strong form of the EMH.

returns in another metal market. The null hypothesis of Unbiasedness is rejected for the tin and zinc markets. However, their methodology does not take into account the autocorrelation in the error term due to the overlapping feature of the futures price data[4]. Canarella and Pollard (1986) test the validity of the UH for the metal futures contracts traded on the LME over the period 1975 to 1983 using both overlapping (monthly price) and non-overlapping (quarterly data) observations and three different estimation methods and their results are in favour of the UH regardless the estimation method or the data employed.

In a theoretical two-period equilibrium model, French (1986) illustrates the factors that influence the forecast power of agricultural futures prices. He suggests that futures prices cannot provide reliable forecasts of the expected spot prices unless the variance of the expected spot price changes is large relative to the variance of the actual spot price. This relative variance is related to a number of factors, including the importance of the seasonal production of the agricultural commodities and the cost of storage. For instance, if the marginal convenience yield from storing a commodity is zero and the marginal storage cost is constant, the spot price elasticity equals one. Therefore, shocks to the current price are transmitted perfectly to the expected price; there is no variation in the expected price changes for the futures prices to forecast. In an empirical paper, Fama and French (1987) carry out the empirical tests on 21 commodity futures markets (animal, agricultural, wood and metal[5]) using a regression method in which the difference between the realised and current spot price is regressed on the current basis. They argue that evidence of a positive slope implies that the basis observed at t contains information about the change in the spot price from t to $t+n$. French (1986) and Fama and French (1987) finds strong forecast power in the basis (the futures price) in the animal and agricultural product futures markets but weak evidence in the metal futures markets (especially the precious metals markets). The reason for the latter results, they argue, may largely be due to the fact that storage costs are low relative to the commodity value and the (precious) metal prices are not affected by seasonal demand or supply or by storage costs.

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[4] Overlapping is caused by the fact that the frequency of observations is shorter than the futures contract length (Gilbert, 1986; Krehbiel and Adkins, 1993). Overlapping in the time series suggests serial correlation in the regression model and thus the OLS estimates are inefficient.
[5] The metal futures markets that French (1986) empirically investigates are copper, gold, platinum and silver traded on NYMEX.

However, given that the spot and futures prices are interrelated, econometric theory suggests that a simultaneous system framework, such as a VAR model, might be a more appropriate methodology for examining the validity of the UH in futures markets.

MacDonald and Taylor (1988, 1989) utilise a modified version of Campbell and Shiller's (1987) methodology, which is a Bivariate Vector Autoregressive (BVAR) approach proposed by Sargent (1979), to test the validity of the UH on the LME metal futures markets over the period 1976 to 1987. The BVAR approach allows imposition of the full set of restrictions implied by the UH. They reject the null hypothesis of the UH in the tin and zinc market at the 5% level but fail to reject the null hypothesis in the copper and lead markets. They argue that the rejection of the UH for the tin and zinc markets may be due to market concentration, while the copper and lead markets are more competitive in the sense that they are not producer dominated. They also suggest the possible existence of risk premium in light of the rejection of the UH.

Following the development of the cointegration technique proposed by Engle and Granger (1987) and extended to a multivariate context by Johansen (1988), several authors have applied the cointegration technique and VECM in testing the validity of the UH in the futures markets. For instance, Chowdhury (1991) tests whether the spot and futures prices of the metal contracts (copper, lead, tin and zinc) that are traded on the LME over the period 1971 and 1988 are cointegrated within and across markets. He argues that the presence of cointegration between two different prices implies predictability which, in turn, "indicates that one market is Granger-caused by the other" and, hence, the market could not be efficient. First, he examines whether spot or futures prices in any one of the metal markets are cointegrated with the corresponding spot or futures price in any of the other three markets. Then he tests for the existence of a cointegrating vector between the spot and futures prices within the four markets and rejects the UH based on the results that all spot prices in the markets are cointegrated with each other and that the spot and futures prices are not cointegrated by a (1 -1) cointegrating vector.

Contradictory results are found when the cointegration technique is applied to test the validity of the UH in other markets as well. Krehbiel and Adkins (1993) test the validity of the UH of NYMEX traded futures contracts (such as, silver, copper, platinum and gold) using quarterly data over the period 1960 to 1990. They apply the

Johansen and Juselius (1990) maximum likelihood estimation to test parameter restrictions in a cointegrated system (a VECM). Cointegration evidence is found in all the four metals markets between futures price and the realised spot price, based on which they conclude that the UH holds in the markets examined in the long run. However, Chowdhury's (1991) and Krehbiel and Adkins's (1993) methodology has a drawback. This is because the existence of cointegration suggests that two economic variables, such as the copper and lead spot price, are linked and driven by a common force. However, this does not suggest that information about the copper spot price can be used in predicting the lead spot price. Thus, the finding of cointegration between prices across markets may not be an appropriate condition on which to reject the UH. Also the restricted version of the VECM imposed by the UH does not lead the cash and futures price relationship back to the original formula under the UH (see, Appendix I for proof). Therefore, the existence of cointegration relationship between spot and futures prices is an indication of the linkage between the two variables, however it is only a necessary but not sufficient condition for the UH.

Brenner and Kroner (1995) propose a no-arbitrage cost-of-carry asset pricing model to theoretically show that the existence of cointegration between spot and futures prices depends on the time-series properties of the cost-of-carry element. They argue that the conditions for cointegration are more likely to hold in currency markets[6] while cointegration only exists in commodity markets when the futures prices have fixed and constant time to maturity. Brenner and Kroner (1995) argue that, instead of allowing a futures contract to expire, many researchers roll over to the next nearest contract when expiration approaches (e.g. within two weeks). Theoretically the variance of the residual from this regression is still time-varying (converges to zero), meaning the cointegration cannot theoretically hold. However, in practice the empirical tests are unlikely to pick this up because the cointegration tests usually applied have very little power to detect shrinking variances, such as that of Krehbiel and Adkins (1993).

[6] It is shown theoretically by Brenner and Kroner (1995) that whether spot and futures prices are cointegrated is dependent on the differential between them. In the case of currency market, the differential is the difference between domestic and foreign interest rates. This differential is likely to be stationary since the same set of underlying economic forces typically drives interest rates in both countries. However, in the case of commodities, the differential is the cost-of-carry element, which consists of interest, storage costs and convenience yield. Assuming that storage costs and convenience yields are stationary, the cointegration condition is dependent on the interest rate, which is often found to be nonstationary. Hence the spot and futures prices are not likely to be cointegrated unless the other cost-of-carry elements are included in the cointegration test.

Nevertheless, Kellard, Newbold, Rayner and Ennew (1999), Chow (2001) and Yang, Bessler and Leatham (2001) find the spot and futures prices are cointegrated in commodity futures markets when rolling over futures prices. In particular, Chow (2001) tests the EMH in the precious metal futures (gold, silver, palladium and platinum) traded on the NYMEX between 1970 and 2000 using the cointegration technique and finds that spot and futures prices are cointegrated in all the metal markets examined.

Fujihara and Mougoue (1997) examine the UH in the petroleum futures markets using daily futures prices for crude oil, heating oil, and unleaded gasoline traded on the NYMEX over the period December 1984 to September 1993. They test the UH in a Martingale framework[7] and reject the UH in all the cases based on the significance of coefficients of the lagged prices[8].

Kellard, Newbold, Rayner and Ennew (1999) test the UH in three agriculture futures (soybeans, live cattle and live hogs), two energy futures (gasoil and crude oil) and one financial futures markets (Deutsche mark/dollar exchange rates) using a Vector Error Correction Model. They argue that the findings of a cointegration relationship between the spot and futures prices with a slope coefficient close to unity suggest that the markets are efficient in the long run. However, there is evidence that in the short run changes in the spot price can be explained by lagged differences in spot and futures prices as well as the basis, suggesting a violation of the UH in the short run.

Yang, Bessler and Leatham (2001) examine the price discovery function of the futures prices of storable (corn, oat, soybean, three types of wheat, and cotton) and nonstorable agricultural commodities (pork bellies, hog, live cattle, and feeder cattle) over the period January 1992 to June 1998. Their results suggest that spot and futures prices are cointegrated in most of the markets examined, however, the parameter restrictions imposed by the UH are rejected for most non-storable commodities while they cannot be rejected for most storable commodities. They argue that the storage facilitation in the storable commodity markets is important to price discovery because "arbitrage may

[7] A martingale process satisfies $E_t(x_s) = x_t$ for every $s \geq t$, i.e. the expectations of x at any point in the future equals the present value of x.

[8] Their testable model is $\Delta F_{t,t+n} = \beta_0 + \sum \beta_i \Delta F_{t-i,t+n} + v_t$, where β_i=0, and v_t is iid.

work through storage". Without storage, arbitrage may not work effectively, and it might appear that there is no other economic force that links cash and futures prices together, which is the case in the non-storable commodity markets.

Guerra (2002) tests the efficiency of the foreign exchange futures markets (German Mark, UK pound, and US dollar vs. Swiss franc) in the form of the UH by testing for cointegration between the realised future spot rate and the forward rate (long-run relationship) in a VECM framework. He also investigates the link between the contemporary forward rate and the present spot rate (short-run relationship) and finds evidence in support of the UH in the long run.

To briefly summarise the results on testing the UH in futures markets in the literature: Krehbiel and Adkins (1993) and Chow (2001) find evidence of a cointegration relationship between spot and futures prices in the NYMEX metal futures market and, thus, they support the UH. Fujihara and Mougoue (1997) find evidence against the UH in petroleum futures market. Kellard *et al.* (1999) find evidence in favour of the UH in the long-run in the agricultural, energy and financial futures market. Yang *et al.* (2001) reject the UH in non-storable agricultural futures markets while they accept it in the storable agricultural futures markets. In testing the UH on the LME data, the results are mixed as well. Table 2.1 summarises the results in the literature.

Table 2.1 Literature results on the validity of the UH for LME data

	Period	Market			
		Copper	Lead	Tin	Zinc
Goss (1981)	07/1971-05/1978	Yes	No	Yes	Yes
Hsieh & Kulatilaka (1982)	01/1970-09/1980	Yes	Yes	No	No
Goss (1983)	07/1971-06/1978	No	No	No	No
Canarella & Polland (1986)	01/1975-12/1983	Yes	Yes	Yes	Yes
MacDonald & Taylor (1988,1989)	01/1976-03/1987	Yes	Yes	No	No
Chowdhury (1991)	07/1971-06/1988	No	No	No	No

- Yes: the results are in favor of the UH;
- No: the results are against the UH.

Despite of the plethora of the studies testing the UH in the market of industrial metals, the results are mixed and inconclusive, partly due to deficiencies in the models and methodologies used and partly due to the dynamic market behavior under different market conditions. The UH is an important implication of the Efficient Market Hypothesis and is a joint test of risk neutrality and rational expectations. Accordingly, rejection of the UH has two possible implications. First, the agents may be risk averse, which means there is a risk premium in the futures price making hedging costly. Second, market participants may not form their expectations rationally, i.e. the market is inefficient. The later possibility is unlikely at the aggregate market level due to the high liquidity and large number of market participants. Markets could still be efficient when the UH is rejected in the case where there is a premium in the price forecast when risks are transferred from hedgers to speculators or there are structural changes during the period examined.

In light of the above, several authors have investigated the nature of a potential risk premium in the commodity futures markets. Chatrath, Liang and Song (1997) study the agricultural futures markets (wheat, soybeans, corn, coffee, and cotton) between 1983 and 1995 and propose to use the hedging imbalance, which is measured as the difference between long and short contract trading volume in proportion to the open interest[9], as a proxy for the risk premium. Their empirical results indicate that large speculators, despite their profitability, do not impose an instantaneous risk premium on hedgers. In fact, the presence of speculators enhances market efficiency and may actually lower the cost of hedging.

Miffre (2000) uses a multi-factor asset pricing model to examine the risk premium in 19 futures markets, which include agricultural commodities, metal futures and financial futures traded in the U.S. over the period May 1982 to October 1996. She uses stock levels, commodity index returns, dividend yield, term structure of interest rates and credit spread (spread between low and high grade bond yields) as the instrumental variables in the model. Based on the results, she argues that there is a risk premium in the futures price and therefore concludes in favour of the normal backwardation theory[10]. In follow-up papers, Miffre (2001, 2002) applies the multi-factor asset pricing model in various futures market using different variables (e.g. interest rate term

[9] This measurement is developed around the cost-of-carry model and is designed to examine whether speculators that interact with hedgers receive a return for their role in the contract.

[10] Keynes (1930) theory of normal backwardation is developed around the assumption that hedgers are net short and pay premia to speculators, so that futures prices will be below expected future cash prices (backwardation). Note that this theory also implies that the futures price will be a biased predictor of the future spot price. Several researchers, such as Houthakker (1957) and Cootner (1960) reformulate the original normal backwardation theory to allow for hedging positions to be net long, so that a premium means the futures prices are above the expected future spot price (contango).

structure and bond yield spread) as systematic risk factors and find evidence in support of the existence of a risk premium in the futures market.

It has been highlighted in Chapter 1 that the commodity futures markets are characterised by two different market conditions: backwardation and contango. Under these two market conditions, the underlying economic theory in determining the spot and futures price relationship and the commodity inventory level conditions are different. For instance the cost-of-carry model determines the spot and futures price relationship and the inventory level is usually high when the market is in contango, while the convenience yield dominates and inventory levels are likely to be low when the market is in backwardation. French (1986) suggests that when the supply elasticity is close to one, i.e. inventory levels are sufficiently high, the current shocks are perfectly transferred to the expected spot price, and thus the futures price forecast power is small. Different market conditions may also attract different market participants with different incentives to trade in terms of hedging or speculating in the futures market. Failure in accounting for such differences in market conditions in the UH testing may cause the mixed empirical results in the literature. Consequently the investigation of the possible existence of a risk premium in the futures markets may be somewhat misleading when the condition of its proper empirical estimation (the validity of the UH) doest not yet have a clear answer.

2.3 Spot and Futures Price Dynamics in Commodity Markets

The futures price dynamics have broadly been examined under three main research topics: (1) the properties of the returns on futures contracts; (2) the term structure of commodity futures prices; and (3) the contemporaneous relationship between the futures and spot prices.

Like many financial time series, the returns on commodity futures contracts are also characterised by negative skewness, excess kurtosis and volatility clustering. However, as opposed to the large body of research in equity returns and exchange rates (see, Ederington and Lee, 1993; Andersen and Bollerslev, 1997; Andersen *et al.*, 2001 among many others), research on the distributional properties of commodity futures returns is relatively scare. Bracker and Smith (1999) investigate the properties, such as excess kurtosis and skewness, exhibited in commodity futures returns using daily NYMEX copper futures prices between December 1974 and June 1996 by fitting four GARCH family models (GARCH, Exponential-GARCH, Asymmetric-GARCH, and Threshold-GARCH) for the copper futures returns. The evidence shows that the GARCH models fit the returns time series better in comparison to the benchmark Random Walk model.

Ng and Pirrong (1994) investigate the implications of the theory of storage and whether fundamentals determine the variance of futures price returns in the metal futures contracts (aluminium, copper, lead, zinc and silver) traded on the LME over the period 1986 to 1992 using an error-correction GARCH model. The implications of the theory of storage highlighted in Ng and Pirrong (1994) are that inventory and demand conditions affect (1) the variances and correlations of commodity spot and forward prices and (2) the spread between spot and futures prices (basis)[11]. The (squared) interest and storage cost adjusted basis is used as an error correction term in the mean process of the spot and futures price changes and as an explanatory variable in the GARCH process to account for the different supply and demand conditions as indicated by the spread. The empirical results suggest that: (1) the spot and futures return

[11] The interest and storage cost adjusted spread is calculated as:

$z_t = \frac{\ln\left(F_{t,t+n} - w_{t,t+n}\right) - \ln S_t}{n} - r_{t,t+n} = -cy_{t,t+n}$, where z_t denotes the adjusted spread; $F_{t,t+n}$ is the futures price at time t with maturity $t+n$; S_t is the spot price; $w_{t,t+n}$ is the storage cost from time t to $t+n$; r_t is the interests; and cy_t denotes the convenience yield.

volatility varies directly with the squared spread, and the latter varies less than the former; (2) futures returns are less volatile than spot returns; and (3) the correlation between spot and futures returns declines as the spread widens.

Pindyck (2001) studies the dynamics of commodity prices, production, and inventories, as well as the sources and effects of market volatility in a competitive equilibrium model. He illustrates how prices, rates of production, and inventory levels are interrelated, and are determined via equilibrium in two interconnected markets: a cash market for spot purchases and sales of the commodity, and a market for storage. Pindyck (2002) uses a structural model that describes equilibrium in these two aforementioned competitive markets to empirically examine the relationship between commodity price dynamics and inventory levels in the petroleum complex (crude oil, heating oil and gasoline) markets over the period January 1984 to January 2001. In Pindyck (2002) the price volatility is calculated as the standard deviation of the daily log changes in spot and futures prices and convenience yield is derived from the futures price. He shows that changes in price volatility are not predicted by market variables such as spot prices, inventory levels or convenience yield, and can be viewed as largely exogenous. However, changes in volatility are found to directly affect those market variables.

The stochastic behaviour of commodity futures prices has also been studied in the context of the term structure of futures prices. In particular the futures price volatility has been investigated in terms of testing the Samuelson Hypothesis, which states the futures price volatility increases as maturity approaches. Samuelson (1965, 1976) argues that one would expect a negative relationship between maturity and futures price volatility, since a piece of information released when there is a long time to maturity will have little effect on futures prices, but the same information released just before maturity will have a large effect. For instance, Black and Tonks (2000) study the fluctuation of agricultural futures price volatility during the life time of the futures in a three-period rational expectation equilibrium model and find evidence in favour of the Samuelson Hypothesis.

Urich (2000) examines the stochastic term structure of metal futures prices using daily futures price for gold, silver, and copper contracts traded on the COMEX over the period January 1990 to December 1996 in a stationary multi-factor model. The empirical results show that the shape of the term structure for gold and silver is much different from that for copper. The volatility of returns on copper futures prices shows a U shape during the life of the futures contract, while the volatility of the gold and silver futures prices is rather flat. Evidence also suggests that the gold or silver futures contracts with different maturities can be used as substitutes for one another, but the copper futures contracts cannot. He suggests the underlying reason for such differences could be due to the inventory effect in the copper market especially when the inventory levels are low and the higher carrying costs of copper relative to its value. On the other hand, gold and silver is usually regarded as value commodity whose price is not directly linked to its inventory[12] or supply-and-demand condition.

Routledge, Seppi and Spatt (2000) develop a competitive rational expectations equilibrium model of the term structure of forward prices for storable commodities and calibrate the model to crude oil futures data. In their model, inventory levels play a crucial role as an endogenous state variable summarizing the cumulative impact of past shocks and convenience yield is calculated using the cost-of-carry relationship. They show that the equilibrium term structure of spot and futures prices is decreasing in the inventory level and that violations of the Samuelson Hypothesis occur when inventory is sufficiently high. In particular, the futures price volatility can initially increase with contract horizon.

Another research frontier on commodity derivatives price formation is represented by the stochastic models of the commodity price. Gibson and Schwartz (1990) develop and empirically test a two-factor model for pricing financial and real assets contingent on the oil price. The two factors considered are to the spot price and the instantaneous convenience yield. Schwartz (1997) modifies the Gibson and Schwartz (1990) two-factor model to a three-factor model by including the stochastic interest rate. Nielsen and Schwartz (2004) propose to incorporate the time-varying correlation between the forward and spot price volatility suggested by the theory of storage when modeling commodity prices. They use daily LME copper 3, 15, 27 months futures and spot prices between July 1993 and December 1999 to empirically test the model. They find that the link between return volatility and convenience yield is statistically significant,

[12] Urich (2000) suggests that the newly mined gold adds only one to two percent per year to the total stock.

but the impact of convenience yield on forward prices is relatively small. In particular when convenience yields are high, spot price return volatility can be more than twice the volatility when convenience yields are near their long term mean. Thus, when forward prices are in backwardation, the probability of large price shock is significantly higher.

Wahab, Cohn and Lashgari (1994) and Wahab (1995) study the futures price dynamics of gold and silver contracts traded on the New York Commodities Exchange (COMEX) for the period January 1982 to July 1992. Given the existence of spread trading activity, i.e. a simultaneous long position in one metal futures market and a short position in another metal futures market of the same maturity, Wahab (1995) estimates the optimal spread ratio, which is defined as the ratio between the USD positions in gold and silver contracts, using a Bivariate GARCH model. He concludes that a bivariate AR (1)–GARCH (1,1)–M model provides a reasonably good description for the joint process generating price changes. The estimated optimal spread ratio apparently generates economic profits on the basis of out-of-sample tests, which provides evidence against the notion of the EMH in precious metals markets.

Brenner and Kroner (1995) use a no-arbitrage, cost-of-carry asset pricing model to theoretically show that the existence of cointegration between spot and futures prices depends on the time-series properties of the cost-of-carry, such as the interest rates, storage costs and convenience yield. They show that if the spot and futures price differential has a stochastic trend, then spot and futures prices will not be cointegrated by themselves and the differential must be included in the system to find cointegration. They also point out some important features when testing the cointegration relationship between spot and futures prices. For instance, if the futures contracts have a fixed date of expiration the spot and futures prices cannot drift apart by nature[13].

In line with Brenner and Kroner (1995), Heaney (1998) tests the equilibrium relationship between the spot and futures prices in the presence of the major cost-of-carry elements (interest rate and inventory level) in the lead futures market using

[13] This point can be observed from the equation: $F_{t,t+n} = S_t + D_{t,t+n} + Q_{t,t+n}$, where $D_{t,t+n}$ is the differential (including interests, storage costs and convenience yield) and $Q_{t,t+n}$ is the marking-to-market term. Any regression of spot price on futures price for a fixed expiration date $t+n$ has a residual that converges to zero as $n \rightarrow 0$, no matter what the time-series properties of the differential are. (Brenner and Kroner, 1995)

quarterly data from 1976 to 1995 on the LME.[14] He finds evidence that spot and futures prices in this market are related through the cost-of-carry relationship based on the existence of a cointegration relationship among the cost-of-carry elements. By including the cointegration relationship defined by the cost-of-carry model as an error correction term in the spot price changes model, Heaney (2002) finds that the one-step ahead forecasting performance of the Error Correction Model is better than that of the simple OLS model using quarterly LME lead date between December 1964 and June 1995.

Sarno and Valente (2000) examine the dynamics of the contemporary relationship between spot and futures prices in stock index futures markets using weekly data for S&P 500 and FTSE 100 indices. They apply Markov Regime Switching vector equilibrium correction models (MRS-VECM) and find that the MRS-VECM explains the return process better than the linear VECM model. In their model, the spot and futures price process is modelled within a three-regime MRS (3)-VECM (1) determined by the Krolzig (1997) "bottom-up" procedure, which starts with a less restricted MRS model with limited number of regime dependent parameters and check the model against alternatives which have a larger number of regime-dependent parameters. They find that two of the regimes characterise a large proportion of the price movements while the third regime seems to only pick up the outliers. This study emphasises that the dynamic relationship between spot and futures prices is likely to be regime dependent.

To summarize, the literature on commodity price dynamics has covered various aspects. In particular, it has been highlighted that the market fundamentals, such inventory levels, play an essential role in determining the price dynamics (volatility). However, the nonlinear relationship between inventory level and commodity price volatility, which is implied by the theory of storage, has not been paid enough attention in the empirical literature. This leaves a gap for further contributions in this area of research.

[14] The cost-of-carry model is defined as: $F_{t,t+n} = S_t \cdot \exp(r_{t,t+n} + sr_{t,t+n} + sle_t)$, where, $r_{t,t+n}$ is the risk-free rate, $sr_{t,t+n}$ is the costs of storage and sle_t is the inventory level at time t.

2.4 The Relationship between Prices and Trading Volume

There are two main theories explaining the relationship between prices and trading volume: the Mixture of Distribution Hypothesis (MDH) of Clark (1973) and the Sequential Information Flow (SIF) of Copeland (1976). The MDH of Clark (1973) is based on the assumption that both price changes and volume follow a joint probability distribution. Consequently, price changes and trading volume should be positively correlated because they jointly depend on a common underlying variable, which is normally interpreted as the random flow of information to the market. Evidence in support of the MDH is provided by Epps and Epps (1976) who suggest that price changes follow a mixture of distributions, with transaction volume being the mixing variable.

The SIF hypothesis proposed by Copeland (1976) and discussed further in Jennings *et al.* (1981) assumes that information is disseminated in the market sequentially and randomly. Therefore, informed traders who obtain the information first, take positions and adjust their portfolios accordingly, which results in shifts in supply and demand and a series of transitory equilibria. Once the information is fully absorbed by all traders, informed and uninformed, then equilibrium is restored. This sequential dissemination of information initiates transactions at different price levels during the day, the number of which increases with the rate of information flow to the market. Consequently, both trading volume and movement in prices increase as the rate of arrival of information to the market increases, which imply the existence of a positive relationship between the two variables.

Karpoff (1987) provides a comprehensive review on previous empirical and theoretical research on the price changes and trading volume relationship in financial markets. He summarizes two stylized facts of the trading volume – price relationship: first, the correlation between trading volume and absolute value of price changes is positive in both equity and futures markets; second, the correlation between volume and price change *per se* is positive in the equity market. He also identifies some issues for further research especially more research on derivative markets due to the lack of empirical evidence.

Lamoureux and Lastrapes (1990) examine the trading volume – volatility relationship for 20 actively traded stocks in the US. They use contemporaneous trading volume as an explanatory variable in the variance equation of an ARCH model and find that the inclusion of volume eliminates the persistence in the volatility. Therefore they suggest that trading volume can explain price volatility. A major concern with this type of investigation is that the use of contemporaneous trading volume to explain volatility raises the issue of simultaneity bias since trading volume is not an exogenous variable. One way to tackle this issue is to include lagged trading volume in the GARCH model. However, when Lamoureux and Lastrapes (1990) include lagged trading volume in the ARCH specification, it is found to have little explanatory power over volatility.

Najand and Yung (1991) examine the trading volume-volatility relationship in the T-bond market traded on the CBOT over the period January 1984 to August 1989 using a GARCH model. By including the lagged trading volume in the GARCH model, they find a significant and positive relationship between the lagged trading volume and volatility. Unlike the study by Lamoureux and Lastrapes (1990), Najand and Yung (1991) find that the GARCH effects remain when contemporaneous trading volume is included in the equation for the conditional variance.

Bessembinder and Seguin (1993) study the relationship between trading volume, price volatility and market depth, which is proxied by open interest, in eight physical and financial futures markets. They find a strong positive relationship between contemporaneous volume and volatility, and the impact of an unanticipated changes in trading volume is between two and 13 times greater than the effect of changes in anticipated or expected trading volume. Further, they suggest that the effect of unanticipated volume shocks on contemporaneous volatility is asymmetric, with positive shocks associated with 76% greater volatility. However, this study does not take into account the stochastic properties of time series such as stationarity.

Foster (1995) examines the price volatility and trading volume relationship in the crude oil futures market using the GARCH framework and GMM estimation method. More specifically he investigates whether the trading volume associated with a price rise is different from that associated with a price fall, as well as whether the market size (International Petroleum Exchange IPE vs. NYMEX contracts) or maturity of a futures contract affects its volume-volatility relationship. He finds that the relationship between trading volume and volatility is symmetric, i.e. the trading volume associated with a price rise is not different from that associated with a price fall, while market size and maturity has little effect on trading volume. Based on the finding that trading volume and price volatility are largely contemporaneously related, he suggests that both variables are driven by the same factors, assumed here to be information flow.

Wang, Yau and Baptiste (1997) examine the relationship between trading volume and transaction cost, which is measured by the bid ask spread (BAS) in seven futures markets in the US over the period January 1990 to April 1994 (Financial futures: S&P500 index futures, Deutsche Mark, T-bond; agricultural futures: wheat, soybean; metal futures: copper and gold). They apply a VAR model to explain the joint determinants of trading volume and BAS. Their results suggest that there is a positive relationship between trading volume and intraday price volatility, and a negative relationship between trading volume and BAS, after controlling for the third factor across all the futures markets under examination.

Malliaris and Urrutia (1998) study the relationship between trading volume and settlement prices of six agricultural futures contract (corn, wheat, oats, soybean, soybean meal, and soybean oil) over the period January 1981 to September 1995. Using cointegration and Granger causality techniques, they find that there exists a long-run relationship between price volatility and trading volume in all the six futures markets. They also find evidence for the existence of a bi-directional causal effect between trading volume and price in corn, soybean and soybean meal markets. Moreover, they suggest that, in general, price tends to lead trading volume changes in the short run.

Wang and Yau (2000) explore the dynamic behaviour of trading volume, bid ask spread and price volatility using S&P500 index, Deutsche Mark, silver and gold futures between January 1990 and April 1994. They apply a three-equation simultaneous structural model to examine the relationship between two of the three variables (trading volume, BAS and price volatility) conditional on the third one. They find a positive relationship between bid ask spread and price volatility and a negative relationship between trading volume and bid ask spread.

Watanabe (2001) examines the relation between price volatility, trading volume and open interest for the Nikkei 225 stock index futures traded on the Osaka Securities Exchange (OSE) over the period August 1990 to December 1997 using Bessembinder and Seguin's (1993) methodology. The trading volume and open interest are partitioned into expected and unexpected components using an autoregressive model in which the residuals are used as the unexpected components. He reports a positive relation between volatility and unexpected trading volume as well as a significant negative relation between volatility and expected open interest.

Locke and Venkatesh (1997) study the factors that influence transaction cost, which is often simply taken as the BAS, using a microstructure model of customers and market makers (sometimes the traders), to examine the BAS difference among the groups. They utilise microstructure data such as the number of trading participants, inventories, and trading volume in each group. The data set comprises futures prices from January 1992 to June 1992 in five agricultural futures (live hogs, pork bellies, live cattle, lumber, and feeder cattle) and seven financial futures markets (Canadian dollar, Swiss franc, Deutsche Mark, Pound sterling, Japanese yen, Eurodollars, and S&P 500). They show that the BAS is inappropriately applied in futures markets as a transaction cost proxy mainly due to two reasons. Firstly direct transactions between customers lower the costs which are below the quoted BAS. Secondly the strategic behaviour by market makers to control inventory and the resulting elaborate pricing mechanism cause the actual transaction costs to be lower than the BAS.

To briefly summarise, most of the early findings of the price-volume relationship suggest that there is a positive relationship between trading volume and prices and price volatility. However, the relationship between trading volume and price volatility has generally been assumed to be linear. Obviously this assumption may not be valid in some markets. For instance, Silvapulle and Choi (1999) show that there exists a nonlinear relationship between the price volatility and trading volume in the Korean stock market. The possibility of the existence of a nonlinear relationship between price volatility and trading volume has not been investigated in the commodity futures markets. Moreover, little attention has been paid to examining the relationship between trading volume and conditional price volatility in commodity futures markets, particularly the metal futures markets traded on the LME.

2.5 Hedging using the Futures Contract

Perhaps the primary reason for the existence of futures markets is that they provide a market place where risks can be transferred among market participants with different risk preferences. Even though hedging is not a primary research topic in this thesis because of the specific characteristics of the metal futures markets examined (the LME introduces new futures contracts every working day and the 3-month futures contracts are settled daily in the prompt day), we feel it is crucial to include the literature on this topic. Moreover, the concept of risk premium is important in the investigation of the price discovery function of the futures prices.

In 1932, Hoffman stated that "hedging is risk shifting" (Hoffman 1932 p.382), where the word 'hedging' referred to holding a long or a short position in the futures market, where the price has been fixed before making actual delivery. This perspective on hedging as the most effective insurance had already been formulated by the prominent English economist Marshall in 1919: "the hedger does not speculate: he insures" (Marshall, 1919 p. 260). Economists, such as Keynes (1930), Hicks (1939) and Kaldor (1939) discuss hedging as an action to avoid risk or to insure. Under such argument, any loss incurred by a hedger on a completed hedge is nothing but an insurance premium, paid to the speculator willing to assume the risk. Until 1950s this view dominated the explanation for hedging activities in different markets.

In the early 1950s the insurance view of hedging was challenged by several researchers, the first of whom was Working (1953). Working (1953) argues that hedgers enter into a position when a profit motive is involved through the exploitation of (expected) changes in the basis. In this view, hedging is a form of arbitrage between cash and futures prices and it is undertaken to profit from predictable changes in the basis and not specifically to reduce risk. Working (1967) stated that (short) hedgers often lose money to speculators on futures transactions, even in periods when the market prices of the contracts under consideration have gone down. Thus, according to Working, the hedgers pay a premium to the speculators and, hence, Working's argument falls back to the aforementioned concept of "insurance". Stein (1961) and Johnson (1960) adopt portfolio theory as founded by Markowitz (1959) to explain hedging as a process of maximization of the expected utility derived from a portfolio of cash and futures positions. According to this theory, the hedger explicitly weighs risk and return against one another.

Over the years, a number of researchers have attempted to explain the theoretical reason to hedge and estimated the Optimal Hedge Ratio (OHR) for different markets. The simplest methodology is to hedge on a one-to-one basis, which is also known as the naïve hedging strategy. This method assumes that the returns on spot and futures contract should be exactly the same and, accordingly, one should take x dollars in the futures market to hedge an x dollars spot position. However, such an assumption is largely dependent on the characteristic of the joint probability distribution of the returns on spot and futures contracts. Ederington (1979) estimates the optimal hedge ratio for a hedger whose objective is to minimize the risk of the hedged portfolio consisting of a risky asset and a futures contract and finds, in this case, that the hedge ratio is equal to the OLS estimate of the slope in a linear regression. The OLS estimated hedge ratio, however, is subject to the regression specification. In particular, it is widely known that the return probability distribution is not normal and has time varying variance, which may make the OLS estimated hedge ratio inaccurate. As a result, more sophisticated estimation methods have been developed and applied in the literature.

Myers (1991) estimates the OHR using a GARCH approach, and compares its hedging performance with "no hedge" and hedge ratios estimated by conventional OLS and moving sample variances and covariance hedge methods. In this model the goal of hedging is to maximize the expected utility which is represented by a von Neumann-Morgenstern utility function (Neumann and Morgenstern, 1944)[15]. The OHR is derived to be the ratio of the conditional covariance between cash and futures prices to the conditional variance of futures ($OHR = \sigma_{sf} / \sigma_{ff}$). The underlying assumption is that the expected return on futures is zero. He empirically tests the hedging performance using variance OHR estimation methods on the wheat futures contract traded on the CBOT between June 1977 and May 1983 and finds that the GARCH hedging strategies reduces the conditional standard deviation of the cash position by 45% to 48%[16] which

[15] Neumann and Morgenstern (1944) defined the von Neumann-Morgenstern utility function over lotteries or gambles. An agent possesses a von Neumann-Morgenstern utility function if she ranks uncertain payoffs according to (higher) expected value of her utility of the individual outcomes that may occur.

[16] The cash position standard deviation is reduced by 45.2% in sample and is reduced by 47.5% out of sample. On aggregate the cash position standard deviation is reduced by 45.7%.

is marginally better in terms of variance reduction than either the OLS hedge or the moving sample variances and covariance hedge.

Low *et al* (2002) show that when futures and spot prices follow the cost-of-carry relationship an OHR can be derived from a VECM, which also incorporates maturity effects. They use Nikkei225 index futures contract and Sulfur Fuel oil on the Singapore International Monetary Exchange (SIMEX) to conduct empirical tests and compare the performance of the model with that of the naïve, OLS, and GARCH hedging strategies. Their results show that the static cost-of-carry hedging model outperforms other hedging strategies for the Nikkei225 index (the hedging effectiveness is between 95% and 98.2% depending on the hedging horizon[17]) on an ex-ante basis. In the Sulfur Fuel Oil market, the dynamic cost-of-carry hedge outperforms the other models when the hedging horizon is one or two weeks (the hedging effectiveness is 82%) and when the horizon is beyond two weeks the static cost-of-carry model outperforms (with hedging effectiveness of 93%).

Based on the argument that the dynamic relationship between spot and futures returns may be characterised by regime shifts, Alizadeh and Nomikos (2004) use a Markov Regime Switching model to estimate the OHR in the FTSE 100 and S&P 500 stock index futures markets. The performance of the MRS hedge ratios is compared to that of alternative models such as GARCH, ECM and OLS models in and out of sample. Their results show that MRS hedge ratios outperform the other models in reducing portfolio risk in the FTSE 100 markets both in and out of sample (with hedging effectiveness of 96.3%), while only within sample in the S&P 500 markets (with hedging effectiveness of 97.7%).

[17] However, the GARCH hedging effectiveness for Nikkei225 is between 33% and 45.3%. The GARCH hedge generates negative hedging efficiency for the Sulfur Fuel Oil market.

2.6 Concluding Remarks

As shown in the previous sections, there exists a large body of research on the functioning of commodity spot and futures markets. The theoretical basis is the theory of storage, which suggests that storable commodity futures markets are characterised by two market conditions – backwardation and contango – depending on the supply-demand situation in the physical commodity market. A market in backwardation is generally associated with scarcity of supply and may well behave differently from a market in contango, for instance due to the absence of arbitrage possibilities in a backwardation market because of the existence of convenience yield.

In light of the above, the review of the literature presented in this chapter has reviewed a number of areas of potential improvement. Firstly, tests of the Unbiasedness Hypothesis are in general based on the assumption that the ability of the futures price to predict the future spot price does not vary with market conditions. It can be argued that backwardated commodity futures markets, for instance, due to supply disruptions or natural disasters, leads to highly volatile prices and increasing uncertainty about the future path of the spot price. Consequently, it is likely that the price discovery role of the futures price is affected by such changes in market conditions. Combined with the mixed empirical results of the existing linear test of the UH, we propose that the test of unbiasedness in the commodity futures markets should account for such variations in the underlying price dynamics.

Secondly, the literature has investigated the cost-of-carry relationship in a cointegration framework, but it has not examined how the market reacts to any divergence from the long-run cost-of-carry equilibrium. From a practical point of view, knowledge of how the market adapts and which factors (such as the spot or futures price, or inventory level) contribute to the restoration of the equilibrium can be informative and economically significant. In this thesis, we therefore build on the literature to show the reaction in prices and inventory level when there are deviations from the long-run cost-of-carry relationship, particularly under different market conditions.

Thirdly, the theory of storage suggests the presence of a nonlinear relationship between commodity futures price volatility and the inventory level. However, there has not been any direct empirical test of this relationship in the literature. The LME data set applied in this thesis is particularly suitable to empirically test and attempt to verify this theoretical relationship. This is due to the strong link between the base metal industry and the exchange (the LME has historically been primarily a hedger's market for producers and consumers) and the resulting availability of inventory data that is reflective of the supply/demand balance. This enables us to directly test the nonlinear relationship between price volatility and inventory levels.

Fourthly, the relationship between price volatility and trading volume, as a proxy for information flow in the market, has been assumed to be independent of market conditions in the literature. However, due to the typically constrained supply conditions in a backwardated market, and therefore presumably a reduced ability to absorb further demand or supply shocks, commodity prices can be expected to be more sensitive to information flow compared to when the market is in contango. Research in this area should therefore allow for a non-linear dynamic volatility – volume relationship.

3 CHAPTER THREE

METHODOLOGY AND DATA

3.1 Introduction

This chapter presents the econometric techniques that are used in the thesis, starting with the unit root tests, VAR, VECM, Granger causality test, GARCH model and the Markov Regime Switching model. These models and techniques are used to perform various tests to investigate the functioning of metal futures markets. In addition to conventional unit root tests, particular emphasis is made on the Perron (1997) unit root test with structural breaks. Johansen (1991, 1995) cointegration test and the Markov Regime Switching model are used to model and test different aspects of futures market dynamics, such as the price discovery. Unless necessary the same content will not be repeated in the following chapters.

3.2 Stationarity and Unit Root Tests

A random process y_t is strictly stationary if its statistical parameters (mean, variance and autocovariance) do not change with time. The most important property of a stationary process is that the second order cumulative distribution functions (such as autocorrelation and autocovariance) depend only on the lags and does not change with the time at which the function is calculated. A time series is trend stationary if it would be stationary after a time dependent trend is removed, and the process is said to be difference stationary if taking differences achieve stationarity. Conventional estimation methods for time series modeling assume that the time series variables in regressions are stationary. Classical regression models often assume that the regression variables are stationary so that the standard proofs of consistency and asymptotic normality may hold for least-squares estimates. As noted by Granger and Newbold (1974), the presence of non-stationary variables might cause a spurious regression. A spurious regression typically has superficially high R-square and significant t-statistics, however, the results may not make economic sense.

3.2.1 Augmented Dickey-Fuller unit root test

Dickey and Fuller (1979) propose the Dickey-Fuller unit root test based on a simple Autoregressive AR(1) model:

$$\Delta y_t = \alpha \cdot y_{t-1} + \varepsilon_t \tag{3.1}$$

where, y_t is the time series under examination; Δ is the lag operator, $\Delta y_t = y_t - y_{t-1}$; and ε_t is an *i.i.d.* process with mean zero and variance one.

The null and alternative hypotheses are: $H_0 : \alpha = 0$; $H_1 : \alpha < 0$ and are evaluated using the conventional *t*-ratio for α: $t_\alpha = \hat{\alpha} / se(\hat{\alpha})$ (where, $\hat{\alpha}$ is the estimate of α and $se(\hat{\alpha})$ is the coefficient standard error. Dickey and Fuller (1979) show that under the null hypothesis of a unit root, this statistic does not follow the conventional Student's *t*-distribution, and they derive asymptotic results and simulate critical values for various test and sample sizes. More recently, MacKinnon (1991, 1996) implements a much larger set of simulations than those tabulated by Dickey and Fuller. The simple DF unit root test is valid only if the series is an AR(1) process. If the series is correlated at higher order lags, the assumption of white noise errors ε_t is violated.

In order to allow for autocorrelation in the error term, ε_t, Said and Dickey (1984) augment the DF test by assuming that the time series follows an AR(p) process and adding p lagged difference terms to the RHS of the test regression. The ADF test is carried out in the form of:

$$\Delta y_t = \alpha \cdot y_{t-1} + \sum_{j=1}^{p} \beta_j \Delta y_{t-j} + \varepsilon_t \tag{3.2}$$

The unit root test is a one-tailed t-test on the parameter $\alpha = 0$ against the stationary alternative $\alpha < 0$. The ADF test is given again by the *t*-statistics $t_\alpha = \hat{\alpha} / se(\hat{\alpha})$. Said and Dickey (1984) demonstrate that the ADF test is asymptotically valid in the presence of a moving average component, provided that sufficient lagged difference terms are included in the test regression. The major practical issue that one has to face when performing an ADF unit root test is to specify the number of lags (lag length) to be added to the test regression (zero yields the standard DF test; integers greater than zero correspond to ADF test).

3.2.2 Phillips-Perron unit root test

The asymptotic distribution in Dickey and Fuller (1976) is valid only for *i.i.d.* innovations. However, Phillips (1987) and Phillips and Perron (1988) demonstrate that the ADF test is not asymptotically justified when innovations follow general forms of serial correlation and heteroscedasticity. They proposed modified versions of the statistics $\hat{\alpha}$ and t_α that allow for fairly general forms of serial correlation and heteroscedasticity (the PP test). The PP test is based on the statistic:

$$\tilde{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0} \right)^{1/2} - \frac{T(f_0 - \gamma_0)se(\hat{\alpha})}{2 f_0^{1/2} s} \tag{3.3}$$

where $\hat{\alpha}$ is the estimate, and t_α is the *t*-ratio of α, $se(\hat{\alpha})$ is the coefficient standard error, and s is the standard error of the test regression. In addition, γ_0 is a consistent estimate of the error variance; f_0 is an estimator of the residual spectrum at frequency zero.

One advantage of the PP test over the ADF test is that the PP test is robust to general forms of heteroscedasticity in the error term. Another advantage is that there is no need to specify a lag length.

Using a Monte Carlo simulation, Schwert (1989) shows that both the ADF and PP tests suffer from Type I error (reject the null $I(1)$ hypothesis much too often when it is true) and that the PP test is worse than ADF in this regard. A further issue with the ADF test is the choice of lag length p. If p is too small then the serial correlation in the errors will bias the test, but if p is too large the power of the test will suffer.

3.2.3 ERS Point-Optimal unit root test

Elliott, Rothenberg and Stock (ERS) (1996) propose a point-optimal test for unit roots. The ERS test follows a two-step procedure by first de-trending the data and then testing for unit roots. They showed that a substantial increase in power is possible by de-trending the data using generalized least squares (GLS) and then running the traditional DF-test on GLS-detrended data. First the GLS estimation is carried out to obtain the detrended residuals.

$$\hat{y}_t = x_t - \hat{\alpha} - \hat{\beta} \cdot t \tag{3.4}$$

Then the Dickey-Fuller (DF) test is applied to the residuals $\hat{y}_t$. The null hypothesis of the ERS test is that there is a unit root in the variable

$$\hat{y}_t = \rho \cdot \hat{y}_{t-1} + \varepsilon_t \tag{3.5}$$

where ε_t is an i.i.d. process with mean zero and finite variance.

The null hypothesis is H_0: $\rho = 0$ against the alternative H_1: $\rho = 1 - \bar{c}/T$ where $\bar{c}$ is a positive constant under which the test is constructed. For example, when the regression (3.5) has an intercept only, $\bar{c}$ is set to -7, whereas $\bar{c}$ is set to -13.5 when regression (3.5) has an intercept and time trend (ERS, 1996). Based on stochastic simulation, ERS (1996) suggest that the two-step detrended ERS unit root test is more powerful than the Dickey-Fuller test.

3.2.4 KPSS Stationarity Test

The abovementioned tests are tests for non-stationarity, as the null hypothesis for the variable under investigation is non-stationarity. Kwiatkowski, Phillips, Schmidt and Shin (KPSS) propose a test that starts from the null hypothesis of stationarity, i.e. the KPSS test assumes the time series y_t to be (trend-) stationary under the null. The KPSS statistic is based on the residuals from the OLS regression model:

$$y_t = \alpha + \beta \cdot t + k(x_1 + \cdots + x_t) + \eta_t \tag{3.6}$$

where y_t is the time series under examination; t is the time trend; x_t is *i.i.d.* and η_t is a zero mean stationary process. So for $k = 0$, the process is trend stationary and for $k \neq 0$ it has a unit root. The null hypothesis is H_0: $k = 0$, against the alternative H_1: $k \neq 0$. Under the null H_0 the regression (3.6) is run using Ordinary Least Square (OLS) obtaining the residuals $\hat{\eta}_t$. The partial sum is calculated as $S_t = \sum_{i=1}^{t} \hat{\eta}_t$ and is integrated under H_0, i.e. the variance of S_t increases with t. The KPSS statistics is a Lagrange Multiplier (LM):

$$KPSS_T = \frac{\sum_{t=1}^{n} S_t^2}{n^2 \hat{\varpi}_T^2} \tag{3.7}$$

where $\hat{\varpi}_T^2 = \hat{\sigma}_\eta^2 + 2\sum_{\tau=1}^{T}(1 - \frac{\tau}{T-1})\hat{\gamma}_\tau$ is an estimator of spectral density at a frequency of zero. $\hat{\sigma}_\eta^2$ is the variance estimator of η_t and $\hat{\gamma}_\tau^2$ is the covariance estimator of η_t. .

A standard way to proceed in empirical work is to first apply the ADF, PP and/or ERS tests. The KPSS test is then used for a final confirmation of either the unit root or stationary property. However, the KPSS test has been shown to have undesirable properties. Caner and Kilian (2001) demonstrate in a Monte Carlo study that the tests massively over-reject the null hypothesis of stationarity in the presence of autocorrelation. Also, somewhat counterintuitive, the performance of the test worsens as the sample size increases. Kuo and Tsong (2004) show that, in the presence of a stationary but highly persistent process, the KPSS-statistics diverge to infinity with probability one as samples increase to infinity.

Müller (2005) studies the KPSS test analytically in the asymptotic local-to-unity framework. He finds that the point-optimal unit root test statistics pioneered by Elliott et al. (1996) (see also Elliott (1999) and Müller and Elliott (2001)) have much more discriminating power than tests for stationarity.

3.2.5 Unit Root test with Structural Breaks

Structural breaks have been discussed intensively in the context of univariate autoregressive time series, and usually refer to a sudden change in (1) the level of the time series, a "crash model"; (2) a change in the trend without any sudden change in the level at the time of the break, a "changing growth model"; and (3) a sudden change in both intercept and slope at the time of the break (Perron, 1989).

Nelson and Plosser (1982) suggest that structural breaks in the time series under examination could influence the unit root test results and hence should be considered while testing. They argue in favour of a difference-stationary model where current shocks have a permanent effect on the long-run level of macroeconomic and financial aggregates. Using Augmented-Dickey-Fuller (ADF) tests, they are not able to reject the unit root null hypothesis against the trend stationary alternative for 13 out of 14 long-term annual U.S. macro series, including real GNP. However, their results have been challenged by Rudebusch (1992, 1993) who demonstrates that traditional unit root tests have low power against estimated trend stationary alternatives.

In general, standard unit root tests are biased towards the null hypothesis of non-stationarity in the face of one-off changes in regime (Zivot and Andrews, 1992; Perron, 1989, 1997). Perron (1989) argues that some macroeconomic time series could be represented as stationary fluctuations around a deterministic trend function if allowance of a possible structural break is made, even though the time series are often found to have a unit root according to conventional testing methods without structural breaks. Accordingly, Perron (1989) proposes a methodology that allows for a structural break in the intercept or slope. The test statistics are constructed by adding dummy variables for different intercepts and slopes at a pre-determined break point. Christiano (1992) among others argues that the Perron (1989) test break point is chosen under the assumption that it is known a priori.

Subsequently Perron (1997) proposes a unit root testing method where the break point is determined endogenously. Knowing that it is impossible to know to what extent the break point choice should be correlated with the data, Perron (1997) argues that by allowing the choice to be perfectly correlated with the data one can test the robustness of the unit root test. If one can still reject the unit-root hypothesis under such a strict scenario, it must be the case that it would be rejected under a less stringent assumption.

Perron's (1997) testing model is:

$$y_t = \mu + \theta DMU_t + \beta trend + \delta DTB_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{y-i} + e_t \tag{3.8}$$

where y_t is the time series of interest; *trend* is the time variable; Δ is the lag operater; e_t is the i.i.d. residual; T_b is the break point, DMU_t is intercept dummy ($DMU_t = 0$ if $t<=T_b$, and $DMU_t = 1$ if $t> T_b$) and DTB_t is the trend dummy ($DTB_t = 1$ if $t = T_b + 1$ and $DTB_t = 0$ otherwise).

Perron (1997) considers two methods to select the break point endogenously: (1) it is chosen to minimize the t-statistics under the null ($\alpha = 1$) or (2) it is chosen to minimize the t-statistic of the parameter associated with the change in the intercept or the change in slope. The limitation of the Perron (1997) unit root test, however, is that it only allows for one endogenous break point. Unit root tests with more than one break point, such as Lumsdaine and Papell (1997) unit root test with two break points, have been proposed in the literature but are computationally demanding. Considering the relatively short time series (10 years of data) examined in the thesis, including more break points might affect the trend stationarity of series adversely, hence resulting in rejection of the alternative hypothesis (stationarity) (Jha and Sharma, 2001). Therefore, we apply the Perron (1997) unit root test along with the KPSS and ERS tests in testing the stationarity of the time series in the thesis.

3.3 Linear Time Series Models

3.3.1 Random Walk and ARIMA Model

The simplest and the most basic univariate time series model is the Random Walk (RW). The Random Walk process is based on the assumption that the past movement or direction of a variable cannot be used to predict its future movement. Hence the current value of the variable is simply its last value plus a "random error". The mathematical form of the RW model can be expressed as:

$$Y_t = Y_{t-1} + \varepsilon_t \tag{3.9}$$

where Y_t is the underlying variable of interest and ε_t is pure noise.

The Autoregressive Moving Average (ARMA) model has been popular in forecasting since Box and Jenkins (1976), although AR and MA models were previously known and used. In an ARMA (p,q) model the current value of a variable is generated from its past, i.e. the weighted average of the historical values and the past news (error terms).

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \cdots + \alpha_p Y_{t-p} + b_1 \varepsilon_{t-1} + \cdots + b_q \varepsilon_{t-q} + \varepsilon_t \tag{3.10}$$

An AR(p) model with lag length p can be written as:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + \varepsilon_t \tag{3.11}$$

A Moving Average (MA) model with q lags of the error is in the form of:

$$Y_t = b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2} + \cdots + b_q \varepsilon_{t-q} + \varepsilon_t \tag{3.12}$$

The ARMA model assumes stationarity in the time series. However, as discussed in the previous section, many economic and financial time series are found to be nonstationary. A well-known result in time series analysis is Wold's (1938) decomposition theorem which states that a stationary time series process, after removal of any deterministic components, has an infinite moving average representation which, in turn, can be represented by a finite ARMA process. However, many time series need to be appropriately differenced in order to achieve stationarity, from which comes the definition of integration: a time series is said to be integrated of order *d*, in short, *I*(*d*), if it has a stationary, invertible, non-deterministic ARMA representation after differencing *d* times. A white noise series and a stable first-order autoregressive $AR(1)$ process are well-known examples of *I*(0) series, a random walk process is an example of an *I*(1) series. Mathematically, the ARIMA model can be expressed as:

$$\Delta_d Y_t = \alpha_0 + \alpha_1 \Delta_d Y_{t-1} + \cdots + \alpha_p \Delta_d Y_{t-p} + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} + \varepsilon_t \tag{3.13}$$

where Δ_d is the lag operator of order *d*.

3.3.2 Vector Autoregressive Model

When investigating a system containing more than one variable and where the variables are interrelated, a simultaneous system of equations is applied to model the variables. One of the most commonly used models is the Vector Autoregressive (VAR) model which treats every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. In other words, a VAR model allows all variables to interact linearly with their own and other variables' lagged values.

In an influential article, Sims (1980) advocates the use of VAR models for macro econometric analysis as an alternative to the large simultaneous equations models. Sims (1980) also criticises the way the classical simultaneous equations models were identified and question the exogeneity assumptions for some of the variables which often reflect the preferences and prejudices of the model builders and are not necessarily fully backed by theoretical considerations. In contrast, in VAR models all observed variables are typically treated as *a priori* endogenous. Mathematically, the VAR model can be written as follows:

$$\mathbf{Y}_t = \mathbf{A}_0 + \mathbf{A}_1 \mathbf{Y}_{t-1} + \mathbf{A}_2 \mathbf{Y}_{t-2} \cdots + \boldsymbol{\varepsilon}_t \tag{3.14}$$

where $\mathbf{Y}_t$ is the variable vector representing the variables which are interrelated in the system, $\mathbf{Y}_t = (Y_1, Y_2, \cdots, Y_n)$; $\mathbf{A}_0$ is a $1 \times n$ vector of constant; $\mathbf{A}_i$ (i=1,...,n) is a $n \times n$ metrics of parameters; and ε_t is a $1 \times n$ vector of error terms.

The bivariate-VAR is used in modelling and examining relationships between two variables such as the spot and futures prices, price volatility and inventory levels, and futures price volatility and trading volume in Chapters 6 and 7.

3.3.3 Granger Causality test

According to Granger (1969), variable y_1 Granger-causes y_2 if the past information of y_1 can predict y_2 and conversely y_2 is said to Granger cause y_1 if past information of y_2 can predict y_1. The Granger Causality test is conducted via a bivariate Vector Autoregressive (VAR) model.

$$\begin{aligned} y_{1t} &= \alpha_0 + \sum_{i=1}^{m} \alpha_i y_{1,t-i} + \sum_{j=1}^{n} \beta_j y_{2,t-j} + \varepsilon_{1t} \\ y_{2t} &= \alpha_0 + \sum_{i=1}^{m} \alpha_i^{'} y_{1,t-i} + \sum_{j=1}^{n} \beta_j^{'} y_{2,t-j} + \varepsilon_{2t} \end{aligned} \tag{3.15}$$

where i and j are the lagged terms of x and y, respectively.

To test Granger causality from y_1 to y_2, a joint test of the null hypothesis $H_0 : \alpha_1^{'} = \cdots = \alpha_i^{'} = 0$ is performed, and the null hypothesis of testing whether y_2 Granger causes y_1 is $H_0 : \beta_1 = \cdots = \beta_j = 0$.

The Granger causality test has been widely applied in various areas in economics to examine whether one economic variable can be used to forecast another variable. For instance, Demetriades and Luintel (1996) test whether there is Granger causality between financial development and economic growth in the banking sector in India. Narayan and Smyth (2005) examine the causality among democracy, emigration and real income, and El-Wassal (2005) examines the Granger causality relationship between stock market growth and economic growth. In this thesis, we use the Granger causality test to examine the lead-lag relationships between variables, such as the spot and futures prices; (spot and futures) prices and inventory levels; prices and interest rates; price volatility and inventory changes and price volatility and trading volume in Chapters 5, 6 and 7.

3.3.4 Cointegration and the Vector Error Correction Model (VECM)

Due to the nonstationarity of many economic and financial time series, econometricians have applied different methodologies to transform nonstationary time series to stationary ones. Box and Jenkins (1976) advocate transforming integrated time series into stationary ones by successive differencing of the series. However, some authors, notably Sargan (1964) and Hendry and Mizon (1978), criticise the differencing method on the ground of specification of models in terms of differenced variables only, especially because of the problems in inferring the long-run equilibrium from the estimated model. After all, if deviations from that equilibrium relationship affect future changes in a set of variables, omitting the former, i.e., estimating a differenced model, may result in a mis-specified model. Granger (1981), resting upon the previous ideas, solved the puzzle by pointing out that a vector of variables, all which achieve stationarity after differencing, could have linear combinations which are stationary in levels. Later, Engle and Granger (1987) were the first to formalise the idea of integrated variables sharing an equilibrium relation and driven by a common trend, which have a lower degree of integration than the original series. They denoted this property cointegration, signifying co-movements among either stationary variables or variables with possible stochastic trend, which could be exploited to test for the existence of equilibrium relationships within a fully dynamic specification framework.

Consider two time series y_{t1} and y_{t2} that are both $I(d)$, i.e. they have long-run compatible properties. In general, any linear combination of y_{t1} and y_{t2} will also be $I(d)$. However, if there exists a vector $(1, \; -\beta)'$ such that the linear combination of y_{t1} and y_{t2},

$$z_t = y_{t1} - \alpha - \beta y_{t2} \tag{3.16}$$

is $I(d-b)$, where $d \geq b \geq 0$, then, following Engle and Granger (1987), y_{t1} and y_{t2} are said to be cointegrated of order (d, b), denoted, $y_t = (y_{t1}, \; y_{t2})' \sim CI(d,b)$ with $(1, \; -\beta)'$ called the cointegrating vector.

The concept of cointegration has been extended to multi-cointegration (Granger and Lee, 1990), whereby the number of variables considered is larger than two and where the possibility of having variables with different order of integration can be addressed.

For example, in a trivariate system, we may have that y_{t1} and y_{t2} are $I(2)$ and y_{t3} is $I(1)$; if y_{t1} and y_{t2} are $CI(2,1)$, it is possible that the corresponding combination of y_{t1} and y_{t2} which achieves that property be itself cointegrated with y_{t3} giving rise to an $I(0)$ linear combination among the three variables.

The concept of cointegration mimics the existence of a long-run equilibrium to which a system converges over time. If, for instance, economic theory suggests the following long-run relationship between y_{t1} and y_{t2}:

$$y_{t1} = \alpha + \beta y_{t2} \tag{3.17}$$

then z_t in equation (3.16) can be interpreted as the equilibrium error (i.e., the distance that the system is away from the equilibrium at any point in time). Note that a constant term has been included in (3.17) in order to allow for the possibility that z_t may have nonzero mean.

Johansen (1988, 1991, and 1995) develop cointegration testing techniques based on a Vector Error Correction model (VECM), which governs the joint behaviour of y_{t1} and y_{t2} over time of the following form:

$$\Delta Y_t = A + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Pi \cdot Y_{t-1} + \varepsilon_t \tag{3.18}$$

where Y_t is a $n\times 1$ vector of the endogenous variables and Y_{t-1} is the error correction term.

In this thesis, the cointegration relationship between the spot and futures prices with the presence of the cost-of-carry elements are tested using the methodology developed in Johansen (1991, 1995) in a VECM and the nonstandard critical values for the cointegration test statistics are from Osterwald-Lenum (1992). The cointegration relationship is tested based on the rank of the parameter matrix Π, i.e. the coefficient of the error correction term. If rank (Π) = 0 then Π is of dimension $n\times n$ implying that there is no cointegration relationship. If rank (Π) = n then all the variables are $I(0)$ and the VECM is reduced to a VAR model. If rank (Π) = k ($0 < k < n$) there are k cointegration relationships among the variables Y_t. Hence Π can be divided into two components: $\Pi = \boldsymbol{\alpha} \cdot \boldsymbol{\beta}'$, where α is a $n\times k$ metrics of error correction coefficients and β

is a $k \times n$ metrics of cointegrating parameters (vectors). The coefficients α denotes the speed of adjustment of the variables toward the equilibrium when there are deviations.

Johansen's (1991, 1995) method considers two statistics. The first test is a trace test in which the null hypothesis is that the rank of Π is less than or equal to r cointegrating vectors and the trace statistic is computed as:

$$LR_{tr}(r|k) = -T\sum_{i=r+1}^{k}\log(1-\lambda_i) \tag{3.19}$$

where λ_i is the i^{th} largest Eigenvalue of Π matrix.

The second test in Johansen (1991, 1995) method is the max-Eigenvalue test with the null hypothesis of r cointegration relations against the alternative or r+1 cointegration relations and the statistic is calculated as:

$$LR_{\max}(r|r+1) = -T\log(1-\lambda_{r+1}) = LR_{tr}(r|k) - LR_{tr}(r+1|k) \tag{3.20}$$

The distributions for these tests are not given by the usual chi-squared distributions. Rather, the asymptotic critical values for these likelihood ratio tests are calculated via numerical simulations (see Johansen and Juselius 1990; and Osterwald-Lenum 1992).

The cointegration test and VECM is applied in Chapter 5 in investigating the long-run equilibrium relationship among the main cost-of-carry elements: the spot price, the futures price, interest rate and the inventory level. The VECM is also used in modelling the mean process of the spot and futures prices in Chapters 6 and 7 where the main purpose is to model the conditional volatility of prices.

3.4 ARCH and GARCH Models

Since the introduction of the Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle (1982), it has gained popularity in the modelling of financial time series as it takes into account the often-observed volatility clustering of financial time series. The basic idea behind the ARCH model is that the second moments (variance) of the distribution of a process may have an autoregressive structure, i.e. the conditional variance changes over time.

The ARCH regression model is obtained by assuming that the mean of a random variable y_t is given as βx_t, a linear combination of lagged endogenous and exogenous variables with β a vector of unknown parameters. Formally,

$$y_t = \beta \cdot x_t + \varepsilon_t, \;\; \varepsilon_t \sim N(0, \sigma_t^2) \tag{3.21}$$

$$\sigma_t^2 = \varpi + \sum_{i=1}^{p} \alpha_i \cdot \varepsilon_{t-i}^2 \tag{3.22}$$

The ARCH model in (3.20) has several characteristics which make it attractive for econometric applications. First, the ARCH model can be used in forecasting the volatility of asset returns in markets where there is evidence of serial correlation in the underlying variance (Engle, 1982). The observation that large and small shocks tend to cluster together was made early on in the financial literature (see, for instance, McNees, 1979).

Second, in the classical framework of Markowitz (1952), portfolios of financial assets are held as functions of the expected means and variances of the rates of return and, hence, any shifts in asset demand must be associated with changes in expected means and variances of the rates of return. If the mean is assumed to follow a standard regression or time-series model, the variance is immediately constrained to be constant over time, which is neither valid nor appropriate. However, the ARCH model allows for the time-varying feature in the volatility process.

A third interpretation set forth by Engle (1982) is that the ARCH model is an approximation to a more complex regression model which has non-ARCH disturbances. The ARCH specification might then be picking up the effect of variables omitted from the estimated model. The existence of an ARCH effect would be interpreted as evidence of misspecification, either by omitted variables or through structural change. If this is the case, ARCH may be a better approximation to reality than marking standard assumptions about the disturbances, but trying to find the omitted variable or determine the nature of the structural change would be even better (Engle, 1982).

Bollerslev (1986) recognises that in the empirical applications of the ARCH model proposed by Engle (1982) a relatively long lag in the conditional variance equation is often called for, and to avoid problems with negative variance parameter estimates a fixed lag length is typically imposed (cf. Engle, 1982; Engle, 1983; and Engle and Kraft, 1983). In light of this, Bollerslev (1986) extends the ARCH model to allow for both a longer memory and a more flexible lag structure by including the past conditional variances in the current conditional variance equation. Formally, assuming the mean process is the same as in Equation (3.21), the GARCH (p, q) is in the form:

$$\sigma_t^2 = \varpi + \sum_{i=1}^{p} \alpha_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \cdot \sigma_{t-j}^2 \qquad (3.23)$$

Thus, $\sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$ is the ARCH (q) component and $\sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2$ is the GARCH (p) component. The GARCH model has been seen as a dramatic improvement over the ARCH model in giving much longer lags and consequently more persistence in conditional variances merely by the addition of a single parameter (Engel, 1995).

Over the last two decades, the ARCH family model has been extended to several forms, for example the ARCH-in-mean model by Engle, Lilien and Robins (1987) which includes the conditional variance process in the mean; the Exponential-GARCH by Nelson (1991) and TGARCH by Glosten, Jaganathan and Runkle (1993) which allow for asymmetric influence by negative returns on the variance. To serve the purpose of investigating the relationships between volatility and other variables in this thesis we use the GARCH model in modelling conditional volatility of the spot and futures prices in Chapters 6 and 7.

3.5 Markov Regime Switching Models

There has been growing evidence that empirical models of many economic time series, particularly macroeconomic and financial series, are characterised by parameter instability. This has led to the introduction of time-varying parameter models which allow coefficients of a model to change over the estimation period. One notable set of such models are switching regressions with latent state variables, in which parameters move discretely between a fixed number of regimes and the switching process is conditioned on either an unobserved or observed state variable. Switching regressions have a rich history in econometrics, dating back to Quandt (1958). Goldfeld and Quandt (1973) introduced a particularly useful version of these models, referred to as a Markov-switching model, in which the latent state variable controlling the regime shifts follows a Markov-chain (See Appendix II for a detailed explanation). Since Hamilton (1989) extended Markov-switching models to ARIMA models, there have been numerous applications of the Markov Regime Switching (MRS) model in financial economics (see, for instance, Lam, 1990; Garcia and Perron, 1999; Raymond and Rich, 1997).

The MRS model assumes that there are m states or regimes which the underlying variables of interest are characterised by, for instance, an "expansion" and "recession" state in the Gross Domestic Product process. The state of the variable at any time is not deterministic, but depends on its previous state and on the transition probability that the variable will switch states at the current time. These transition probabilities in turn may be fixed, or may depend on other variables. The transition probabilities are given as:

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{pmatrix} \tag{3.24}$$

where the transition probabilities $P_{12} \cdots P_{1m}$ give the probabilities that state 1 will be followed by state 2, 3, ..., m, and the transition probabilities $P_{m1} \cdots P_{mm}$ give the probabilities that state m will be followed by state 1, 2, ..., m. Transition probabilities on the diagonal of the matrix $P_{11}, P_{22}, \cdots, P_{mm}$ give the probabilities that there will be no change in the state of the market in the following period.

We assume that there are two states in the system, as do most recent literature (see, for instance, Hamilton and Lin, 1996; Cecchetti, Lam and Mark, 2000) and as implied by the two distinctive market conditions in commodity futures markets (backwardation and contango). Based on the transition probabilities, the conditional regime probabilities that the process will be in a given state at a point in time can be written as:

$$\begin{aligned} P_{11} &= \Pr[s_t = 1 | s_{t-1} = 1], \quad P_{12} = \Pr[s_t = 2 | s_{t-1} = 1] \\ P_{21} &= \Pr[s_t = 1 | s_{t-1} = 2], \quad P_{22} = \Pr[s_t = 2 | s_{t-1} = 2] \end{aligned} \tag{3.25}$$

$$\Pr(s_t = 1) = P_{1,t} = \frac{1 - P_{22,t}}{2 - P_{11,t} - P_{22,t}} \quad \Pr(s_t = 2) = P_{2,t} = \frac{1 - P_{1,t}}{2 - P_{11,t} - P_{22,t}} \tag{3.26}$$

The transition probabilities, P_{12} and P_{21}, can be endogenous or dependent on exogenous variables, denoted z_t. The dependence can be modelled by a logit model:

$$P_{12,t} = \frac{1}{1 + \exp(m_0 + m_1 \cdot z_t)}, \quad P_{21,t} = \frac{1}{1 + \exp(n_0 + n_1 \cdot z_t)} \tag{3.27}$$

where m_0, m_1, n_0 and n_1 are the parameters to be estimated.

Consider a system of time series with autocorrelation where the interrelation is dependent on states, i.e. where nonlinearity is allowed for in a VAR system:

$$\mathbf{Y}_t = \mathbf{A}_{0,st} + \mathbf{A}_{1,st} \mathbf{Y}_{t-1} + \cdots + \boldsymbol{\varepsilon}_t \tag{3.28}$$

where $\mathbf{Y}_t$ is the variable vector and st represents the different states of the prices series. Assuming normality, the density function for each regime (state of the market) can be written as follows:

$$f(\mathbf{Y}_t | s_t; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma_{s_t,t}^2}} \exp\left\{ \frac{-(\mathbf{Y}_t - \alpha_{0,s_t} - \alpha_{1,s_t} \mathbf{Y}_{t-1})^2}{2\sigma_{s_t,t}^2} \right\} \tag{3.29}$$

where $\boldsymbol{\theta}$, s_t=1, 2 , is the vector of parameters to be estimated.

Once the density functions for each state of the market and probabilities of being in the respective states are defined, the likelihood function for the entire sample is formed by a mixture of the probability distribution of the state variable and the density function for each regime as follows:

$$
\begin{aligned}
f(\mathbf{Y}_t;\boldsymbol{\theta}) = {} & \frac{P_{1,t}}{\sqrt{2\pi\sigma_{1,t}^2}}\exp\left\{\frac{-(\mathbf{Y}_t-\alpha_{0,1}-\alpha_{1,1}\mathbf{Y}_{t-1})^2}{2\sigma_{1,t}^2}\right\}+ \\
& \frac{P_{2,t}}{\sqrt{2\pi\sigma_{2,t}^2}}\exp\left\{\frac{-(\mathbf{Y}_t-\alpha_{0,2}-\alpha_{1,2}\mathbf{Y}_{t-1})^2}{2\sigma_{2,t}^2}\right\}
\end{aligned}
\tag{3.30}
$$

where $P_{1,t}$, $P_{2,t}$ are the probabilities of the regime being in state 1 or 2, respectively. The log-likelihood of the above density function can then be defined as:

$$
L(\boldsymbol{\theta}) = \sum_{t-1}^{T}\log\left(f(\mathbf{Y}_t;\boldsymbol{\theta})\right) \tag{3.31}
$$

which can be maximized using numerical optimization methods, subject to the constraint that $P_{1,t} + P_{2,t} = 1$ and $0 \le P_{1,t}, P_{2,t} \le 1$.

The Markov Regime Switching model is used in the thesis when examining the relationship between variables with possible structural breaks, such as the relationship between the futures price and settlement price in Chapter 4, the dynamic short-run adjustments in the prices and inventory level to the long-run equilibrium in Chapter 5, the relationship between spot and futures price volatility, as well as the price volatility and inventory level relationship in Chapter 6.

3.6 The London Metal Exchange and Data Descriptions

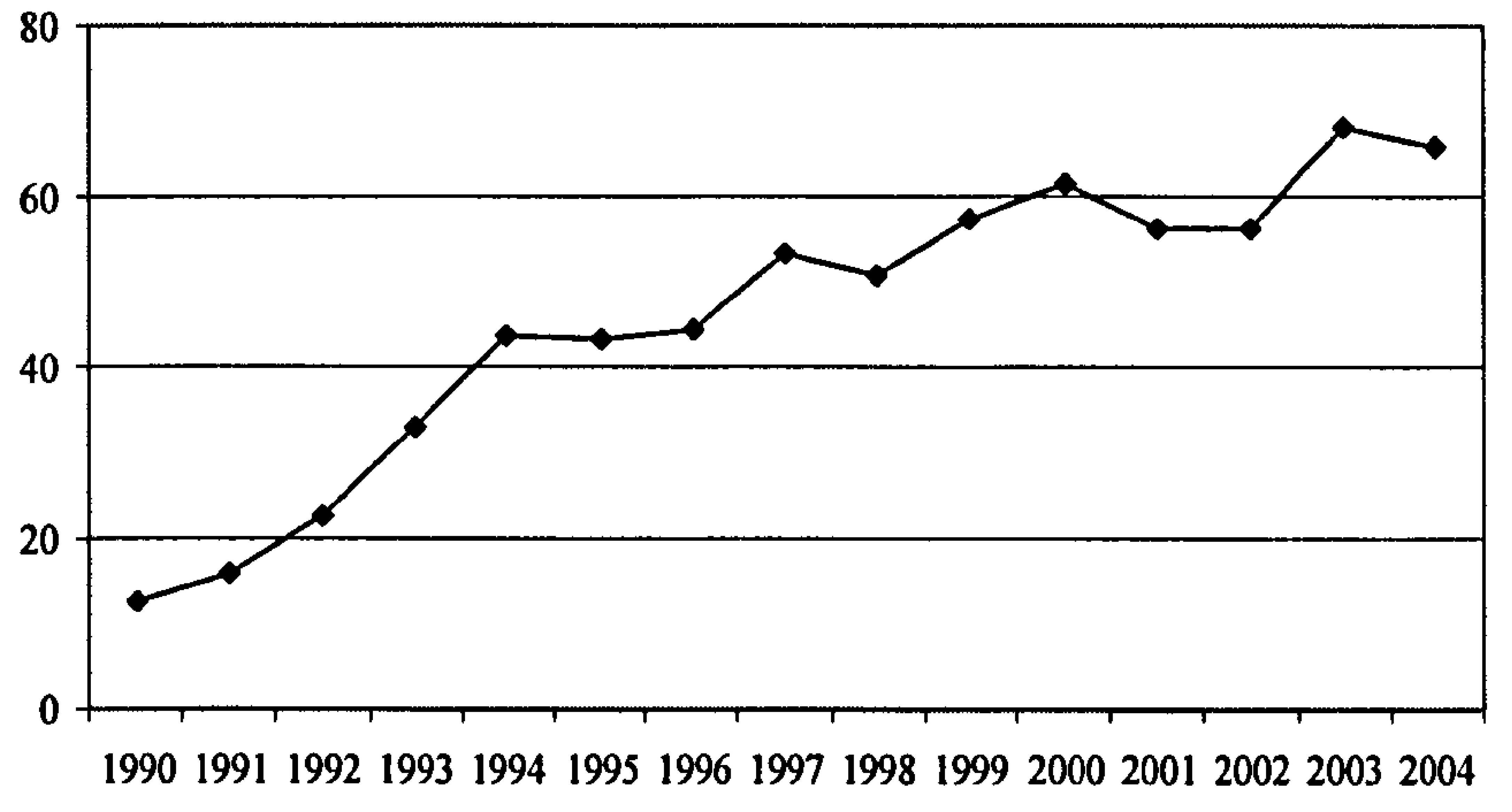
The empirical focus in this thesis is the industrial metal futures market, in particular the futures and cash contracts traded on the London Metal Exchange. There are several reasons to choose the LME market. Firstly, according to the United Nations Conference on Trade and Development (UNCTAD, 2001) statistics on the world's commodity exchanges, the London Metal Exchange, with over 59 million traded contracts in 2001, is the fourth largest commodity exchange in the world and is the largest metal exchange worldwide. Secondly there is a strong link between the exchange and the industry. As a consequence, physical prices of the industrial metals are set according to LME spot prices. Thirdly, the LME data gives the opportunity to simultaneously observe cash and futures contracts for the same market with a constant time until maturity. Fourthly, the access to LME inventory data gives in depth insight into the market conditions.

3.6.1 Metal Futures Prices on the LME

The price data is the daily official price quotation for 3-month futures contracts[18] from 05 April 1994 till the present provided by the London Metal Exchange, which also provides the daily trading volume data over the same time period. The yearly trading volume of the futures contracts is calculated based on the official published daily trading volume. Over the last decade, the trading volume of the metal futures contracts traded on the LME has increased from 12.6 million in 1990 to 67 million in 2004, an increase of 532% in 15 years. Especially in the first half of the 1990s, the trading volume increased dramatically, with around a 37% per annum growth rate between 1990 and 1994. In the past five years trading volumes have been increasing steadily. Figure 3.1 shows the trading volume of the metal futures contracts over the period 1990 to 2004 on the LME.

[18] Unlike other commodity markets, which are usually based on monthly prompt dates, LME metal futures contracts run on a daily basis for a period of three months. After the 3-month date, the daily prompts for forward trading are reduced to weekly and then monthly contracts out to 15 or 27 months forward. This means that when one enters into a 15 or 27 months futures contracts, these are not priced against the future spot price on a particular day but rather on the average over a month.

Figure 3.1 LME Metal Futures Contracts trading volume 1990 – 2004 (million contracts)

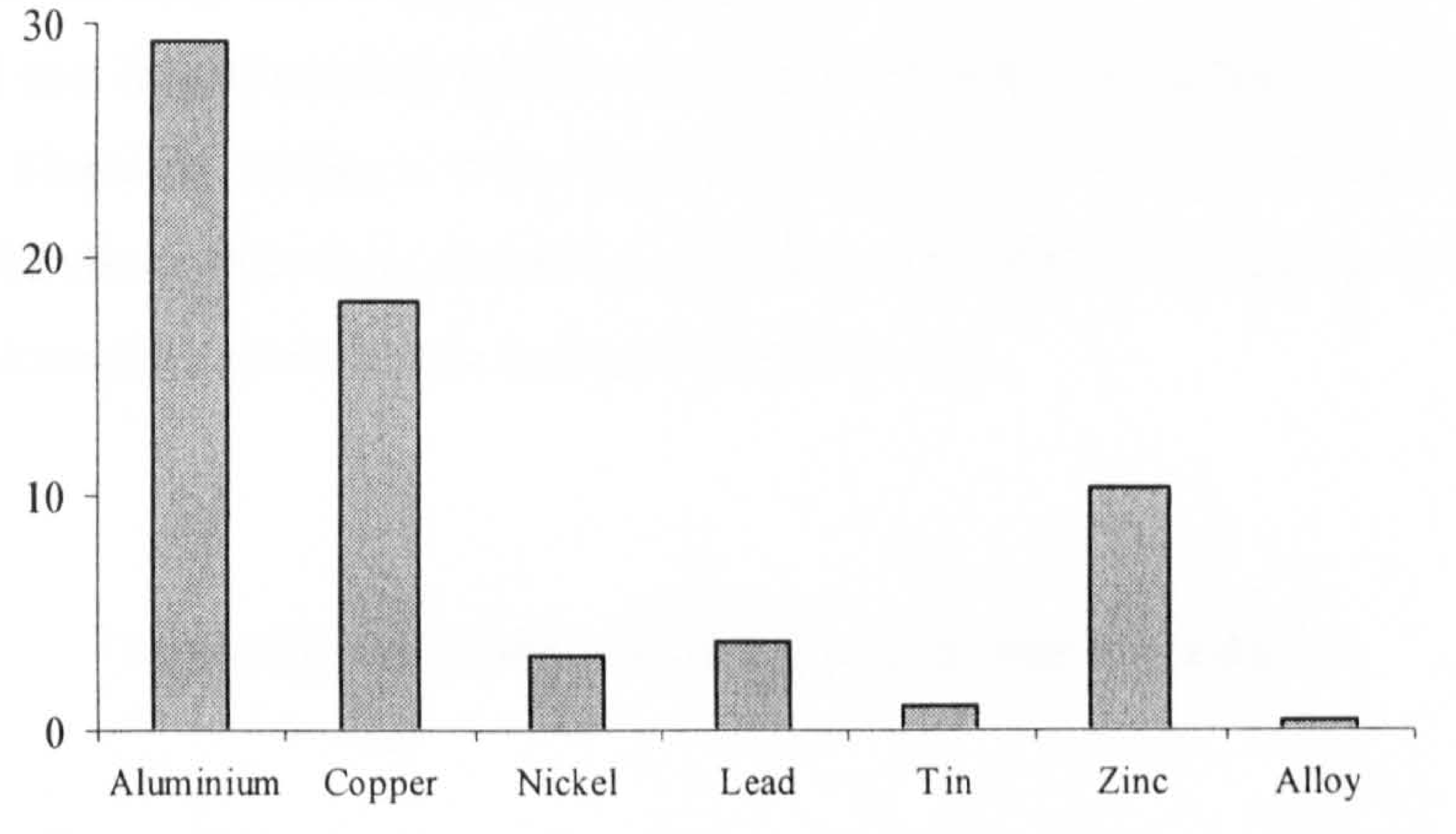


The trading volume of the seven metal futures traded on the LME in 2004 is shown in Figure 3.2. Aluminium futures contracts are the most liquid contracts on the exchange with 29.23 million lots, followed by copper (18.17 million) and zinc (10.21 million) futures contracts. Aluminium alloy futures and tin futures are the most thinly traded contracts on the exchange with 0.43 million and 0.97 million contracts respectively.

All LME contracts assume delivery of physical metal. To meet this need, large stocks of metal are held in a worldwide network of warehouses approved, but not owned, by the LME. Currently there are over 400 warehouses in some 32 locations covering the USA, Europe, the Middle East and the Far East. Very few LME contracts result in a delivery, the vast majority of contracts are bought or sold back before falling due. As a result, deliveries that do take place either in or out of a warehouse strongly reflect the demand and supply in the physical market. The LME approved warehouses where the physical delivery can take place are located in the United States (Baltimore, Chicago, Detroit, Long Beach, Los Angeles, New Orleans, and St. Louis), Sweden (Gothenburg and Helsingborg), UK (Avonmouth, Hull, Sunderland, Newcastle, Liverpool), Netherlands (Vlissingen and Rotterdam), Belgium (Antwerp), Germany (Bremen and Hamburg), Italy (Genoa, Leghorn, Trieste), Spain (Barcelona and Bilbao), Japan (Hakata, Moji, Nagoya, and Yokohama), Korea (Busan and Gwangyang) and Singapore.

Note that the LME inventory level does not include stocks held by private companies outside of the LME system. In general, both producers and consumers of industrial metals may hold private inventory, the extent to which is determined by their attitude towards operational risk. However, the total volume of such private inventory is small compared to aggregate LME stocks and the latter is representative of the supply and demand balance of the metals.

Figure 3.2 LME Futures Trading Volume in 2004



Delivery of LME contracts is in the form of warrants, which are bearer documents. Each warrant entitles the holder to take possession of one lot of metal at a specific LME approved warehouse. In 1999, the LME introduced an electronic transfer system, SWORD, for the production and transfer of title of LME warrants. SWORD is a joint initiative between the LME and the London Clearinghouse. All LME warrants are produced to a standard format with a barcode. Warehouse companies issuing these warrants ensure that the details are known to SWORD, which acts as a central database, holding details of ownership and is subject to stringent security controls. The ownership of LME warrants can be transferred between SWORD members in a matter of seconds and all rent payments are automatically calculated.

3.6.2 Estimation Periods, Frequency, and Time Series Properties

The empirical analysis is undertaken using seven LME metals, namely aluminium, aluminium alloy, copper, lead, nickel, tin and zinc. The examination time period is between 01 April 1994 and 31 July 2004 for all the time series. Graphs of the spot and futures prices, inventory level and trading volume for the seven metals contracts are shown in Appendix I. In general, spot and futures prices move closely together and the futures prices exceed the spot prices. However, there are cases when the spot prices move above the futures prices, i.e. the relationship is not driven by the cost-of-carry model as discussed in Chapter 1.

To further illustrate the dynamic relationship between the spot and futures prices and, more interestingly, their links to the inventory levels, Figure 3.3 to Figure 3.9 plot the basis and inventory level for the seven industrial metal markets. It is evident from the graphs that the basis has a time-varying upper limit, intuitively being the full cost-of-carry, and that the downward spikes occur either because of extraordinary events (e.g. the Asian Financial Crisis) or when the stocks are at low levels. In most of the metal markets, the strong industrial demand post 2003, particularly from China, is reflected in declining inventory levels in the final part of the sample.

Figure 3.3 Basis and inventory level of the aluminium market

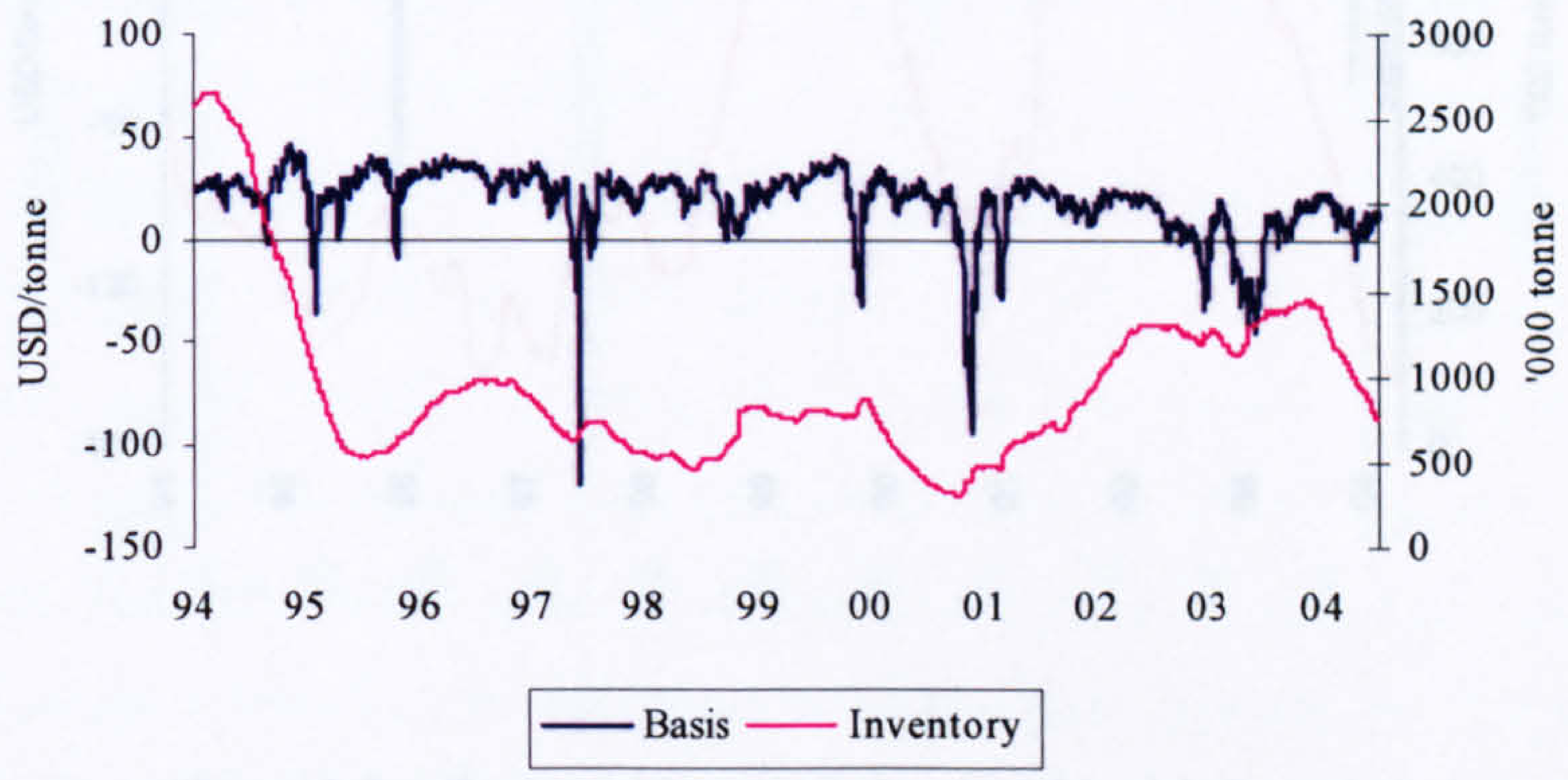


Figure 3.4 Basis and inventory level of the aluminium alloy market

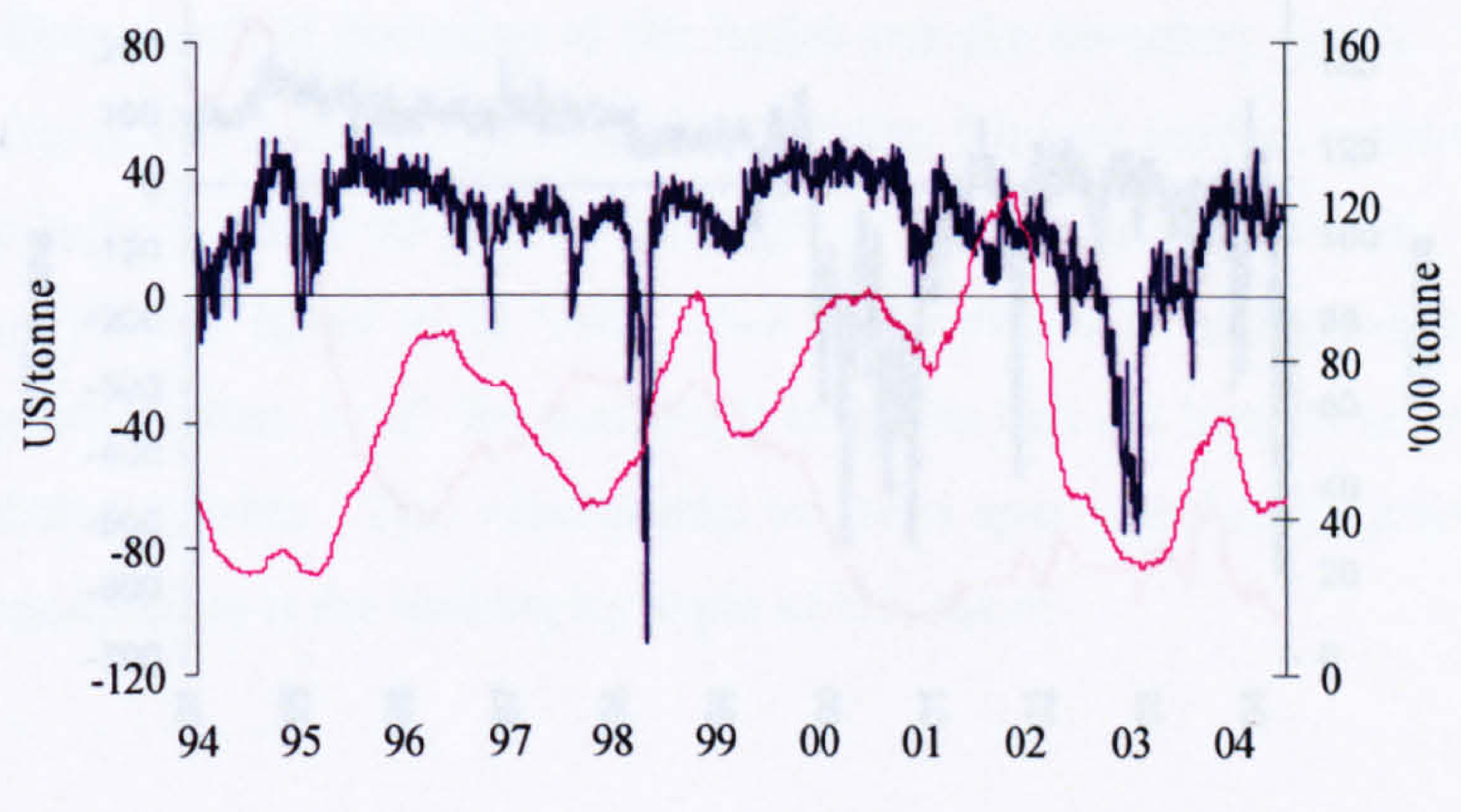


Figure 3.5 Basis and inventory level of the copper market

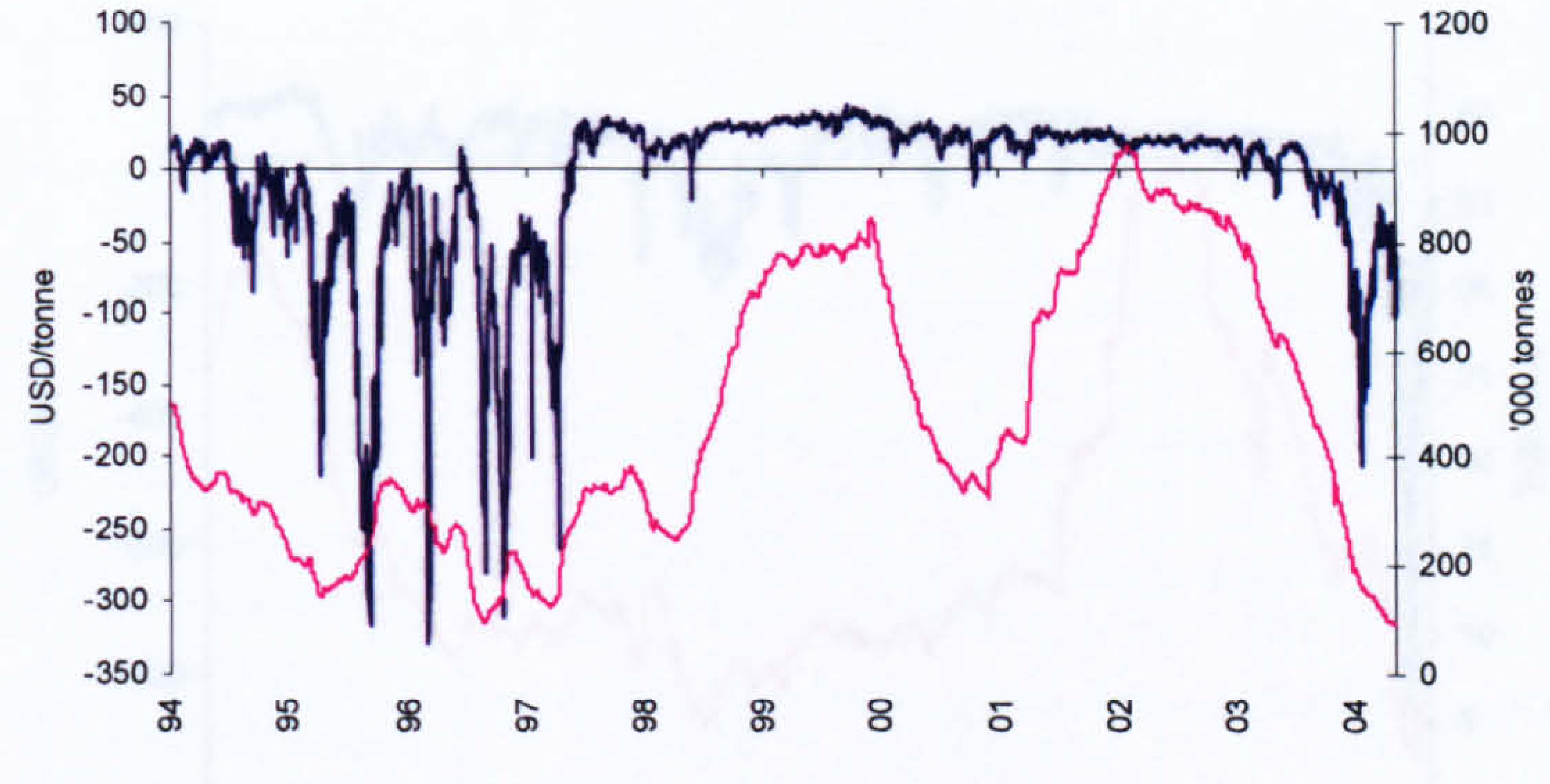


Figure 3.6 Basis and inventory level of the lead market

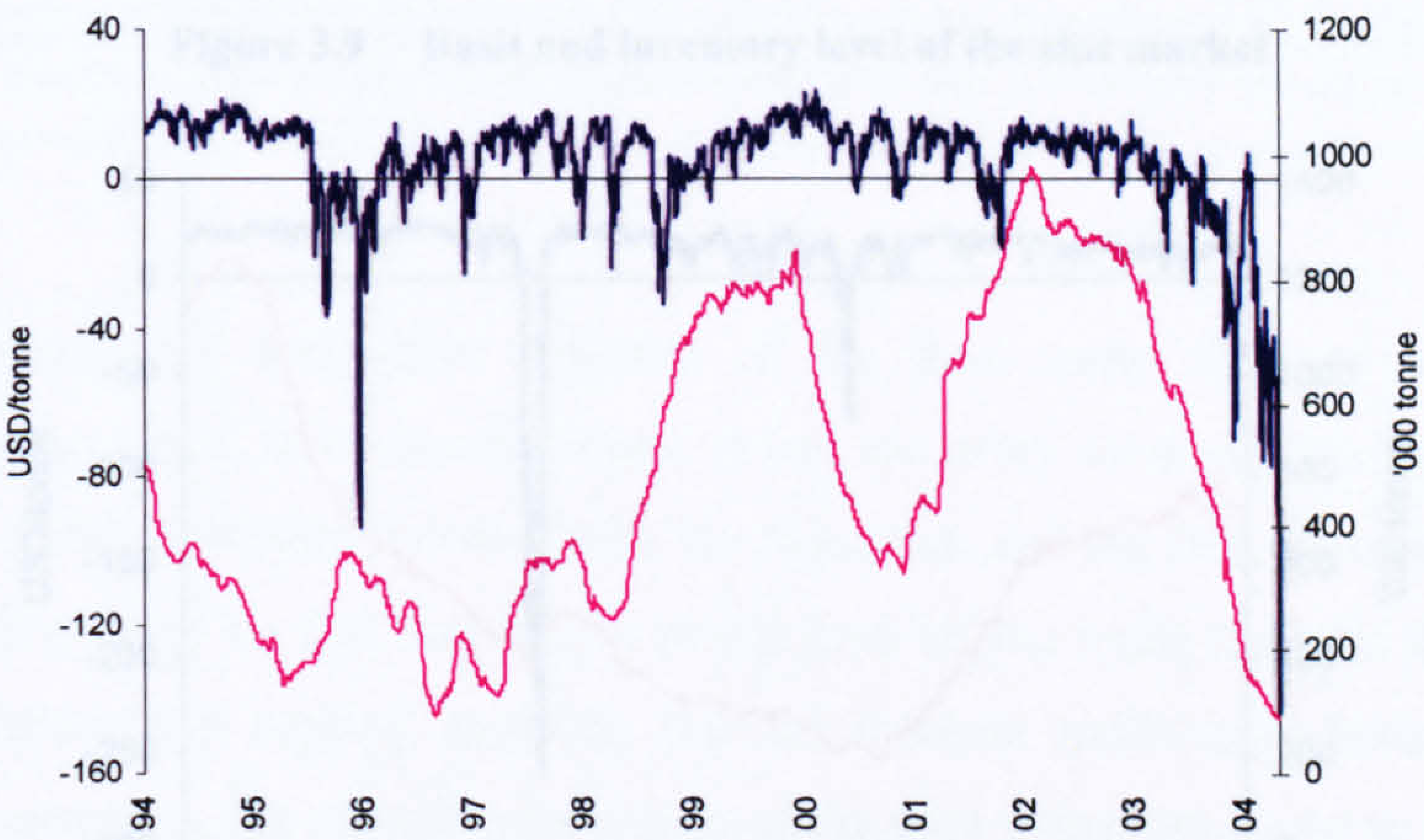


Figure 3.7 Basis and inventory level of the nickel market

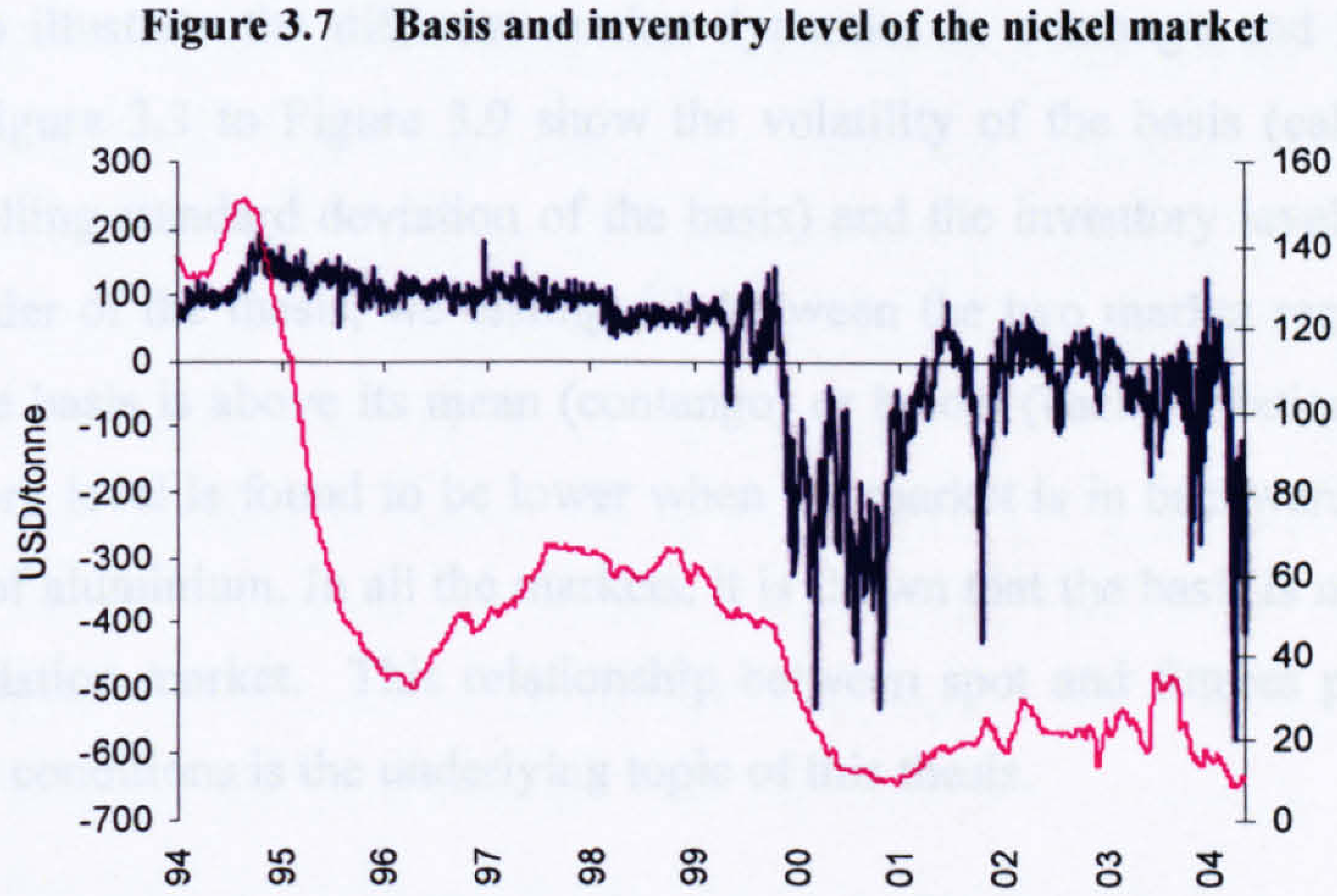


Figure 3.8 Basis and inventory level of the tin market

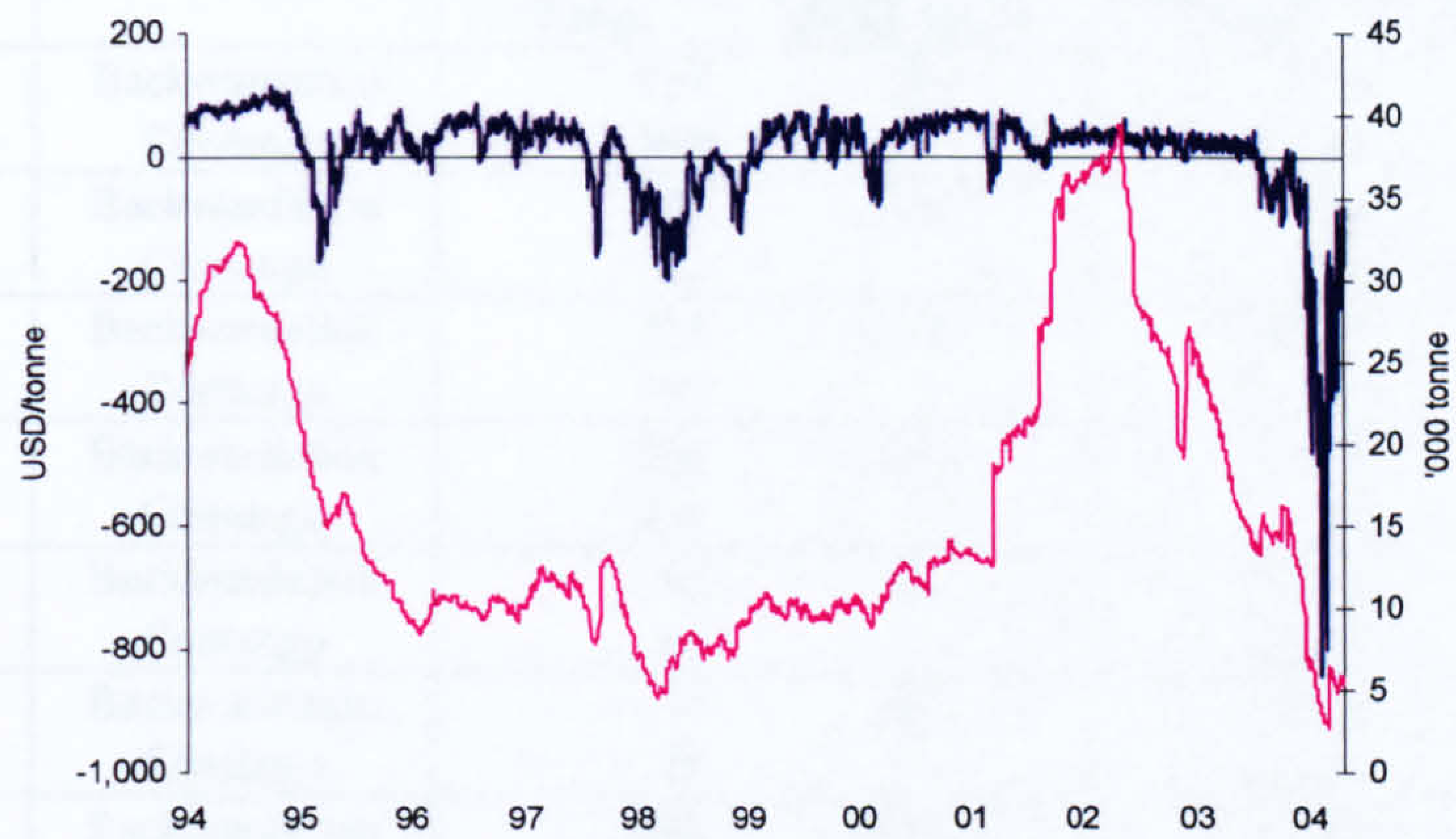
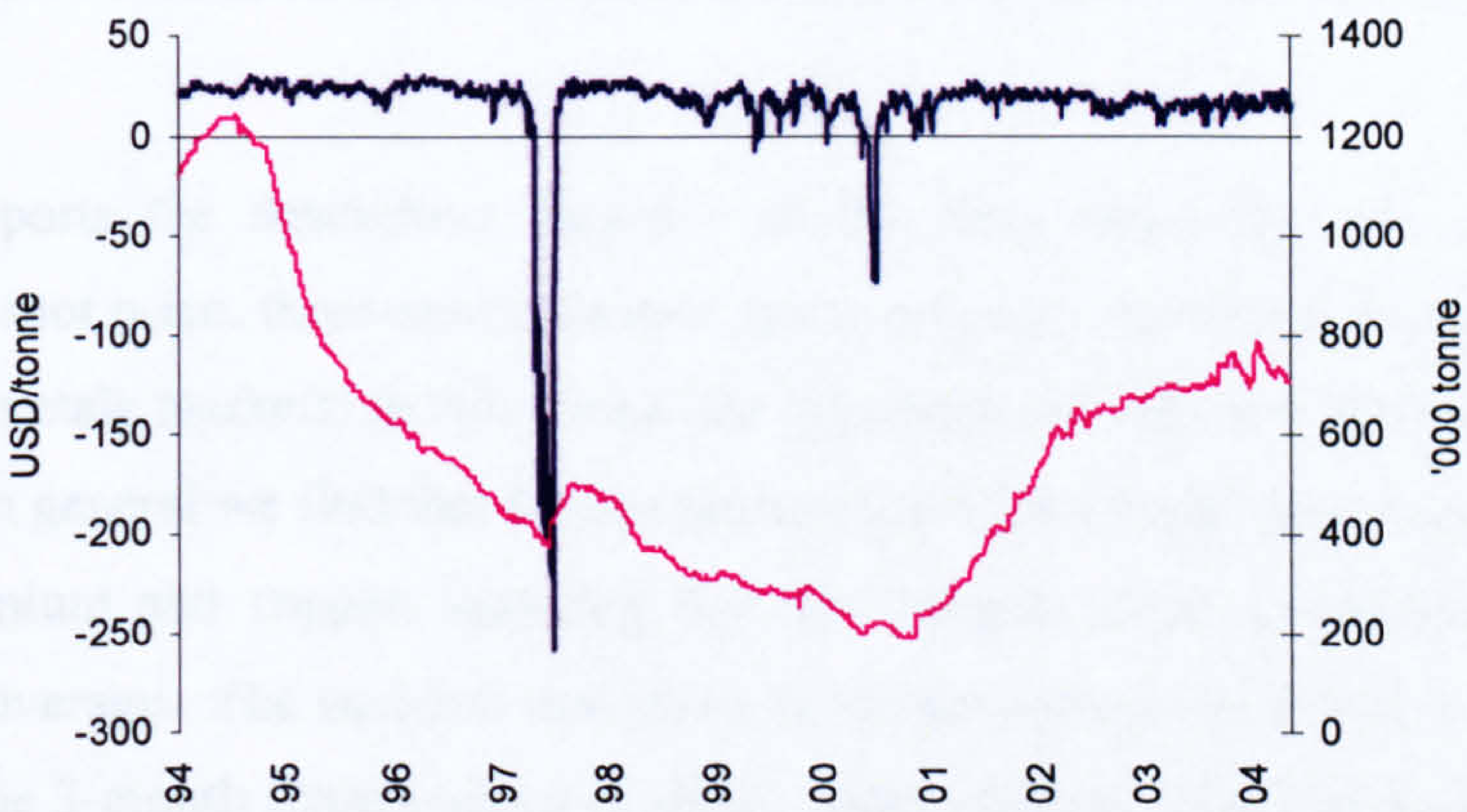


Figure 3.9 Basis and inventory level of the zinc market



In order to illustrate the different market dynamics in contango and backwardation markets, Figure 3.3 to Figure 3.9 show the volatility of the basis (calculated as the monthly rolling standard deviation of the basis) and the inventory levels. Here, as in the remainder of the thesis, we distinguish between the two market regimes based on whether the basis is above its mean (contango) or below (backwardation). In general, the inventory level is found to be lower when the market is in backwardation with the exception of aluminium. In all the markets, it is shown that the basis is more volatile in a backwardation market. This relationship between spot and futures price dynamics and market conditions is the underlying topic of this thesis.

Table 3.1 **Inventory level and basis volatility under different market conditions**

		Inventory ('000 tonne)		Basis volatility*	
		Value	Difference *	Value	Difference
Aluminium	Backwardation	969	29	7.03	3.71
	Contango	940		3.33	
Al alloy	Backwardation	55	(14)	7.25	3.27
	Contango	70		3.98	
Copper	Backwardation	228	(354)	28.05	11.39
	Contango	582		4.09	
Lead	Backwardation	426	(69)	6.43	3.79
	Contango	495		2.65	
Nickel	Backwardation	20	(45)	42.92	29.85
	Contango	65		13.07	
Tin	Backwardation	11	(8)	34.66	23.67
	Contango	18		10.99	
Zinc	Backwardation	440	(152)	10.10	8.10
	Contango	592		2.01	

Note: the difference is calculated by deducting the value in a contango market from the value in a backwardation market. Basis volatility is calculated as the one month rolling standard deviation of the daily basis (3-month futures price minus the spot price).

Table 3.2 reports the descriptive statistics of the time series that are considered (namely, the spot price, three-month futures price, inventory level and trading volume of the seven metals markets) in two forms: the logarithm and the first difference of the log values. In general we find that futures prices have higher mean than the spot prices except aluminium and copper, implying that the markets under examination are in contango on average. The standard deviations of the spot prices are found to be higher than that of the 3-month futures prices in all the seven markets. The distribution of the (log) price changes is found to be right skewed with excess kurtosis in all the markets with an exception of aluminium alloy spot and futures prices which do not show significant excess kurtosis.

Table 3.2 Descriptive Statistics of the main time series

		Logarithm of the time series				Logarithm changes			
		Average	Std Dev.	Skewness	Kurtosis	Average	Std Dev.	Skewness	Kurtosis
Al	Cash	7.310	0.111	0.351	-0.105	4.5E-05	0.005	-0.124	3.340
	3-M futures	7.322	0.110	0.377	-0.021	4.1E-05	0.004	-0.235	4.181
	Inventory	13.115	0.487	-0.011	-0.806	-7.8E-05	0.003	8.903	261.039
	TV	11.262	0.402	-0.043	-0.025	7.9E-05	0.143	0.210	0.414
Al alloy	Cash	7.197	0.136	0.496	0.064	2.9E-05	0.005	0.166	2.461
	3-M futures	7.213	0.134	0.573	0.215	3.1E-05	0.004	0.001	2.924
	Inventory	13.115	0.487	-0.011	-0.806	-7.8E-05	0.003	8.903	261.039
	TV	7.407	0.771	-0.532	0.424	2.4E-05	0.261	0.065	4.134
Copper	Cash	7.584	0.238	0.454	-1.114	6.9E-05	0.006	0.187	8.228
	3-M futures	7.583	0.222	0.462	-1.051	6.3E-05	0.006	-0.216	4.984
	Inventory	13.115	0.487	-0.011	-0.806	-7.8E-05	0.003	8.903	261.039
	TV	11.092	0.304	0.055	0.099	-3.9E-05	0.126	0.305	0.612
Lead	Cash	6.323	0.205	0.688	-0.457	1.4E-04	0.007	-0.009	4.818
	3-M futures	6.334	0.192	0.601	-0.741	1.2E-04	0.006	-0.362	5.915
	Inventory	13.115	0.487	-0.011	-0.806	-7.8E-05	0.003	8.903	261.039
	TV	9.256	0.451	0.025	0.090	2.1E-04	0.163	0.216	0.825
Nickel	Cash	8.878	0.285	0.330	0.611	1.6E-04	0.009	-0.153	4.337
	3-M futures	8.882	0.281	0.337	0.596	1.5E-04	0.008	-0.233	4.477
	Inventory	13.115	0.487	-0.011	-0.806	-7.8E-05	0.003	8.903	261.039
	TV	9.598	0.388	0.144	-0.068	-2.8E-05	0.146	0.090	0.494
Tin	Cash	8.596	0.176	0.283	1.420	8.5E-05	0.005	-0.822	8.320
	3-M futures	8.598	0.171	0.144	1.094	8.2E-05	0.005	-1.054	10.233
	Inventory	13.115	0.487	-0.011	-0.806	-7.8E-05	0.003	8.903	261.039
	TV	8.539	0.417	0.124	0.119	-1.0E-04	0.172	-0.028	1.455
Zinc	Cash	6.907	0.161	0.185	0.629	1.4E-05	0.006	-0.767	8.675
	3-M futures	6.924	0.152	-0.119	-0.078	1.3E-05	0.005	-0.664	8.087
	Inventory	13.115	0.487	-0.011	-0.806	-7.8E-05	0.003	8.903	261.039
	TV	10.145	0.426	0.065	-0.017	1.9E-04	0.165	0.403	0.892

- Daily data over the period 05/04/1994 and 30/07/2004;
- The time series presented are the logarithm of the underlying;
- TV – trading volume.

Given that many financial data are found to have a unit root, we perform conventional KPSS and EPS unit root tests on the time series. Moreover, to account for the possible structural breaks in the data, we apply the Perron (1997) unit root test with endogenous break points. The results are presented in Table 3.3 and Table 3.4. The unit root tests are firstly carried out on the levels of the logarithm of the time series. When nonstationarity is detected in levels, the unit root tests are conducted on the first differences. Whether to include an intercept of time trend in the tests is determined by whether the intercept or trend is statistically significant. The critical values are presented in the lower part of the tables. The null hypothesis of the ERS and Perron (1997) test is that there is a unit root in the time series and the null of the KPSS test is that the time series is stationary.

The results of the unit root tests as reported in Table 3.3 are consistent with the findings in the literature. In particular, we cannot reject the null hypothesis of a unit root according to the ERS test in the log price levels (spot and futures) and inventory level in all the seven metals markets at the 95% confidence level. These results are further confirmed by the rejection of the null hypothesis of stationarity at the 95% confidence level according to the KPSS test. The hypothesis of a unit root in the trading volume is rejected at the 5% significance level according to the ERS test. However, the null hypothesis of stationarity is rejected according to the KPSS test for the levels of the trading volume. To avoid the possibility of spurious regression, we therefore use detrended trading volume in Chapter 7.

Consequently, nonstationarity in the underlying variables is taken into account in the empirical analysis in the follow chapters. In Chapter 4, when testing the UH, the spot price is deducted from both sides of the equation which is suggested by the UH to achieve stationarity in the regression variables. In Chapter 5, a VECM is used to examine the relationships among the variables. In Chapters 6 and 7, the first differences of the spot and futures prices are modelled in the mean process in a VECM when investigating the characteristics of the volatility.

Table 3.3 ERS and KPSS Unit Root tests for the main time series

		Intercept / trend	ERS stats (log levels)	ERS Stats (1st difference)	KPSS Stats. (log levels)	KPSS (1st difference)
Libor interests		I + T	67.169	0.094*	0.464	0.409*
Al	Spot	I + T	12.588	0.070*	0.388	0.078*
	3-Month	I + T	14.633	0.071*	0.376	0.093*
	Inventory	I + T	54.010	1.222*	0.896	0.489
	Trading Volume	I + T	0.101*		0.405	0.162*
Al alloy	Spot	I	16.07	0.101*	1.636	0.111*
	3-Month	I	19.235	0.0998*	1.7229	0.118*
	Inventory	I	8.900	3.355*	1.068	0.1756*
	Trading Volume	I+T	1.117*		0.778	0.059*
Copper	Spot	I + T	30.361	0.069*	0.844	0.268*
	3-Month	I + T	29.501	0.076*	0.836	0.265*
	Inventory	I + T	21.423	0.885*	0.447	0.345*
	Trading Volume	I + T	0.105*		0.327	0.036*
Lead	Spot	I + T	34.295	0.050*	0.681	0.333*
	3-Month	I + T	39.175	0.044*	0.680	0.311*
	Inventory	I + T	44.958	0.216*	0.600	0.375*
	Trading Volume	I + T	0.092*		0.188	0.053*
Nickel	Spot	I + T	16.123	0.087*	0.692	0.154*
	3-Month	I + T	17.053	0.093*	0.711	0.152*
	Inventory	I + T	12.517	0.260*	0.301	0.089*
	Trading Volume	I + T	1.616*		0.753	0.053*
Tin	Spot	I + T	29.351	0.067*	0.431	0.37*
	3-Month	I + T	30.451	0.065*	0.43	0.211*
	Inventory	I	26.145	0.133*	0.814	0.208*
	Trading Volume	I + T	0.871*		0.564	0.189
Zinc	Spot	I + T	14.994	0.074*	0.50	0.078*
	3-Month	I + T	16.632	0.074*	0.517	0.094*
	Inventory	I + T	299.14	0.115*	1.879	1.693
	Trading Volume	I + T	0.264*		0.368	0.090*
Critical value			10%	5%	1%	
ERS		Intercept	4.48	3.26	1.99	
		I + T	6.89	5.62	3.96	
KPSS		Intercept	0.347	0.463	0.739	
		I + T	0.119	0.146	0.216	

- I: intercept, T: trend; when I + T are included in the level test, only the intercept is included in 1st difference test;
- The null hypothesis for the ERS test is that there is a unit root in the series. The null hypothesis for the KPSS test is that the time series is stationary.
- * represents that the series is stationary at the 5% significance level.

Table 3.4 Perron (1997) Unit Root Test

		Log Levels		First difference	
		Break point	Stats on null (α = 1)	Break point	Stats on null L (α = 1)
Libor interests		1778	-3.545	205	-14.951*
Al	Spot	943	-3.142	221	-14.878*
	3m futures	1356	-2.987	221	-15.016*
	Inventory	1898	-2.394	339	-8.944*
	Trading Volume	1428	-10.311	162	-25.021*
Al alloy	Spot	1087	-3.752	215	-18.785*
	3m futures	916	-3.548	215	-18.512*
	Inventory	2039	-3.650	2285	-7.113*
	Trading Volume	2321	-8.746	3366	-22.880*
Copper	Spot	2060	-3.894	563	-14.212*
	3m futures	2060	-3.804	561	-39.400*
	Inventory	2315	-3.489	663	-9.099*
	Trading Volume	818	-12.171	822	-25.586*
Lead	Spot	2187	-4.437	220	-33.717*
	3m futures	2186	-4.526	219	-17.742*
	Inventory	2446	-1.982	1644	-13.178*
	Trading Volume	1016	-11.099	1958	-25.371*
Nickel	Spot	1798	-3.124	215	-22.142*
	3m futures	1798	-3.182	215	-21.963*
	Inventory	1455	-2.693	2379	-15.137*
	Trading Volume	1199	-8.403	427	-23.649*
Tin	Spot	1812	-4.333	2462	-15.336*
	3m futures	1812	-4.353	1925	-17.080*
	Inventory	1817	-2.909	2568	-16.172*
	Trading Volume	1014	-9.326	3813	-23.394*
Zinc	Spot	1749	-3.460	883	-22.650*
	3m futures	1749	-3.451	213	-16.788*
	Inventory	1727	-3.024	1728	-16.385*
	Trading Volume	592	-10.642	2396	-21.877*
Critical value		10%	5%	1%	
		-4.82	-5.08	-5.57	

- The test is conducted on the logarithm of the variables;
- * represents that the series is stationary at the 5% significance level;
- The null hypothesis for the Perron(97) test is nonstationarity.

3.7 Conclusions

This chapter has outlined the econometric methodologies, including the unit roots tests and time series models that are used in the thesis. The unit root tests applied herein include the KPSS and ERS tests as well as the Perron (1997) test. The KPSS and ERS tests differ in terms of their null hypothesis, stationarity and the existence of a unit root, respectively. The Perron (1997) test allows for an endogenous structural break in the time series under examination and the break point is determined based on the minimum of the *t*-statistic of that point. The tests for stationarity suggest that the levels of spot and futures prices and inventory (log) levels all have a unit root but that their first differences are stationary even after including a structural break in the tests.

The time series methodology section focuses on the Vector Autoregressive model, Cointegration, VECM and the MRS model. The VAR model provides a framework for investigating the inter-relationship between two or more variables, such as the spot and futures prices relationship and the prices and inventory level relationship in Chapter 4 and Chapter 6. The VECM allows us to examine the long-run equilibrium relationship among several variables, such as the spot, futures price, carrying costs and convenience yield in Chapter 5. The MRS model is used in subsequent chapters to investigate whether these relationships are subject to regime changes.

The last section in this chapter provided a description of the data and market where the metal futures contracts are traded, the London Metal Exchange. In general, the descriptive statistics suggest that futures prices have higher mean than the spot prices, implying that the markets were in contango on average during the time period under investigation. Moreover, spot price volatility, as measured by the standard deviation, is higher than futures price volatility in all the seven markets. Visual inspection of plots of the basis and inventory levels suggests that periods of backwardation occur when inventory levels are comparatively low. The above observations form the motivation and background for this work.

4 CHAPTER FOUR

PRICE DISCOVERY OF METAL FUTURES PRICES UNDER DIFFERENT MARKET CONDITIONS

4.1 Introduction

The notion of market efficiency is of considerable importance to investors who wish to use futures as alternative investments as well as hedgers who use the futures markets for risk management. Perhaps the most important feature of an efficient market is the absence of any arbitrage opportunities, and consequently agents can engage in hedging in an efficient market at lower transaction costs than in markets that require extensive information search. In the Efficient Market Hypothesis (EMH) framework, the price, P_t, incorporates all relevant information and the only reason for prices to change between time t and t+1 is the arrival of news or information due to unanticipated events. This implies that $E(P_{t+1}) = P_t + \varepsilon_{t+1}$, so the forecast errors $\varepsilon_{t+1} = E(P_{t+1}) - P_t$ should be zero on average because there are "bad" news as well as "good" news in the long run, and they should be uncorrelated with any information set Ω_t that is available at time t (the time of forecasting).

Accordingly, in an efficient futures market, futures prices should be able to reflect or "predict" the future cash price of the underlying assets. This statement is often referred to as the price discovery function of the futures markets and is tested based on the Unbiasedness Hypothesis (UH), which states that the futures (forward) price should be an unbiased predictor of the future spot price.

Several authors have examined the validity of the UH in the metal futures market. For instance, Canarella and Pollard (1986) investigate the three-month futures price of the metals traded on the LME and find evidence in support of the UH, even after accounting for autoregressive and moving average terms in the model. MacDonald and Taylor (1989) model the lagged spot prices and basis in a VAR framework and test the validity of the UH using copper, lead, tin and zinc metal futures traded on the LME. They find evidence in favour of the UH in the copper and lead markets and reject the UH in the tin and zinc markets. They argue that the latter is due to greater industry concentration in the zinc market and the collapse of the tin market toward the end of 1985. Chowdhury (1991) uses a cointegration framework to model futures and spot prices and find that in all the markets studied (copper, lead, tin and zinc on the LME), futures and spot prices are cointegrated and, therefore, he concludes that the metal futures markets are efficient. Krehbiel and Adkins (1993) test the UH on the metal futures (silver, gold, platinum and copper) traded on the New York Mercantile

Exchange (NYMEX) using the VECM and Likelihood Ratio tests. They find that while futures and realised spot prices are cointegrated in all the markets, the UH holds only in the platinum market. They suggest that a structural break caused by the Hunt brothers' manipulation[19] accounts for the UH rejection in the silver market.

Previous research on the validity of the Unbiasedness Hypothesis in futures markets has focused on testing the relationship between futures price and the realised spot price in a linear regression framework. However, this relationship may be characterised by different regimes and market conditions, as noted by Krehbiel and Adkins (1993) and Sarno and Valente (2000). Hence, rejection of the UH may not reflect the biasedness of futures prices but rather failure to account for such regime shifts in the market.

This chapter re-examines the price discovery function of metal futures traded on the LME by testing the UH in a framework where changes in the market conditions are taken into account. As argued in Chapter 1, market conditions (as proxied by contango and backwardation) are closely related to inventory levels. We therefore introduce the stock level as an exogenous variable which determines the probability of regime changes in the markets. To our knowledge, this is the first academic work where the validity of the UH is tested for the commodity futures markets subject to changing market conditions.

4.2 Conventional Methodologies for Testing the UH

Fama (1970) makes a distinction between three forms of the EMH: the weak form, the semi-strong form and the strong form. The weak form suggests that asset prices or returns reflect the information embedded in historical prices or returns. The semi-strong form suggests that securities prices reflect all publicly available information and the strong form EMH implies that the prices reflect all available information including private information. The UH is a more restrictive version of the weak form EMH, since most testing methodologies are based on historical prices.

[19] The oil tycoon brothers Nelson Bunker Hunt and William Herbert Hunt, with associates, controlled more than 200 million ounces of silver, about half of the world's deliverable supply during 1979 and 1980, which caused a market boom.

An early test of the UH in the futures markets (see, for instance, Goss 1981) was to regress the realised spot price at time $t+n$ (S_{t+n}) on the futures price at time t ($F_{t,t+n}$) and test the joint parameter restriction $\alpha=0$, $\beta=1$ as the null hypothesis. Formally:

$$S_{t+n} = \alpha + \beta F_{t,t+n} + \eta_{t,t+n} \tag{4.1}$$

where $\eta_{t,t+n}$ is an error term containing all the shocks from time t to $t+n$.

Note that the UH literature has developed somewhat independently from the theoretical cost-of-carry model which defines the relationship between the futures price at time t ($F_{t,t+n}$) and the spot price (S_t) as:

$$F_{t,t+n} = S_t + coc_{t,t+n} - cy_{t,t+n} \tag{4.2}$$

If we assume that the spot price follows a Random walk, i.e. $S_{t+n}=S_t+\varepsilon_t$, and substituting S_t by $S_{t+n} - \varepsilon_t$ in Equation (4.1), we get:

$$F_{t,t+n} = S_{t+n} + coc_{t,t+n} - cy_{t,t+n} + \varepsilon_t \tag{4.3}$$

The UH requires $\alpha = coc_{t,t+n} - cy_t = 0$, which consequently suggests that the UH (α=0, β=1) holds only when the cost-of-carry equals the convenience yield. This is a rather strict restriction that cannot generally be expected to hold, in particular as convenience yield is typically taken to be negligible in a contango market and possibly very large during periods of strong backwardation. The fact that the convenience yield is unobservable adds another challenge for empirical tests of the UH. Furthermore, the above lends credibility to the hypothesis that, at best, the validity of the UH is dependent on market conditions, which is the basis for this chapter.

A technical issue related to regression (4.1) is that conventional estimation methods require stationarity of S_{t+n} and $F_{t,t+n}$, while many empirical studies have found that asset prices are nonstationary. Engle and Granger (1987) show that if the variables under consideration are nonstationary, then standard statistical hypothesis tests (F and t tests) based on Equation (4.1) will not be valid. A simple way to tackle nonstationarity in S_t and $F_{t,t+n}$ in equation (4.1) is to subtract the current spot price S_t from both sides of the equation. Provided that the basis is stationary, both the LHS and RHS variables can then become stationary. This means that conventional estimation methodologies can be applied to the following equation:

$$\Delta_n S_{t+n} = \alpha + \beta B_{t,t+n} + \eta_{t,t+n} \tag{4.4}$$

where Δ_n is the n^{th} lag operator, i.e. $\Delta_n S_{t+n} = S_{t+n} - S_t$ and $B_{t,t+n} = F_{t,t+n} - S_t$ is the basis at time t for maturity $t+n$.

Another issue in regression (4.1) and effectively in equation (4.4) is the overlapping property in the data, which is encountered when the sampling frequency is greater than the futures contract length. It follows that the residuals in the regressions are autocorrelated $E(\eta_t, \eta_{t-1}) \neq 0$ (Krehbiel and Adkins, 1993). Formally, the error terms follow a moving average process as a result of new information that becomes available within the contract interval, $\eta_{t,t+n} = \varepsilon_t + \varepsilon_{t+1} + \cdots + \varepsilon_{t+n}$, where ε_t is *i.i.d.* pure noise with mean zero.

Several approaches have been proposed in the literature to tackle the overlapping problem, for instance to use an average of the data (see, for instance, Gilbert, 1986); to select a sampling frequency that avoids overlapping (Krehbiel and Adkins, 1993); and to apply an estimation methodology that accommodates serial correlation (Hansen, 1982 GMM estimation method). Using lower frequency data or average data may not be an efficient way of using all available information. In fact, Gilbert (1986) shows that taking the average does not eliminate the serial correlation in the error term.

The OLS estimates from a regression with overlapping data are unbiased and consistent but inefficient. In order to correct for serial autocorrelation in the error term several heteroscedasticity and autocovariance consistent (HAC) estimators have been proposed in the literature, such as Newey-West (NW) (1987), Andrews and Monahan (AM) (1990), and West (1997), among which the NW correction is the most widely applied and used in the current chapter.

4.3 Testing the UH under Different Market Conditions

Several studies in the literature empirically investigate the validity of the UH in different commodity and financial markets using equation (4.4) (for instance, Goss, 1981, 1983; Hisieh and Kulatilaka, 1982; Canarel and Pollard, 1986; Fama and French, 1987; MacDonald and Taylor, 1988; Chowdhury, 1991; Tim and Adkins, 1993; Beck, 1994; Yang, Bessler and Leatham, 2001). However, this form of the UH assumes a constant linear relationship between the variables, which may not be an appropriate assumption. As discussed in Chapter 1, the commodity futures market is linked to the spot market via a cost-of-carry relationship, which implies that futures markets can be characterised by backwardation and contango market conditions. When the convenience yield of holding the physical asset is large (i.e. the market is in backwardation), the commodity is an asset. On the other hand, when the benefit of holding it is offset by the costs of storing (i.e. the market is in contango), it may be optimal to consume it immediately. Scheinkman and Schechtman (1983) show that it is possible to model commodity prices in two pricing regimes: the commodity being priced as a consumption good when it is optimal to consume it immediately and the commodity being priced as an asset when it is optimal to store the commodity for future consumption. Following this line of thought, Heaney (2005) uses a MRS model to fit in the interest-adjusted basis of industrial metal contracts and suggests that the process follow two types of distributions: storage-based and value-based.

The existence of two distinct market conditions and consequently two different pricing regimes may lead to the possible existence of changes in the relationship between the futures price and spot price, such as a nonlinear relationship between basis ($F_t - S_t$) and the settlement – spot price difference (S_{t+n} - S_t) in Equation (4.4). For instance, from an economic point of view, futures prices may be unbiased predictors of future spot prices only when there are no obstacles to arbitrage trading[20].

The Markov Regime Switching model developed by Hamilton (1989) can be used to allow for changes in the market conditions and the relationship between spot and

[20] In this case, generally a contango market, the inventory level is sufficiently high, and hence, the convenience yield of holding the physical asset is low to non-existent. If the futures price exceeds the full cost-of-carry price, a cash-and-carry (buy spot and sell futures) arbitrage trade can be carried out without difficulties by borrowing the underlying commodity.

futures prices. The empirical test of the UH in equation (4.4) can therefore be extended to the following form in which parameters depend on the state of the market:

$$\Delta_n S_{t+n} = \alpha_{st} + \beta_{st} B_{t,t+n} + \eta_{st,t,t+n} \tag{4.5}$$

where st represents the market states and α_{st} and β_{st} are state dependent parameters.

When estimating the MRS model, the mean and the variance of the variables are regime dependent and the realization of the regimes are governed by a discrete-state stochastic Markov process (Hamilton, 1989). The estimation of the Markov Regime Switching model is illustrated in Chapter 3. The null hypothesis of the UH is tested through the joint parameter restriction H_0: $\alpha_1 = \alpha_2 = 0, \beta_1 = \beta_2 = 1$, in Equation (4.5). We apply the standard Likelihood Ratio test with an asymptotic χ^2 distribution with degree of freedom as r, where r is the number of restrictions. Let L_{UR} be the maximum value of the likelihood of the unrestricted model (4.5) and L_R be the maximum value of the likelihood when the parameters are restricted, i.e. $\alpha_1 = 0,\ \beta_1 = 1$ in state one and $\alpha_2 = 0,\ \beta_2 = 1$ in state two in model (4.5). The ratio $\lambda = L_R / L_{UR}$ should be between zero and one and the less likely the assumption is, the smaller λ will be. The statistics of the likelihood ratio test is calculated as -2lnλ which asymptotically follow a chi-square distribution with r degrees of freedom due to the presence of a nuisance parameter[21]. We note that the standard likelihood ratio test results need to be interpreted with caution. Tillmann (2003) suggests to instead compare the LR statistics with critical values of an asymptotic χ^2 distribution with degree of freedom $r+n$, where n is number of nuisance parameters in the MRS. Therefore, the null hypothesis is rejected if -2lnλ is larger than a Chi-square 5% critical value with $r+n$ degrees of freedom.

[21] We recognize that the existence of a nuisance parameter (the transition probability) could cause the asymptotic distribution of the test statistics (-2lnλ) to become a non-standard chi-square distribution (see, for instance, Davies, 1977, 1987; Hansen, 1991; Garcia, 1998 for detailed discussion on this issue). However, the alternative tests having been proposed (Hansen, 1991; Garcia, 1998) are computationally intensive and beyond the scope of this work.

4.4 Empirical Results

4.4.1 The Conventional UH tests

We first test the UH in the form of equation (4.4), using weekly data (Wednesday prices) over the period 05 April 1994 to 30 June 2004. Since observations are overlapping, we use the Hansen (1982) Generalized Method of Moment (GMM) estimation method (with the lagged basis as an instrumental variable) and the Newey-West robust error autocorrelation correction methodology (Newey and West, 1987) to correct the variance covariance matrix for the existence of serial autocorrelation in the error terms, as discussed in Section 4.2. Hansen (1982) and Hansen and Singleton (1982) show that the GMM estimation produces consistent estimators subject to heteroscedasticity and serially correlated errors. The restrictions implied by the UH are then tested using the Likelihood Ratio test and the results are reported in Table 4.1. Over the full sample period, the UH ($H_0: \alpha = 0, \beta = 1$) cannot be rejected in all the markets based on the Chi-square statistics.

Table 4.1 UH test in a simple linear regression

$\Delta^n S_{t+n} = \alpha + \beta B_{t,t+n} + \eta_{t+n}$				
	α	β	$\overline{R}^2$	χ^2 –statistics of H_0: $\alpha = 0$, $\beta = 1$
Aluminium	-0.0034 [0.841]	0.4789 [0.636]	0.0059	1.3211 [0.517]
Aluminium alloy	-4.32e-06 [0.999]	-0.0710 [0.897]	0.0021	6.5254 [0.038]
Copper	0.0119 [0.481]	0.4786 [0.347]	0.0109	1.1486 [0.563]
Lead	0.0133 [0.442]	-0.0920 [0.868]	0.0022	4.4682 [0.107]
Nickel	0.0182 [0.369]	0.9725 [0.339]	0.0121	0.8138 [0.666]
Tin	0.0152 [0.256]	-0.2249 [0.855]	0.0024	1.7248 [0.422]
Zinc	-0.0159 [0.233]	**0.9313** **[0.001]**	0.9319	1.8890 [0.389]

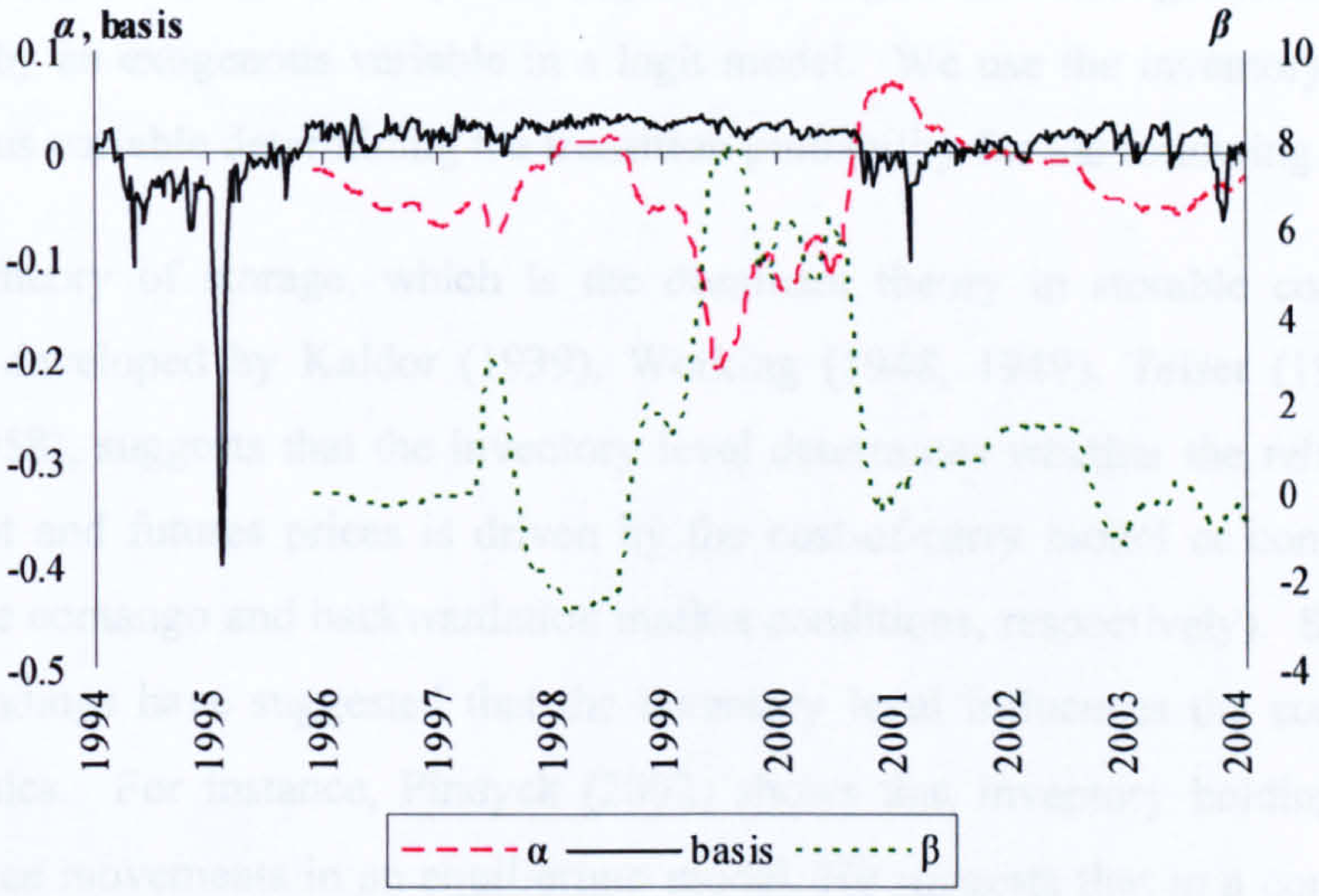
- The sample period is between 04/1994 and 06/2004.
- Figures in brackets [ ] are p-values.
- Estimation is Newey-West error autocorrelation corrected.
- Bold numbers represent statistical significance at the 5% level.

However, even though the futures prices of all seven metal futures contracts, with an exception of aluminium alloy, are found to be unbiased predictors of the settlement prices on average, they may not perform the price discovery function well in sub-sample periods due to changes in the market conditions and the dynamics of the spot and futures price relationship. For instance, Yang, Bessler and Leatham (YBL) (2001) show that the price discovery function of futures prices in agricultural market performs differently over different sub-samples. They suggest that the UH is more likely to hold in the long run than in the short run, however, they argue that this may be due to some short-term effect, for instance, the application of regulations.

As a first attempt to document the time-varying predictive ability of futures prices, we estimate the parameters in equation (4.4) using a rolling-window Generalized Method of Moments (GMM) technique (Hansen, 1982). The model in equation (4.4) is estimated based on a rolling window with sample length equal to 104 weeks using the lagged basis as the instrumental variable. The output consists of 422 estimates (the total sample length of 526 weeks less the window length) of the "rolling" α and β, the descriptive statistics of which are shown in Appendix I. The average α estimate is negative in all the markets and the average β estimate is positive in all the markets except copper. Both α and β estimates show strong time-varying features. For instance, the β estimate ranges from -35 to 13 in the aluminium market.

As an illustration, Figure 4.1 plots the rolling α and β estimates against the basis in the lead market. It appears that the β estimate distributes around one with large variance. Mathematically, the estimates are linked to the covariance between $\Delta_n S_{t+n}$ and B_t, and the variance of the basis (basis risk). However, due to the time-varying nature of the covariance and variance, it is difficult to draw any strong conclusions regarding the relationship between the time-varying estimates in the UH test and basis volatility or, implicitly, market conditions.

Figure 4.1 Rolling estimates of α, β in the lead market



The rolling-window technique suffers from a couple of drawbacks. Firstly, the results are sensitive to the window length used and there are no robust statistical guidelines for the optimal choice of window size (see, Swanson 1998 for a discussion). Choosing a narrow window makes the results sensitive to outliers and sampling errors, while the use of too wide a window makes it likely that short-lived changes will not be detected. Secondly, although the rolling-window estimation results are able to detect a time-varying behaviour in the model, it does not provide a statistical sound way of identifying the exact dates when changes have taken place, let alone statistical test for the significance of these changes.

4.4.2 Testing the UH using Regime Switching method

Parameter instability, as illustrated by the rolling window estimates above, has led to the development of models with time-varying parameters. One notable set of such models are switching regressions, in which parameters of the model switch discretely between a fixed number of regimes and the switching process is conditioned on either an unobserved or observed state variable. Since Hamilton's (1989) seminal paper on Markov-switching models, there have been extensive applications of the Markov Regime Switching (MRS) model in financial economics (see, for instance, Lam, 1990; Garcia and Perron, 1999; Raymond and Rich, 1997). The transition probability may be fixed as in the original Hamilton (1989) paper or may be time varying. It has been suggested (see, for instance, Diebold, Lee and Weinbach, 1994; Filardo, 1994; and Peria, 2002) that the transition probability in the regime switching model can be determined by an exogenous variable in a logit model. We use the inventory level as the exogenous variable determining the transition probability for the following reasons.

Firstly the theory of storage, which is the dominant theory in storable commodity market and developed by Kaldor (1939), Working (1948, 1949), Telser (1958) and Brennan (1958), suggests that the inventory level determines whether the relationship between spot and futures prices is driven by the cost-of-carry model or convenience yield (i.e. the contango and backwardation market conditions, respectively). Secondly, empirical findings have suggested that the inventory level influences the commodity price dynamics. For instance, Pindyck (2002) shows that inventory holdings affect short-run price movements in an equilibrium model. He suggests that in a competitive commodity market, inventories can be used to reduce costs of varying production (when marginal cost is increasing), and to reduce marketing costs by facilitating production and delivery scheduling and avoiding stockouts. These latter factors make it costly for firms to reduce inventories beyond some minimal level, even if the marginal production cost is constant. The extent to which prices will move in the short run therefore depends on the cost of varying production as well as the cost of drawing down inventories.

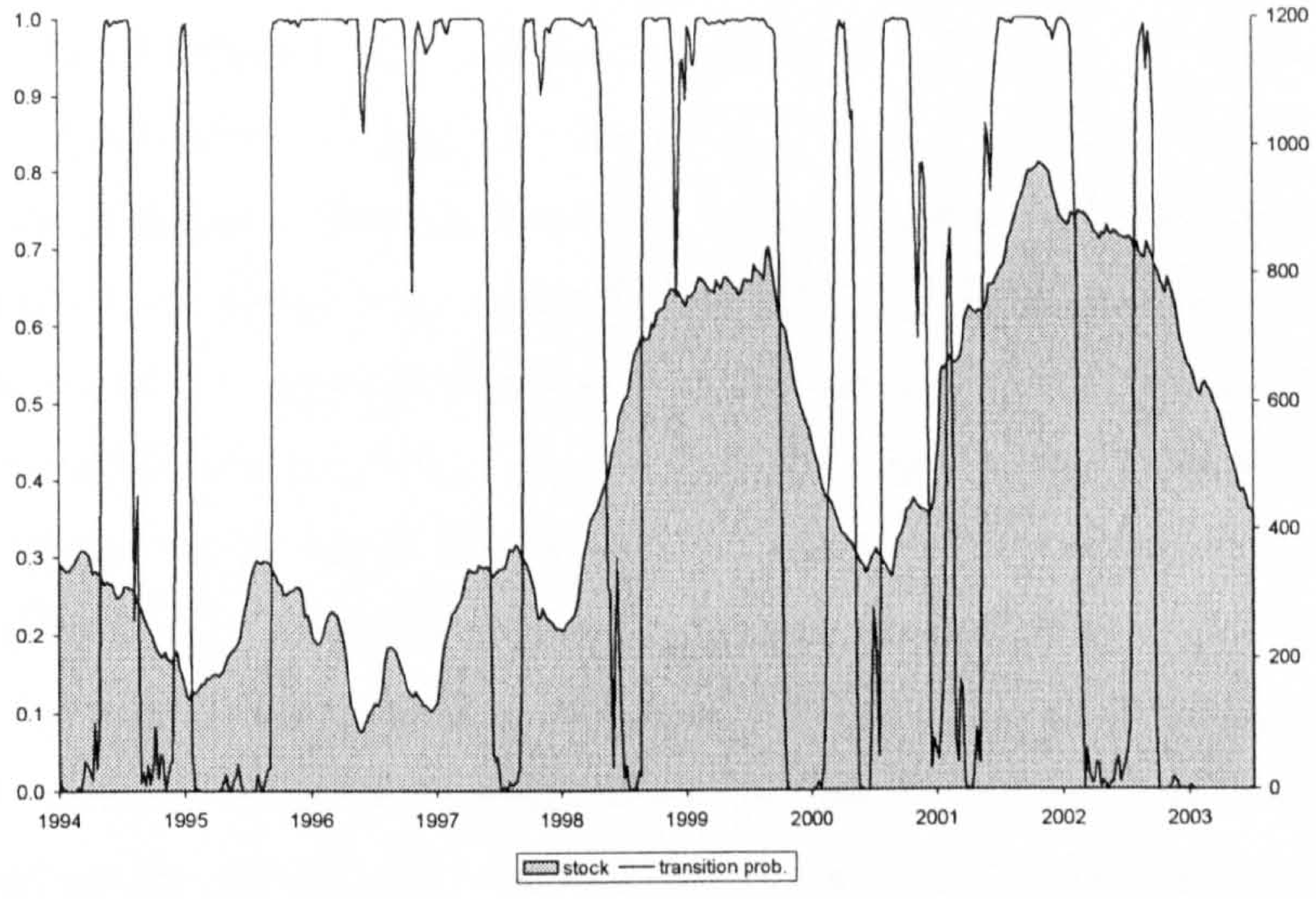
The estimation of transition probabilities in the MRS model conditional on the inventory level is based on the following logit model:

$$p_{12,t} = \frac{1}{1+e^{m_0+m_1 \cdot ls_t}}, \quad p_{21,t} = \frac{1}{1+e^{n_0+n_1 \cdot ls_t}} \tag{4.6}$$

where $p_{12,t}$ is the probability of transiting from state one to state two, $p_{21,t}$ is the probability of transiting from state two to state one, ls_t is the inventory level, and m_0, m_1, n_0, and n_1 are constant parameters.

The parameter estimates for the MRS model and the UH test results are presented in Table 4.2. Figure 4.2 graphs the transition probability and the inventory level in the lead market as an example. Essentially the process is separated into two states: a high-volatility state and a low-volatility state. The high-volatility state (state one in the model) is typically associated with a low inventory level and the low-volatility state (state two) is generally associated with a high inventory level.

Figure 4.2 Transition probability and inventory level in the lead market



When the market is in backwardation, there is usually a low inventory level in the physical commodity market and it is the convenience yield that dominates the relationship between spot and futures price. In this case, the supply curve is less elastic resulting in higher volatility *ceteris paribus*. In a contango market, on the other hand, there are usually sufficient stocks in the physical commodity market and, as a result, the spot and futures prices are driven by the cost-of-carry relationship. In this case prices are less volatile as the inventory can more easily absorb supply and demand shocks. This has been documented by Fama and French (1988) and Ng and Pirrong (1994) who observe that the price volatility in periods of low inventory is greater than the volatility during periods of high inventory.

The restrictions under the UH, i.e. α_{st}=0 and β_{st}=1 of equation (4.5), are rejected at a 5% significance level in all the markets in both states, suggesting that the futures prices are not unbiased predictors of the settlement prices when market conditions are taken into account. While the coefficients α_1, α_2, β_1 and β_2 appear rather different between the markets in terms of sign and size, this cannot be taken as an indication of poor model performance or indeed taken to have any sort of practical consequences. This is because the MRS model, by definition, will endogenously separate the data into the two states and this separation will differ between markets.

As an attempt to further explore the predictive ability of the futures prices, we relax the restriction by allowing for a nonzero constant α_{st} in the MRS model and only restricting $\beta = 1$. This parameter can be interpreted as a constant forecasting bias or a constant risk premium in the futures prices[22]. The parameter restriction of $\beta_{st}=1$ in equation (4.5) is tested and the likelihood ratio statistics are presented in Table 4.2. Subject to the presence of a non-zero α estimate, the restriction of H_0: $\beta = 1$ cannot be rejected in both states in the aluminium, aluminium alloy and nickel market, it is rejected only in the low-volatility state in the copper, lead and tin markets, while it is rejected in both states in the zinc market. In the high-volatility state, conditional on $\beta = 1$, the α estimates are found to be statistically positive at the 10% significance level in the copper, lead, nickel and tin markets, suggesting that the difference between the settlement price and futures price is positive. In other words, the futures prices are found to be below the settlement prices in the high-volatility state (when the market is said to be in backwardation) in four of the markets. In the low-volatility state (conditional on $\beta = 1$) the α estimates are found to be statistically negative at the 5% significance level in the lead, nickel, tin and zinc markets, suggesting that the futures prices are above the settlement prices.

[22] The restricted version of equation (4.4), hence, becomes $S_{t+n} = \alpha_{s_t} + F_{t,t+n}$.

Table 4.2 MRS testing the UH

$$\Delta_n S_{t+n} = \alpha_{st} + \beta_{st} B_{t,t+n} + \eta_{st,t,t+n}, \quad p_{12,t} = \frac{1}{1+e^{m_0+m_1 ls_t}}, \quad p_{21,t} = \frac{1}{1+e^{n_0+n_1 \cdot ls_t}}$$

	α_1	β_1	m_0	m_1	σ_1	α_2	β_2	n_0	n_1	σ_2	χ^2 H_0: α_1=0, β_1=1	χ^2 H_0: α_2=0, β_2=1	χ^2 H_0: β_1=1	χ^2 H_0: β_2=1
Al	0.0104	2.633	-0.6185	0.491	**0.0638**	-0.007	-3.2741	3.5394	-0.1406	**0.0421**	**10.5889**	**76.6593**	0.4764	1.7344
	[0.870]	[0.266]	[0.876]	[0.424]	[0.000]	[0.892]	[0.313]	[0.682]	[0.915]	[0.000]	[0.005]	[0.000]	[0.490]	[0.188]
Al alloy	**-0.052**	0.3145	**13.0348**	**-2.2416**	**0.0502**	**0.0721**	**1.1328**	**6.093**	**-0.7716**	**0.0497**	**75.8232**	**21.0409**	2.0756	0.0602
	[0.000]	[0.509]	[0.000]	[0.000]	[0.000]	[0.000]	[0.036]	[0.001]	[0.036]	[0.000]	[0.000]	[0.000]	[0.150]	[0.806]
Copper	**0.0999**	**4.0221**	2.1131	0.1402	**0.2022**	-0.0013	-0.1819	-0.8425	0.7905	**0.0683**	**6.3313**	**21.0357**	2.781	**19.1188**
	[0.048]	[0.026]	[0.477]	[0.498]	[0.000]	[0.918]	[0.501]	[0.782]	[0.124]	[0.000]	[0.042]	[0.000]	[0.095]	[0.000]
Lead	0.1314	-1.8454	2.3045	0.1268	**0.0786**	**-0.0471**	**-0.5921**	4.8273	-0.2496	**0.0542**	**15.6509**	**79.0915**	1.5575	**20.823**
	[0.053]	[0.418]	[0.493]	[0.819]	[0.000]	[0.001]	[0.090]	[0.135]	[0.633]	[0.000]	[0.000]	[0.000]	[0.212]	[0.000]
Nickel	**0.1581**	1.1476	**3.2405**	-0.0327	**0.0942**	**-0.0889**	0.9286	1.4437	0.5509	**0.0825**	**98.806**	**60.4905**	0.0316	0.0106
	[0.000]	[0.167]	[0.040]	[0.939]	[0.000]	[0.000]	[0.181]	[0.406]	[0.286]	[0.000]	[0.000]	[0.000]	[0.859]	[0.918]
Tin	**0.1001**	-4.6571	0.6646	0.8438	**0.1065**	**-0.0319**	-0 3399	**7.02**	**-1.4374**	**0.0352**	**10.5067**	**32.1187**	2.4215	**10.1706**
	[0.001]	[0.200]	[0.729]	[0.242]	[0.000]	[0.000]	[0.419]	[0.000]	[0.010]	[0.000]	[0.005]	[0.000]	[0.120]	[0.001]
Zinc	**-0.1426**	**9.203**	-2.1963	0 8602	**0.1413**	**-0.0226**	**0.5904**	-4.5616	1.3551	**0.046**	**12.8295**	**10.9785**	**7.8486**	**7.6808**
	[0.070]	[0.002]	[0.672]	[0.330]	[0.000]	[0.005]	[0.000]	[0.405]	[0.141]	[0.000]	[0.002]	[0.004]	[0.005]	[0.006]

- Figures in brackets [ ] are p-values;
- Bold numbers are statistically significant at the 5% level;
- The data set is weekly data from 04/1994 to 06/2004;
- Time to maturity n equals to 13 weeks, i.e. three months futures.

4.5 Predictive Accuracy of Futures Prices under Different Market Conditions

In previous sections we found that the validity of the UH is dependent on market conditions and that the futures prices appears to be a biased predictor of the future spot price. In this section we use a nonparametric method to directly examine the predictive accuracy of futures prices under different market conditions.

4.5.1 Forecasting Accuracy in Backwardation and Contango

As discussed in Chapter 1, a backwardation market is usually associated with low inventory level which causes high convenience yield. Low inventory level means the short-run supply curve is less elastic and, therefore, the spot price and, to a lesser extent, the futures price is more sensitive to shocks. Intuitively, the inherent higher price volatility in a backwardation market may cause larger differences ex-post between the futures price and the realised settlement price.

Here, the benchmark to separate backwardation from contango is taken as the average of the basis, i.e. the difference between the logarithm of futures and spot prices $basis = f_{t,t+n} - s_t$. That is, when the basis is smaller than its mean, the market is said to be in backwardation, and otherwise it is in contango. The reason we use the average of the basis rather than zero basis as the benchmark is to take into account, at least partly, the cost-of-carry relationship. This is in contrast to the definition of backwardation and contango in Edwards and Ma (1992) in which zero basis is the benchmark.

The Forecast Error (FE) is defined as the difference between the (logarithm) futures prices and settlement prices.

$$FE = f_{t,t+n} - s_{t+n} \tag{4.7}$$

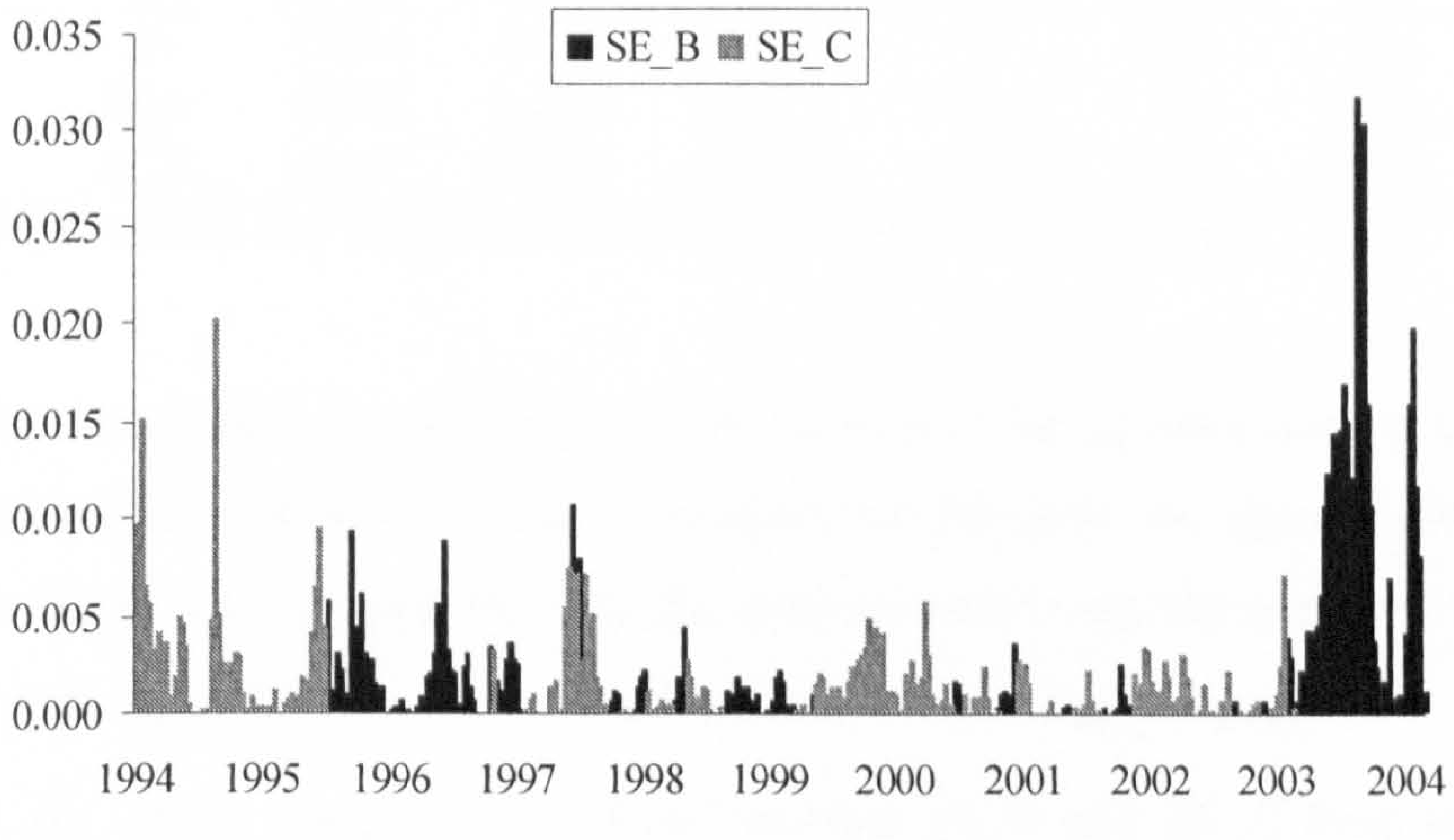
where s_{t+n} is the logarithm of the settlement price and f_t is the log futures price at time t.

When the forecast error is greater than zero, the futures price is said to be an upward-biased predictor of the settlement price, and otherwise it is a downward-biased predictor. The Squared Error (SE) is calculated for the seven metal futures prices in the form of (4.8).

$$SE = (f_{t,t+n} - s_{t+n})^2 \tag{4.8}$$

As an example, Figure 4.3 plots the SE of the lead futures price over the period April 1994 to June 2004. The dark area represents the SE in the backwardation market and the grey area represents the SE in the contango market condition. It shows that the market is in contango more often than in backwardation and that large forecast errors occurred in late 2003 and 2004 when the lead market was in backwardation.

Figure 4.3 The squared forecast error of lead futures price



The descriptive statistics of the SE in the seven metal futures markets are shown in Table 4.3.

Table 4.3 **Descriptive statistics of the forecasting squared error**

		Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Obs.
Aluminium	*SE*	0.0012	0.0016	3.3097	19.7	7096	526
	SE_B	0.0009	0.0014	2.952	13.6	1238	202
	SE_C	0.0013	0.0017	3.4131	21	5015	324
Aluminium alloy	*SE*	0.0013	0.0018	2.5922	11.8	2290	526
	SE_B	0.0012	0.0014	1.7404	6.6	218	211
	SE_C	0.0014	0.0019	2.6873	11.6	1348	315
Copper	*SE*	0.0034	0.0085	4.885	28.3	11824	385
	SE_B	0.0054	0.0114	3.555	15.5	1344	156
	SE_C	0.002	0.0054	6.9456	57	29710	229
Lead	*SE*	0.0022	0.0038	3.8661	22.4	9596	526
	SE_B	0.003	0.005	3.0549	13.9	1489	228
	SE_C	0.0016	0.0023	3.5055	21.4	4805	298
Nickel	*SE*	0.0043	0.0057	2.8107	15.8	4273	526
	SE_B	0.005	0.0066	3.0265	17	2092	216
	SE_C	0.0038	0.0049	2.0856	7.6	495	310
Tin	*SE*	0.0017	0.0037	4.1345	23	10249	526
	SE_B	0.0028	0.0055	2.7678	10.4	635	178
	SE_C	0.0012	0.002	3.327	15.5	2892	348
Zinc	*SE*	0.0016	0.0025	3.3514	17.7	5733	526
	SE_B	0.0022	0.0035	2.3522	8.4	324	152
	SE_C	0.0013	0.0019	3.8717	29.3	11709	374

- SE_B: squared error in backwardation; SE_C: squared error in contango.

A priori and according to the argument so far, we expect the squared error to be larger in a backwardation market than in a contango market. Let *SE_B* be the squared error when the market is in backwardation and *SE_C* be the squared error when the market is in contango. Thus the null hypothesis under consideration is $H_0 : \mu_{SE\_B} - \mu_{SE\_C} = 0$ against the alternative $H_0 : \mu_{SE\_B} - \mu_{SE\_C} \neq 0$. Given that the *SE_B* and *SE_C* time series are not normally distributed according to the Jarque-Bera test results presented in Table 4.3, and as each group has different sample size, we use the bootstrap approach (Efron, 1979) to generate empirical estimates of the sampling distributions of *SE_B* and *SE_C*. The bootstrap approach entails drawing *n* random observations with replacement (where *n* equals the respective sample size of *SE_B* or *SE_C* for each of the metals markets) from the population of *SE_B* and *SE_C* calculated as defined above. This resampling procedure is repeated *N*=5000 times, resulting in *N* estimates of the statistic of interest. As each new sample will deviate slightly from the original population, the resulting statistics, such as the mean, will take on slightly different values. The central assertion of the bootstrap method is that the relative frequency distribution of these statistics is an estimate of the sampling distribution of its true mean.

For each bootstrapped *SE_B* and *SE_C* series, the mean is calculated and forms the distribution of the average of the *SE_B* and *SE_C*. The statistics of the bootstrapped distribution of the *SE_B* and *SE_C* are presented in Table 4.4. The confidence interval is taken as the 90% percentile of the mean distribution. By comparing the mean of bootstrapped *SE_B* (*SE_C*) average distribution with the confidence interval of the bootstrapped *SE_C* (*SE_B*) distribution, we can formally test whether *SE_B* and *SE_C* has the same mean. The *p*–value is obtained by taking the maximum of the percentile ranking of the mean of the *SE_B* falling in the distribution of the *SE_C* average and the mean of *SE_C* falling in the distribution of the *SE_B* averages.

Table 4.4 Bootstrapped SE_B and SE_C difference

		Mean SE	90% Confidence interval	$SE\_B - SE\_C$
Aluminium	*SE_B*	0.000937	[0.00078, 0.00110]	-0.00036
	SE_C	0.001295	[0.00115, 0.00145]	(0.000)
Al Alloy	*SE_B*	0.001189	[0.00103, 0.00135]	-0.00022
	SE_C	0.001411	[0.00123, 0.00159]	(0.017)
Copper	*SE_B*	0.005293	[0.00389, 0.00682]	0.00341
	SE_C	0.001887	[0.00140, 0.00246]	(0.000)
Lead	*SE_B*	0.002964	[0.00244, 0.00352]	0.00139
	SE_C	0.001578	[0.00136, 0.00181]	(0.000)
Nickel	*SE_B*	0.005003	[0.00430, 0.00578]	0.00125
	SE_C	0.003756	[0.00330, 0.00422]	(0.001)
Tin	*SE_B*	0.002757	[0.00210, 0.00344]	0.00161
	SE_C	0.001147	[0.00098, 0.00132]	(0.000)
Zinc	*SE_B*	0.002236	[0.00178, 0.00272]	0.00095
	SE_C	0.001281	[0.00112, 0.00145]	(0.000)

- Statistics for the 5000 bootstrapped averages of SE_B and SE_C;
- Numbers in parenthesis ( ) are p-values

It can be observed that the mean of the distribution of bootstrapped averages of *SE* in a backwardation market is statistically different from that in a contango market in all the markets. In five out of the seven markets the forecast errors are found to be larger in the backwardation market compared to a contango market, with the exception of the aluminium and aluminium alloy markets. In particular, the SE in a backwardation market is 180% higher than that in a contango market in the copper market and 33%, 75%, 88% and 140% higher in the nickel, zinc, lead and tin markets, respectively. It seems reasonable to argue that in a backwardated market, when the price volatility tends to be high, it may be more difficult for market participants to collectively predict the future spot price, resulting in the larger *ex-post* forecast errors in Table 4.4. However, this may also be a result of a consistent forecasting bias, as discussed in the next sections.

4.5.2 The Unbiasedness of Futures Price Forecast Error

Having examined the UH in a regression framework, we here investigate whether the futures prices are unbiased predictors of the settlement prices in a nonparametric framework. The forecast error is calculated as in Equation (4.7), i.e. the difference between futures at time t with maturity at $t+n$ and settlement price at time $t+n$. The bootstrap technique as described above is used to generate the distribution of the mean of the forecast error and the 90% percentile of the mean distribution is obtained. The forecast errors are again separated according to market conditions (backwardation or contango). Table 4.5 presents the mean and 90% percentile of the average of forecast errors distribution. If the 90% confidence interval of the average distribution includes zero, we say that the forecast error is not statistically different from zero.

Table 4.5 Bootstrapped distribution of forecast error average

		Mean	90% confidence interval	Sign of the forecast error
Aluminium	*FE*	0.0031	[0.0007 , 0.0055]	+
	FE_B	0.0005	[-0.0031 , 0.0040]	Zero
	FE_C	0.0047	[0.0015 , 0.0079]	+
Aluminium alloy	*FE*	0.0063	[0.0038 , 0.0088]	+
	FE_B	-0.0033	[-0.0072 , 0.0005]	Zero
	FE_C	0.0128	[0.0094 , 0.0161]	+
Copper	*FE*	-0.0066	[-0.0106 , -0.0026]	-
	FE_B	-0.0141	[-0.0201 , -0.0083]	-
	FE_C	0.0028	[-0.0022 , 0.0077]	Zero
Lead	*FE*	-0.0015	[-0.0049 , 0.0018]	Zero
	FE_B	-0.0116	[-0.0176 , -0.0058]	-
	FE_C	0.0056	[0.0018 , 0.0092]	+
Nickel	*FE*	-0.0080	[-0.0127 , -0.0032]	-
	FE_B	-0.0170	[-0.0248 , -0.0095]	-
	FE_C	-0.0018	[-0.0075 , 0.0039]	Zero
Tin	*FE*	-0.0043	[-0.0073 , -0.0013]	-
	FE_B	-0.0102	[-0.0166 , -0.0037]	-
	FE_C	-0.0012	[-0.0042 , 0.0018]	Zero
Zinc	*FE*	0.0070	[0.0043 , 0.0098]	+
	FE_B	0.0154	[0.0093 , 0.0214]	+
	FE_C	0.0036	[0.0006 , 0.0067]	+

- FE_B: forecast error ($f_t - s_{t+n}$) in backwardation; FE_C: forecast error in contango.

At the 10% significance level, the overall forecast error is found to be statistically significant in all the markets with the exception of lead. When the market is in backwardation, the null hypothesis (*forecast error* = 0) is accepted only for the aluminium and aluminium alloy markets. On the other hand, when the market is in contango, the null hypothesis is accepted in the copper, nickel and tin markets. Moreover, the average of the bootstrapped mean distribution of the forecast error is negative in four of the markets (copper, lead, nickel and tin) in backwardation and it is positive in four markets (aluminium, aluminium alloy, lead and zinc) in a contango market.

Table 4.6 summarizes the result of the sign of the forecast error obtained by both the regression method and bootstrapping method in Sections 4.4.2 and 4.5.2. It can be seen that the sign of the forecast error is consistent across the two methods. Thus, it is safe to conclude that, in general, the average forecast error is negative when the market is in backwardation and it is positive when the market is in contango.

Table 4.6 **Parametric and nonparametric forecast error comparison**

	Empirical estimation[1] Forecast error: $f_T s_{tt+n}$ ($-\alpha$)		Bootstrapped forecast error : $f_T s_{tt+n}$	
	Backwardation	Contango	Backwardation	Contango
Aluminium	Zero	Zero	Zero	+
Al alloy	+	-	Zero	+
Copper	-	Zero	-	Zero
Lead	-	+	-	+
Nickel	-	+	-	Zero
Tin	-	+	-	Zero
Zinc	+	+	+	+

Note: the empirical estimation is obtained from the MRS UH testing regression.

One of the explanations with respect to the difference between the realised spot price and futures prices is the existence of a risk premium. The theory of risk premium in the futures market (see, for instance Keynes, 1930; Houthakker, 1957; Cootner, 1960) suggests that hedgers need to compensate speculators for providing the insurance that hedgers seek. In particular, the theory of normal backwardation developed by Keynes (1930) states that futures prices are, in general, downward-biased estimates of future spot prices. Keynes (1930) argues, assuming hedgers are net short, that the spot price must exceed the forward price by the amount which the producers is ready to sacrifice in order to hedge himself, i.e. to avoid the risk of price fluctuations during his production period. Thus, in Keynes's view, under normal market conditions the spot price exceeds the forward price, i.e., there is a backwardation.

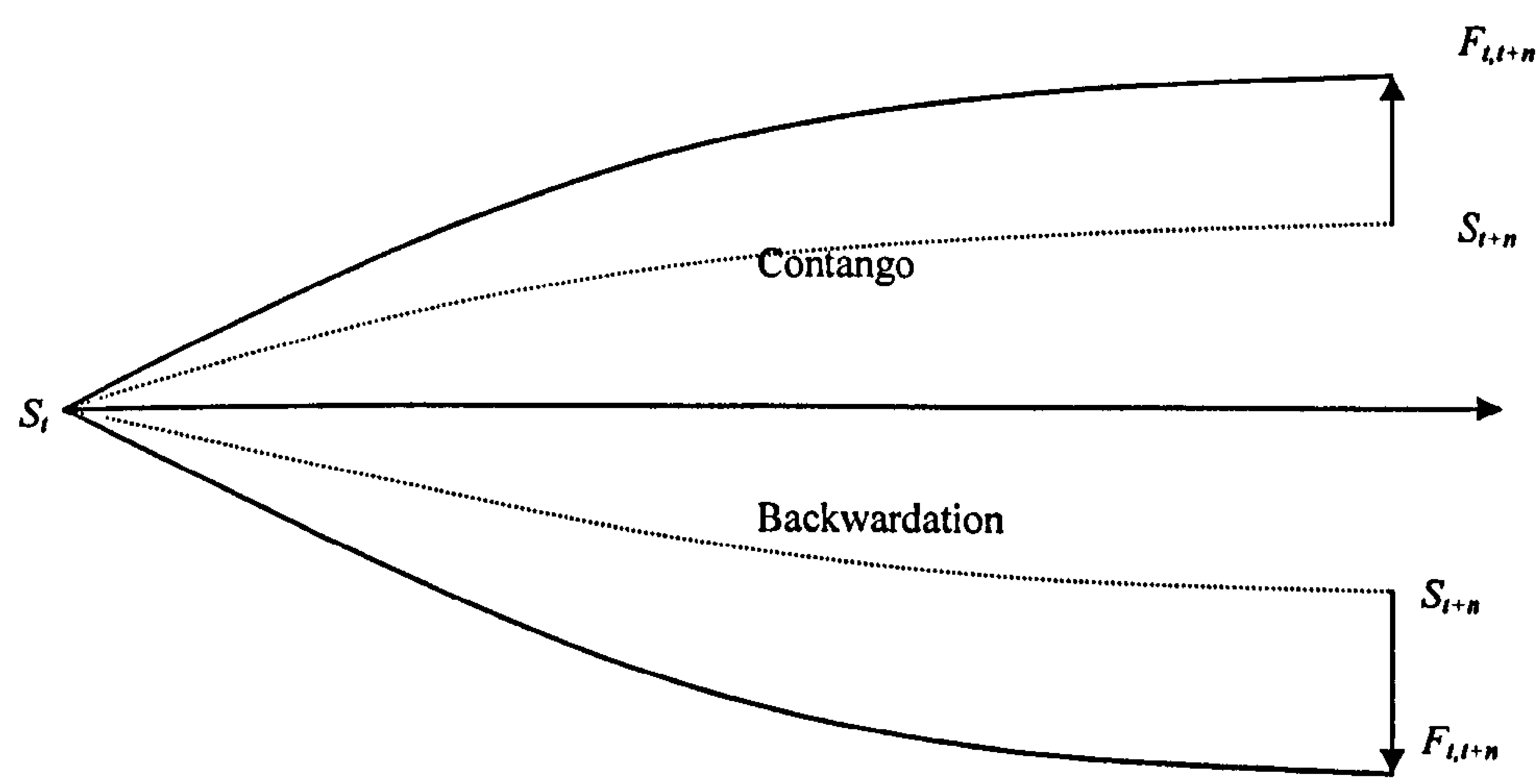
However, Geman (2005) states that:

> *"... the theory of normal backwardation may be somewhat obsolete ...(and thus) ...the sign of the "risk premium" (and the existence of 'normal backwardation') depends on the specific commodity under analysis and, in particular, the level of available inventory... "*
>
> *-- Geman (2005, p. 34)*

Assuming that hedgers are mainly composed of consumers and producers of metals, the consumers are naturally short while producers are naturally long in the physical market. In terms of using the futures contract to hedge their price risks, it follows that producers are net short and consumers are net long in the futures market. Consequently, in order for the risk premium to change sign within this theoretical framework, it must be the consumers and producers that are the main hedgers in contango and backwardation, respectively. When the market is in backwardation, it is reasonable to argue that agents expect spot prices to decrease and producers will hedge their physical position in this case by being net short in the futures market. In a contango market, the empirical results suggest that consumers who are net long in the futures market are the main hedgers. However, we recognise that it is difficult to find a sound theoretical economic explanation for this.

Another explanation of the rejection of the UH would be that the price expectation of market participants consistently "overshoot" the realised future spot price. In particular, the market expectation at time t with regards to the spot price at time $t+n$ is downward biased in a backwardation market and upward biased when the market is in contango. Figure 4.4 illustrates the relationship between the futures and realised spot prices found in this chapter. It shows that the futures price at time t ($F_{t,t+n}$) is always further away from the current spot price (S_t) than the realised spot price (S_{t+n}). However, this explanation typically finds little support in the academic literature, given the large number of market participants who are trading on the LME and the fact that it would be difficult for everybody to form the same biased expectations regarding the future.

Figure 4.4 Relationship between the futures price and the realised spot price



4.6 Discussion and Concluding Remarks

This chapter investigates the validity of the EMH in the industrial metals markets in terms of testing the Unbiasedness Hypothesis, which states that current futures price should reflect the rational expectation of the market participants regarding the future spot price subject to a zero risk premium. The empirical findings suggest that the UH cannot be rejected in any of the seven metal markets for the whole sample using a linear testing framework. However, a recursive rolling window estimation of the testing model documents a time-varying behaviour in the parameter estimates in the UH testing model.

In light of these findings, we argue that the efficiency of commodity futures markets are subject to regime shifts and examine the validity of the UH using a Markov Regime Switching model allowing for two market states. In the MRS model, the transition probabilities are linked to and determined by the inventory levels and the price process is separated into a high-volatility and a low-volatility states which are associated with backwardation and contango markets, respectively.

Our empirical results suggest that the UH is rejected in almost all the markets in either of the states when market conditions are taken into account. Further, after we allow for a non-zero constant forecast error or risk premium in the testing methodology, the restriction that the futures price equals to the settlement price minus (plus) an error or a risk premium is rejected in two of the seven markets in the high-volatility state and in five markets in the low-volatility state. Moreover, the difference between the futures price and the realised spot price is found to be negative in the high-volatility state and is positive in the low-volatility state.

To further test the price discovery role of the futures prices under different market conditions, we use a nonparametric method to examine the distribution of forecast errors (the difference between the futures and settlement prices). The bootstrap resampling technique is used to generate the distribution of the mean of forecast errors and provides a statistical framework to examine the dependency on the market conditions. The results reveal that the Squared Error is statistically larger in a backwardation market in four of the markets, confirming the proposition that forecast errors of futures prices are larger when the volatility is high.

The unbiasedness of futures prices is also re-examined using the bootstrap methodology. The forecast error is found to be statistically different from zero in most markets. Also, the forecast error is generally found to be negative when the market is in backwardation and positive when the market is in contango, confirming the results from the MRS model.

We argue that the difference between the futures price and the realised spot price has two possible explanations. First, the forecast error may be a premium for the transfer of risk from hedgers to speculators. Producers are naturally net short and consumers are net long in the futures markets. We argue that the producers are the main hedgers in the futures market when the market is in backwardation as the expected spot price is believed to be lower than the current spot price, conditional on the rational expectation hypothesis. Therefore, the existence of a risk premium that the hedgers (producers in this case) pay to the speculators drives the futures price lower than the realised spot price. Conversely, when the market is in contango, the consumers are main hedgers in the futures market and they are net short as the expected spot price is higher than the current spot price. Thus the presence of a premium that hedgers (the consumers) pay to the speculators will drive the futures price above the realised spot price.

Second, the participants may be consistently over or under estimating the future spot price. However, to assume that all the market participants are irrational has little support in the financial economics literature due to the large number of agents in the market.

The scope of this chapter, however, is not to determine whether the differences between the futures and realised spot prices are due to a risk premium or biasedness of the market participants, but rather to highlight the different behaviour of the commodity spot and futures prices under the two market conditions. Further investigation into the hedgers' and speculators' (or producers' and consumers') positions in the futures markets may give more insight into the results in this chapter.

5 CHAPTER FIVE

COST OF CARRY RELATIONSHIP AND MARKET CONDITIONS

5.1 Introduction

It is argued in the literature that the spot and futures price of a storable commodity is linked by a cost-of-carry relationship. Theoretically, the futures price at time t for delivery at time $t+n$ should represent the current spot price plus any costs associated with purchasing and holding the underlying asset from time t to $t+n$ as well as the convenience yield from holding the asset. 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 (for instance, wastage for perishable commodities and transportation costs related to delivery). If the futures price exceeds this cost-of-carry equilibrium, the deviation will be eliminated by "cash-and-carry" arbitrage traders buying the underlying commodity and selling the futures contracts. However, when futures price are below the full cost-of-carry price, for instance, if there is a shortage in the physical market or due to political instability, market participants may not be willing to lend or sell the physical assets that they have, implying the existence of a convenience yield from holding the assets. Hence, this situation does not necessarily imply an opportunity for reverse cash-and-carry arbitrage.

The equilibrium relationship between spot and futures prices has been well documented and tested in the literature on the storable commodity futures markets. Particularly, the long-run co-movement between the two prices has been investigated using the cointegration techniques developed by Engle and Granger (1987) and Johansen (1988, 1991). For instance, Chowdhury (1991) and Franses and Kofman (1991) examine the long-run relationship between spot and futures prices on the LME market and find evidence of cointegration between spot and futures prices. Krehbiel and Adkins (1993) also find that the futures prices and realised spot prices of silver, copper, platinum and gold futures that are traded on COMEX and NYMEX are cointegrated. Beck (1994) studies the market efficiency of the US agricultural and metal commodity futures markets using the cointegration technique and finds that in general the spot and futures prices are cointegrated, albeit with periodical disturbances.

Brenner and Kroner (1995) apply a no-arbitrage asset pricing model to derive the relationship between the contemporaneous spot and futures prices and empirically test their arguments in the foreign exchange, commodity, and equity markets. They argue that if any of the cost-of-carry elements are nonstationary, the difference between the futures and cash price, which they refer to as the cost-of-carry (financing, storage costs and convenience yield), is also nonstationary and, hence, the spot and futures prices cannot be cointegrated. Brenner and Kroner (1995) suggest that in order to examine the long-run cointegration relationship between spot and futures prices in the storable commodity market, researchers should include the cost-of-carry elements in the cointegration tests. Unfortunately, this point has been ignored by most subsequent research works in the area. One exception is Heaney (1998) who examines the relationship between the main factors in the cost-of-carry model (the spot and futures price, interest rate and stock level) in the lead futures market on the LME. He finds that in the long run the cost-of-carry relationship holds based on the results of cointegration tests.

The aim of this chapter is to investigate the long-run equilibrium relationship between the spot and futures price in the storable commodity market and the dynamics of the short-run adjustment towards this equilibrium. We follow Brenner and Kroner (1995) and Heaney (1998) and test the long-run equilibrium relationship amongst the main cost-of-carry elements, namely, the spot price, the futures price, interest rate and convenience yield. In line with Heaney (1998), we use the inventory level of the commodity as a proxy for the convenience yield. The long-run cost-of-carry relationship is investigated using the cointegration test by Johansen (1991, 1995), and Granger causality among the variables is tested in the VECM framework. We also investigate the dynamic short-run adjustment in the prices and convenience yield to the long-run equilibrium. The dynamic short-run adjustment of the system is investigated using a nonlinear VECM (MRS-VECM) in which market conditions are accounted for. The latter is motivated by findings in recent studies which suggest that the dynamic relationship between cash and futures prices may be characterised by nonlinear equilibrium-correction relationships (see, for instance, Sarno and Valente 2000). Examining foreign exchange markets, Sarno and Valente (2000) argue that the nonlinearity may be due to factors such as non-zero transaction costs, infrequent trading, or simply the existence of structural changes in the dynamic adjustment of cash and futures prices towards the long-run equilibrium. In this chapter, we test whether the short-run adjustments in the prices (and convenience yield) are subject to changes in market conditions.

To date the cointegrating properties and regime-switching behaviour of commodity spot and futures prices are two separate strands of the literature in the futures market. This chapter integrates these areas of research and introduce regime shifts into a VECM in investigating the dynamic adjustment in the markets towards the long-run equilibrium. This provides a formal test of the proposition by Sarno and Valente (2000) that the short-run adjustment in spot and futures prices is subject to changes in market condition. As opposed to Heaney (1998) who uses quarterly data for only one market in his analysis, we use weekly data of all the seven industrial metal futures markets on the LME. This data set is of more interest to both economists and practitioners as higher frequency data should reveal more information about the market behaviour. Using higher frequency data is especially important for practitioners as knowledge of the dynamics of short-run deviations from the equilibrium may be helpful in forming trading strategies. However, we settle on the use of weekly data rather than daily data because it is easier to detect a significant and consistent long-run equilibrium and a short-term adjustment towards the equilibrium in weekly data. Moreover, investigation in all the industrial metals contracts that are traded in the world gives one a broader understanding of the industrial metals market and any consistency in the empirical results may allow one to draw conclusions in the respect in the entire industrial metals markets.

5.2 Cost-of-Carry and Convenience Yield

According to the cost-of-carry and convenience yield model, the relationship between futures and cash prices can be expressed as follows:

$$F_{t,t+n} = S_t \cdot \exp(r_{t,t+n} + c_{t,t+n} + cy_{t,t+n}) \tag{5.1}$$

where $F_{t,t+n}$ is the futures price at time t with maturity at $t+n$, S_t is the underlying spot price at time t, $r_{t,t+n}$ is the compounded risk-free interest over the period, $c_{t,t+n}$ is the storage costs from time t to $t+n$, and $cy_{t,t+n}$ is the convenience yield over the period. Taking the logarithm of both sides of Equation (5.1), we obtain the following equation:

$$f_{t,t+n} = s_t + r_{t,t+n} + c_{t,t+n} + cy_{t,t+n} \tag{5.2}$$

where $f_{t,t+n}$ is the logarithm of the futures price, and s_t is the logarithm of the spot price at time t. Assuming the storage costs are constant as in Heaney (1998), this theoretical cost-of-carry relationship can then be tested empirically using the following linear regression model:

$$f_{t,t+n} = c + \beta_1 \cdot s_t + \beta_2 \cdot r_{t,t+n} + \beta_3 \cdot cy_{t,t+n} + \varepsilon_t \tag{5.3}$$

where c is a constant, β_i are parameters and ε_t is a white noise error term.

The convenience yield ($cy_{t,t+n}$), i.e. the benefit from holding the underlying commodity, however, is not observable. In the structural models of Working (1949), Brennan (1958), Deatonne and Laroque (1992), and Routledge, Seppi and Spatt (2000), convenience yield arises endogenously as a result of the interaction between supply, demand and storage decisions. In particular, Routledge, Seppi and Spatt (2000) show that, in a competitive rational expectations model of storage, when storage in the economy is driven to its lower bound, e.g. in periods of relative scarcity of the commodity available for trading, convenience yield is high. Another branch of the literature, also referred to as the no-arbitrage based theory of commodity pricing, models the convenience yield as an exogenous stochastic process (see, for instance, Brennan, 1991; Gibson and Schwartz, 1990; Amin, Ng, and Pirrong, 1995; Schwartz, 1997; and Nielsen and Schwartz, 2004). We follow the idea behind the structural models and use the logarithm of inventory levels of the commodities as proxy for the convenience yield, as in Heaney (1998). Accordingly, the (log) stock level (ls_t) is used in the empirical testing model:

$$f_{t,t+n} = c + \beta_1 \cdot s_t + \beta_2 \cdot r_{t,t+n} + \beta_3 \cdot ls_t + \varepsilon_t \tag{5.4}$$

Equation (5.4) suggests that the major cost-of-carry and convenience yield elements are linked through this linear relationship in the long run. Theoretically, the spot and futures price should move closely to each other due to the cost-of-carry relationship, implying that β_1 should be close to one, and the spread should be positively correlated with financing costs (interest rates) and negatively correlated with the convenience yield which is again negatively correlated with inventory levels. Therefore, we expect β_1, β_2 and β_3 to be positive. To empirically test this model, one of the most important issues is the stationarity of the underlying variables. The stationarity test results of the variables are shown in Table 3.3 and Table 3.4 in Chapter 3, suggesting that all time series are $I(1)$ processes and therefore non-stationary. As noted by Granger and Newbold (1974), if any of the variables are found to be non-stationary, conventional regression analysis, such as OLS, is not valid and may produce spurious results. In this case, the cointegration and Vector Error Correction Model (VECM) of Engle and Granger (1987) and the Johansen (1989) cointegration testing methodology discussed in Chapter 3 can be applied to test the long-run co-movement among the cost-of-carry and convenience yield elements using the following VECM:

$$\Delta Y_t = A + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Pi \cdot Y_{t-1} + \varepsilon_t \tag{5.5}$$

where Y_t is a $n \times 1$ (n = 4 in this case) vector of the endogenous variables, $Y_t = \left(f_{t,t+n} \quad s_t \quad r_{t,t+n} \quad ls_t\right)'$; Γ_i and **Π** are $n \times n$ parameter matrices; **A** is a $n \times 1$ vector of constants, and Δ is the lag operator.

Johansen's (1991, 1995) method considers two statistics: the trace test in which the null hypothesis is that the rank of Π is less than or equal to r cointegrating vectors; and the max-Eigenvalue test with the null hypothesis of r cointegration relations against the alternative or r+1 cointegration relations (see Chapter 3 for details). The asymptotic critical values for these likelihood ratio tests are calculated via numerical simulations (see Johansen and Juselius 1990; and Osterwald-Lenum 1992). The nonstandard critical values for the cointegration test statistics are from Osterwald-Lenum (1992).

5.3 Causality among the Cost-of-Carry Factors

Once cointegration relationships are established and cointegration vectors have been identified, the Granger causality test can be conducted on the VECM in the form below:

$$\begin{pmatrix} \Delta f_t \\ \Delta s_t \\ \Delta r_t \\ \Delta ls_t \end{pmatrix} = \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} \end{pmatrix} \cdot \begin{pmatrix} \Delta f_{t-1} \\ \Delta s_{t-1} \\ \Delta r_{t-1} \\ \Delta ls_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{pmatrix} \cdot ect_{t-1} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{pmatrix} \tag{5.6}$$

where the error correction term $ect_t = f_t - c - \beta_1 \cdot s_t - \beta_2 \cdot r_t - \beta_3 \cdot ls_t$ represents the long-run cointegration relationship among the variables.

The Granger causality test is performed on the parameter restrictions of the coefficients of the lagged differences, $\gamma_{ij}(i, j=1, 2, 3, 4)$ and the coefficients of the cointegrating vector, α_i. For instance, in testing the null hypothesis that futures prices (f_t) are not Granger caused by spot prices (s_t), the parameter restrictions imposed are $\gamma_{12} = 0$ and $\alpha_1 = 0$. Compared to the usual Granger causality test in a VAR model in which the restrictions are only imposed on the coefficients of the lagged differences (γ_{ij}), the joint parameter restrictions on γ_{ij} and α_i enables one to test the null hypothesis that variable x is not Granger caused by variable y both in the short-run and in the long-run.

5.4 The Dynamic Short-Run Adjustment to Equilibrium

While the long-run cointegration relationship between the cash and futures prices is believed to be governed by the cost-of-carry and convenience yield model as defined in Equation (5.3), we propose that the short-run adjustment towards this long-run equilibrium might behave differently under different market conditions. For instance, one could argue that it is easier for arbitrageurs to take positions in the physical market when the convenience yield of holding the commodity is low (or non-existent), i.e. when the market is in contango. Under such circumstances, holders of the physical asset in the market might be willing to sell to facilitate reverse cash-and-carry arbitrage strategies. Consequently, one would expect a faster speed of adjustment towards the long-run equilibrium. Conversely, when the inventory levels are low (usually a backwardated market) the benefit from holding the physical asset can offset the benefit from selling spot and buying futures to pursue the reverse cash-and-carry arbitrage opportunities. Intuitively, this reduced arbitrage activity (albeit not necessarily reduced overall trading volume) should lead to slower speed of convergence toward the long run equilibrium. This argument implies that the short-term coefficients in Equation (5.5) should be state dependent and the speed of adjustment, α, should be larger in a contango market condition than in a backwardation market condition.

We assume that the long-run cointegrating properties of the cost-of-carry elements are robust to regime shifts, but allow for the speed of adjustment towards this equilibrium to be dependent on market conditions. This lends itself to plausible economic interpretation and at the same time preserves the Engle and Granger (1987) notion of cointegration (Francis and Owyang, 2004).

In order to allow for state dependent short term adjustments to the long-run relationship in the cost-of-carry model, we modify Equation (5.5) and let the coefficients of the error correction term to be time varying in the following MRS-VECM:

$$\Delta Y_t = A_{st} + \sum_{i=1}^{p-1} \Gamma_{i,st} \Delta Y_{t-i} + \Pi_{st} \cdot Y_{t-1} + \varepsilon_{st,t} \tag{5.7}$$

where st = 1, 2 represents different market states; A_{st} is the state-dependent vector of constants; $\Gamma_{i,st}$ is the 4×4 state-dependent parameter matrix of the first difference of the variables and $\Pi_{st} = \boldsymbol{\alpha}_{st} \cdot \boldsymbol{\beta}'$ in which β is a 1×4 cointegrating vector (constant across the states) and $\boldsymbol{\alpha}_{st}$ is a 4×1 state-dependent speed of adjustment vectors. We assume that st is a two-state first-order Markov process governed by the transition probability P, where $P_{i,j} = \Pr(st = i | st - 1 = j)$.

This model endogenously identifies different market conditions as two states, characterised by low and high volatility, respectively. As in Chapter 4, we argue that the two states are directly linked to the backwardation and contango market conditions in the storable commodity market. The theory of storage developed by Kaldor (1939), Working (1948, 1949), Telser (1958) and Brennan (1958) implies that high price volatility is linked to low inventory levels due to the inelastic nature of the supply curve when stock levels are low. At the same time, low inventory levels are associated with high convenience yields and periods of backwardation in the market. On the other hand, high inventory levels are associated with periods of low price volatility, zero or very low convenience yield, which leads to contango condition in the market. This is because that there are sufficient stock levels to absorb production-and-demand shocks. The volatility and market condition linkage has also been empirically investigated by Nielsen and Schwartz (2004) who find that when the commodity inventory level is low, the price volatility can be twice the volatility when the inventory level is high.

5.5 Empirical Results

The data set used for this analysis comprise of weekly data from April 5, 1994 to July 30, 2004. The inventory level, which is measured in tonnes and based on information from the over 400 LME warehouses worldwide, is obtained from the exchange over the sample period. The three-month London Inter Bank Offered Rate (LIBOR)[23] is chosen as the short-term risk free rate and is obtained from DataStream and the British Bankers Association. The futures contracts traded on the LME are different, in principle, from many other futures contracts traded in other major exchanges. Every working day, the exchange introduces new futures contracts with a maturity of 3, 15, and 27 months with an exact "prompt date", a feature more commonly seen in "over-the-counter" forward markets. In this study we use weekly time series of 3-month (fixed maturity) futures prices. This important feature of the data gives us the opportunity to investigate the cost-of-carry or cointegration relationship between futures and spot prices free from testing

[23] LIBOR is the rate of interest at which banks borrow funds from other banks, in marketable size, in the London interbank market.

discrepancy. In contrast, Brenner and Kroner (1995) show that if the time to maturity changes, i.e. each observation has a different time to maturity as in many research works, the spot and futures price cannot be cointegrated.

5.5.1 The Cost-of-Carry Long-run Equilibrium

We have shown in Chapter 3 (Table 3.3 and Table 3.4) that spot prices, futures prices, LIBOR interest rate and inventory levels are all $I(1)$ processes according to the KPSS, ERS and Perron (1997) unit root tests. Therefore, in what follows, we use the cointegration technique developed by Engle and Granger (1987) and Johansen (1988) to investigate the long and short run relationships among the cost-of-carry and convenience yield elements.

The Johansen (1991, 1995) method is to estimate the parameter matrix Π in the VECM and to test the null hypothesis imposed on the rank of Π (r) using the maximum Eigenvalue and trace statistics. The results for the long-run equilibrium relationship in Equation (5.4) are presented in Table 5.1. Panel A presents the Maximum Eigenvalue and trace statistics of the cointegration relationship. The trace statistics reported in Table 5.1 Panel A test the null hypothesis of r cointegration relationships against the alternative of k cointegration relationships, where k is the number of endogenous variables (k = 4 in this case), for $r = 0,1,\ldots,k\text{-}1$. The null hypothesis is rejected at the 5% significance level if the statistic is less than the critical value computed by Osterwald-Lenum (1992). The result of both trace and maximum-Eigenvalue test statistics suggest that there is one cointegration relationship in all the markets, with the exception of the aluminium and zinc markets where the results suggest the existence of two cointegration relationships.

Panel B of Table 5.1 also presents the estimated cointegration vector in each market[24]. Reported cointegrating vectors are normalised in the sense that the cointegrating coefficient of the futures price is set to be one. The cointegrating coefficients (β_1) of the spot price are close to one but smaller than one in all the markets, with the exception of the aluminium alloy market, indicating that: (1) the spot and futures prices move very closely to each other with the presence of interest and effect of inventory levels, and (2) in the long

[24] Note that according to either the trace test or the maximum Eigenvalue statistics, there are three cointegration relationships in the aluminium market and two in the nickel and zinc markets. The cointegration vectors that are reported in Table 5.1 are reported in Table 2 in Appendix I.

run, futures prices are above the spot prices and the cost-of-carry model dominates the futures – spot price relationship. The coefficient of interest rate in the cointegrating vector, β_2 is found to be statistically negative in four of the markets, indicating that the spread between the futures and spot prices (basis) is positively correlated with interest rates (higher interest rate increases the financing cost). More importantly, the coefficient of the inventory levels in the cointegrating vector, β_3 is found to be statistically negative in five markets (aluminium alloy, copper, lead, nickel and tin), which implies that the futures-spot price spread is positively correlated with inventory levels. This is because the higher the inventory level, the further away (upward) the futures prices are from the spot prices with the upper limit being the full cost-of-carry price. On the other hand, the lower the inventory level, the larger the convenience yield and thus the smaller is the basis, and eventually the basis becomes negative when the convenience yield exceeds the carrying costs. The results in Table 5.1 with regards to the signs of the parameters are qualitatively similar to those of Heaney (1998), who investigates the long-run cointegration property of the LME lead market.

Table 5.1 Cointegration tests on the cost-of-carry elements

Panel A: Cointegration test among the cost-of-carry and convenience yield elements

		Eigenvalue	Trace statistics	Maxi-Eigen Stat.
Aluminium	$H_0: r = 0; H_1: r = 1$	0.0850	106.1516 *	47.3627 *
	$H_0: r \le 1; H_1: r = 2$	0.0595	58.7889 *	32.6932 *
	$H_0: r \le 2; H_1: r = 3$	0.0422	26.0957 *	22.9973 *
	$H_0: r \le 3; H_1: r = 4$	0.0058	3.0984	3.0984
Al alloy	$H_0: r = 0; H_1: r = 1$	0.0933	76.9613 *	51.9904 *
	$H_0: r \le 1; H_1: r = 2$	0.0286	24.971	15.4325
	$H_0: r \le 2; H_1: r = 3$	0.0138	9.5384	7.3854
	$H_0: r \le 3; H_1: r = 4$	0.0040	2.1531	2.1531
Copper	$H_0: r = 0; H_1: r = 1$	0.0922	72.4554 *	51.4693 *
	$H_0: r \le 1; H_1: r = 2$	0.0224	20.9861	12.0561
	$H_0: r \le 2; H_1: r = 3$	0.0157	8.9300	8.395
	$H_0: r \le 3; H_1: r = 4$	0.0010	0.5350	0.535
Lead	$H_0: r = 0; H_1: r = 1$	0.1217	102.5702 *	69.0324 *
	$H_0: r \le 1; H_1: r = 2$	0.0358	33.5377	19.3944
	$H_0: r \le 2; H_1: r = 3$	0.0175	14.1433	9.4150
	$H_0: r \le 3; H_1: r = 4$	0.0088	4.7283	4.7283
Nickel	$H_0: r = 0; H_1: r = 1$	0.0666	76.8212 *	36.6905 *
	$H_0: r \le 1; H_1: r = 2$	0.0386	40.1307 *	47 3627
	$H_0: r \le 2; H_1: r = 3$	0.0281	19.2152	15.1632
	$H_0: r \le 3; H_1: r = 4$	0.0076	4.0520	4.0520
Tin	$H_0: r = 0; H_1: r = 1$	0.0751	71.8199 *	41.5255 *
	$H_0: r \le 1; H_1: r = 2$	0.0367	30.2944	19.8709
	$H_0: r \le 2; H_1: r = 3$	0.0175	10.4235	9 4073
	$H_0: r \le 3; H_1: r = 4$	0.0019	1.0162	1.0162
Zinc	$H_0: r = 0; H_1: r = 1$	0.1125	103.0791 *	63.468 *
	$H_0: r \le 1; H_1: r = 2$	0.0438	39 6111 *	23.8067 *
	$H_0: r \le 2; H_1: r = 3$	0.0208	15.8044	11.2027
	$H_0: r \le 3; H_1: r = 4$	0 0086	4.6017	4.6017

Panel B: the long-run equilibrium relationship $f_{t,t+n} = c + \beta_1 \cdot s_t + \beta_2 \cdot r_{t,t+n} + \beta_3 \cdot ls_t$

	c	β_1	β_2	β_3
Aluminium	**0.3526**	**0.9573**	3.37E-02	-0.005
	(0.101)	(0.015)	(0.021)	(0.003)
Al alloy	**-0.357**	**1.0346**	**6.01E-04**	**0.0285**
	(0.141)	(0.018)	(0)	(0.005)
Copper	**0.4769**	**0.9257**	**6.16E-04**	**0.0118**
	(0.129)	(0.014)	(0)	(0.005)
Lead	**0.1842**	**0.9521**	**0.0019**	**0.0242**
	(0.065)	(0.009)	(0 001)	(0.004)
Nickel	-0.0224	**0.9974**	**-1.61E-04**	**0.0175**
	(0.059)	(0.006)	(0)	(0.003)
Tin	**0.2051**	**0.9713**	**2.17E-04**	**0.0115**
	(0.079)	(0.009)	(0)	(0.003)
Zinc	**0.7733**	**0.8978**	9.52E-05	-0.0081
	(0.158)	(0.024)	(0.001)	(0.004)

- Weekly data over the period April 1994 and July 2004; Figures in parenthesis ( ) are standard errors, Figures in bold are statistically significant at the 5% level.
- It assumes no deterministic trend in the cointegration relationship;
- * represents the rejection of the null at the 5% significance level.
- The 5% critical values: (CE = Cointegration equation)

	None CE	At most 1 CE	At most 2 CEs	At most 3 CEs
Trace	53.12	34.91	19.96	9.24
Max-Eigen	28.14	22.00	15.67	9.24

5.5.2 Lead-lag relationship among the major cost-of-carry elements

In order to examine the lead-lag relationship among the cost-of-carry factors, we use the VECM model of Equation (5.6) to perform the Granger causality tests. The null hypothesis is that the dependent variable in an equation is not Granger caused by any of the independent variables in Equation (5.6) either in the short run or in the long run. The test statistics of the joint parameter restrictions are estimated based on the Wald test and are reported in Table 5.2. Panel A reports the test statistics for the null hypothesis that futures prices are not Granger caused by either spot prices, interests or inventory levels. Panel B reports the test statistics for the null hypothesis that spot prices are not Granger caused by either futures prices, interests or inventory levels. Panel C reports the test statistics for the null hypothesis that inventory levels are not Granger caused by either futures prices, spot prices, or interests rates. The fourth column in Table 5.2 reports the Wald statistic which test for exogeneity of the futures prices, spot prices and inventory level in the VECM, i.e. a Wald test for the joint hypothesis of no Granger causality from the independent variables.

The results in Panel A show that while the futures price is not Granger caused by the spot price in any of the markets, they seem to be influenced by interest rates (in the cases of the aluminium and nickel markets) and inventory levels (in the aluminium alloy, lead and nickel markets). Moreover, the joint hypothesis of the futures price is not Granger caused by the spot price, interest rates and inventory levels is rejected in three markets with exceptions of copper and zinc, suggesting that the futures price is largely endogenous.

In Panel B, the results indicate that the spot price seems to be Granger caused by the futures price in three markets (aluminium alloy, copper and zinc) at the 10% significance level. There is also evidence suggesting that spot prices are Granger caused by interest rates in three markets (aluminium alloy, copper and tin) and by inventory levels in six markets (aluminium alloy, copper, lead, nickel, tin and zinc). The exogeneity test results suggest that the spot price is endogenous in five markets at the 10% significance level.

Table 5.2 Granger Causality test among the cost-of-carry elements

Panel A: H_0: f_t is not Granger caused by s_t r_t or ls_t

	s_t	r_t	ls_t	Block exogeneity Wald test
Al	1.1525 [0.317]	1.7692 [0.171]	0.3991 [0.671]	1.4490 [0.217]
Al alloy	2.6965 [0.068]	**4.3273** [0.014]	**4.8881** [0.008]	**4.2933** [0.002]
Copper	1.1212 [0.327]	1.2905 [0.276]	1.6310 [0.197]	1.0132 [0.400]
Lead	1.8666 [0.156]	0.5798 [0.560]	**7.7098** [0.001]	**4.6902** [0.001]
Nickel	2.0169 [0.134]	**3.7960** [0.023]	**3.0465** [0.048]	**2.5386** [0.039]
Tin	2.1437 [0.118]	0.0053 [0.995]	1.2394 [0.290]	1.7591 [0.136]
Zinc	0.4696 [0.625]	0.2432 [0.784]	0.6378 [0.529]	0.4392 [0.780]

Panel B: H_0: s_t is not Granger caused by f_t r_t or ls_t

	f_t	r_t	ls_t	Block exogeneity Wald test
Al	1.8190 [0.163]	2.4105 [0.091]	1.8833 [0.153]	**2.3923** [0.050]
Al alloy	**8.1063** [0.000]	**9.9908** [0.000]	**11.8628** [0.000]	**7.0421** [0.000]
Copper	**4.3506** [0.013]	**3.4806** [0.031]	**7.4689** [0.001]	**4.1259** [0.003]
Lead	0.8937 [0.410]	0.9825 [0.375]	**8.4063** [0.000]	**4.2841** [0.002]
Nickel	0.9363 [0.393]	2.4719 [0.085]	2.3344 [0.098]	1.9602 [0.099]
Tin	1.0897 [0.337]	0.7083 [0.493]	2.8563 [0.058]	1.7573 [0.136]
Zinc	2.3456 [0.097]	2.0906 [0.124]	**3.2938** [0.038]	1.7923 [0.129]

Panel C: H_0: ls_t is not Granger caused by f_t s_t or r_t

	f_t	s_t	r_t	Block exogeneity Wald test
Al	**15.3414** [0.000]	**17.9678** [0.000]	**12.1949** [0.000]	**9.7858** [0.000]
Al alloy	2.6322 [0.073]	2.1219 [0.121]	0.3423 [0.710]	1.4833 [0.206]
Copper	**16.5498** [0.000]	**16.5473** [0.000]	**17.1707** [0.000]	**9.0885** [0.000]
Lead	**4.1703** [0.016]	**5.9759** [0.003]	**5.9905** [0.003]	**3.6675** [0.006]
Nickel	1.7254 [0.179]	1.1568 [0.315]	1.5905 [0.205]	1.6240 [0.147]
Tin	**17.8009** [0.000]	**21.8222** [0.000]	**5.1857** [0.006]	**11.6846** [0.000]
Zinc	**16.5822** [0.000]	**16.2033** [0.000]	**16.1422** [0.000]	**9.0810** [0.000]

- Weekly data over the period 05/04/1994 and 30/07/2004;
- Figures in brackets [ ] are p-values;
- Figures in bold are significant at the 5% level.

Furthermore, Panel C presents the results of causality tests when the inventory level is considered as the dependent variable. The evidence suggests that inventory levels are Granger caused by the spot and futures prices in all markets with the exceptions of aluminium alloy and nickel. Also, there is evidence that the interest rates Granger cause inventory levels in three markets (aluminium, copper and zinc). In addition, the joint exogeneity test results suggest that the inventory levels are endogenous in all the markets.

There are a couple of points worth emphasizing in light of the above findings. Firstly, the one-way Granger causality between the spot and futures prices suggests that it is the futures price that primarily leads the information flow in these commodity markets. This finding is consistent with the literature on financial and commodity futures markets (see, for instance, Stoll and Whaley, 1990; Wahab and Lashgari, 1993; Hung and Zhang, 1995; Ates and Wang, 2005) and is generally explained by the greater liquidity and lower transaction costs in the futures market compared to the spot market. Secondly, the evidence of inventory levels leading the changes in spot and futures prices once again highlights the importance of the inventory effect not only in the long-run, as identified in the cointegration vector, but also in the short-run. The inventory level serves as an indicator of the production and consumption balance in the commodity market and thus has an impact on the current and expected spot price (the futures price) in the long run. In particular, inventory holders can use stocks to absorb short-run unexpected shocks by selling or building up inventories and these changes will lead changes in the spot prices (and to a lesser extent the futures prices).

Table 5.3 The VECM estimation results

$$(\Delta f_t \quad \Delta s_t \quad \Delta ls_t)' = \Gamma_t (\Delta f_{t-1} \quad \Delta s_{t-1} \quad \Delta r_{t-1} \quad \Delta ls_{t-1})' + \alpha \cdot ect_{t-1} + \varepsilon_t$$

	$j = 1,2,3$	$\gamma_{j,1}$	$\gamma_{j,2}$	$\gamma_{j,3}$	$\gamma_{j,4}$	α_j	LM(5)	LM(20)
Aluminium	Δf_t	0.2017	-0.244	-0.0234	0.0042	0.0451		
		(0.9419)	(-1.2112)	(-0.5415)	(1.7261)	(0.4334)		
	Δs_t	0.229	-0.274	-0.0416	0.0041	0.1453	18.9769	15.4095
		(0.9861)	(-1.2542)	(-0.888)	(1.578)	(1.2891)	[0.270]	[0.495]
	Δls_t	**-0.3524**	**0.4055**	**0.6232**	-0.0033	**-0.3544**		
		(-2.1028)	(2.5721)	(18.4249)	(-1.7649)	(-4.3571)		
Aluminium alloy	Δf_t	-0.2228	0.2151	**0.0051**	**-0.081**	**0.1607**		
		(-1.5562)	(1.5959)	(2.0056)	(-2.3678)	(2.0869)		
	Δs_t	-0.1962	0.1866	0.0051	**-0.1058**	**0.3384**	16.0413	21.4764
		(-1.2529)	(1.2658)	(1.8272)	(-2.8283)	(4.019)	[0.450]	[0.161]
	Δls_t	**-0.3238**	**0.2738**	-0.0008	**0.6327**	0.0586		
		(-2.2858)	(2.0535)	(-0.3292)	(18.6916)	(0.7687)		
Copper	Δf_t	-0.0008	-0.0142	0.0015	-0.0163	0.111		
		(-0.0053)	(-0.0868)	(0.7298)	(-0.5383)	(1.408)		
	Δs_t	0.1006	-0.1212	0.0013	-0.0579	**0.2186**	22.6654	12.6349
		(0.5847)	(-0.6834)	(0.5727)	(-1.764)	(2.5565)	[0.123]	[0.699]
	Δls_t	0.3011	-0.2809	-0.0022	**0.6159**	**-0.5004**		
		(1.7194)	(-1.5573)	(-0.9532)	(18.4536)	(-5.7524)		
Lead	Δf_t	-0.216	0.1778	-0.0025	**-0.1343**	-0.0985		
		(-1.49)	(1.2707)	(-0.3417)	(-3.7036)	(-1.0402)		
	Δs_t	-0.0801	0.0927	-0.0031	**-0.169**	0.1481	20.5158	15.1163
		(-0.4697)	(0.5634)	(-0.3584)	(-3.9627)	(1.3307)	[0.198]	[0.516]
	Δls_t	1.1063	-1.2184	0.0386	-0.4622	0.8127		
		(0.7815)	(-0.8918)	(0.5452)	(-1.3051)	(0.8795)		
Nickel	Δf_t	-0.1061	-0.0266	**0.0015**	-0.0592	**-0.3669**		
		(-0.2742)	(-0.0700)	(2.0471)	(-1.6462)	(-1.9708)		
	Δs_t	-0.0164	-0.1075	0.0014	-0.067	-0.2553	11.5167	16.1820
		(-0.0411)	(-0.2749)	(1.8626)	(-1.808)	(-1.3304)	[0.777]	[0.440]
	Δls_t	0.7248	-0.5535	-0.0015	**0.3625**	0.1067		
		(1.6431)	(-1.2800)	(-1.7379)	(8.8463)	(0.5029)		
Tin	Δf_t	-0.4343	**0.4707**	0.0000	-0.0265	0.0136		
		(-1.8298)	(2.0169)	(0.0403)	(-1.5438)	(0.0963)		
	Δs_t	-0.2884	0.3377	0.0000	-0.0338	0.1745	12.0798	21.6938
		(-1.1683)	(1.3915)	(0.0380)	(-1.8921)	(1.1894)	[0.739]	[0.153]
	Δls_t	**3.5900**	**-3.9214**	**0.0039**	0.0697	**-0.8288**		
		(5.9260)	(-6.5842)	(2.1013)	(1.5906)	(-2.3019)		
Zinc	Δf_t	-0.1123	0.1231	-0.001	-0.0403	0.0405		
		(-0.7552)	(0.8463)	(-0.2955)	(-0.6914)	(0.6611)		
	Δs_t	-0.2096	0.2109	-0.0024	-0.0634	**0.1398**	13.9905	20.4088
		(-1.244)	(1.2788)	(-0.5908)	(-0.9600)	(2.0118)	[0.599]	[0.202]
	Δls_t	0.0408	-0.1034	0.0011	**0.1640**	**-0.2567**		
		(0.3725)	(-0.9643)	(0.4343)	(3.8170)	(-5.6783)		

- Weekly data over the period 05/04/1994 and 30/07/2004;
- LM test is the Lagrange Multiplier test for serial correlation in the residuals up to order p with 16 degree of freedom (5 parameters in 3 equations + 1);
- Figures in parenthesis ( ) are t-statistics; figures in brackets [ ] are p – values;
- Figures in bold are statistically significant at the 5% level.

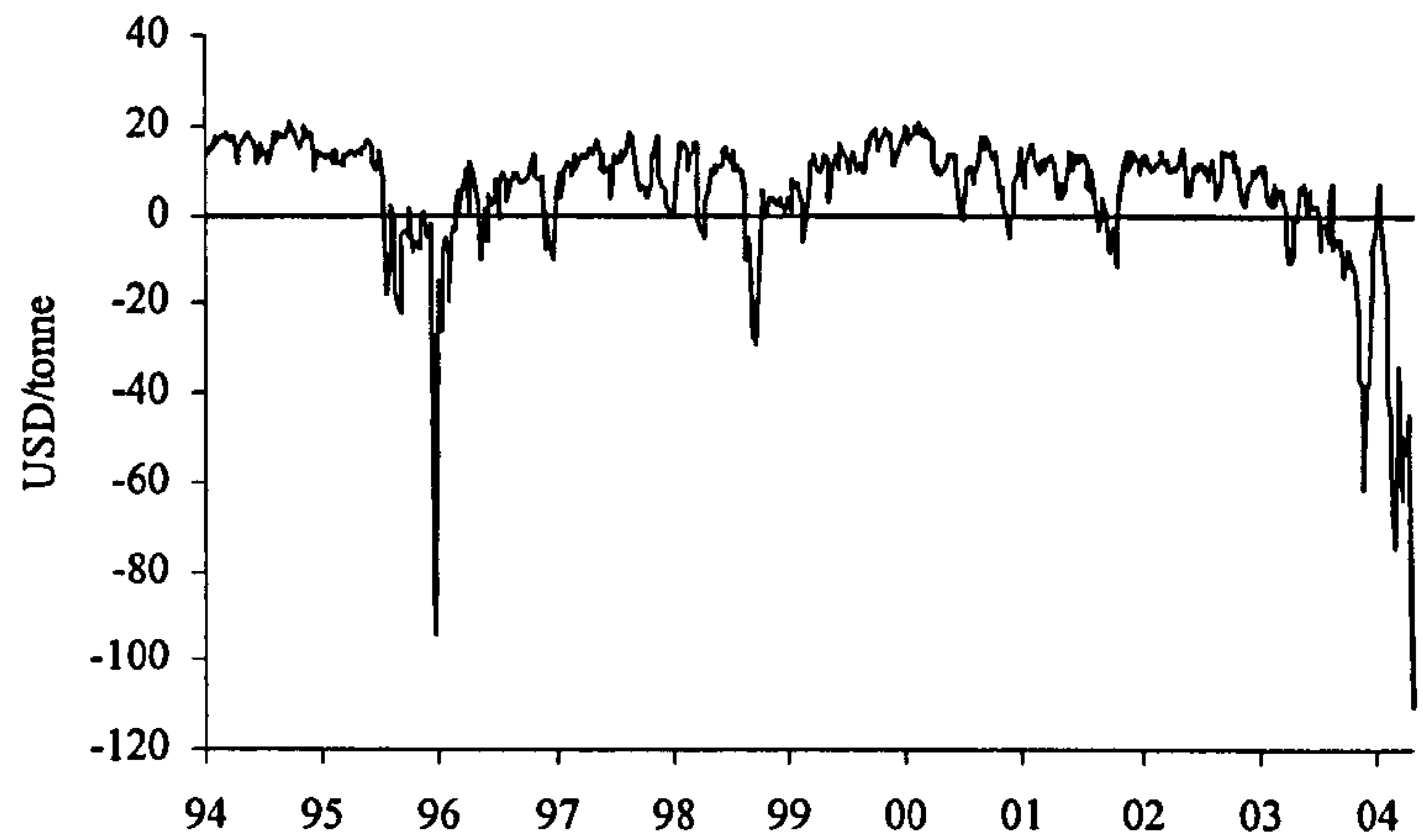
5.5.3 The Dynamic Short-run Adjustment

In this section, we investigate the short-run adjustments of the cost-of-carry elements towards the long-run equilibrium. The short-run adjustment is measured by the loading coefficient vector α in the VECM. The coefficients α_s, α_f, α_{ls} represent how the spot price, futures price, and convenience yield respond to any divergence from the long-run equilibrium, respectively. Table 5.3 presents estimation results of the VECM. The Lagrange Multiplier serial autocorrelation diagnostic test suggests the VECM is well specified. The first four columns are the coefficients of the lagged first difference of the four variables (spot, futures price, interests and inventory level) in the VECM Γ estimates. The parameters of interest are the speed of adjustment coefficients α.

The results suggest that futures prices adjust to the long-run equilibrium in two markets (aluminium alloy and nickel), while spot prices adjust to the equilibrium in three markets (aluminium alloy, copper and zinc). In addition, the inventory level is found to respond to the long-run equilibrium in four markets, namely the aluminium, aluminium alloy, copper and zinc markets. Moreover, the sign of short-run adjustments in the spot prices towards the long-run equilibrium is positive while the sign of the adjustment in the inventory levels is statistically negative in all the aforementioned markets. However, the signs of the adjustment in the futures prices are mixed.

Figure 5.1 plots the basis ($f_{t,t+n} - s_t$) of the lead 3-month futures contract in USD/tonne. It can be seen that the basis has an upper bound (supposedly the full cost-of-carry) while there are large deviations when the basis is negative and this applies to all the metals markets. Consequently we argue that a divergence from the long-run cost-of-carry relationship usually suggests the market is in backwardation in which case the interest-adjusted basis is negative. One may argue that futures prices can also drift away upward from the spot prices, however this should be quickly eliminated by cash-and-carry arbitrage trading. Essentially it is the spot price drifting away upward that represents the divergence in the market, and due to the presence of convenience yield this divergence is less likely to be quickly eliminated by arbitrage trading. Therefore, any adjustments in the prices and inventory levels to the deviation from the equilibrium are mainly a reaction to the market being in backwardation.

Figure 5.1 Basis of the lead 3-month futures price



The positive speed of adjustment in the spot prices (and to a lesser extent the futures prices) suggests that spot prices tend to fall[25] when the market diverges from equilibrium to be in backwardation. Essentially a backwardated market condition occurs when demand is high relative to supply and which, in turn, suggests that spot prices and short-maturity futures prices are high. Accordingly, it is necessary for spot prices to drop in order to restore the cost-of-carry equilibrium. The negative speed of adjustment in the inventory level can be explained by a similar argument. For instance, when the market is in backwardation (i.e. a divergence from the equilibrium), it is likely that the inventory is at a low level. In order to restore the market to equilibrium condition (i.e. where the cost-of-carry relationship dominates), the convenience yield of holding the commodity needs to fall and thus inventories need to build up.

The postulation in section 5.4 is that the speed of adjustment is dependent on market conditions. Specifically, it is expected that the speed of adjustment is quicker when the market is in contango than that in a backwardation market. The MRS-VECM provides a framework to examine this postulation. The estimation results are shown in Table 5.4. State one is the low-volatility state in which the market is said to be in contango and state two is the high-volatility state in which the market is said to be in backwardation. Unfortunately, the empirical results do no provide a clear-cut conclusion. In particular, it

[25] When there is a divergence from equilibrium, the error correction term, i.e. the adjusted-basis, is typically negative. Therefore a positive coefficient of speed of adjustment suggests that the price will decline.

is only in the aluminium and copper markets that the inventory level adjusts to the long-run equilibrium in both states and where the absolute value of the adjustment is found to be larger in the high-volatility state. However, an encouraging result in the regime switching VECM is the evidence that spot and futures prices adjust to the divergence in at least one of the states is detected. For instance, evidence of adjustments in the futures prices towards the equilibrium is found in both of the states in the aluminium market and in one of the states in the copper (high-volatility state), and lead (low-volatility state) markets while no evidence of such adjustments is detected in the linear-VECM framework. There is also some evidence that the spot price (nickel) and inventory level (aluminium alloy) adjusts to the equilibrium in the MRS-VECM but no such evidence is found in the linear VECM. Despite the mixed results in this regard, this further highlights the importance of modelling the market dynamics in a framework where changing market conditions are accounted for.

Table 5.4 The VECM with structural breaks: MRS-VECM

$$(\Delta f_t \quad \Delta s_t \quad \Delta ls_t)' = \Gamma_{i,st}(\Delta f_{t-1} \quad \Delta s_{t-1} \quad \Delta r_{t-1} \quad \Delta ls_{t-1})' + \alpha_{st}\beta \cdot ect_{t-1} + \varepsilon_t$$

		$(j = 1,2,3)$	Γ_{1j}	Γ_{2j}	Γ_{3j}	Γ_{4j}	α_j	σ_i
Aluminium	Δf_t	State 1	0.2566	-0.2754	0.0018	-0.0349	**0.2060**	**0.0183**
			[0.210]	[0.153]	[0.468]	[0.459]	[0.084]	[0.000]
		State 2	-0.7939	0.9223	0.0174	-0.1492	**-1.8106**	**0.0339**
			[0.742]	[0.674]	[0.293]	[0.587]	[0.061]	[0.000]
	Δs_t	State 1	**0.9213**	**-0.8837**	0.0046	**-0.1221**	-0.1019	**0.0198**
			[0.003]	[0.002]	[0.139]	[0.013]	[0.174]	[0.000]
		State 2	-0.9710	0.6281	0.0076	0.1613	0.2288	**0.0342**
			[0.386]	[0.526]	[0.620]	[0.555]	[0.594]	[0.000]
	Δls_t	State 1	0.1750	-0.1545	0.0001	**0.8500**	**0.0741**	**0.0081**
			[0.279]	[0.305]	[0.947]	[0.000]	[0.067]	[0.000]
		State 2	**-0.6054**	**0.7911**	**-0.0108**	**0.4043**	**-0.4464**	**0.0242**
			[0.089]	[0.010]	[0.001]	[0.000]	[0.000]	[0.000]
Aluminium alloy	Δf_t	State 1	-0.2495	0.2110	0.0034	-0.0630	**0.1915**	**0.0111**
			[0.264]	[0.308]	[0.297]	[0.171]	[0.094]	[0.000]
		State 2	-0.2041	0.2246	0.0067	-0.1047	0.1258	**0.0245**
			[0.601]	[0.554]	[0.189]	[0.300]	[0.529]	[0.000]
	Δs_t	State 1	0.2889	-0.1561	0.0018	**-0.1004**	**0.3399**	**0.0159**
			[0.269]	[0.518]	[0.615]	[0.034]	[0.004]	[0.000]
		State 2	-0.6919	0.4314	0.0117	-0.1251	0.3040	**0.0300**
			[0.416]	[0.583]	[0.286]	[0.527]	[0.344]	[0.000]
	Δls_t	State 1	-0.1149	0.0798	-0.0001	**0.5586**	**0.1607**	**0.0105**
			[0.452]	[0.576]	[0.950]	[0.000]	[0.034]	[0.000]
		State 2	-0.5374	0.4508	-0.0030	**0.6533**	-0.0091	**0.0266**
			[0.209]	[0.222]	[0.705]	[0.000]	[0.953]	[0.000]
Copper	Δf_t	State 1	**0.2892**	**-0.2893**	0.0013	**-0.0537**	-0.0505	**0.0237**
			[0.062]	[0.068]	[0.500]	[0.055]	[0.499]	[0.000]
		State 2	**-3.3145**	**0.9912**	**0.0401**	**-0.3626**	**3.5222**	**0.0376**
			[0.000]	[0.002]	[0.000]	[0.058]	[0.000]	[0.000]
	Δs_t	State 1	0.2675	-0.2823	0.0000	**-0.0869**	0.0642	**0.0244**
			[0.143]	[0.139]	[0.996]	[0.005]	[0.488]	[0.000]
		State 2	-0.2896	-0.0203	0.0124	-0.0465	0.7234	0.0554
			[0.650]	[0.988]	[0.735]	[0.795]	[0.109]	[0.000]
	Δls_t	State 1	0.1566	-0.1861	**0.0027**	**0.6641**	**-0.3988**	**0.0154**
			[0.249]	[0.161]	[0.052]	[0.000]	[0.000]	[0.000]
		State 2	0.2396	0.2097	-0.0202	**0.5917**	**-0.5961**	**0.0533**
			[0.563]	[0.707]	[0.108]	[0.000]	[0.006]	[0.000]

- Weekly data over the period 05/04/1994 and 30/07/2004
- Figures in brackets [ ] are p-values;
- Figures in bold are statistically significant at the 10% significance level.

Table 5.4 The VECM with structural breaks: MRS-VECM (continued)

			Γ_{1j} $j = 1,2,3$	Γ_{2j}	Γ_{3j}	Γ_{4j}	α_j	σ_t
Lead	Δf_t	State 1	**-0.5207**	0.3696	0.0092	**-0.1918**	**-0.3070**	**0.0137**
			[0.132]	[0.165]	[0.351]	[0.000]	[0.051]	[0.000]
		State 2	-0.1962	0.1775	-0.0054	**-0.1200**	-0.0644	**0.0304**
			[0.234]	[0.281]	[0.550]	[0.021]	[0.585]	[0.000]
	Δs_t	State 1	-0.0540	-0.0321	0.0018	**-0.1442**	0.1156	**0.0264**
			[0.803]	[0.868]	[0.851]	[0.001]	[0.309]	[0.000]
		State 2	-0.2176	0.4539	-0.0188	**-0.4425**	0.5903	**0.0511**
			[0.780]	[0.596]	[0.550]	[0.084]	[0.291]	[0.000]
	Δls_t	State 1	0.0912	-0.0483	0.0003	**0.3017**	0.0353	**0.0116**
			[0.340]	[0.595]	[0.943]	[0.000]	[0.492]	[0.000]
		State 2	0.3841	-0.7259	**0.0700**	**0.2932**	0.6844	**0.0534**
			[0.473]	[0.125]	[0.000]	[0.000]	[0.106]	[0.000]
Nickel	Δf_t	State 1	0.1662	-0.2908	**0.0017**	-0.0203	-0.2190	**0.0356**
			[0.634]	[0.391]	[0.025]	[0.588]	[0.207]	[0.000]
		State 2	-0.2042	-0.0196	0.0019	-0.1899	**-2.5806**	**0.0686**
			[0.412]	[0.876]	[0.412]	[0.130]	[0.072]	[0.000]
	Δs_t	State 1	0.3643	-0.4938	**0.0017**	-0.0317	-0.0709	**0.0370**
			[0.437]	[0.281]	[0.032]	[0.402]	[0.709]	[0.000]
		State 2	-0.6298	0.4330	0.0016	-0.1985	**-2.1990**	**0.0688**
			[0.847]	[0.893]	[0.544]	[0.272]	[0.080]	[0.000]
	Δls_t	State 1	**0.6295**	**-0.5107**	**-0.0009**	**0.6743**	-0.0226	**0.0139**
			[0.000]	[0.003]	[0.011]	[0.000]	[0.808]	[0.000]
		State 2	0.6933	-0.4843	-0.0024	**0.3199**	0.2231	**0.0777**
			[0.621]	[0.734]	[0.586]	[0.000]	[0.776]	[0.000]
Tin	Δf_t	State 1	-0.0019	-0.0276	0.0000	-0.0273	-0.0924	0.0153
			[0.994]	[0.908]	[0.962]	[0.204]	[0.520]	[0.000]
		State 2	**-1.0900**	**1.1331**	0.0006	-0.0395	0.2504	**0.0389**
			[0.068]	[0.055]	[0.772]	[0.343]	[0.569]	[0.000]
	Δs_t	State 1	-0.0148	-0.0404	0.0000	**-0.0465**	-0.0156	**0.0154**
			[0.958]	[0.882]	[0.977]	[0.039]	[0.915]	[0.000]
		State 2	-0.5944	0.6725	0.0003	-0.0310	0.4640	**0.0366**
			[0.179]	[0.109]	[0.849]	[0.456]	[0.214]	[0.000]
	Δls_t	State 1	0.5637	**-0.6013**	0.0010	**0.1608**	**-0.3192**	**0.0256**
			[0.114]	[0.084]	[0.353]	[0.000]	[0.072]	[0.000]
		State 2	**6.4989**	**-7.6380**	0.0071	0.0090	-1.9007	**0.1290**
			[0.000]	[0.000]	[0.683]	[0.961]	[0.285]	[0.000]
Zinc	Δf_t	State 1	-0.6000	0.5004	**0.0076**	-0.0406	0.1599	**0.0135**
			[0.264]	[0.342]	[0.091]	[0.491]	[0.302]	[0.000]
		State 2	-0.1213	0.1675	-0.0046	-0.0287	0.0238	**0.0261**
			[0.526]	[0.409]	[0.384]	[0.772]	[0.755]	[0.000]
	Δs_t	State 1	**-0.2460**	**0.2063**	0.0017	-0.1170	0.0177	**0.0221**
			[0.000]	[0.000]	[0.46]	[0.052]	[0.801]	[0.000]
		State 2	0.7134	0.1172	**-0.0404**	**1.6566**	**1.2599**	**0.0584**
			[0.019]	[0.690]	[0.058]	[0.000]	[0.000]	[0.000]
	Δls_t	State 1	0.1358	-0.1917	0.0038	**0.2910**	**-0.1711**	**0.0098**
			[0.185]	[0.053]	[0.031]	[0.000]	[0.000]	[0.000]
		State 2	-1.1647	1.5429	-0.0822	-0.1390	-0.2334	**0.0451**
			[0.446]	[0.275]	[0.131]	[0.769]	[0.493]	[0.000]

- Weekly data over the period 05/04/1994 and 30/07/2004
- Figures in brackets [ ] are p-values;
- Figures in bold are statistically significant at the 10% significance level.

5.6 Concluding Remarks

This chapter tests the long-run equilibrium relationship between the spot and futures prices subject to the presence of the major cost-of-carry elements in a VECM framework and investigates the dynamic short-run adjustment toward this equilibrium using a Markov Regime Switching model to allow for structural changes. We find that the major cost-of-carry elements, namely the spot and futures prices, interest rate and inventory level, are cointegrated in the long-run in all the seven metals markets. This finding is in line with that in Heaney (1998) and Brenner and Kroner (1995) who argue that in order to test the cointegration between spot and futures prices, one should include the cost-of-carry factors, especially if any of them are nonstationary. The causal relationships among the cost-of-carry factors suggest that the futures price is largely led by the interest rate and inventory level, rather than the spot price, while the spot price is led by the futures price, interest rate and inventory level.

The dynamic short-run adjustment towards the long-run cost-of-carry equilibrium is measured by the speed of adjustment in the VECM. The empirical results suggest that the spot and futures price respond to the deviations from the long-run equilibrium by decreasing, while the inventory levels react to the divergence by increasing. When the dynamic short-run adjustments are investigated in a framework where market conditions are taken into account, we find further evidence that in the prices and inventory level adjust to the long-run equilibrium. However, the postulation that the speed of adjustment is higher in a contango market does not find clear support.

6 CHAPTER SIX

METAL PRICE VOLATILITY AND INVENTORY LEVEL

6.1 Introduction

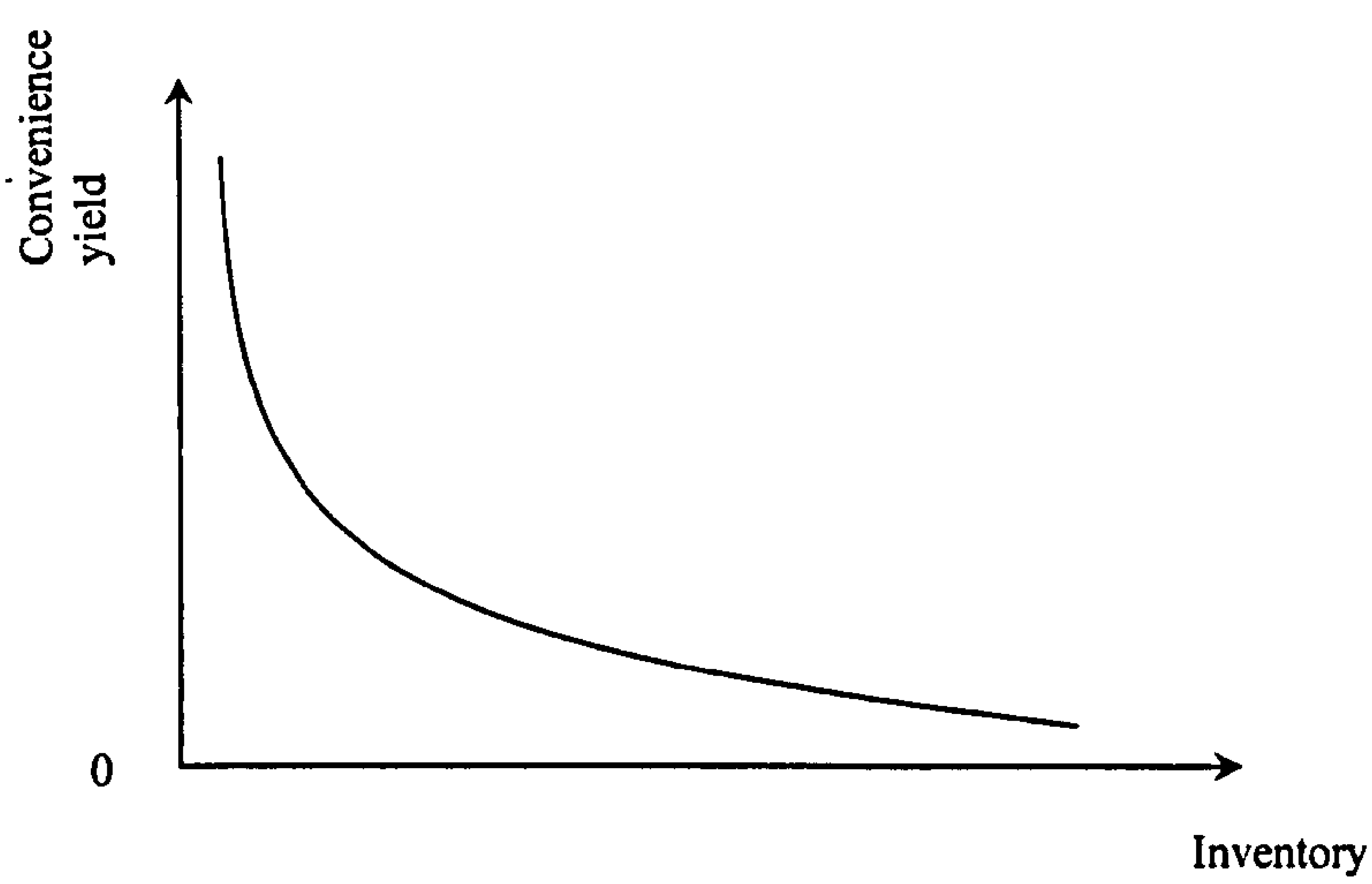
In the storable commodity markets, inventories play a crucial role in price formation. In a competitive commodity market subject to stochastic fluctuations in production and/or consumption, producers and to a lesser extent, consumers and third parties will hold inventories (Pindyck, 2001). Producers hold them to reduce costs of adjusting production over time, and also to reduce marketing costs by facilitating production and delivery scheduling and avoiding stockouts. If marginal production costs are increasing with the rate of output and if demand is fluctuating, producers can reduce costs over time by selling out inventory during high-demand periods, and restocking inventories during low-demand periods. Industrial consumers of a commodity also hold inventories to facilitate their own production processes. Kahn (1987, 1992), Miron and Zeldes (1988) and Ramey (1991) have investigated the important role of holding inventories in manufacturing industries. They suggest that producers make decisions on production levels with an expectation on the commodity inventory level. This means that production and consumption decisions are made not only based on the cash price, but also on the storage availability. Pindyck (2001) suggests that to the extent that inventories can be used to reduce production and marketing costs in the face of fluctuating demand conditions, they will have the effect of reducing the magnitude of short-run price fluctuation.

One feature shared by most commodities is the sharp change in prices. Pindyck (2004) documents that price volatility can affect the demand for storage, and can also affect the total marginal cost of current production. This is because commodity producers hold operating options with an exercise price equal to the direct marginal production cost and a payoff equal to the price of the commodity. The total marginal production cost is equal to the direct marginal cost plus an opportunity cost when producers exercise the operating options rather than wait for new price information. An increase in the price volatility leads to an increase in this operating option value as well as the opportunity cost and consequently, an increase in the total marginal production cost which can result in a production decline.

The theory of storage suggests that the motivation for a producer or consumer to store a commodity could be that the benefit (convenience yield) from storing the commodity exceeds the costs of storing it. Moreover, the convenience yield falls when inventory levels (ls_t) increase, but at a decreasing rate: $\partial c_t / \partial ls_t < 0$ and $\partial^2 c_t / \partial^2 ls_t > 0$. The marginal convenience yield is likely to be small when inventory levels are high because one more unit of inventory will be of little extra benefit, but it can rise sharply when the inventory levels are very low. French (1986), Fama and French (1987, 1988), and Williams and Wright (1991) derive the implications of a convex, decreasing relation between convenience yield and inventory level for spot and futures price volatility. Figure 6.1 shows the convenience yield as a function of inventory, as illustrated first by French (1986).

To serve the purpose in this thesis, we highlight two primary implications of the theory of storage as in Ng and Pirrong (1994).

Figure 6.1 Relative Convenience Yield as a function of inventory



First Implication: The variance of spot and futures prices is positively correlated with the convenience yield, and negatively correlated with inventory level. A decline in stock levels results in an increase in the convenience yield and at the same time constrains supply conditions. This reduces the elasticity of supply which will increase the volatility of prices, *ceteris paribus*. Thus when the convenience yield is high (i.e. when the market is in backwardation) the market price volatility is high. Conversely, when the market is in contango the price volatility is low.

Second Implication: Supply and demand shocks generate relatively larger changes in spot prices than in forward prices when inventory is low, while changes in spot and forward prices are roughly equal when inventory is high. For instance, suppose there is a permanent unexpected increase in an industry's demand for copper. This shock will cause the demand curve to shift, increasing both current and expected spot prices, while inventory levels decrease. Because of the convexity of the convenience yield function, the decline in inventories has practically no effect on the convenience yield when stock levels are high. Thus, spot and futures prices respond equally to such shocks. In the case of low inventory levels and a backwardation market, while spot prices respond sharply shocks due to the lower elasticity of the supply curve, expected spot prices, and therefore futures prices, do not change at the same rate because supply is more elastic in the long run. Therefore, futures prices are less volatile than spot prices when inventories are low (Ng and Pirrong, 1994; Pindyck, 2001).

Since the convenience yield is not directly observable, we propose the following additional implication, which links the price volatility with the inventory levels and hence can be empirically tested.

Third Implication: Inventory build-ups are associated with low spot and futures price volatility and inventory draw-downs are associated with high price volatility (i.e. there is a negative relationship between inventory level changes and spot and futures price volatility). As pointed out by Pindyck (2001), it is primarily producers that hold inventory and they can reduce costs over time by selling out inventory during high-demand periods and building up inventory during low-demand periods. High-demand periods will tend to correspond to periods of high commodity prices, and therefore high price volatility (Pindyck, 2001) and *vice versa*. Consequently one would expect a negative relationship between price volatility and inventory changes.

This chapter examines these three implications empirically in terms of three relationships, namely: (i) the contemporaneous relationship between price volatility and inventory level; (ii) the lead-lag relationship between inventory and spot and futures price volatility; and (iii) the relationship between the volatility of spot and futures prices. The relationships are investigated using a Markov Regime Switching framework in which the system switches between two market conditions of high and low volatility states. The existence of nonlinear relationships follows from the theoretical literature (see, for instance, French, 1986; Fama and French, 1987, 1988; Williams and Wright, 1991; Ng and Pirrong, 1994; Pindyck, 2001) (cf. Figure 6.1), and to date there has been no direct empirical test. This chapter is an attempt at filling in this gap.

6.2 Price Volatility and Inventory Levels

Given the heteroscedasticity observed in the spot and futures price time series, the conditional volatility of the (log) price change of futures and spot price is modelled using a GARCH model. The mean of the futures and spot price changes is modelled in an error correction model where the long-run cost-of-carry relationship identified in Chapter 5 is the error correction term.

$$\begin{aligned} \Delta f_t &= \theta_{f,1} \cdot \Delta s_{t-1} + \theta_{f,2} \cdot \Delta f_{t-1} + \rho_f \cdot ect_{t-1} + \varepsilon_t \\ \Delta s_t &= \theta_{s,1} \cdot \Delta s_{t-1} + \theta_{s,2} \cdot \Delta f_{t-1} + \rho_s \cdot ect_{t-1} + \varepsilon_t \end{aligned}, \quad \begin{aligned} \varepsilon_{f,t} &\sim N(0, \sigma_{f,t}^2) \\ \varepsilon_{s,t} &\sim N(0, \sigma_{s,t}^2) \end{aligned} \tag{6.1}$$

$$\begin{aligned} \sigma_{f,t}^2 &= \varpi_f + \sum_{i=1}^{q} \alpha_{s,i} \cdot \varepsilon_{f,t-i}^2 + \sum_{j=1}^{p} \beta_{s,j} \cdot \sigma_{f,t-j}^2 \\ \sigma_{s,t}^2 &= \varpi_s + \sum_{i=1}^{q} \alpha_{s,i} \cdot \varepsilon_{s,t-i}^2 + \sum_{j=1}^{p} \beta_{s,j} \cdot \sigma_{s,t-j}^2 \end{aligned} \tag{6.2}$$

where, $ect_t = f_t - b_0 - b_1 s_t - b_2 \text{int}_t - b_3 ls_t$ representing the equilibrium relationship among the cost-of-carry elements (futures price f_t, spot price s_t, interest rate int_t and inventory level ls_t), the estimation method for the cointegration coefficients b_i (i=0, 1, 2, 3) are described in Chapter 5; $\sigma_{f,t}^2$ and $\sigma_{s,t}^2$ are the conditional volatility time series for futures price and spot price respectively.

The results for the cointegration test and cointegrating vector are reported in Table 6.1. The methodology is the same as that in Chapter 5, but the data frequency is daily as opposed to the weekly data used in Chapter 5. After identifying the equilibrium error correction term among the spot and futures prices, interest rate and inventory level, the GARCH process is fitted to the residuals of the VECM. The estimation results of the GARCH conditional volatility process of the spot and futures prices Equation (6.1) are shown in Table 3.1. The Ljung-Box (1978) $Q(20)$ statistic for the 20^{th} order autocorrelation in the residual is statistically insignificant[26] and the Engle (1982) ARCH Lagrange Multiplier diagnostic test suggests that heteroscedasticity in the spot and futures price changes is eliminated. The sum of α and β denotes the degree of persistence in the conditional variance given a shock to the system. In particular, the sum should be less than 1 in order to have a stationary variance. As the sum tends to 1 the higher is the instability in the variance and shocks tend to persist instead of dying out (see Engle and Bollerslev, 1986). The results show that the conditional volatility of the prices is highly persistent as the sum of α and β is close to one in all the markets.

[26] With exceptions of aluminium alloy and lead markets, where the 20^{th} order residual autocorrelation is detected.

Table 6.1 The cointegration test and cointegrating vector

Panel A: Cointegration test among the cost-of-carry and convenience yield elements

		Eigenvalue	Trace statistics	Maxi-Eigen Stat.
Aluminium	H_0: $r=0$; H_1: $r=1$	0.0165	100.3582 *	43.439 *
	H_0: $r\leq 1$; H_1: $r=2$	0.0118	56.9191 *	30.872 *
	H_0: $r\leq 2$; H_1: $r=3$	0.0089	26.0471 *	23.3832 *
	H_0: $r\leq 3$; H_1: $r=4$	0.0010	2.6639	2.6639
Al alloy	H_0: $r=0$; H_1: $r=1$	0.0194	81.9662 *	50.9812 *
	H_0: $r\leq 1$; H_1: $r=2$	0.0071	30.985	18.6251
	H_0: $r\leq 2$; H_1: $r=3$	0.0032	12.3599	8.448
	H_0: $r\leq 3$; H_1: $r=4$	0.0015	3.9119	3.9119
Copper	H_0: $r=0$; H_1: $r=1$	0.0199	73.6315 *	52.3877 *
	H_0: $r\leq 1$; H_1: $r=2$	0.0046	21.2439	12.061
	H_0: $r\leq 2$; H_1: $r=3$	0.0033	9.1829	8.6106
	H_0: $r\leq 3$; H_1: $r=4$	0.0002	0.5723	0.5723
Lead	H_0: $r=0$; H_1: $r=1$	0.0310	124.5137 *	81.904 *
	H_0: $r\leq 1$; H_1: $r=2$	0.0123	42.6097 *	32.1126 *
	H_0: $r\leq 2$; H_1: $r=3$	0.0027	10.4971	6.9403
	H_0: $r\leq 3$; H_1: $r=4$	0.0014	3.5568	3.5568
Nickel	H_0: $r=0$; H_1: $r=1$	0.0156	92.8233 *	40.8934 *
	H_0: $r\leq 1$; H_1: $r=2$	0.0111	51.9299 *	29.0615 *
	H_0: $r\leq 2$; H_1: $r=3$	0.0069	22.8684 *	17.9843 *
	H_0: $r\leq 3$; H_1: $r=4$	0.0019	4.8841	4.8841
Tin	H_0: $r=0$; H_1: $r=1$	0.0216	91.2036 *	56.9706 *
	H_0: $r\leq 1$; H_1: $r=2$	0.0078	34.233	20.3872
	H_0: $r\leq 2$; H_1: $r=3$	0.0049	13.8458	12.7883
	H_0: $r\leq 3$; H_1: $r=4$	0.0004	1.0575	1.0575
Zinc	H_0: $r=0$; H_1: $r=1$	0.0301	116.4511 *	79.5769 *
	H_0: $r\leq 1$; H_1: $r=2$	0.0092	36.8741 *	24.0597 *
	H_0: $r\leq 2$; H_1: $r=3$	0.0032	12.8145	8.3117
	H_0: $r\leq 3$; H_1: $r=4$	0.0017	4.5028	4.5028

Panel B: the long-run equilibrium relationship $f_{t,t+n} = c + \beta_1 \cdot s_t + \beta_2 \cdot r_{t,t+n} + \beta_3 \cdot ls_t + \varepsilon_t$

	c	β_1	β_2	β_3
Aluminium	**0.3892**	**0.9505**	**0.0005**	-0.0017
	(0.105)	(0.015)	(0.000)	(0.003)
Al alloy	**-0.5217**	**1.033**	0.0005	**0.0269**
	(0.176)	(0.018)	(0.000)	(0.005)
Copper	**0.3666**	**0.9276**	**0.0006**	**0.0129**
	(0.16)	(0.014)	(0.000)	(0.005)
Lead	0.1047	**0.9427**	**0.0022**	**0.0216**
	(0.083)	(0.009)	(0.001)	(0.004)
Nickel	**-0.2388**	**1.0039**	**-0.0001**	**0.0209**
	(0.065)	(0.006)	(0.000)	(0.002)
Tin	0.0811	**0.9754**	**0.0002**	**0.0126**
	(0.08)	(0.008)	(0.000)	(0.002)
Zinc	**0.7264**	**0.9133**	-0.0008	-0.0079
	(0.166)	(0.024)	(0.001)	(0.005)

- Daily data over the period April 1994 and July 2004; Figures in parenthesis ( ) are *std. errors*, Figures in bold are statistically significant at the 5% level.
- It assumes no deterministic trend in the cointegration relationship;
- * represents the rejection of the null at the 5% significance level.
- CE: Cointegration Equation.

	None CE	At most 1 CE	At most 2 CEs	At most 3 CEs
Trace	53.12	34.91	19.96	9.24
Max-Eigen	28.14	22.00	15.67	9.24

Table 6.2 Futures and spot price conditional volatility

Panel A: Futures price volatility $\Delta f_t = \theta_{f,1} \cdot \Delta s_{t-1} + \theta_{f,2} \cdot \Delta f_{t-1} + \rho_f \cdot ect_{t-1} + \varepsilon_{f,t}$

$\sigma^2_{f,t} = \varpi_f + \alpha_f \cdot \varepsilon^2_{f,t-1} + \beta_{f,j} \cdot \sigma^2_{f,t-1}$

	$\theta_{f,1}$	$\theta_{f,2}$	ρ_f	ϖ_f	α_f	β_f	$Q(20)$ – stats	ARCH LM test	LL Fn value
Al	0.0942	-0.1183	0.0121	**3.90E-06**	**0.0554**	**0.9081**	28.628	0.5222	8324.8
	[0.265]	[0.200]	[0.545]	[0.000]	[0.000]	[0.000]	[0.095]	[0.760]	
Al alloy	0.1315	**-0.2099**	0.0184	**9.09E-06**	**0.1077**	**0.7956**	**32.973**	0.1818	8481.7
	[0.002]	[0.000]	[0.260]	[0.000]	[0.000]	[0.000]	[0.034]	[0.970]	
Copper	0.0843	**-0.1352**	0.0220	**4.12E-06**	**0.0490**	**0.9260**	19.446	0.3942	7775.6
	[0.117]	[0.032]	[0.176]	[0.000]	[0.000]	[0.000]	[0.493]	[0.853]	
Lead	**0.1213**	**-0.1947**	-0.0255	**6.92E-06**	**0.0740**	**0.8924**	**40.609**	0.2045	7514.8
	[0.010]	[0.001]	[0.207]	[0.000]	[0.000]	[0.000]	[0.004]	[0.961]	
Nickel	0.1653	-0.1552	**-0.0920**	**9.65E-05**	**0.1585**	**0.5716**	18.658	0.1962	6732.5
	[0.074]	[0.105]	[0.019]	[0.000]	[0.000]	[0.000]	[0.544]	[0.964]	
Tin	**0.2104**	**-0.2335**	-0.0019	**4.40E-06**	**0.0853**	**0.8861**	23.895	0.1489	8139.0
	[0.001]	[0.000]	[0.944]	[0.000]	[0.000]	[0.000]	[0.247]	[0.980]	
Zinc	-0.0357	-0.0088	0.0019	**1.50E-06**	**0.0460**	**0.9450**	26.151	0.7287	8033.0
	[0.554]	[0.901]	[0.873]	[0.000]	[0.000]	[0.000]	[0.161]	[0.602]	

Panel B : Spot price volatility $\Delta s_t = \theta_{s,1} \cdot \Delta s_{t-1} + \theta_{s,2} \cdot \Delta f_{t-1} + \rho_s \cdot ect_{t-1} + \varepsilon_{s,t}$

$\sigma^2_{s,t} = \varpi_s + \alpha_s \cdot \varepsilon^2_{s,t-1} + \beta_s \cdot \sigma^2_{s,t-1}$

	$\theta_{s,1}$	$\theta_{s,2}$	ρ_s	ϖ_s	α_s	β_s	$Q(20)$ – stats	ARCH LM test	LL Fn value
Al	0.0338	-0.0513	0.0406	**5.22E-06**	**0.0636**	**0.8956**	29.744	0.6857	8100.4
	[0.664]	[0.546]	[0.051]	[0.000]	[0.000]	[0.000]	[0.074]	[0.634]	
Al alloy	**-0.2198**	**0.1573**	**0.0695**	**1.03E-05**	**0.0941**	**0.8169**	**37.099**	0.5649	8198.8
	[0.000]	[0.002]	[0.001]	[0.000]	[0.000]	[0.000]	[0.011]	[0.727]	
Copper	0.1023	**-0.1826**	**0.0551**	**6.04E-06**	**0.0744**	**0.8972**	23.118	0.6127	7502.3
	[0.111]	[0.011]	[0.001]	[0.000]	[0.000]	[0.000]	[0.283]	[0.69]	
Lead	-0.0051	-0.0503	0.0356	**1.18E-05**	**0.0758**	**0.8832**	**32.970**	0.7193	7070.1
	[0.935]	[0.472]	[0.101]	[0.000]	[0.000]	[0.000]	[0.034]	[0.609]	
Nickel	-0.1670	0.1774	-0.0595	**9.38E-05**	**0.1543**	**0.6028**	16.869	0.5901	6634.5
	[0.078]	[0.067]	[0.129]	[0.000]	[0.000]	[0.000]	[0.661]	[0.708]	
Tin	-0.0563	0.0317	0.0555	**6.16E-06**	**0.0877**	**0.8741**	26.994	0.2062	7965.5
	[0.416]	[0.666]	[0.061]	[0.000]	[0.000]	[0.000]	[0.135]	[0.960]	
Zinc	-0.1072	0.0726	0.0110	**2.17E-06**	**0.0474**	**0.9404**	20.979	1.2908	7819.1
	[0.134]	[0.370]	[0.402]	[0.000]	[0.000]	[0.000]	[0.398]	[0.265]	

- Daily data over the period 05/04/1994 and 30/07/2004;
- Numbers in brackets [ ] are *p*-values;
- Numbers in bold are statistically significant at the 5% level;
- * indicates the null hypothesis in the test is rejected at a 5% significance level;
- Q (20) statistics are Ljung Box statistics for a test of 20th order autocorrelation in residuals (the nul hypothesis is that there is no autocorrelation in the residuals).
- The Engle (1982) ARCH Lagrange Multiplier (LM) test for the heteroscedasticity in the residuals i based on the regression: $z_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i z_{t-i}^2$ where the residual $z_t = \hat{\varepsilon}_t / \hat{\sigma}_t^2$, $\hat{\varepsilon}_t$ is the residua from the TGARCH equation $\hat{\sigma}_t^2$ is the estimated conditional variance. The null is $\beta_i = 0$;
- LL Fn Value: Log Likelihood Function Value.

As an attempt to examine the relationship between the conditional volatility and inventory levels, the lagged change of the (logarithm) inventory levels (Δls_t) is included as an explanatory variable in the GARCH model:

$$
\begin{aligned}
\sigma_{f,t}^2 &= \varpi_f + \sum_{i=1}^{q} \alpha_{f,i} \cdot \varepsilon_{f,t-i}^2 + \sum_{j=1}^{p} \beta_{f,j} \cdot \sigma_{f,t-j}^2 + \mu_f \cdot \Delta ls_{t-1} \\
\sigma_{s,t}^2 &= \varpi_s + \sum_{i=1}^{q} \alpha_{s,i} \cdot \varepsilon_{s,t-i}^2 + \sum_{j=1}^{p} \beta_{s,j} \cdot \sigma_{s,t-j}^2 + \mu_s \cdot \Delta ls_{t-1}
\end{aligned}
\tag{6.3}
$$

Table 6.3 shows the estimation results of model (6.3). The Ljung-Box (1978) 20th order residual autocorrelation diagnostic test statistics $Q(20)$ suggest that there is generally no autocorrelation in the residuals . The Engle (1982) ARCH Lagrange Multiplier diagnostic test suggests that there is no heteroscedasticity in the residuals in all the markets. Panel A and B reports the estimation results on the relationship between the change of inventory levels and futures and spot price volatility in a GARCH model, respectively.

In Panel A, the coefficient μ_f represents the impact of the lagged change of inventory levels on the futures price volatility. It can be seen that μ_f is statistically negative in five of the markets (aluminium, copper, lead, nickel and zinc) at the 10% level, suggesting that the futures price volatility is negatively associated with changes in inventory levels, i.e. the futures price volatility is higher during periods of decreasing inventory. In Panel B, the coefficient μ_s represents the impact of the lagged change of inventory levels on the spot price volatility. Similar results are found, i.e. the coefficients μ_s are statistically negative in all the markets, with an exception of tin at the 10% level, suggesting that spot price volatility is also higher during periods of decreasing inventory.

The empirical findings of negative relationships between the spot and futures price volatility and changes in inventory levels largely confirm the third implication discussed in section 6.1 which argues that low price volatility should be associated with inventory build-ups and high volatility should be associated with decline in inventory levels. Moreover, the changes in inventory levels seem to have a stronger impact on the spot price volatility than on the futures price volatility, as shown by the absolute value of the coefficients, μ_f and μ_s in Panel A and Panel B. Specifically, the coefficient μ_s is found to be larger than coefficient μ_f in six markets, namely the aluminium, aluminium alloy, copper, lead, nickel and tin markets. This is mainly due to the fact that any changes in the inventory levels largely reflect the current balance between production and consumption, and therefore ultimately have a stronger impact on the current price volatility than on the nearby futures price volatility.

Table 6.3 Volatility and changes in inventory levels in GARCH

Panel A: Futures price volatility

$$\Delta f_t = \theta_{f,1} \cdot \Delta s_{t-1} + \theta_{f,2} \cdot \Delta f_{t-1} + \rho_f \cdot ect_{t-1} + \varepsilon_{f,t}$$

$$\sigma^2_{f,t} = \varpi_f + \alpha_f \cdot \varepsilon^2_{f,t-1} + \beta_f \cdot \sigma^2_{f,t-1} + \mu_f \cdot \Delta ls_{t-1}$$

	$\theta_{f,1}$	$\theta_{f,2}$	ρ_f	ϖ_f	α_f	β_f	μ_f	Q(20) – stats	ARCH LM test
Al	0.1003 [0.182]	-0.1233 [0.135]	0.0088 [0.621]	**4.64E-06** [0.000]	**0.0457** [0.000]	**0.9091** [0.000]	**-0.3483** [0.000]	28.391 [0.100]	0.455 [0.810]
Al alloy	**0.1327** [0.001]	**-0.2113** [0.000]	0.0186 [0.249]	**9.30E-06** [0.000]	**0.1071** [0.000]	**0.7937** [0.000]	-0.0835 [0.165]	33.219 [0.059]	0.194 [0.965]
Copper	0.0781 [0.136]	**-0.1290** [0.035]	0.0219 [0.162]	**3.95E-06** [0.000]	**0.0458** [0.000]	**0.9299** [0.000]	**-0.0717** [0.044]	19.128 [0.514]	0.4352 [0.824]
Lead	**0.1180** [0.013]	**-0.1914** [0.001]	-0.0246 [0.224]	**6.72E-06** [0.000]	**0.0696** [0.000]	**0.8966** [0.000]	**-0.2353** [0.000]	**41.053** [0.004]	0.230 [0.950]
Nickel	0.1615 [0.080]	-0.1516 [0.113]	**-0.0922** [0.019]	**9.42E-05** [0.000]	**0.1563** [0.000]	**0.5794** [0.000]	-0.2848 [0.081]	18.482 [0.556]	0.199 [0.963]
Tin	**0.2087** [0.001]	**-0.2303** [0.000]	-0.0005 [0.986]	**4.56E-06** [0.000]	**0.0875** [0.000]	**0.8827** [0.000]	-0.0634 [0.130]	24.418 [0.225]	0.151 [0.980]
Zinc	-0.0283 [0.646]	-0.0158 [0.827]	0.0028 [0.816]	**1.88E-06** [0.000]	**0.0474** [0.000]	**0.9404** [0.000]	**-0.1530** [0.012]	25.987 [0.166]	0.588 [0.709]

- Daily data over the period 05/04/1994 and 30/07/2004;
- Numbers in brackets [ ] are p-values;
- Numbers in bold are statistically significant at the 5% level;
- Q (20) statistics are Ljung Box statistics for the test of 20th order residual autocorrelation (H_0: no autocorrelation);
- ARCH LM tests the null hypothesis that there is no heteroscedasticity in the residuals;
- LL Fn Value: Log Likelihood Function Value.

Table 6.3 Volatility and changes in inventory levels in GARCH (continued)

Panel B: Spot price volatility

$$\Delta s_t = \theta_{s,1} \cdot \Delta s_{t-1} + \theta_{s,2} \cdot \Delta f_{t-1} + \rho_s \cdot ect_{t-1} + \varepsilon_{s,t}$$

$$\sigma^2_{s,t} = \varpi_s + \alpha_s \cdot \varepsilon^2_{s,t-1} + \beta_s \cdot \sigma^2_{s,t-1} + \mu_s \cdot \Delta ls_{t-1}$$

	$\theta_{s,1}$	$\theta_{s,2}$	ρ_s	ϖ_s	α_s	β_s	μ_s	$Q(20)$ – stats	ARCH LM test
Al	0.0467	-0.0643	**0.0413**	**5.26E-06**	**0.0549**	**0.9025**	**-0.3812**	30.113	0.565
	[0.511]	[0.410]	[0.033]	[0.000]	[0.000]	[0.000]	[0.000]	[0.068]	[0.727]
Al alloy	**-0.2187**	**0.1556**	**0.0703**	**1.01E-05**	**0.0919**	**0.8202**	-0.1359	**37.259**	0.608
	[0.000]	[0.002]	[0.001]	[0.000]	[0.000]	[0.000]	[0.065]	[0.011]	[0.694]
Copper	0.1014	**-0.1816**	**0.0567**	**5.72E-06**	**0.0704**	**0.9021**	**-0.1438**	22.564	0.770
	[0.102]	[0.009]	[0.000]	[0.000]	[0.000]	[0.000]	[0.011]	[0.311]	[0.571]
Lead	-0.0171	-0.0396	0.0371	**1.05E-05**	**0.0676**	**0.8948**	**-0.3481**	**34.187**	0.692
	[0.778]	[0.564]	[0.087]	[0.000]	[0.000]	[0.000]	[0.000]	[0.025]	[0.63]
Nickel	-0.1733	0.1836	-0.0600	**8.96E-05**	**0.1502**	**0.6167**	**-0.4164**	16.854	0.608
	[0.066]	[0.057]	[0.124]	[0.000]	[0.000]	[0.000]	[0.011]	[0.662]	[0.694]
Tin	-0.0548	0.0312	0.0574	**6.30E-06**	**0.0889**	**0.8717**	-0.0907	27.382	0.207
	[0.425]	[0.667]	[0.055]	[0.000]	[0.000]	[0.000]	[0.112]	[0.125]	[0.96]
Zinc	-0.1057	0.0717	0.0116	**2.41E-06**	**0.0483**	**0.9378**	-0.1424	20.582	1.142
	[0.140]	[0.377]	[0.372]	[0.000]	[0.000]	[0.000]	[0.080]	[0.422]	[0.336]

- Daily data over the period 05/04/1994 and 30/07/2004;
- Numbers in brackets [ ] are *p*-values;
- Numbers in bold are statistically significant at the 5% level;
- * indicates that the null of the diagnostic test is rejected at the 5% significance level;
- Q (20) statistics are Ljung Box statistics for the test of 20th order residual autocorrelation (H_0: no autocorrelation);
- ARCH LM tests the null hypothesis that there is no heteroscedasticity in the residuals;
- LL Fn Value: Log Likelihood Function Value.

6.3 Lead lag relationship between volatility and inventory level

As discussed in the first section of this chapter, there is a theoretical argument for the existence of an inter-temporal relationship between volatility and changes in inventory levels. The theory of storage suggests that increases in price volatility lead to increases in production cost, decreases in production, and decline in the inventory level, *ceteris paribus*. On the other hand, declines in the inventory levels result in a less elastic supply curve, thereby leading to rises in price volatility for a given distribution of supply and demand shocks. In this section we use the Granger Causality test in a VAR(p) framework as shown in Equations (6.4) and (6.5) to investigate the lead-lag relationship between inventory levels (Δls_t) and volatility of prices (spot $\sigma^2_{s,t}$ and futures $\sigma^2_{f,t}$).

$$\begin{aligned} \hat{\sigma}^2_{s,t} &= \varpi_{s,1} + \sum_{i=1}^{p} \rho_{s,1,i}\hat{\sigma}^2_{s,t-1,i} + \sum_{i=1}^{p} \pi_{s,1,i}\Delta ls_{t-1,i} + \upsilon_{t,1} \\ \Delta ls_t &= \varpi_{s,2} + \sum_{i=1}^{p} \rho_{s,2,i}\hat{\sigma}^2_{s,t-1,i} + \sum_{i=1}^{p} \pi_{s,2,i}\Delta ls_{t-1,i} + \upsilon_{t,2} \end{aligned} \tag{6.4}$$

$$\begin{aligned} \hat{\sigma}^2_{f,t} &= \varpi_{f,1} + \sum_{i=1}^{p} \rho_{f,1,i}\hat{\sigma}^2_{f,t-1,i} + \sum_{i=1}^{p} \pi_{f,1,i}\Delta ls_{t-1,i} + \zeta_{t,1} \\ \Delta ls_t &= \varpi_{f,2} + \sum_{i=1}^{p} \rho_{f,2,i}\hat{\sigma}^2_{f,t-1,i} + \sum_{i=1}^{p} \pi_{f,2,i}\Delta ls_{t-1,i} + \zeta_{t,2} \end{aligned} \tag{6.5}$$

Where $\hat{\sigma}^2_{f,t}$ and $\hat{\sigma}^2_{s,t}$ are the GARCH estimated conditional volatility process of the futures and spot price, respectively; error terms, $\upsilon_{t,1}, \upsilon_{t,2}, \zeta_{t,1}$, and $\zeta_{t,2}$ are *i.i.d.* processes with mean zero and constant variance.

Changes in inventory levels are said to Granger cause spot and futures price volatility if the coefficient $\pi_{s,1,i}$ and $\pi_{f,1,i}$ is statistically significant in the first equation in model (6.4) and (6.5), respectively. Similarly, spot and futures price volatility is said to Granger cause the changes in inventory levels if the coefficients $\rho_{s,2,i}$ and $\rho_{f,2,i}$ are statistically significant. The VAR model estimation and Granger causality test results are shown in Table 6.4. The lag length p in the VAR model is determined according to the standard Schwarz Criteria (Schwarz, 1978) and so p is different across the markets (p=2 in the tin market and p=1 for the rest). The Johansen (1995) multivariate LM test for residual autocorrelation suggests the VAR(p) model is well specified. According to the $\overline{R}^2$, the lagged volatility and inventory changes in the multivariate VAR model can explain the spot and futures price volatility well (generally $\overline{R}^2$ is above 90%), however the explanatory power of the equation for inventory levels is relatively low. The former is largely due to persistency in the variance. The results suggest that volatility changes Granger cause the changes in inventory levels in the sense that an increase in the futures price volatility leads to a decrease in the inventory level in all the markets with an exception of the zinc market, while spot price volatility is found to Granger cause inventory changes in the aluminium, copper, lead, and nickel markets.

These findings are consistent with the theoretical argument that high price volatility increases the producers' operation option value and the total production costs which causes a decline in the production as argued by Pindyck (2001). Assuming that the demand for the commodity remains the same, the inventory level will then decrease when the market volatility is high (see Section 6.1). Changes in inventory levels are found not to Granger cause the price volatility in all the markets, which goes against the discussion in the previous section, suggesting that the forecasting power of the inventory levels upon the metal spot and futures price volatility is virtually none. This may be because it is the *level* of the inventory that primarily influences volatility rather than inventory changes. When the inventory levels are high, any changes will have little effect on the market volatility, whereas when stock levels are low and there may even be a risk of stock-out, changes in inventory may have a great impact on price volatility. In aggregate, no evidence is found that changes in inventory levels Granger cause spot or futures price volatility.

Table 6.4 Granger causality test of price volatility and inventory level

Panel A: futures price volatility

$$\sigma^2_{f,t} = \varpi_{f,1} + \rho_{f,1,1}\sigma^2_{f,t-1} + \rho_{f,1,2}\sigma^2_{f,t-2} + \pi_{f,1,1}\Delta ls_{t-1} + \pi_{f,1,2}\Delta ls_{t-2} + \zeta_{t,1}$$
$$\Delta ls_t = \varpi_{f,2} + \rho_{f,2,1}\sigma^2_{f,t-1} + \rho_{f,2,1}\sigma^2_{f,t-2} + \pi_{f,2,1}\Delta ls_{t-1} + \pi_{f,2,2}\Delta ls_{t-2} + \zeta_{t,2}$$

	j=12	$\varpi_{f,j}$	$\rho_{f,j,1}$	$\rho_{f,j,2}$	$\pi_{f,j,1}$	$\pi_{f,j,2}$	SIC	$\overline{R}^2$	LM test	$H_0: \Delta ls \not\Rightarrow \sigma^2_f$ $\chi^2(df)$	$H_0: \sigma^2_f \not\Rightarrow \Delta ls$ $\chi^2(df)$
Al	σ^2_f	**4.33E-06** (6.578)	**0.9592** (172.095)		-2.00E-05 (-0.487)		-19.4423	0.921	6.671 [0.154]	0.2371 [0.626]	
	Δls	**0.0013** (4 220)	**-15.0115** (-5.809)		0 244 (12 816)		-7.1623	0.079			**33.7501** [0.000]
Al alloy	σ^2_f	**1.20E-05** (11.993)	**0.8703** (90.046)		5.38E-05 (0.942)		-18.5522	0.757	8.172 [0.086]	0.8873 [0.346]	
	Δls	0 0006 (1.877)	**-6.7558** (-2.086)		**0.215** (11.224)		-6.9237	0 048			**4.3527** [0.037]
Copper	σ^2_f	**3.30E-06** (4.360)	**0.9802** (252.370)		-3.56E-07 (-0.012)		-18.7617	0.961	**15.210** [0 004]	0.0001 [0.991]	
	Δls	**0.0011** (2.280)	**-10.0562** (-4.064)		**0.1645** (8.503)		-5.8031	0.035			**16.5184** [0.000]
Lead	σ^2_f	**9.57E-06** (6.086)	**0.954** (162.827)		3.82E-05 (0.445)		-16 9475	0.911	2.053 [0.726]	0 1983 [0.656]	
	Δls	0.0002 (0 610)	**-4.1974** (-3.208)		**0.2096** (10.929)		-6.1305	0.049			**10.2931** [0.001]
Nickel	σ^2_f	**1.01E-04** (17 840)	**0.72** (52.731)		5.80E-05 (0.329)		-14.8507	0.517	1.597 [0 809]	0.1083 [0.742]	
	Δls	0.0005 (0.841)	**-3.2668** (-2.279)		**0.3324** (17.964)		-5.5495	0.113			**5.1916** [0.023]
Tin	σ^2_f	**7.29E-06** (6.229)	**0.9722** (49.555)	-2.35E-02 (-1.197)	**7.44E-05** (1.998)	-2.73E-05 (-0.733)	-17.4208	0.901	0.2489 [0.993]	4.2288 [0.121]	
	Δls	0.0007 (1.122)	0.8004 (0.078)	-8.9161 (-0.868)	**0.1104** (5.670)	**0.1207** (6.200)	-4.9012	0.032			**6.3812** [0.041]
Zinc	σ^2_f	**3.25E-06** (4.708)	**0.9770** (234.948)		5.47E-06 (0.107)		-18.8768	0.955	6.8867 [0.142]	0.0115 [0 915]	
	Δls	0.0002 (0.588)	-2.3749 (-1.485)		0.0330 (1.684)		-6.9800	0.001			2.2058 [0.138]

* The Autocorrelation LM test (Johansen 1995) is the multivariate Lagrange Multiplier test statistics for no residual serial correlation up to the 20[th] order. The LM statistic is asymptotically distributed χ^2 with degree of freedom k^2 where k is the number of endogenous variables (k = 2 in this case).

Table 6.4 Granger causality test of price volatility and inventory level (continued)

Panel B: Spot price volatility

$$\sigma^2_{s,t} = \varpi_{s,1} + \rho_{s,1,1}\sigma^2_{s,t-1} + \rho_{s,1,2}\sigma^2_{s,t-2} + \pi_{s,1,1}\Delta ls_{t-1} + \pi_{s,1,2}\Delta ls_{t-2} + \zeta_{t,1}$$

$$\Delta ls_t = \varpi_{s,2} + \rho_{s,2,1}\sigma^2_{s,t-1} + \rho_{s,2,2}\sigma^2_{s,t-2} + \pi_{s,2,1}\Delta ls_{t-1} + \pi_{s,2,2}\Delta ls_{t-2} + \zeta_{t,2}$$

	j=12	ϖ_f	$\rho_{f,j,1}$	$\rho_{f,j,2}$	$\pi_{f,j,1}$	$\pi_{f,j,2}$	SIC	$\overline{R}^2$	LM test[l]	$H_0: \Delta ls \nRightarrow \sigma^2_f$ $\chi^2(df)$	$H_0: \sigma^2_f \nRightarrow \Delta ls$ $\chi^2(df)$
Al	σ^2_s	**5.93E-06** (7 076)	**0.9533** (159.873)		1.90E-05 (0.366)		-18.9629	0 908	7.161 [0 128]	0.1342 [0.714]	
	Δls	**0.0007** (2 218)	**-7.8208** (-3.581)		**0.2544** (13.407)		-7.1563	0.072			**12.8261** [0.000]
Al alloy	σ^2_s	**1.51E-05** (12.375)	**0.8671** (88 73)		1.07E-04 (1.653)		-18.3036	0.752	7.059 [0 133]	2.7338 [0 098]	
	Δls	0 0003 (0.710)	-2.2326 (-0.772)		**0.2166** (11.311)		-6.9223	0.047			0.5953 [0.440]
Copper	σ^2_s	**5.34E-06** (4.177)	**0.9753** (225.607)		-3.39E-05 (-0.519)		-17.1811	0.952	**18.270** [0.001]	0 2699 [0 603]	
	Δls	0.0001 (0 352)	**-3.1917** (-2.493)		**0.1691** (8.745)		-5 7992	0.031			**6.2143** [0.013]
Lead	σ^2_s	**1.23E-05** (6 303)	**0.9571** (168.129)		5.85E-05 (0.625)		-16.7784	0.916	3 166 [0.531]	0.3908 [0 532]	
	Δls	0 0006 (1 615)	**-4.5598** (-3.907)		**0.2076** (10.821)		-6.1324	0.051			**15.2658** [0 000]
Nickel	σ^2_s	**9.61E-05** (16.592)	**0.7526** (58.107)		5.93E-05 (0.326)		-14.7884	0.565	2.536 [0.638]	0 1064 [0 744]	
	Δls	0.0004 (0.709)	**-2.8162** (-2.136)		**0.3327** (17.978)		-5.5425	0.113			**4.5627** [0.033]
Tin	σ^2_s	**8.84E-06** (6 712)	**0.9717** (49.551)	-2.78E-02 (-1.419)	**8.05E-05** (1.999)	-6.70E-05 (-1.663)	-17.2636	0.893	0.7563 [0.944]	**6.0184** [0.049]	
	Δls	0.0006 (0.871)	-3.6013 (-0.380)	-2 8328 (-0.298)	**0.1114** (5.719)	**0.1218** (6.252)	-4.9004	0.031			4.1919 [0.123]
Zinc	σ^2_s	**3.09E-06** (3 938)	**0.9821** (267.41)		1.12E-04 (1.695)		-18.4089	0.965	6 5687 [0 161]	2.8739 [0.090]	
	Δls	-0.0002 (-0.773)	0.0384 (0.035)		0 0338 (1.726)		-6.9779	0.004			0.0012 [0.972]

- [l] - The Autocorrelation LM test (Johansen 1995) is the multivariate Lagrange Multiplier test statistics for no residual serial correlation up to the 20[th] order. The LM statistic is asymptotically distributed χ^2 with degree of freedom k^2 where k is the number of endogenous variables (k = 2 in this case).

6.4 Spot and Futures Price Volatility

The second implication of the theory of storage suggests that the spot price volatility should be higher than the futures price volatility and that the difference is larger when the inventory levels are low. This relationship is first empirically tested in a simple linear regression in Equation (6.6) and the results are shown in Table 6.5.

$$\sigma_{f,t}^2 = k_0 + k_1 \cdot \sigma_{s,t}^2 + \varepsilon_t \tag{6.6}$$

The joint null hypothesis of k_0=0, k_1=1 in Equation (6.6) is rejected in all the markets. The estimated coefficients k_1 are statistically significant and less than one in all the markets, confirming that the spot price volatility is higher than the futures price volatility in all the industrial metals markets in general.

In order to evaluate the nonlinear relationship between spot and futures price volatility and market conditions, we first introduce a dummy variable in Equation (6.6) to account for the market conditions.

$$\sigma_{f,t}^2 = k_0 + k_1 \cdot \sigma_{s,t}^2 + k_b \cdot \sigma_{s,t}^2 \cdot D_b + \varepsilon_t \tag{6.7}$$

where D_b is a dummy variable: D_b = 1 when the market is in backwardation and D_b = 0 when the market is in contango. The benchmark to separate a market from backwardation and contango is the basis: if the basis is smaller than its historical mean, the market is considered to be in backwardation and otherwise the market is considered to be in contango. The coefficient k_1 represents the relationship between the spot and futures price volatility when the market is in contango and k_1+k_b represents the relationship when the market is in backwardation. A statistically negative k_b is expected based on our postulation.

In a backwardation market the spot price volatility is argued to be larger than the futures price volatility (Ng and Pirrong, 1994), thus one would expect the k_b estimate to be statistically negative. The estimation results are presented in Table 6.5 Panel B. The empirical results confirm the postulation that the difference between the spot and futures price volatility is greater when the market is in backwardation in all the markets.

Next, we apply the Markov Regime Switching model, which is able to separate the market endogenously into two states (backwardation vs. contango), to investigate the nonlinear spot and futures volatility relationship. Formally, let:

$$\sigma_{f,t}^2 = k_{0,st} + k_{1,st} \cdot \sigma_{s,t}^2 + \eta_{t,st} \tag{6.8}$$

where st represents the two states, $st = 1, 2$.

The transition probabilities are determined by the inventory levels in the following logit model:

$$p_{12,t} = \frac{1}{1+\exp(m_0 + m_1 ls_t)}, \quad p_{21,t} = \frac{1}{1+\exp(n_0 + n_1 ls_t)} \tag{6.9}$$

where ls_t is the inventory level.

Table 6.5- Panel C presents the estimation results of the Markov Regime Switching model which explains the relationship between the spot and futures price volatility under the two market conditions (high and low volatility). The null hypothesis $H_0 : k_{1,1} = k_{1,2}$ is tested using the Likelihood Ratio test. It can be observed that the coefficient k_1 is smaller in state one (high-volatility state) in all the markets with an exception of nickel, suggesting the difference between spot and futures price volatility is larger in state one. In particular, the ratio $k_{1,1}/k_{1,2}$ ranges from 0.59 (zinc) to 0.93 (aluminium).

Table 6.5 Spot and futures price volatility

	Panel A: Linear spot and futures price volatility relationship $\sigma^2_{f,t} = k_0 + k_1 \cdot \sigma^2_{s,t} + \varepsilon_t$		
	k_0	k_1	$\chi^2(2)$ H_0: $k_0 = 0$ $k_1 = 1$
Aluminium	**4.66e-06** [0.000]	**0.8141** [0.000]	**2695.479** [0.000]
Aluminium alloy	1.03e-06 [0.230]	**0.8218** [0.000]	**2174.732** [0.000]
Copper	**5.95e-05** [0.000]	**0.4888** [0.000]	**14431.334** [0.000]
Lead	**-3.10e-05** [0.000]	**0.8337** [0.000]	**2622.222** [0.000]
Nickel	**7.20e-06** [0.000]	**0.9168** [0.000]	**1402.657** [0.000]
Tin	**-7.93e-06** [0.000]	**0.9487** [0.000]	**999.790** [0.000]
Zinc	**3.37e-05** [0.000]	**0.6283** [0.000]	**3308.772** [0.000]

	Panel B: the asymmetric spot and futures price volatility relation with a dummy $\sigma^2_{f,t} = k_0 + k_1 \cdot \sigma^2_{s,t} + k_b \cdot \sigma^2_{s,t} \cdot D_b + \varepsilon_t$		
	k_0	k_1	k_b
Aluminium	**4.76E-06** [0.000]	**0.8244** [0.000]	**-0.0569** [0.000]
Aluminium alloy	-8.22E-07 [0.324]	**0.8497** [0.000]	**-0.0748** [0.000]
Copper	**4.14E-05** [0.000]	**0.6474** [0.000]	**-0.1490** [0.000]
Lead	**-3.58E-05** [0.000]	**0.9175** [0.000]	**-0.1659** [0.000]
Nickel	**2.66E-06** [0.046]	**0.9360** [0.000]	**-0.0418** [0.000]
Tin	**-8.52E-06** [0.000]	**0.9803** [0.000]	**-0.0806** [0.000]
Zinc	**2.36E-05** [0.000]	**0.7274** [0.000]	**-0.1353** [0.000]

- Daily data over the period 05/04/1994 to 30/07/2004;
- Numbers in brackets [ ] are p-values; Numbers in bold are statistically significant at the 5% level.

Table 6.5 Spot and futures price volatility (Continued)

Panel C: Nonlinear spot and futures volatility relationship

$$\sigma^2_{f,t} = k_{0,st} + k_{1,st} \cdot \sigma^2_{s,t} + \eta_t \quad p_{t,12} = \frac{1}{1+\exp(m_0 + m_1 \cdot ls_t)} \quad p_{t,21} = \frac{1}{1+\exp(n_0 + n_1 \cdot ls_t)}$$

	State one					State two					H$_0$: k_{11}=k_{12}
	$k_{0,1}$	$k_{1,1}$	m_0	m_1	Sigma 1	$k_{0,2}$	$k_{1,2}$	n_0	n_1	Sigma 2	
Aluminium	-4.73e-06	0.8116	6.5979	-0.2737	3.12e-05	-1.05e-07	0.8684	3.1575	0.0692	3.49e-06	10.089
	[0.121]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]	[0.006]
Aluminium alloy	-3.56e-06	0.8186	2.6034	-0.0337	3.15e-05	-6.42e-06	0.8884	-1.7179	0.4457	5.54e-06	11.133
	[0.207]	[0.000]	[0.000]	[0.047]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]
Copper	5.90e-05	0.4000	3.3480	0.0979	2.37e-05	6.60e-05	0.5778	3.6343	0.0337	1.65e-05	462.232
	[0.000]	[0.000]	[0.000]	[0.023]	[0.000]	[0.000]	[0.000]	[0.098]	[0.825]	[0.000]	[0.000]
Lead	-1.94e-05	0.8320	-3.6436	0.6257	5.74e-04	-8.87e-05	0.9085	9.6520	-0.5671	9.961e-05	29.047
	[0.000]	[0.000]	[0.262]	[0.017]	[0.000]	[0.000]	[0.000]	[0.020]	[0.105]	[0.000]	[0.000]
Nickel	-3.89e-06	0.9144	6.2419	-0.4576	6.69e-05	5.71e-06	0.9179	-3.3962	0.5915	9.69e-06	0.197
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.906]
Tin	1.40e-05	0.9387	11.8295	-0.9063	2.50e-05	-1.60e-05	1.0701	-0.1168	0.3745	5.00e-06	186.271
	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Zinc	3.70e-05	0.5526	10.0892	-0.5107	6.70e-05	-7.00e-06	0.9334	-8.2230	1.0241	6.00e-06	381.150
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

- Daily data over the period 05/04/1994 and 30/07/2004;
- Numbers in brackets [ ] are p-values; Numbers in bold are statistically significant at the 5% level.
- Sigma: the variance of the residual in the low (high) volatility state.

6.5 Volatility and Inventory in a Regime Switching Framework

The theory of storage also suggests that the relationship between convenience yield and volatility might be nonlinear which in turn may induce nonlinearity in the relationship between volatility and changes in the inventory level. To investigate this, we use a Markov Regime Switching – VAR model in which the transition probability is dependent on the inventory level to relate spot and futures price volatility and inventory changes. In order to increase computational efficiency, the lag length in the VAR model is chosen to be one. The MRS-VAR model is of the form below.

$$\begin{aligned} \sigma^2_{f,t} &= \varpi_{f,1,st} + \rho_{f,1,st} \cdot \sigma^2_{f,t-1} + \pi_{f,1,st} \cdot \Delta ls_{t-1} + e_{f,1,t} \\ \Delta ls_t &= \varpi_{f,2,st} + \rho_{f,2,st} \cdot \sigma^2_{f,t-1} + \pi_{f,2,st} \cdot \Delta ls_{t-1} + e_{f,2,t} \end{aligned} \quad (6.10)$$

$$\begin{aligned} \sigma^2_{s,t} &= \varpi_{s,1,st} + \rho_{s,1,st} \cdot \sigma^2_{s,t-1} + \pi_{s,1,st} \cdot \Delta ls_{t-1} + e_{s,1,t} \\ \Delta ls_t &= \varpi_{s,2,st} + \rho_{s,2,st} \cdot \sigma^2_{s,t-1} + \pi_{s,2,st} \cdot \Delta ls_{t-1} + e_{s,2,t} \end{aligned} \quad (6.11)$$

where st = 1, 2 represent the two states. The transition probabilities, P_{12} and P_{21}, are modelled as dependent on the (logarithm of) inventory level, ls_t, in a logit model:

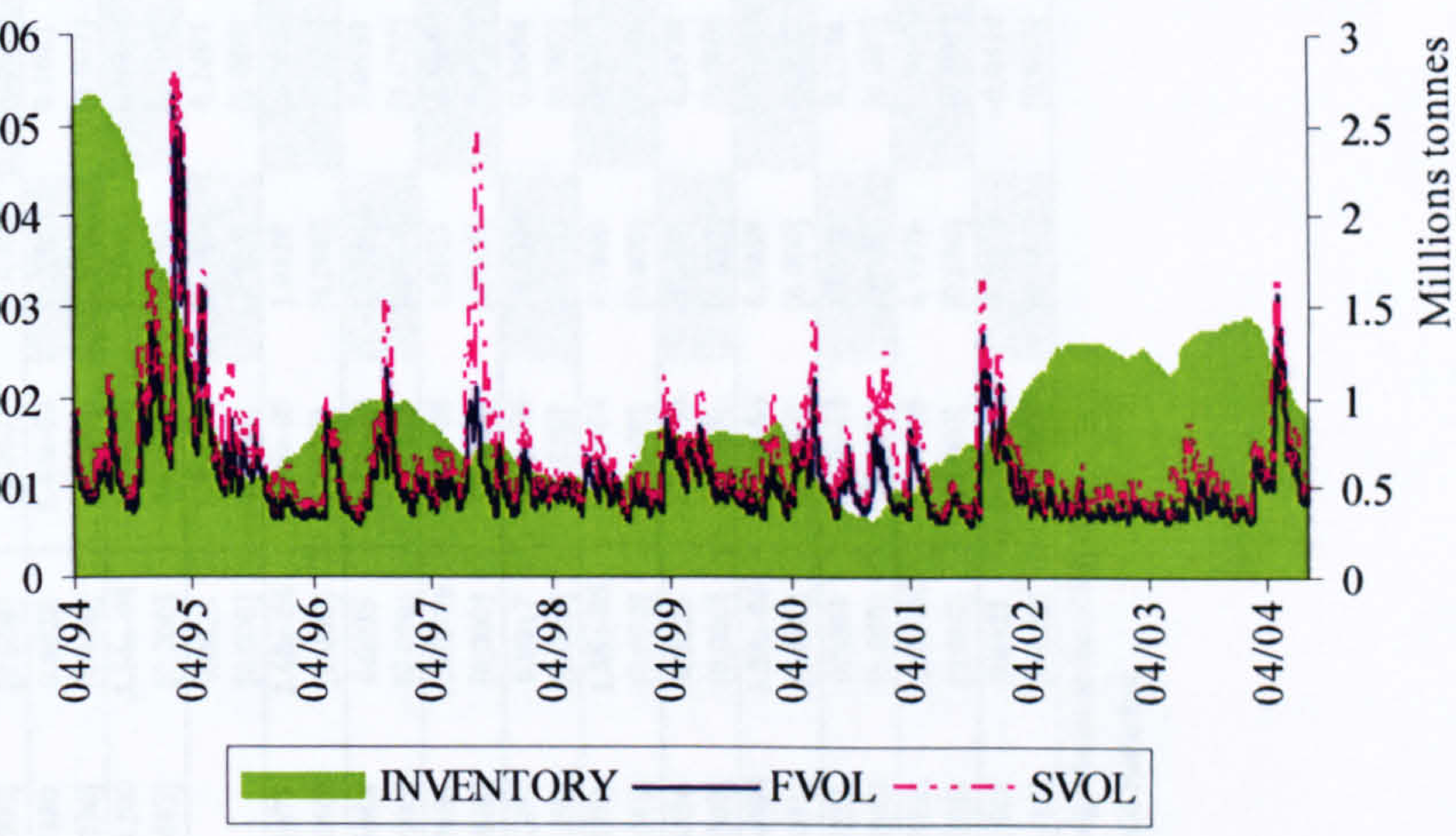
$$p_{12,t} = \frac{1}{1+\exp(m_0 + m_1 ls_t)}, \quad p_{21,t} = \frac{1}{1+\exp(n_0 + n_1 ls_t)} \quad (6.12)$$

where m_0, m_1, n_0 and n_1 are parameters to be estimated.

As an example, Figure 6.2 plots the GARCH-measured volatility and inventory levels in the aluminium market. It appears that the spot and futures price volatility move very closely in general, but the spot price volatility has larger spikes than the futures price volatility periodically. It can also be seen that there is a seemingly negative relationship between the volatility and inventory level; that is when the price volatility increases inventory level falls.

In the MRS model, the stock level is used as an explanatory variable to model transition probabilities in all the markets with the exception of aluminium alloy (inventory equation) for which the transition probabilities are estimated endogenously due to an estimation convergence problem. In this setting, transition probabilities are dependent on the level of inventories. Hence, when inventory levels are high, there is a higher probability that the market is in state one (the low-volatility regime) and when inventory levels are low, there is a higher probability that the system shifts to state two, the high-volatility regime.

Figure 6.2 The Aluminium spot and futures price volatility and inventory levels



Note: FVOL – futures price volatility; SVOL – spot price volatility.

Table 6.6 Price volatility and inventory levels under different market conditions

Panel A: Futures volatility and Inventory

$$\sigma^2_{f,t} = \varpi_{f,1,st} + \rho_{f,1,st} \cdot \sigma^2_{f,t-1} + \pi_{f,1,st} \cdot \Delta ls_{t-1} + e_{f,1,t}$$

$$\Delta ls_t = \varpi_{f,2,st} + \rho_{f,2,st} \cdot \sigma^2_{f,t-1} + \pi_{f,2,st} \cdot \Delta ls_{t-1} + e_{f,2,t}$$

$$p_{12,t} = \frac{1}{1+\exp(m_0 + m_1 ls_t)}, \quad p_{21,t} = \frac{1}{1+\exp(n_0 + n_1 ls_t)}$$

		State one – low-volatility state						State two – high-volatility state						
(j=12)		$\varpi_{f,j,1}$	$\rho_{f,j,1}$	$\pi_{f,j,1}$	$m_{f,j,0}$	$m_{f,j,1}$	$\sigma_{f,j,1}$	$\varpi_{f,j,2}$	$\rho_{f,j,2}$	$\pi_{f,j,2}$	$n_{f,j,0}$	$n_{f,j,1}$	$\sigma_{f,j,2}$	H_0: $\rho_{ff1} = \rho_{ff2}$, $\pi_{ff1} = \pi_{ff2}$
Al	σ^2_f	5.47e-06 [0.000]	0.9112 [0.000]	-1.63e-05 [0.004]	4.1401 [0.000]	-0.2065 [0.000]	1.96e-06 [0.000]	1.45e-05 [0.000]	0.9797 [0.000]	-9.73e-06 [0.930]	2.8779 [0.000]	-0.2755 [0.000]	2.59e-05 [0.000]	17.168 [0.000]
	Δls_t	-1.73e-04 [0.357]	-4.2377 [0.020]	0.5838 [0.000]	-6.9935 [0.118]	0.7180 [0.030]	0.0025 [0.000]	5.44e-03 [0.000]	-31.1569 [0.000]	0.1061 [0.001]	-5.3031 [0.224]	0.5201 [0.104]	0.0113 [0.000]	102.23 [0.000]
Al alloy	σ^2_f	2.72e-05 [0.000]	0.8932 [0.000]	2.41e-04 [0.197]	0.7916 [0.622]	-0.1200 [0.415]	3.54e-05 [0.000]	1.14e-05 [0.000]	0.7946 [0.000]	-1.30e-05 [0.101]	2.5482 [0.041]	-0.1375 [0.221]	2.39e-06 [0.000]	18.059 [0.000]
	Δls_t	-5.51e-04 [0.002]	0.1980 [0.906]	0.0733 [0.000]			0.0025 [0.000]	1.80e-03 [0.004]	-13.4804 [0.025]	0.2407 [0.000]			0.0104 [0.000]	22.230 [0.000]
Copper	σ^2_f	6.31e-06 [0.000]	0.9281 [0.000]	1.40e-06 [0.749]	-3.3622 [0.012]	0.3677 [0.000]	2.68e-06 [0.000]	1.56e-05 [0.000]	1.0120 [0.000]	1.87e-05 [0.821]	2.7818 [0.220]	-0.2935 [0.099]	3.78e-05 [0.000]	55.881 [0.000]
	Δls_t	2.23e-05 [0.918]	-3.1165 [0.019]	0.6538 [0.000]	-18.2189 [0.000]	1.6064 [0.000]	0.0035 [0.000]	3.39e-03 [0.012]	-15.3346 [0.004]	0.0630 [0.072]	11.4576 [0.001]	-0.8154 [0.003]	0.0243 [0.000]	125.672 [0.000]
Lead	σ^2_f	1.29e-05 [0.000]	0.8808 [0.000]	-1.68e-05 [0.156]	-2.8408 [0.120]	0.3656 [0.018]	5.67e-06 [0.000]	2.46e-05 [0.000]	1.0623 [0.000]	1.18e-04 [0.622]	1.6288 [0.556]	-0.2071 [0.377]	9.38e-05 [0.000]	73.764 [0.000]
	Δls_t	-8.96e-04 [0.000]	-0.1078 [0.753]	-0.0012 [0.812]	2.4388 [0.229]	-0.1067 [0.530]	0.0017 [0.000]	1.91e-03 [0.059]	-10.3315 [0.003]	0.3504 [0.000]	32.1644 [0.000]	-2.7144 [0.000]	0.0186 [0.000]	79.240 [0.000]
Nickel	σ^2_f	1.09e-04 [0.000]	0.5853 [0.000]	-6.41e-06 [0.828]	-0.9143 [0.314]	0.2192 [0.011]	1.85e-05 [0.000]	2.07e-04 [0.000]	0.7860 [0.000]	2.04e-04 [0.798]	-1.0268 [0.493]	0.0200 [0.889]	2.57e-04 [0.000]	24.589 [0.000]
	Δls_t	-2.46e-04 [0.105]	-1.4264 [0.000]	0.0052 [0.470]	-5.3717 [0.000]	0.6036 [0.000]	0.0025 [0.000]	1.25e-03 [0.359]	-5.6817 [0.072]	0.4779 [0.000]	29.0624 [0.000]	-2.7848 [0.000]	0.0224 [0.000]	114.599 [0.000]
Tin	σ^2_f	6.56e-06 [0.000]	0.8921 [0.000]	-6.46e-06 [0.132]	5.4852 [0.000]	-0.4004 [0.001]	3.38e-06 [0.000]	3.85e-05 [0.000]	0.9489 [0.000]	1.02e-04 [0.370]	-2.0760 [0.243]	0.1513 [0.413]	8.08e-05 [0.000]	8.103 [0.017]
	Δls_t	-2.05e-03 [0.000]	0.1523 [0.901]	0.0232 [0.126]	-15.7359 [0.000]	1.8252 [0.000]	0.0063 [0.000]	9.08e-03 [0.000]	-35.0411 [0.006]	0.1736 [0.000]	10.9388 [0.001]	-1.2005 [0.001]	0.0405 [0.000]	16.638 [0.000]
Zinc	σ^2_f	2.98e-06 [0.000]	0.9489 [0.000]	-3.82e-06 [0.441]	4.3005 [0.000]	-0.2135 [0.008]	2.24e-06 [0.000]	1.72e-05 [0.000]	0.9970 [0.000]	7.35e-05 [0.694]	1.4614 [0.562]	-0.2104 [0.270]	3.91e-05 [0.000]	9.629 [0.008]
	Δls_t	-6.30e-04 [0.000]	-2.4594 [0.002]	0.0424 [0.000]	-3.9594 [0.085]	0.4549 [0.010]	0.0021 [0.000]	5.59e-03 [0.000]	-8.1729 [0.185]	-0.0410 [0.608]	16.1951 [0.001]	-1.3051 [0.000]	0.0175 [0.000]	1.660 [0.436]

- Numbers in brackets [ ] are *p*-values; Numbers in bold are statistically significant at the 5% level.
- The null hypothesis of H₀: $\rho_{f1} = \rho_{f2}$ $\pi_{f1} = \pi_{f2}$ is conducted by the Likelihood Ratio test.

Table 6.6 Price volatility and inventory levels under different market conditions (continued)

Panel B: Spot volatility and Inventory

$$\sigma^2_{s,t} = \varpi_{s,1,st} + \rho_{s,1,st} \cdot \sigma^2_{s,t-1} + \pi_{s,1,st} \cdot \Delta ls_{t-1} + e_{s,1,t}$$

$$\Delta ls_t = \varpi_{s,2,st} + \rho_{s,2,st} \cdot \sigma^2_{s,t-1} + \pi_{s,2,st} \cdot \Delta ls_{t-1} + e_{s,2,t}$$

		State one – low-volatility state						State two – high-volatility state						H_0:
(j=12)		$\varpi_{s,j,1}$	$\rho_{s,j,1}$	$\pi_{s,j,1}$	$m_{s,j,0}$	$m_{s,j,1}$	$\sigma_{s,j,1}$	$\varpi_{s,j,2}$	$\rho_{s,j,2}$	$\pi_{s,j,2}$	$n_{s,j,0}$	$n_{s,j,1}$	$\sigma_{s,j,2}$	$\rho_{sj1}=\rho_{sj2}$ $\pi_{sj1}=\pi_{sj2}$
Al	σ^2_s	7.27e-06	0.8983	-1.98e-05	2.5050	-0.0977	2.46e-06	1.76e-05	0.9799	5.20e-05	2.6563	-0.2524	3.08e-05	23.286
		[0.000]	[0.000]	[0.030]	[0.169]	[0.464]	[0.000]	[0.000]	[0.000]	[0.763]	[0.357]	[0.233]	[0.000]	[0.000]
	Δls_t	-4.03e-04	-1.5299	0.5893	-6.9385	0.7138	0.0025	4.63e-03	-21.0697	0.1253	-5.2671	0.5172	0.0114	97.359
		[0.022]	[0.281]	[0.000]	[0.121]	[0.032]	[0.000]	[0.000]	[0.000]	[0.000]	[0.233]	[0.111]	[0.000]	[0.000]
Al alloy	σ^2_s	1.47e-05	0.7905	-1.15e-05	1.5669	-0.0569	2.85e-06	3.37e-05	0.8732	3.05e-04	3.3482	-0.3482	3.87e-05	16.644
		[0.000]	[0.000]	[0.228]	[0.289]	[0.671]	[0.000]	[0.000]	[0.000]	[0.060]	[0.088]	[0.053]	[0.000]	[0.000]
	Δls_t	-4.89e-04	-0.3868	0.0727			0.0025	1.08e-03	-4.6953	0.2441			0.0104	18.549
		[0.013]	[0.808]	[0.001]			[0.000]	[0.127]	[0.407]	[0.000]			[0.000]	[0.000]
Copper	σ^2_s	1.02e-05	0.9033	-1.22e-04	-8.5317	0.7765	5.00e-06	3.28e-05	1.0014	6.44e-05	7.7952	-0.6899	8.67e-05	66.234
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.750]	[0.001]	[0.000]	[0.000]	[0.000]
	Δls_t	6.63e-05	-2.9036	0.6522	-17.7631	1.5728	0.0035	1.84e-03	-4.6437	0.0686	11.8613	-0.8457	0.0245	121.648
		[0.732]	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]	[0.134]	[0.090]	[0.054]	[0.001]	[0.002]	[0.000]	[0.000]
Lead	σ^2_s	1.69e-05	0.8871	-1.51e-05	-2.2365	0.3016	6.55e-06	2.95e-05	1.0449	1.50e-04	8.8815	-0.8122	9.39e-05	69.359
		[0.000]	[0.000]	[0.387]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.524]	[0.001]	[0.000]	[0.000]	[0.000]
	Δls_t	-8.88e-04	-0.1118	-0.0013	2.4480	-0.1075	0.0017	3.02e-03	-11.0404	0.3451	32.1903	-2.7166	0.0185	83.190
		[0.000]	[0.678]	[0.802]	[0.225]	[0.526]	[0.000]	[0.008]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Nickel	σ^2_s	1.05e-04	0.6167	-4.59e-05	-1.9677	0.3077	1.82e-05	2.00e-04	0.8092	5.91e-05	-0.3297	-0.0454	2.56e-04	29.886
		[0.000]	[0.000]	[0.064]	[0.016]	[0.000]	[0.000]	[0.000]	[0.000]	[0.922]	[0.824]	[0.748]	[0.000]	[0.000]
	Δls_t	-1.99e-04	-1.4470	0.0047	-5.3307	0.5993	0.0024	1.10e-03	-4.8518	0.4785	29.0721	-2.7852	0.0224	115.194
		[0.182]	[0.000]	[0.452]	[0.000]	[0.000]	[0.000]	[0.393]	[0.084]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tin	σ^2_s	8.58e-06	0.8821	-1.96e-06	4.0934	-0.2564	4.05e-06	4.08e-05	0.9610	1.23e-04	-0.4431	-0.0161	8.55e-05	13.293
		[0.000]	[0.000]	[0.689]	[0.000]	[0.024]	[0.000]	[0.000]	[0.000]	[0.296]	[0.780]	[0.923]	[0.000]	[0.001]
	Δls_t	-2.04e-03	0.0795	0.0231	-15.7602	1.8282	0.0063	8.80e-03	-28.4418	0.1774	10.9580	-1.2029	0.0406	14.941
		[0.000]	[0.949]	[0.118]	[0.000]	[0.000]	[0.000]	[0.000]	[0.011]	[0.000]	[0.003]	[0.003]	[0.000]	[0.001]
Zinc	σ^2_s	4.17e-06	0.9433	-5.46e-06	1.7262	-0.0204	2.72e-06	1.85e-05	1.0098	9.54e-04	-0.4867	-0.0622	4.96e-05	36.564
		[0.000]	[0.000]	[0.474]	[0.28]	[0.867]	[0.000]	[0.000]	[0.000]	[0.014]	[0.830]	[0.707]	[0.000]	[0.000]
	Δls_t	-8.62e-04	-0.5812	0.0448	-3.2967	0.4037	0.0021	5.01e-03	-3.5984	-0.0417	16.6588	-1.3425	0.0175	1.498
		[0.000]	[0.356]	[0.000]	[0.133]	[0.016]	[0.000]	[0.000]	[0.415]	[0.618]	[0.001]	[0.000]	[0.000]	[0.473]

- Numbers in brackets [ ] are p-values; Numbers in bold are statistically significant at the 5% level.
- The null hypothesis of H_0: $\rho_{sj1}=\rho_{sj2}$ $\pi_{sj1}=\pi_{sj2}$ is conducted by the Likelihood Ratio test.

The estimation results of Equations (6.10) and (6.11) are shown in Table 6.6 Panels A and B for futures and spot price volatility and inventory changes, respectively. First of all, there seems to exist a nonlinear relationship between price volatility and inventory changes as the null hypothesis of equality of coefficients in the two states, $H_0 : \rho_1 = \rho_2, \pi_1 = \pi_2$, is rejected in all the markets with an exception of zinc based on the Likelihood Ratio tests. Secondly, the relationship between changes in inventory levels and futures price volatility is found to be statistically negative at least in one state in all the markets. Similarly, a negative relationship between changes in inventory levels and spot price volatility is found in the aluminium, lead, nickel, tin and zinc markets. In other words, in most of the markets high (low) spot and futures price volatility levels cause declines (increases) in inventory levels. This finding is consistent with the third implication of the theory of storage discussed earlier where the high-volatility state indicates that the market is likely to be in backwardation (i.e. the expected future spot price is lower than current spot price) which gives inventory holders (producers) incentive to reduce inventory (Pindyck, 2001).

The results also suggest that changes in inventory levels only respond to price volatility in the high-volatility state in the aluminium alloy, lead and tin markets in the case of futures volatility and in the aluminium, lead and tin markets in the case of spot price volatility. Moreover when the inventory levels are low (i.e. the high-volatility state), the marginal changes in the inventory levels caused by changes in volatility are significantly larger compared to periods when inventory levels are high. For instance, in the aluminium, copper and zinc markets, the ρ_1 / ρ_2 ratios (ρ_1 and ρ_2 are the coefficients of the lagged volatility in the inventory equation in the low-volatility and high-volatility state, respectively) range between 13% (aluminium) and 25% (nickel) in the futures volatility equation. However, there are a few exceptions, for instance, futures price volatility does not seem to have any impact on the inventory level changes in the aluminium alloy, lead and tin markets in state one. Also, the impact of spot price volatility on change in inventory levels is statistically insignificant in five of the markets (aluminium, aluminium ally, lead, tin and zinc) in the low-volatility state and is insignificant in the aluminium alloy and zinc markets in the high-volatility state at the 5% level.

6.6 Concluding Remarks

Inventories play a crucial role in price formation in storable commodity markets. Inventories are used by producers to reduce production and marketing costs in the face of fluctuating demand conditions and industrial consumers also hold inventories to facilitate their own production processes. The theory of storage suggests that the motivation to store a commodity is that the benefit (convenience yield) exceeds the cost of storage, but that this convenience yield is a decreasing function of the inventory level. This nonlinear relationship has been shown to have two main implications. Firstly, a decline in stock levels reduces the elasticity of supply and increases the convenience yield and the volatility of prices *ceteris paribus*. Secondly, futures prices are less volatile than spot prices when inventory levels are low. We argue in this chapter that there is a third implication: given that producers can reduce costs over time by selling out inventories during high demand periods and building up inventory during low demand periods, inventory build-ups should be associated with low price volatility and inventory draw-downs should be associated with high price volatility.

In this chapter, we have examined the three implications of the theory of storage empirically. The relationship between the spot price volatility and futures price volatility is examined in both a linear and nonlinear (MRS) regression framework. The relationship between price volatility and changes in inventory level is investigated in a GARCH-X framework with the change in inventory as an explanatory variable and the causal relationship is tested in a VAR model. Finally, we investigate the causal relationship between price volatility and changes in inventory level in a MRS model to account for market conditions. The primary contribution of the chapter is the derivation of the relationship between inventory dynamics and price volatility as a proxy for market conditions and the subsequent direct empirical test of this relationship using the MRS model.

The empirical findings largely support the implications derived from the theory of storage. Firstly, the spot and futures volatility is found to be similar when inventory levels are high, while spot price volatility is substantially greater than the futures volatility when stock levels are low. Secondly, volatility is found to be negatively related to changes in inventory levels, i.e. low (high) price volatility is found to be associated with inventory build-ups (draw-downs). Thirdly, the empirical evidence suggests that there is a one directional causal relationship from spot and futures price volatility to changes in inventory levels and the casual relationship is stronger the higher the volatility in the markets. However, little evidence is found for the lead-lag relationship between inventory levels and price volatility. Though this is consistent with the findings in Pindyck (2001), who argues that the price volatility is largely exogenous and not caused by inventory shocks, we also argue that it is the inventory level that in principle has an impact on volatility rather than inventory changes.

7 CHAPTER SEVEN

METAL FUTURES PRICE VOALTILITY AND TRADING VOLUME

7.1 Introduction

The liquidity of an asset is one of its most important characteristics which are taken into account by portfolio managers and investment analysts when considering the asset for investment and hedging strategies. For example, when futures contracts are illiquid, the cost of hedging may increase or hedging may not be optimal. The importance of liquidity stems from the greater risk investors incur when trading illiquid assets, a fact not missed by the financial press:

> *The possibility that liquidity might disappear from the market, and so not be available when it is needed, is a big source of risk to investors.*
>
> -- *The Economist, 23 September, 1999*

Trading volume also plays an important role in futures markets. Economic reports published by futures exchanges and regulatory agencies use volume data to measure the growth or decline of futures contracts, as well as shifts in the composition of market players in different futures markets.

This liquidity risk and cost stems from high bid-ask spreads, slower execution of trades, and greater risk of price slippage usually associated with illiquid securities. A survey by Karpoff (1987) provides two explanations for the importance of trading volume in financial markets. Firstly, examining the price – volume relationship can provide insight into the market microstructure, because it is believed that more information is available for heavily traded assets than for thinly traded assets. Secondly, higher trading volume results in more competitive trades and lower the bid-ask spreads.

As a consequence, there is substantial interest in how trading volume is related to price movement in stock markets (see, for instance, Amihud and Mendelson, 1986; Murphy, 1986; and DeMark, 1994), foreign exchange markets (see, for instance, Harvey and Huang, 1991), fixed income markets (for instance, Najand and Yung, 1991) and in commodity and financial futures markets (see, for instance, Bessembinder and Seguin, 1993; Foster, 1995, Wang, Yau and Baptiste, 1997; Malliaris and Urrutia, 1998).

In general the literature suggests a positive correlation between price volatility and trading volume and theoretically it is argued that the two processes are driven by the same factor which is believed to be the information flow to the market. For instance, Bessembinder and Seguin (1993) investigate the volatility – volume relationship in eight commodity and financial futures markets (Deutsche Mark, Japanese Yen, gold, silver, cotton, wheat, T-bonds and T-bills). They find a strong positive relationship between contemporaneous trading volume and price volatility (measured as the standard deviation of the percentage returns of the futures contract). Watanabe (2001) uses the same methodology and finds that the price volatility is positively related to the trading activity of Nikkei 225 stock index futures. However, the widely observed volatility clustering in financial time series suggests that the simple measure of standard deviation in such studies may not be appropriate. As a result, some researchers adopted GARCH models in studying the volatility – trading volume relationship (see e.g. Lamoureux and Lastrapes, 1990; Najand and Yung, 1991; Foster, 1995; and Chen *et al*, 2001, among others). For example, Lamoureux and Lastrapes (1990) investigate the contemporaneous relationship between volatility and volume in a GARCH framework and find that the persistence in stock return volatility is eliminated for the most part when trading volume is included in the conditional variance equation. While their study suggests that trading volume and return volatility are driven by identical factors, the use of contemporaneous trading volume to explain the conditional volatility may cause simultaneity bias[27]. Njand and Yung (1991) include the lagged trading volume in a GARCH model and find a significant positive relationship between the lagged trading volume and volatility in the bond market.

As discussed in Section 2.4, the two main theories to explain the relationship between trading volume and price volatility are the Mixture of Distribution Hypothesis (MDH) (Clark, 1973) and the Sequential Information Flow (SIF) theory (Copeland, 1976). Both theories attempt to justify the existence of a positive relationship between price changes and volume. They differ in that the MDH assumes that dissemination of information is symmetrical and all traders view changes in supply and demand simultaneously, which results in an immediate restoration of equilibrium, whereas in the SIF hypothesis, it is assumed that information is disseminated asymmetrically and equilibrium is restored

[27] Simultaneity bias is caused when two variables in the same regression are driven by the same source so that the independent variable is not exogenous any more, resulting the conventional estimation method biased (see, Pindyck and Rubinfeld, 1991 for a detailed discussion).

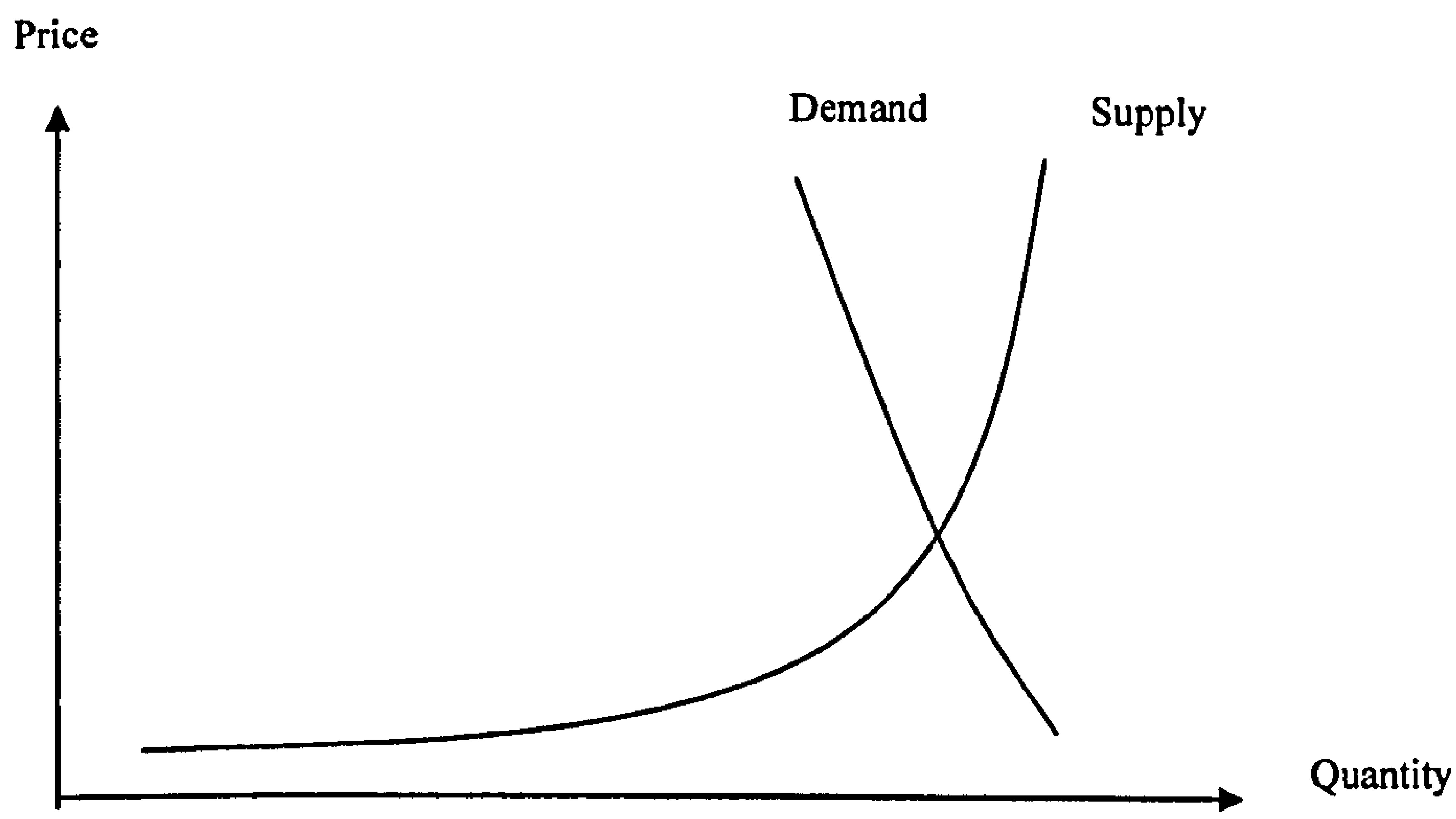
gradually. The MDH implies strong positive contemporaneous but no causal linkages between volume and price volatility, while the SIF implies the existence of contemporaneous as well as causal relationship between price volatility and trading volume.

An alternative theory, based on the information content of trading volume, is proposed by Blume, Easley and O'Hara (1994). Based on the assumption that trading volume is a proxy for the quality and precision of information in the market and consequently contains information about price movements, they suggest that trading volume plays an important role in the price formation process. As a result, they propose that technical trading based on both the information in price movements and trading volume may produce superior results, which implies that there must be some form of inefficiency in the price determination process.

This chapter investigates the relationship between the futures price volatility and trading volume in the industrial metal futures markets on the LME, which has not been investigated previously. In particular, we examine whether trading volume is an important determinant of futures price volatility changes by testing the causal relationship between the futures price volatility and trading volume. We also investigate whether the futures price volatility is greater in response to information flow when the futures market is in backwardation in comparison to when the market is in contango. We use the GARCH framework to model and extract volatility and test the lead – lag relationship between price volatility and trading volume using the Granger causality test (Granger, 1969).

Furthermore, we examine the asymmetry of price volatility – trading volume relationship by introducing a dummy variable in the GARCH model to differentiate between the backwardation and contango market conditions. The underlying argument for the existence of asymmetric relationship between futures price volatility – trading volume is that trading volume is considered to be a proxy for information flow (i.e. the arrival of news). Because of the varying price elasticity of supply and demand in the commodity markets (see Figure 7.1), commodity prices are believed to be more sensitive to news when inventory levels are low (a backwardation market) than when inventory levels are high (a contango market) (See Chapter 6). Therefore, any changes in trading volume (information) may have a greater impact on price volatility when the stock levels are low and the market is in backwardation compared to when stock levels are high and the market is in contango. In other words, when stock levels are high any shocks due to changes in trading volume can be absorbed by the market with less impact on prices compared to when inventory levels are low.

Figure 7.1 The Supply and demand curve of a commodity



7.2 Methodology

Harris (1987) argues that the commonly observed heteroscedasticity in price returns is a consequence of the joint distribution of price change and trading volume, which are driven by information flow according to the MDH. This inspires the use of GARCH models when investigating the volatility – trading volume relationship. Lamoureux and Lastrapes (1990) suggest that the GARCH process can characterise the volatility clustering in asset returns well since information enters the market in clusters. Therefore, following the literature, we use the same methodology to model futures price volatility as in Chapter 6, i.e. a GARCH framework with the mean process modelled by a VECM with the long-run cost-of-carry as the error correction term. A error correction-GARCH model is in the form of Equation (6.1) and (6.2).

As mentioned, the introduction of the contemporaneous trading volume in the volatility process may lead to the problem of simultaneity (Najand and Yung, 1991; Foster, 1995), in that trading volume will not be exogenous. Najand and Yung (1991) include the lagged trading volume in a GARCH model and find a significant positive relationship between the lagged trading volume and price volatility. To avoid the simultaneity problem, we follow the literature (for instance, Najand and Yung, 1991; Darrat *et al.*, 2003; Yang, Balyeat and Leatham, 2005) and use lagged trading volume to assess the relationship between volatility and trading volume. The GARCH model in the form of Equation (6.2) is thus transformed to:

$$\Delta f_t = \theta_1 \cdot \Delta s_{t-1} + \theta_2 \cdot \Delta f_{t-1} + \rho \cdot ect_{t-1} + \varepsilon_t \qquad (7.1)$$

$$\sigma_t^2 = \varpi + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2 + \varphi \cdot TV_{t-1} \qquad (7.2)$$

where σ_t^2 is the conditional volatility of the futures price and TV_{t-1} is the lagged trading volume which is detrended. The detrending method will be explained shortly in Section 7.3.

To the extent that trading volume is a good proxy of the information flow into the market, one may expect that price fluctuations in response to changes in trading volume would be higher when the market is in backwardation compared to when the market is in contango. The theory of storage suggests that the volatility of commodity futures prices is related to the level of convenience yield and, thus, implicitly the market conditions (backwardation and contango). When the market is in backwardation, prices may be more sensitive to news (e.g. supply and demand shocks) since there is limited inventory to absorb any such shocks in the cases of and increase in demand or a decrease in supply. In other words, the same information may have different effects on the price volatility in a backwardation market and a contango market. To assess such asymmetry in the volatility – trading volume relationship, we include a dummy variable in the variance equation (7.2) to account for different market conditions:

$$\Delta f_t = \theta_1 \cdot \Delta s_{t-1} + \theta_2 \cdot \Delta f_{t-1} + \rho \cdot ect_{t-1} + \varepsilon_t \tag{7.3}$$

$$\sigma_t^2 = \varpi + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varphi \cdot TV_{t-1} + \varphi_b \cdot Db_{t-1} \cdot TV_{t-1} \tag{7.4}$$

where the dummy $Db_t = 1$ when the market is in backwardation. In this setting, the market is considered to be in backwardation when the basis is smaller than its long-run mean[28], otherwise the market is considered to be in contango.

As the rate of information flow to the market increases (higher trading volume) the price volatility may increase. Conversely, higher price volatility may influence trading activity due to the change in the level of risk when trading in the market. In order to assess the causal relationship between the futures price volatility and trading volume, we first estimate the time-varying futures price volatility using Equation (6.2) and then use the following VAR(p) model to examine the lead-lag relationships between the two variables:

[28] To use the long-run mean of the basis rather than zero as the benchmark to separate backwardation from contango market condition is to take carrying costs into account. Moreover, the use of zero basis as the benchmark makes virtually no difference regarding the sign or quantity of the relationships examined.

$$
\begin{aligned}
\hat{\sigma}_t^2 &= k_{1,0} + \sum_{i=1}^{p} k_{1,i}\hat{\sigma}_{t-i}^2 + \sum_{i=1}^{p} g_{1,i} TV_{t-i} + \varepsilon_{1,t} \\
TV_t &= k_{2,0} + \sum_{i=1}^{p} k_{2,i}\hat{\sigma}_{t-i}^2 + \sum_{i=1}^{p} g_{2,i} TV_{t-i} + \varepsilon_{2,t}
\end{aligned} \tag{7.5}
$$

where $\hat{\sigma}_t^2$ is the GARCH estimated conditional volatility process of the futures price; $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are *i.i.d.* white noise. The null hypothesis is $H_0 : g_{1,1} = g_{1,2} = \cdots = g_{1,p} = 0$ when testing whether trading volume Granger causes the price volatility, and the null is $H_0 : g_{2,1} = g_{2,2} = \cdots = g_{2,p} = 0$ when testing whether the futures price volatility Granger causes trading volume.

7.3 Empirical Results

The empirical investigation into the volatility – trading volume relationships is performed on daily time series of the seven metal futures contracts over the period 05 April 1994 to 30 July 2004. Based on the observation that the trading volume of the futures contracts considered here[29] is time dependent, we follow the literature (see, for instance, Galant *et. al.* 1992) and de-trend trading volume series[30]. Table 7.1 presents the estimation results for the detrending model.

Table 7.1 Detrending the trading volume

$TV_t = \kappa_0 + \kappa_1 \cdot t + \xi_t$			
	k_0	k_1	$\overline{R}^2$
Aluminium	**0.555** [0.000]	**2.22e-05** [0.000]	0.2264
Aluminium alloy	**0.0008** [0.000]	**1.03e-06** [0.000]	0.2407
Copper	**0.0660** [0.000]	**2.10e-06** [0.000]	0.0049
Lead	**0.0063** [0.000]	**4.06e-06** [0.000]	0.2934
Nickel	**0.0159** [0.000]	1.78e-07 [0.298]	0.0004
Tin	**0.0049** [0.000]	**5.01e-07** [0.000]	0.0222
Zinc	**0.0179** [0.000]	**7.65e-06** [0.000]	0.2082

- Figures in brackets [ ] are p – values;
- TV_t is in million contracts;
- Daily data over the period 05/04/1994 to 30/07/2004.

The KPSS, ERS and Perron (1997) unit root tests are conducted on the detrended trading volume to test for stationarity and the results are presented in Table 7.2. The detrended trading volume is found to be stationary according to the ERS and Perron (1997) test in all the markets. The KPSS test suggests that the trading volume is not stationary in the aluminium alloy and nickel markets.

[29] The trading volume of the seven metal futures contracts are shown in Figures 2, 4, 6, 8, 10, 12 and 14 in Appendix I.

[30] The trading volume time series is detrended via the following regression with time as the independent variable: $TV_t = \kappa_0 + \kappa_1 \cdot t + \xi_t$ where TV_t is the raw trading volume, t is time, and ξ_t is white noise $\xi_t \sim i.i.d.(0, \sigma_\xi^2)$. The estimation results of the equation are presented in Table 7.1.

Table 7.2 Unit root test on detrended trading volume

	ADF	KPSS	ERS	Perron97	
Aluminium	-18.6155*	0.4048 *	0.9435*	-13.0545*	(699)
Aluminium alloy	-8.5706*	0.7784	0.1359*	-12.2983*	(1966)
Copper	-28.0677*	0.3266 *	0.5618*	-13.7021*	(687)
Lead	-32.9201*	0.1880 *	0.6854*	-13.1559*	(2327)
Nickel	-7.3295*	0.7527	1.2448*	-10.8425*	(1557)
Tin	-9.2714*	0.5641 *	0.3062*	-10.5645*	(1137)
Zinc	-15.7458*	0.3683 *	1.0205*	-12.1460*	(1663)

- * represents the that series is stationary at the 5% significance level;
- Numbers in parenthesis ( ) are the break points in the Perron (1997) test.

The GARCH model estimation results for the futures price volatility are presented in Table 6.2 Panel A in Chapter 6. The Ljung-Box (1978) $Q(20)$ statistic for the 20th order autocorrelation in the residual is statistically insignificant and the Engle (1982) ARCH Lagrange Multiplier diagnostic test suggests that heteroscedasticity in the futures price changes is eliminated in most of the markets. The results also indicate that the conditional volatility of the prices is highly persistent as the sum of α and β is close to one in all the markets. The sum of α and β denotes the degree of persistence in the conditional variance given a shock to the system, and when the sum is less than 1 the variance is said to be stationary. As the sum of α and β tends to 1 the higher is the instability in the variance and shocks tend to persist instead of dying out (see Engle and Bollerslev, 1986).

Table 7.3 reports the estimation results on the relationship between the futures price volatility and the lagged trading volume which is an explanatory variable in the GARCH model. The diagnostic tests for autocorrelation and heteroscedasticity of the residuals suggest that the model is well specified in general. The lagged trading volume is found to be statistically positive in four of the markets (aluminium alloy, copper, tin and zinc), suggesting that an increase in the trading volume leads to an increase in the price volatility over the next period. This finding is in line with the theory and empirical results in the literature (see, for instance, Bessembinder and Seguin, 1993; Foster, 1995; Malliaris and Urrutia, 1998; Watanabe, 2001). It suggests that the lagged trading volume is an important factor in determination of price volatility in metal futures markets and thus trading volume can be used as a proxy for the information flow in the market.

Table 7.3 Volatility and trading volume in TGARCH

$$\Delta f_t = \theta_1 \cdot \Delta s_{t-1} + \theta_2 \cdot \Delta f_{t-1} + \rho \cdot ect_t + \varepsilon_t$$

$$\sigma_t^2 = \varpi + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2 + \varphi \cdot TV_{t-1}$$

	θ_1	θ_2	ρ	ϖ	α	β	φ	$Q(20)$ – stats	ARCH LM test	LL Fn value
Al	-0.1140	0.0942	0.0129	**4.93e-06**	**0.0564**	**0.8974**	0.0547	27.494	0.4365	8310.94
	[0.140]	[0.377]	[0.372]	[0.000]	[0.000]	[0.000]	[0.080]	[0.122]	[0.823]	
Al alloy	**-0.2133**	**0.1338**	0.0189	**1.01e-05**	**0.1150**	**0.7783**	**1.1980**	**33.197**	0.1671	8483.64
	[0.000]	[0.001]	[0.253]	[0.000]	[0.000]	[0.000]	[0.005]	[0.032]	[0.975]	
Copper	**-0.1370**	0.0859	0.0212	**4.14e-06**	**0.0450**	**0.9297**	**0.0613**	19.063	0.4285	7777.43
	[0.038]	[0.135]	[0.199]	[0.000]	[0.000]	[0.000]	[0.008]	[0.518]	[0.829]	
Lead	**-0.1957**	**0.1217**	-0.0260	**6.88e-06**	**0.0721**	**0.8943**	0.1536	**40.672**	0.2172	7514.94
	[0.001]	[0.010]	[0.199]	[0.000]	[0.000]	[0.000]	[0.475]	[0.004]	[0.955]	
Nickel	-0.1543	0.1642	**-0.0918**	**9.43e-05**	**0.1568**	**0.5791**	-0.3287	18.519	0.1987	6732.68
	[0.110]	[0.078]	[0.020]	[0.000]	[0.000]	[0.000]	[0.544]	[0.553]	[0.963]	
Tin	**-0.2377**	**0.2148**	-0.0012	**3.23e-06**	**0.0757**	**0.9044**	**0.5137**	23.641	0.2061	8142.77
	[0.000]	[0.000]	[0.965]	[0.000]	[0.000]	[0.000]	[0.000]	[0.258]	[0.960]	
Zinc	-0.0394	-0.0053	0.0035	**2.79e-06**	**0.0384**	**0.9422**	**0.1749**	25.256	0.4126	8043.46
	[0.598]	[0.935]	[0.777]	[0.000]	[0.000]	[0.000]	[0.000]	[0.192]	[0.840]	

- Daily data over the period 05/04/1994 and 30/07/2004;
- The Engle (1982) ARCH Lagrange Multiplier (LM) test for the heteroscedasticity in the residuals is based on the regression: $z_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i z_{t-i}^2$, where the residual $z_t = \hat{\varepsilon}_t / \hat{\sigma}_t^2$, $\hat{\varepsilon}_t$ is the residual from the GARCH equation, $\hat{\sigma}_t^2$ is the estimated conditional variance. The null is $\beta_i = 0$;
- LL Fn value denotes the Log Likelihood Function value.
- Numbers in brackets [ ] are *p*-values;
- Numbers in bold are statistically significant at the 5% level.

To examine the possible asymmetric relationship between price volatility and trading volume under different market conditions, we estimate model (7.4) which includes the lagged trading volume and a dummy variable accounting for market conditions. The results are presented in Table 7.4. Conditional on the assumption that trading volume is a good proxy for information flow, one would expect φ_b to be statistically positive, since $\varphi+\varphi_b$ represents the response of the price volatility to trading volume when the market is in backwardation. The estimation results show that there is a positive relationship between price volatility and trading volume in general in five of the markets (aluminium, lead, nickel tin and zinc), and that φ_b is positive and statistically significant at the 10% level in the aluminum alloy, copper and zinc markets.

Table 7.4 Asymmetric volatility – trading volume relationship

$$\Delta f_t = \theta_1 \cdot \Delta s_{t-1} + \theta_2 \cdot \Delta f_{t-1} + \rho \cdot ect_t + \varepsilon_t$$

$$\sigma_t^2 = \varpi + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \varphi \cdot TV_{t-1} + \varphi_b \cdot Db_{t-1} \cdot TV_{t-1}$$

	θ_1	θ_2	ρ	ϖ	α	β	φ	φ_b	Q (20) – stats	ARCH LM test[1]	LL Fn value[2]
Al	-0.1148	0.0950	0.0130	**4.89e-06**	**0.0560**	**0.8980**	**0.0466**	0.0197	27.611	0.4557	8311.04
	[0.230]	[0.282]	[0.543]	[0.000]	[0.000]	[0.000]	[0.027]	[0.535]	[0.119]	[0.809]	
Al alloy	**-0.2119**	**0.1327**	0.0187	9.71e-06	**0.1096**	**0.7878**	0.5064	1.6997	**32.890**	0.1852	8484.5
	[0.000]	[0.002]	[0.258]	[0.000]	[0.000]	[0.000]	[0.280]	[0.064]	[0.035]	[0.968]	
Copper	**-0.1414**	0.0885	0.0209	**3.61e-06**	**0.0430**	**0.9344**	0.0126	**0.0977**	18.923	0.4285	7778.52
	[0.031]	[0.121]	[0.206]	[0.000]	[0.000]	[0.000]	[0.730]	[0.040]	[0.527]	[0.829]	
Lead	**-0.1877**	**0.1175**	-0.0220	**1.08e-05**	**0.0870**	**0.8625**	**0.8661**	**-1.984**	39.434	0.2414	7518.22
	[0.001]	[0.009]	[0.280]	[0.000]	[0.000]	[0.000]	[0.004]	[0.000]	[0.006]	[0.944]	
Nickel	-0.1587	0.1681	**-0.0932**	**1.09e-04**	**0.1724**	**0.5243**	1.6817	**-3.4589**	18.566	0.1759	6734.53
	[0.099]	[0.070]	[0.016]	[0.000]	[0.000]	[0.000]	[0.085]	[0.006]	[0.550]	[0.972]	
Tin	**-0.2206**	**0.1983**	-0.0064	**3.88e-06**	**0.0724**	**0.9022**	**1.2957**	**-2.0961**	25.205	0.3945	8160.25
	[0.001]	[0.001]	[0.814]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.194]	[0.853]	
Zinc	-0.0478	0.0015	0.0037	**2.53e-06**	**0.0351**	**0.9467**	**0.1259**	**0.1026**	25.498	0.4087	8045.19
	[0.523]	[0.981]	[0.768]	[0.000]	[0.000]	[0.000]	[0.000]	[0.008]	[0.183]	[0.843]	

- Daily data over the period 05/04/1994 and 30/07/2004;
- The Engle (1982) ARCH Lagrange Multiplier (LM) test for the heteroscedasticity in the residuals is based on the regression: $z_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i z_{t-i}^2$, where the residual $z_t = \hat{\varepsilon}_t / \hat{\sigma}_t^2$, $\hat{\varepsilon}_t$ is the residual from the GARCH equation, $\hat{\sigma}_t^2$ is the estimated conditional variance. The null is $\beta_i = 0$;
- LL Fn value denotes the Log Likelihood Function value.
- Numbers in brackets [ ] are p-values;
- Numbers in bold are statistically significant at the 5% level.

By including the dummy variable to account for the market conditions, the empirical evidence in the aluminium alloy and copper markets suggests that the response in the futures price volatility to trading volume mainly occurs when the market is in backwardation in comparison to the results reported in Table 7.3. The estimation result in the zinc market provides further evidence that the futures price volatility is more sensitive to the trading volume in a backwardation market, based on the statistically positive φ and φ_b estimates.

However we note that the φ_b estimate is statistically negative in three markets (lead, nickel and tin), while the φ estimate is statistically positive at conventional levels. This suggests that the futures price volatility is less sensitive to changes in trading volume when the market is in backwardation. This result rather contradicts our proposition. The daily trading volume in the seven futures markets are reported in Table 7.5, which shows that the trading volume is lower when the market is in backwardation in comparison to when the market is in contango. The higher trading volume in a contango market may be caused by the generally risk averse market participants (mainly hedgers and arbitrageurs) who may trade more when the market is less risky (i.e. when the market is in contango). Following the line that there exists a positive relationship between futures price volatility and trading volume, one would then expect the futures price volatility to be higher when the market is in contango. However, the opposite has been argued theoretically and empirically tested in the previous chapters (Chapter 1, 4 and 6). Therefore, we argue that trading volume does not represent all the information flow in these markets and thus the high futures price volatility in a backwardation market may be largely caused by factors other than trading activity (e.g. inventory changes). Therefore, the above result does not necessarily mean that the volatility is less sensitive to information flow in the markets.

Table 7.5 The daily average trading volume in the backwardation and contango market

	Aluminium	Al alloy	Copper	Lead	Nickel	Tin	Zinc
TV – backwardation	36,009	910	25,027	4,445	5,952	1,650	7,919
TV – contango	48,324	1,233	43,745	7,151	9,965	3,932	19,973

- The statistics are calculated based on the daily trading volume of the futures contracts over the period 05/04/1994 and 30/07/2004;
- The market is considered to be in backwardation when the basis (the difference between the futures and spot prices) is below its mean, and the market is considered to be in contango when the basis is above its mean.

Having shown that there exists a positive relationship between the futures price volatility and trading volume, we next investigate whether there is a causal relationship between the two variables. The conditional volatility of the futures prices is extracted from the GARCH model as in Equation (6.2). The estimated volatility is then used along with trading volume in a VAR setting in Equation (7.5). The estimation results of model (7.5) are presented in Table 7.6. The lag length in the VAR is determined according to the Schwarz information criterion.

The results suggest that the trading volume Granger causes price volatility in all the markets (with the exception of aluminium alloy) at the 5% significance level according to the statistically significant coefficients of g_{11} and g_{12}. On the other hand, volatility is found to Granger cause trading volume in the nickel, tin and zinc markets based on the significance of k_{21} and k_{22}. The signs of the lagged volatility and trading volume in the Granger causality as reported in Table 7.6 reveal further insights. For instance, an increase in trading volume causes an increase in futures price volatility in all the markets, indicating that as trading volume increases, futures price volatility tends to increase. This is consistent with the positive volatility – trading volume relationship we found in the previous section. However, higher price volatility does not necessarily increase trading activity, as shown by the mixed signs of the coefficients of the lagged volatility in the trading volume equation (the coefficients are statistically negative in the nickel and tin markets and statistically positive in the zinc market).

Table 7.6 Causality between conditional volatility and volume relationship

$$\hat{\sigma}_t^2 = k_{1,0} + \sum_{i=1}^{p} k_{1,i}\hat{\sigma}_{t-i}^2 + \sum_{i=1}^{p} g_{1,i}TV_{t-i} + \varepsilon_{1,t} \quad TV_t = k_{2,0} + \sum_{i=1}^{p} k_{2,i}\hat{\sigma}_{t-i}^2 + \sum_{i=1}^{p} g_{2,i}TV_{t-i} + \varepsilon_{2,t}$$

$j = 1\ 2$		$k_{j,0}$	$k_{j,1}$	$k_{j,2}$	$g_{j,1}$	$g_{j,2}$	$\bar{R}^2$	LM test[l]	$H_0: TV \not\Rightarrow \sigma^2$ $\chi^2(df)$	$H_0: \sigma^2 \not\Rightarrow TV$ $\chi^2(df)$
Al	$\hat{\sigma}_t^2$	**4.83E-06** (7.528)	**0.9546** (176.667)		**9.90E-05** (10.950)		0.925	7.2072 [0 125]	**119.895** [0 000]	
	TV_t	-0.0009 (-0 748)	8.4015 (0.815)		**0.482** (27.965)		0.233			0 6645 [0.415]
Al alloy	$\hat{\sigma}_t^2$	**1.17E-05** (11.409)	**0.8469** (43.15)	0.0264 (1.348)	5.18E-04 (1.440)	8.61E-05 (0.239)	0.757	9.2479 [0 055]	3.0037 [0 223]	
	TV_t	1.66E-05 (0.299)	-0.6493 (-0.614)	0.4711 (0.446)	**0.3646** (18 817)	**0.1658** (8 555)	0.211			0 4088 [0.815]
Copper	$\hat{\sigma}_t^2$	**4.62E-06** (6 353)	**1.0723** (54.964)	**-0.1001** (-5.181)	**3.23E-04** (15.208)	**-7.66E-05** (-3.476)	0 965	1.9783 [0.740]	**255.6441** [0.000]	
	TV_t	-0.0011 (-1.704)	5.8567 (0.325)	1.1596 (0.065)	**0.5365** (27 345)	-0 0094 (-0 463)	0.287			4 1156 [0.128]
Lead	$\hat{\sigma}_t^2$	**1.01E-05** (6.561)	**0.9513** (166.21)		**2.16E-03** (10.607)		0.915	1.5268 [0 822]	**112.4989** [0 000]	
	TV_t	2.31E-05 (0 171)	-0.1266 (-0.252)		**0.4119** (23.027)		0.169			0.0636 [0.801]
Nickel	$\hat{\sigma}_t^2$	**9.35E-05** (15.966)	**0.6652** (34 262)	0.0746 (3 934)	**7.34E-03** (13.560)	**-3.51E-03** (-6.331)	0.552	**10.8693** [0.028]	**193.045** [0 000]	
	TV_t	**4.91E-04** (2.322)	**-1.7834** (-2.543)	0.416 (0 608)	**0.5864** (30 013)	**0.1018** (5.078)	0.423			**9.4852** [0 009]
Tin	$\hat{\sigma}_t^2$	**6.65E-06** (5.745)	**0.9734** (49.654)	-0.0203 (-1.031)	**3.22E-03** (8.703)	**-1.15E-03** (-3.076)	0.904	8.5451 [0 074]	**79.5455** [0 000]	
	TV_t	**1.62E-04** (2.684)	**-2.9689** (-2.897)	1.8064 (1.758)	**0.4509** (23.293)	**0.1708** (8.732)	0.322			**18.6399** [0.000]
Zinc	$\hat{\sigma}_t^2$	**4.76E-06** (7 206)	**0.9661** (241.475)		**5.42E-04** (16.795)		0.959	1.9474 [0 745]	**282.0852** [0.000]	
	TV_t	**-9.36E-04** (-2.630)	**6.7118** (3.117)		**0.4752** (27 371)		0.236			**9.7141** [0.002]

- Daily data over the period 04/1994 and 07/2004;
- Figures in brackets ( ) are t-statistics figures in brackets [ ] are p – value;
- Figures in bold are statistically significant at the 5% level;
- [l] - The Autocorrelation LM test (Johansen 1995) is the multivariate Lagrange Multiplier test statistics for residual serial correlation up to the 20th order. The null is no serial correlation. The LM statistic is asymptotically distributed χ^2 with degree of freedom k^2 where k is the number of endogenous variables (k = 2 in this case)

7.4 Concluding Remarks

Trading volume plays an important role in futures markets, both as an indicator of the information flow in the market and the liquidity of individual contracts. Examination the price – trading volume relationship can provide insight into the market micro structure as well as the level of transaction costs in the market. In general, the literature suggests a positive correlation between price volatility and trading volume as both processes are believed to be driven by the information flow to the market.

This chapter extends the investigation on price volatility – trading volume relationship in a number of ways. Firstly, it provides evidence of the relationship between futures price volatility and trading volume in the industrial metal futures markets, which have not been previously examined. The high trading volume and variety of market participants make the LME the primary exchange for industrial metals trading. In-depth understanding of the market price dynamics and its relationship with trading volume is crucial for market participants, such as metal miners, manufactures, energy providers, investment banks and trading houses, who use the metal futures contracts as alternative investments or hedging instruments.

Secondly, this chapter tests whether lagged trading volume is an important factor in the determination of futures price volatility. The results suggest that an increase in the trading volume leads to an increase in the price volatility over the next period (statistically significant in the aluminium alloy, copper, tin and zinc markets). This finding is in line with the theory and empirical results in the literature and confirms that the lagged trading volume is an important factor in the determination of price volatility also in metal futures markets. Moreover, it is found that trading volume Granger causes futures price volatility in six markets and that this relationship is positive. This indicates that trading volume can generally be used to predict futures price volatility, in the sense that high trading volume tends to cause high price volatility. This might be of particular importance to market participants who trade option contracts as a hedging method as price volatility is one of the primary variables in option pricing and thus the predictability of volatility may be of economic benefit. While volatility is found to Granger cause trading volume in the nickel, tin and zinc markets. There is no consistency with regards to the signs of the coefficients. Accordingly we cannot conclude that high volatility increases trading activity. This could be related to the fact that the LME market has historically been primarily a hedgers' market where producers and consumers of industrial metals match their physical positions with a long-term view. It is possible that investigations of time periods with a greater participation of speculators would yield a different result.

Thirdly, given the finding that the lagged trading volume is an important determinant of price volatility and assuming trading volume is a proxy for information flow, we test the hypothesis that price volatility is more sensitive to changes in trading volume when the futures market is in backwardation compared to when the market is in contango. This is based on the proposition that metal prices are more sensitive to shocks when the inventory level is low (thus, the market is more likely to be in backwardation) due to the lower price elasticity of supply. The asymmetric relationship is investigated by including a dummy variable to account for market conditions in the GARCH model. The empirical results suggest that trading volume has a stronger impact on the futures price volatility in the aluminium alloy, copper and zinc markets, however, contradictory results are found in the lead, nickel and tin markets. We argue that this inconsistency need not be taken as an indication of mis-specified models but rather a sign that the trading volume by itself does not represent all the information flow in these markets. Consequently the latter result does not necessarily mean that the futures price is less sensitive to information when the market is in backwardation, as we have hypothesized on theoretical grounds.

8 CHAPTER EIGHT

CONCLUSIONS AND FUTURE RESEARCH

8.1 Summary of Findings

The main objective of this thesis is to investigate the linkage between market dynamics and market conditions in the industrial metal futures market. Several important issues have been addressed including the price discovery function of the futures prices, the long-run equilibrium relation between the spot and futures prices, and the dynamic short-run adjustment towards equilibrium as well as the futures and spot price volatility dynamics and its relationships with inventory level and trading volume.

The first chapter of the thesis outlines the background information of the research, defines the research topics, explains the motivation behind the research objectives and highlights the contributions. The second chapter reviews the academic literature on related research topics in the futures markets, which is followed by Chapter 3 presenting the methodology and the description of the data used in this thesis. The empirical examination is carried out in Chapters 4 to Chapter 7. In the following sections we present the summary of the empirical findings, important implications, concluding remarks as well as guidelines for future research.

8.1.1 Price Discovery of Metal Futures Market under Different Market Conditions

The empirical results in Chapter 4 show that the Unbiasedness Hypothesis cannot be rejected for the whole sample in all the seven metal futures markets, thereby suggesting that the futures prices are unbiased predictors of the future spot price overall. However, subsequent rolling window estimation suggests strong evidence of parameter instability in the linear testing model. When we allow for regimes shifts in testing the UH, the empirical results show that the UH is rejected in both of the market conditions, i.e. the low-volatility and high-volatility states. Moreover, the empirical evidence suggests that futures prices are generally downward biased predictors when the market is in backwardation and are upward biased predictors when the market is in contango.

We also apply a nonparametric method to examine the futures price forecasting performance under different market conditions. The empirical results suggest that the forecast errors, on average, are statistically larger when the market is in backwardation than in a contango market. Furthermore, the bootstrapped distribution of the forecast errors suggests that the mean forecast error is statistically negative when the market is in backwardation and statistically positive when the market is in contango. The nonparametric results thus confirm the findings from the parametric regression method.

The test of the UH is a joint test of rational expectations and risk neutrality. Assuming that the market participants are rational, our findings suggest that the hedgers need to pay a risk premium to take a long futures position in a contango market and need to pay a risk premium to short futures in a backwardation market. The main function of the LME is hedging which reportedly represents 75-85% of turnover. Producers are naturally long and consumers are naturally short in the physical market. Accordingly, in terms of using the futures contract to hedge, producers tend to be net short and consumers tend to be net long in the futures market. When the market is in backwardation (a downward sloping forward price curve), the future spot price is expectedly lower. Under such circumstances, the producers are the main hedgers in the market and they pay a premium to speculators for the transfer of risk. Conversely, when the market is in contango, the results suggest that the consumers are the main hedgers in the futures market.

An alternative explanation would be that if we relax the rational expectations hypothesis, there are consistently positive forecast errors in a contango market and consistently negative forecast errors in a backwardation market. When the market is in contango, i.e. when the futures prices are above the spot prices, market agents expect the future spot price to be higher on average than the realised spot price. Conversely, when the market is in backwardation, i.e. when the futures prices are below the spot prices, participants are, on average, too pessimistic about the future spot price. In other words, the price expectation of market participants consistently "overshoots" the realised future spot price. However, it would be difficult to argue that all the market participants have the same biased expectation, especially as the markets under examination has a very long trading history, high trading volume and a large number of participating agents.

8.1.2 Cost of Carry Relationship and Market Conditions

In order to investigate the long-run relationship between spot and futures prices with the presence of cost-of-carry elements, as well as the short-run adjustments towards this equilibrium, we first use the Johansen (1991, 1994) cointegration technique to establish the cointegrating relationship between the variables. The empirical findings suggest that: (1) the spot and futures prices move together in the long run with interest rates and inventory levels linking the two prices in the cointegrating vector; (2) in the long run, futures prices are above the spot prices and the cost-of-carry model dominates the futures – spot price relationship; and (3) the futures – spot price spread is positively correlated with interest rate (higher interest rate increases the financing cost) and the inventory level in the long run. The latter finding suggests that the higher the inventory level, the further away (upward) the futures prices are from the spot prices with the upper limit being the full cost-of-carry price. On the other hand, the lower the inventory level, the larger the convenience yield and thus the smaller is the basis, and eventually the basis becomes negative when the convenience yield exceeds the carrying costs.

The Granger causality tests are conducted to examine the lead-lag relationship amongst the main cost-of-carry variables, namely the spot and futures prices, the interest rate and inventory levels. The empirical findings reveal that there is a one-directional causal relationship between futures and spot prices, indicating spot prices respond to changes in futures prices but not *vice versa*. The results also suggest that both spot and futures prices are Granger caused by the interest rates in some markets. Also there is evidence of a bi-directional Granger causality between prices (spot and futures) and the inventory level, which highlights the important role of the inventory levels in the metal futures market dynamics both in the short run and the long run.

The results of the VECM reveal that both spot and futures prices tend to fall, while inventory levels tend to increase, in response to a divergence from the long-run equilibrium relationship. It is argued that the divergence from the long-run cost-of-carry relationship usually occurs when the market is in backwardation, in which case the interest-adjusted basis is negative. One may argue that futures prices can also drift upward from the spot prices, however this would be quickly eliminated by cash-and-carry arbitrage. On the other hand, the upward drift of spot price (eventually exceeding the futures price creating a backwardation market) also causes divergence in the market, but in this case due to the presence of convenience yield this divergence is less likely to be quickly eliminated by arbitrage. A market in backwardation is generally associated with low inventory levels and thus high spot prices. Accordingly, in order to restore the long-run equilibrium in the market, inventory levels need to be built up which results in a reduction in spot prices (and to a lesser extent, nearby futures prices), as suggested by the empirical findings in Chapter 5.

We postulate that the speed of adjustment towards the long-run equilibrium in a contango market is faster than that in a backwardation since we argue that it is easier for arbitrageurs to take positions in the physical market when the convenience yield of holding the commodity is low (or non-existent), i.e. when the market is in contango. Here the empirical results do no provide a clear-cut conclusion. In particular, it is only in the aluminium and copper markets that the inventory level adjusts to the long-run equilibrium in both states and the absolute value of the speed of adjustment is found to be larger in the high-volatility state. However, an interesting result in the regime switching VECM is the evidence that spot and futures prices adjust to restore equilibrium in at least one of the states. For instance, evidence of adjustments in the futures prices towards the equilibrium is found in both of the states in the aluminium market and in one of the states in the copper (high-volatility state), and lead (low-volatility state) markets, while no evidence of such adjustments is detected in the linear-VECM framework. There is also some evidence that the spot price (nickel) and inventory level (aluminium alloy) adjusts to restore the long-run equilibrium in the MRS-VECM but no such evidence is found in the linear VECM. This further highlights the importance of modelling the market dynamics in a framework where changing market conditions are accounted for.

8.1.3 Spot & Futures Price Volatility and Inventory Level

In Chapter 6, the dynamic relationship between the spot and futures price volatility and inventory levels is investigated. The empirical results support a negative relationship between price volatility and inventory levels, as predicted by the theory of storage. In particular, the empirical evidence shows that high spot and futures price volatility tends to be associated with inventory draw-down and low volatility is associated with inventory build-up. The causal relationship between the spot & futures price volatility and inventory levels is tested using Granger causality tests in a VAR model. Economic theory suggests a bi-directional causality between the two variables: increases in price volatility lead to increases in production cost and decreases in production, and therefore a decline in the inventory level, *ceteris paribus* (Pindyck, 2001). On the other hand, declines in the inventory levels result in a less elastic supply curve, thereby leading to an increase in price volatility for a given distribution of supply and demand shocks. We find evidence that price volatility Granger causes inventory level changes, but less evidence of inventory level changes causing volatility. We argue that the failure of the latter is because it is the inventory *level* that primarily leads changes in the price volatility, rather than marginal changes in the stock level.

In addition, we investigate the relationship between the spot and futures price volatility modelled using a GARCH process. This relationship is examined both in a linear and a regime switching framework. The theory of storage implies that the spot and futures price volatility move together, but that spot price volatility exceeds the futures price volatility when the commodity is in short supply or there is a risk of stockouts. To account for the nonlinear pattern in this relationship, we apply a Markov regime switching model in examining the dynamic relationship between the spot and futures price volatility. The empirical results indicate that when we allow for changing market conditions with transition probability conditional on inventory levels, the spot price volatility in the high-volatility state can be twice the futures price volatility.

8.1.4 Metal Futures Prices Volatility and Trading Volume

Using the trading volume of futures contracts as a proxy for the information flow in the market, the relationship between the futures price volatility and trading volume is examined using a GARCH-*X* (*X* being the explanatory variable) model in which trading volume enters as an explanatory variable in the volatility process. The empirical results reveal that the price volatility is positively associated with (lagged) trading volume, i.e. increases in trading volume cause increases in the futures price volatility. This suggests that the lagged trading volume is an important factor in the determination of price volatility in metal futures markets.

To examine the possible asymmetric relationship between price volatility and trading volume under different market conditions, we include a dummy variable accounting for market conditions in the GARCH-*X* model. The empirical evidence in the aluminium alloy, copper and zinc markets suggests that the futures price volatility is more sensitive to the trading volume when the market is in backwardation compared to when the market is in contango.

However, there is also evidence suggesting the opposite. In particular, in three of the markets (lead, nickel and tin) the empirical results suggest the futures price volatility is *less* sensitive to the trading volume in a backwardation market. By calculating the average daily trading volume when the market is in backwardation vs. when the market is in contango, we show that the trading volume is lower in the former market condition than in the latter. We argue that the higher trading volume in a contango market may be caused by the generally risk averse market participants (mainly hedgers and arbitrageurs) who may trade more when the market is less risky (i.e. when the market is in contango). Following the line that there exists a positive relationship between futures price volatility and trading volume, one would then expect that the futures price volatility is higher in a contango market. However, it has been well documented both theoretically and empirically that the futures price and spot price volatility is higher in a backwardation market (see, for instance, Fama and French, 1986; Williams and Wright, 1991; Ng and Pirrong, 1994; Nielsen and Schwartz, 2004). Therefore, we argue that trading volume does not represent all the information flow in these markets and thus the high futures price volatility in a backwardation market may be largely caused by factors other than trading activity (e.g. inventory changes). Therefore, the above result in the lead, nickel and tin markets does not necessarily mean that the volatility is less sensitive to information flow in the markets; it is merely an indication that the trading volume may not be a sufficient proxy.

The lead-lag relationship between the futures price volatility and trading volume is also investigated using the VAR framework. The results suggest that there is a bi-directional causal relationship between volatility and trading volume in most of the markets. Moreover, an increase in trading volume is found to cause an increase in futures price volatility in all the markets, indicating that as trading volume increases, futures price volatility tends to increase. This is consistent with the positive volatility – trading volume relationship we find in the previous section. However, higher price volatility does not necessarily increase trading activity, as shown by the mixed signs of the coefficients of the lagged volatility in the trading volume equation.

8.2 Implications

Commodities are important assets in the world economy for both developed and developing countries. Over the last two decades, we have experienced dramatic changes in the world commodity markets. Political disturbances in some countries, economic transformation, new environmental regulation, deregulation and market liberalization, a huge rise in the consumption of commodities in countries such as China and other structural changes have contributed to increase the volatility of supply, demand, and prices. All these facts have stimulated a booming trading activity in the commodity markets. Market participants are still involved with spot trading with physical delivery while the remarkable development of liquid derivative markets – forward, futures and options – has paved the way for cost-efficient risk management and alternative investment vehicles. The ability to manage price risks in the commodity derivative markets has been crucial for many sectors of the economy.

Commodity futures contracts facilitate the trading of various commodities as financial instruments for investments, speculation and hedging. In many markets, ranging from metal to electricity, commodity futures contracts are used as a substitute for the spot market by hedge funds, investment banks or any class of investors wishing to take a position in commodities. Importantly, a position in the commodity futures market is not subject to the physical constraints of spot trading and provides the flexibility of short and long positions irrespective of market conditions.

The fact that any transaction on commodities may be physical (delivery of the commodity) or financial (a cash flow from one party to the other) is in sharp contrast to bonds and stock markets where all trades are of a financial nature. However, physical and financial commodity markets are strongly interrelated. Price and volatility observed in financial transactions are correlated to those of the physical market, both because of the physical delivery that may take place at maturity of a futures (forward) contract and the existence of the theoretical relationship between the spot and futures markets.

Therefore, research herein on the linkage between the physical commodity market conditions and the spot and futures price dynamics provides a knowledge platform for trading houses, investment funds, metal merchants and any other participating institutions and individuals in the non-ferrous metal markets.

For instance, the investigation in Chapter 5 regarding the long-run equilibrium and short-run dynamic adjustments to any deviations from the equilibrium provides a test of the market efficiency in the storable commodity futures markets. Any empirical findings that pose potential challenges to the EMH may suggest that the spot and futures prices are not driven by market fundamentals as defined in the cost-of-carry relationship. Thus, this is of particular interest to regulators in the commodity exchange and policy committees.

The empirical evidence of asymmetric relationships between the spot and futures price volatility, volatility and inventory levels, and to a lesser extent volatility and trading volume as found in Chapters 6 and 7 may assist traders in forming trading strategies, rebalancing portfolios and exercise arbitrage under different market conditions.

8.3 Suggestions for Future Research

The rejection of the Unbiasedness Hypothesis in Chapter 4 under both market conditions according to the Markov Regime Switching testing method may be due to violation of rational expectations hypothesis or the risk neutrality assumption. Given its long trading history and the enormous trading volume on the LME metal futures market, it is not particularly plausible to suggest that the market participants are consistently irrational. This makes the investigation of the existence of a time-varying risk premium, particularly in a regime switching framework, an interesting research area going forward.

In Chapter 5, it is assumed that the long-run equilibrium is consistent through the whole time period but that the short-run adjustment is time varying and subject to structural changes. Given that the futures markets can be broadly characterised by two market conditions – backwardation and contango where the cost-of-carry elements and the convenience yield dominate respectively, it is reasonable to argue that the long-run equilibrium may also be dependent on market conditions. A possible modification of the model is therefore a nonlinear cointegration test as suggested by, for instance, Breitung (2001), where the test is based on the rank transformation of the time series and the cointegration form can be linear or nonlinear.

In Chapter 5, the convenience yield is proxied by the logarithm of the inventory level, which is a simplified economic measure. Though it provides an intuitive solution to the economic relationship among the cost-of-carry and convenience yield elements, other numerical measures of the convenience yield might also be applicable. For instance, the stochastic process in Nielsen and Schwartz (2004) three-factor model or a latent variable estimation of the convenience yield could be implemented when examining the long-run relationship among the cost-of-carry elements.

In Chapter 6, the volatility of spot and futures prices is modelled separately in a GARCH model. The multivariate-GARCH model proposed by Engle, Ng and Rothschild (1990) and Bollerslev (1990) might be able to improve the model specification since the inter-dependency in the variance-covariance matrix between the spot and futures price volatility can be taken into account. Also, in Chapter 6 and 7, the volatility is modelled by a

GARCH process. However intraday price variance (the realised volatility) can be integrated to form a measure of daily volatility as suggested by Andersen and Bollerslev (1997) and Andersen *et al* (2001). The implied volatility from traded options on the futures contracts can also be a measure of the volatility in the futures market as shown by Donaldson and Kamstra (2004). Also it may be possible to model the volatility process of the spot and futures price in a multivariate GARCH framework to incorporate the dynamic interrelationship between the spot and futures prices.

Appendix I Price and Trading Volume Graphs

Figure 1 Aluminium cash, futures prices and inventory level

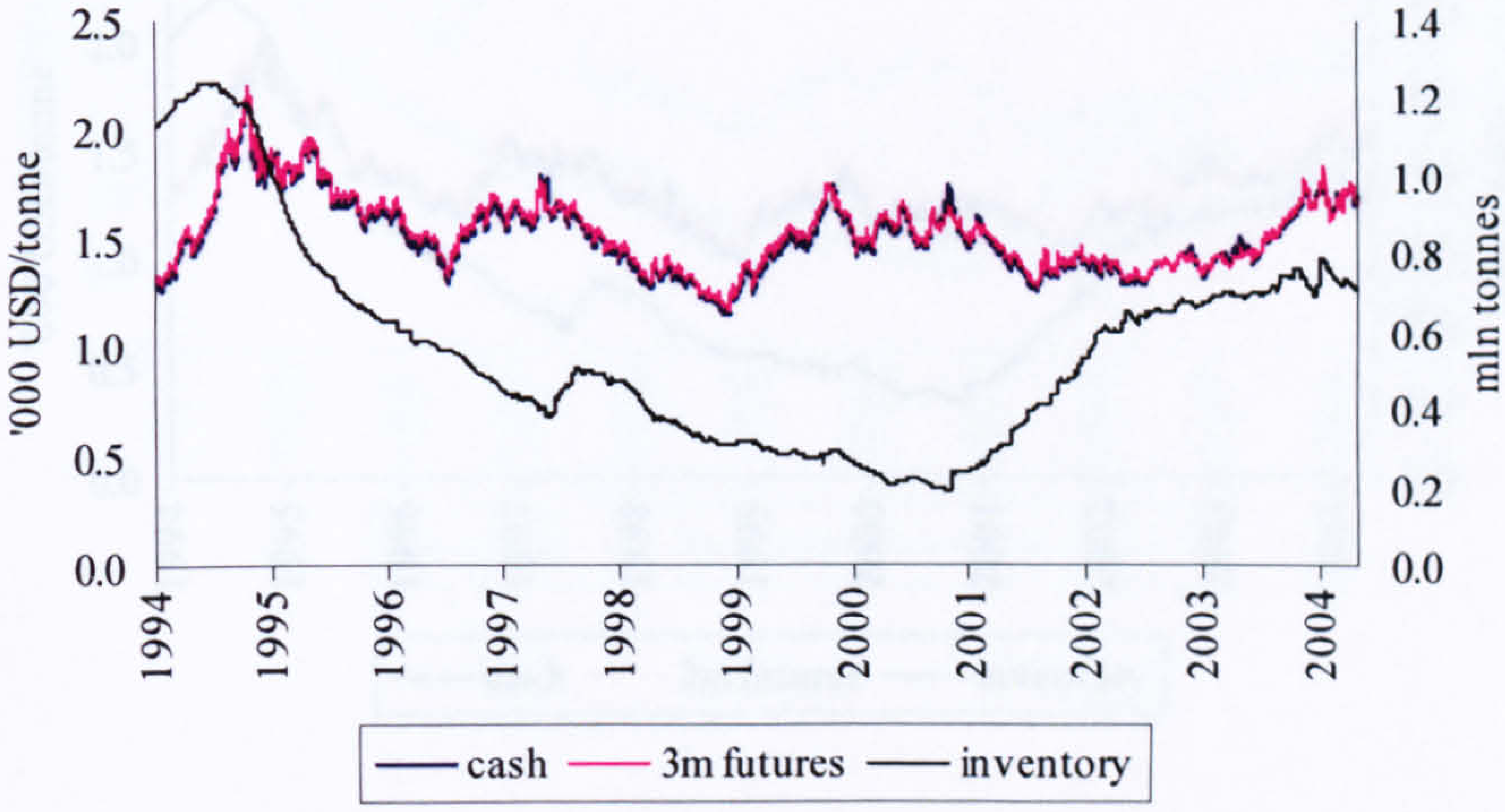


Figure 2 Aluminium 3m futures contract trading volume

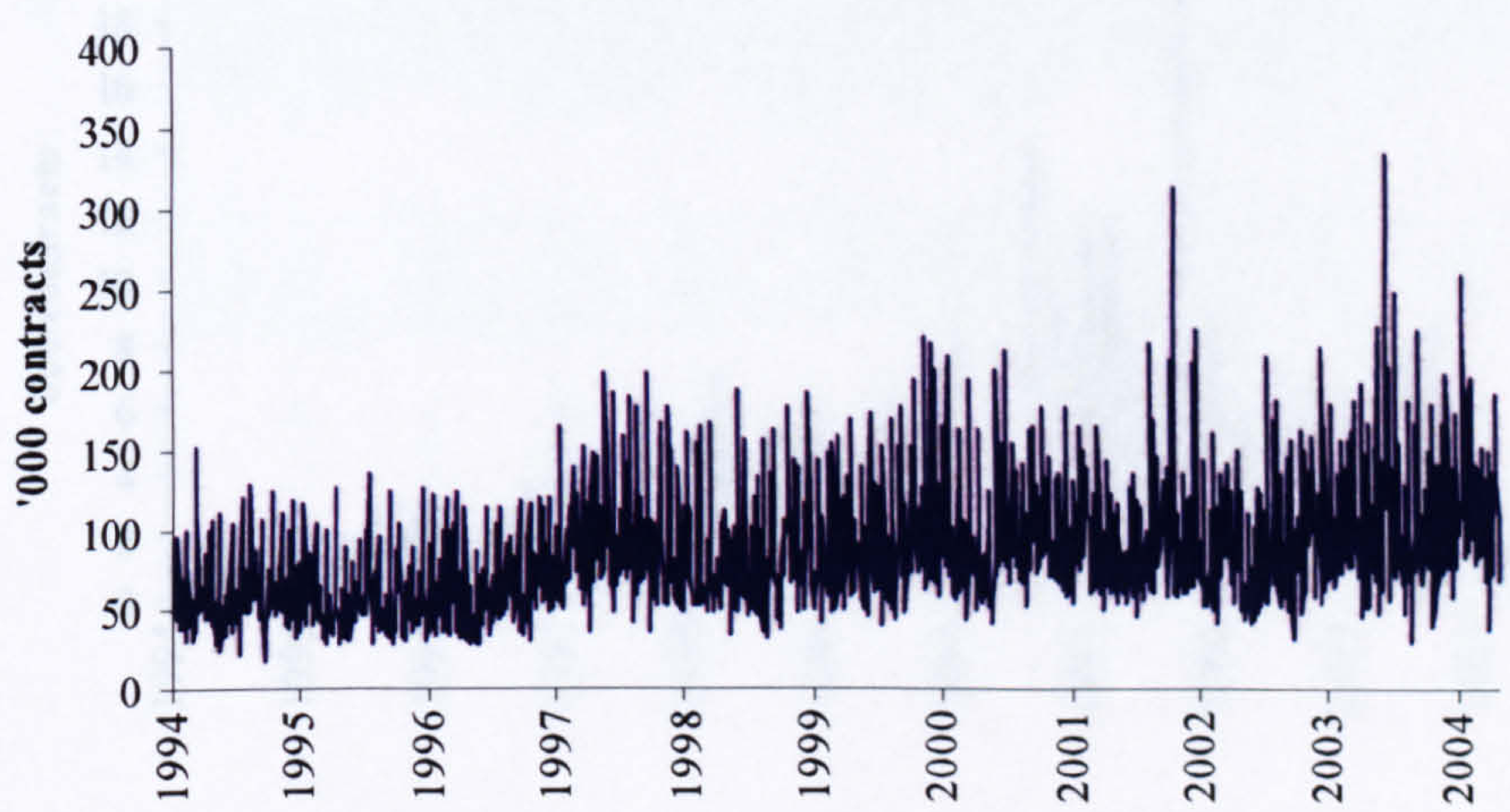


Figure 3 Aluminium alloy cash, futures price and inventory level

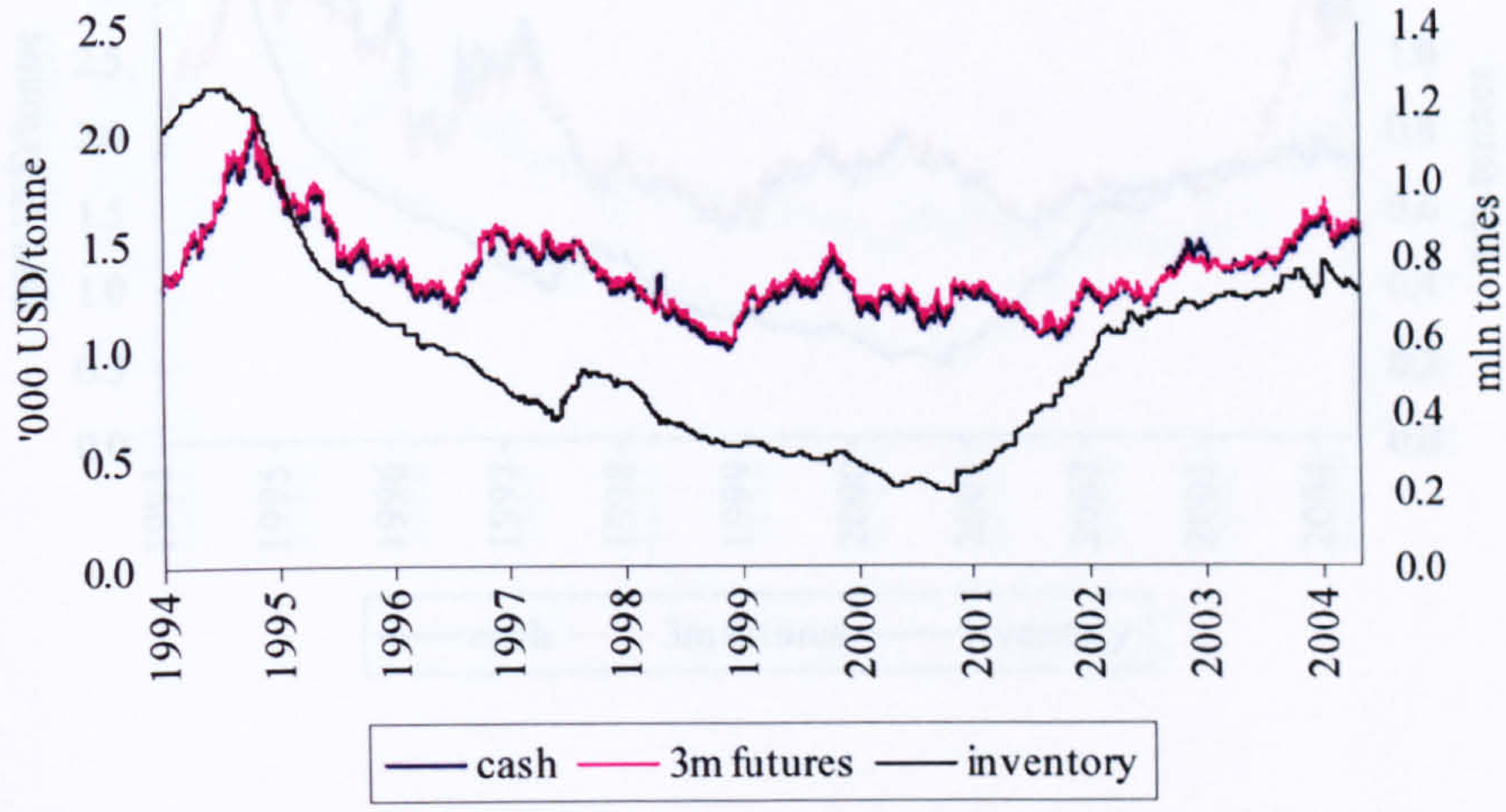


Figure 4 Al alloy futures contract trading volume

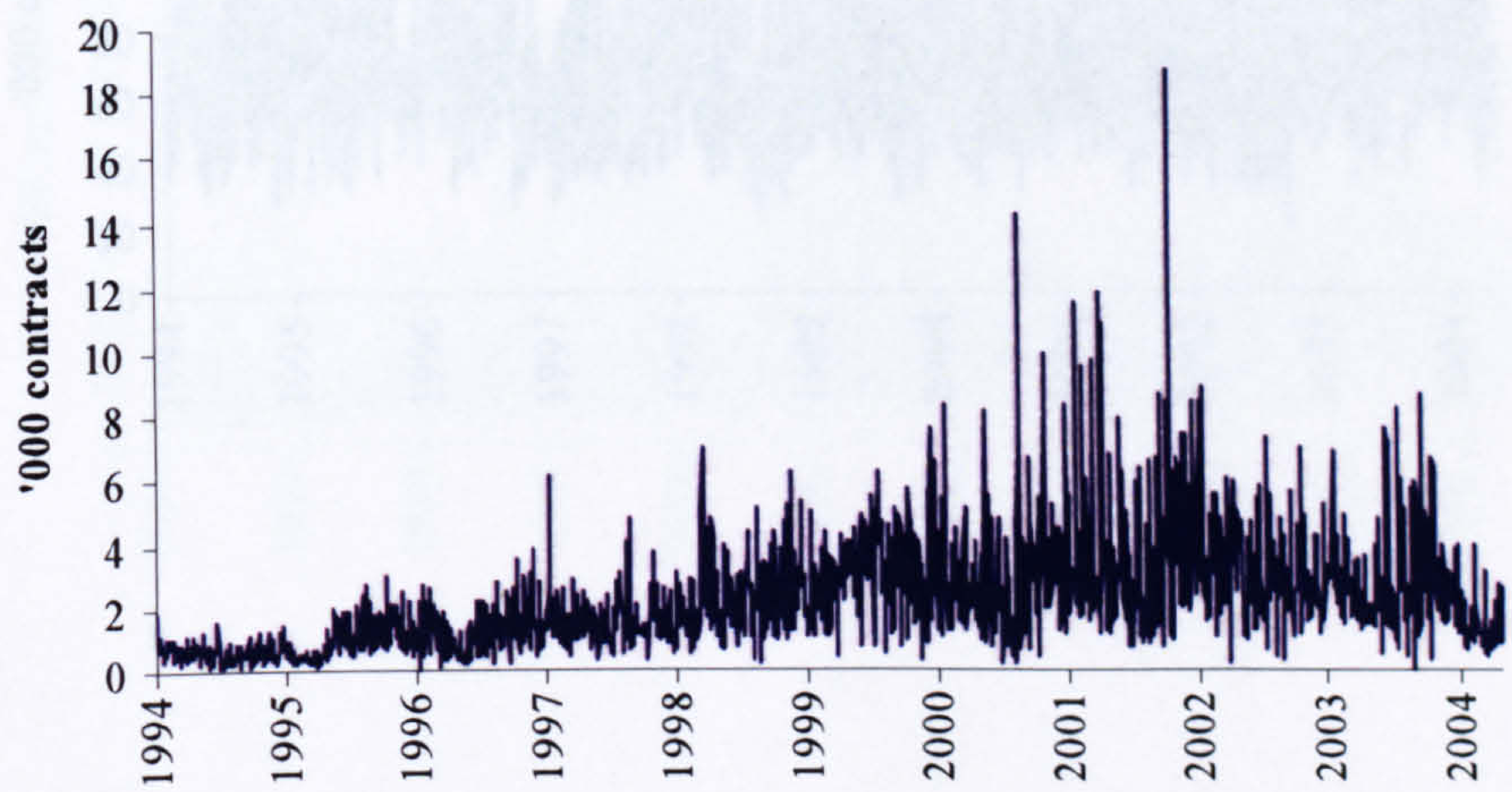


Figure 5 Copper cash, futures price and inventory levels

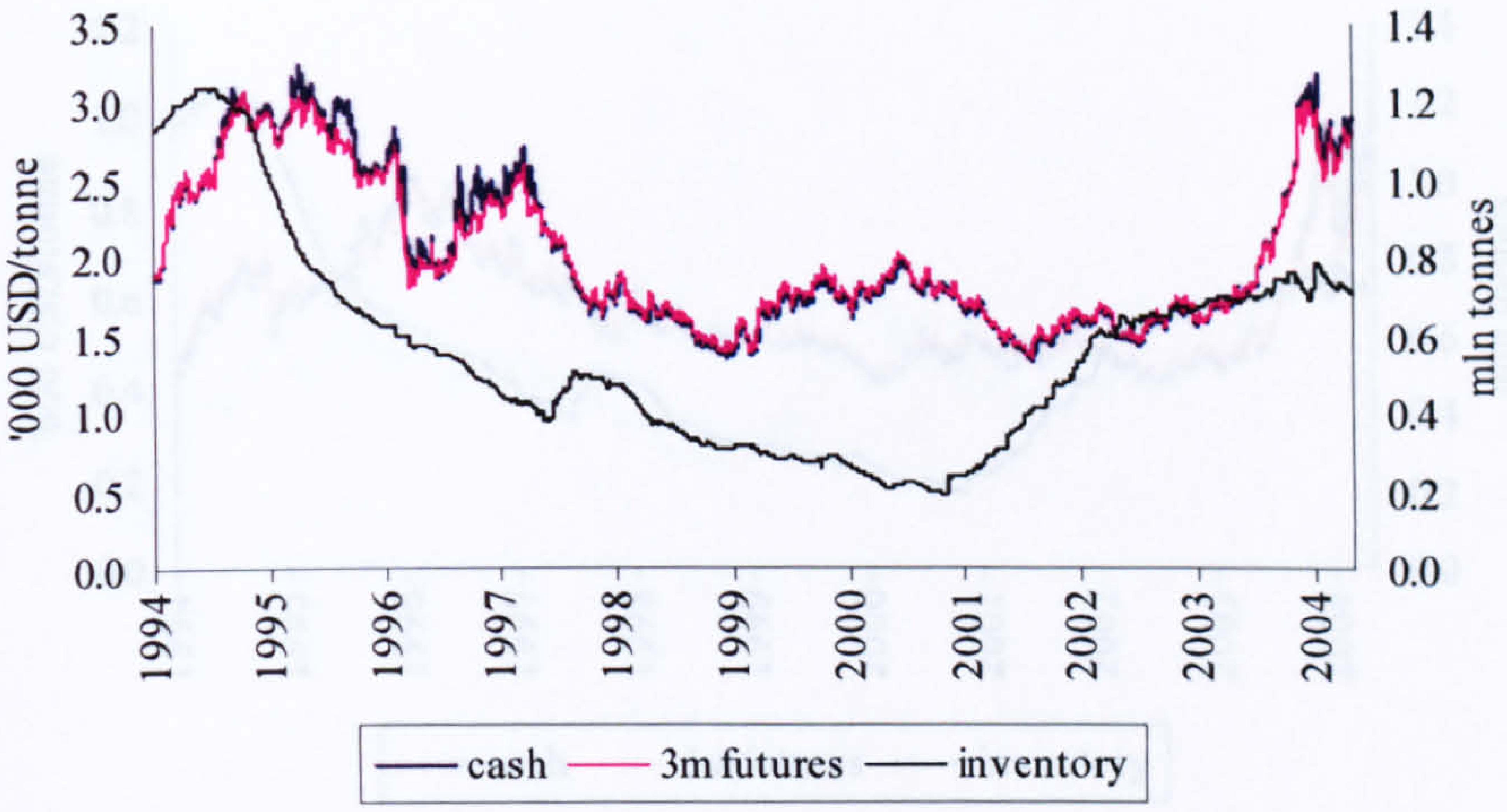


Figure 6 Copper 3m futures contract trading volume

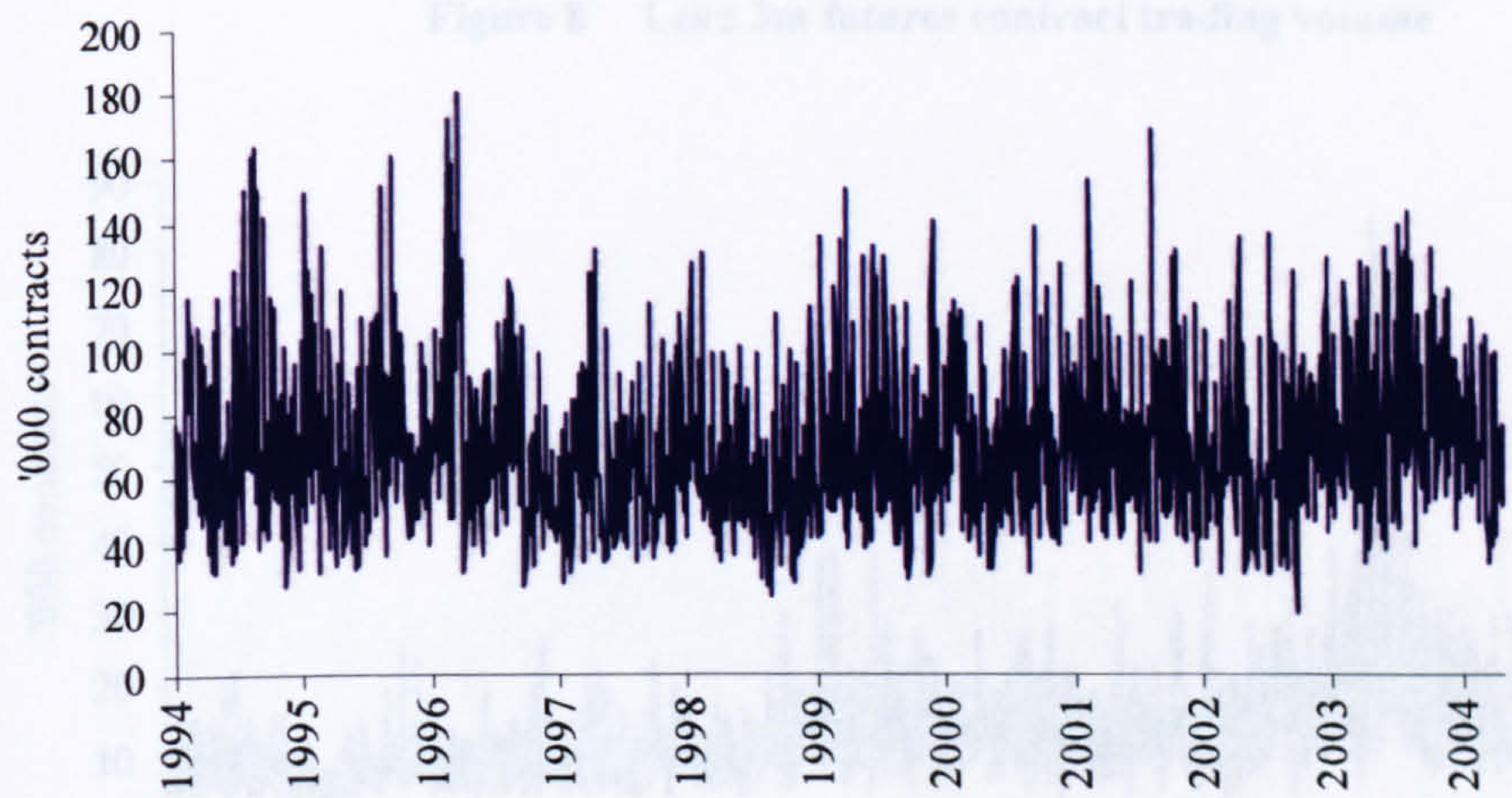


Figure 7 Lead cash, futures price and inventory level

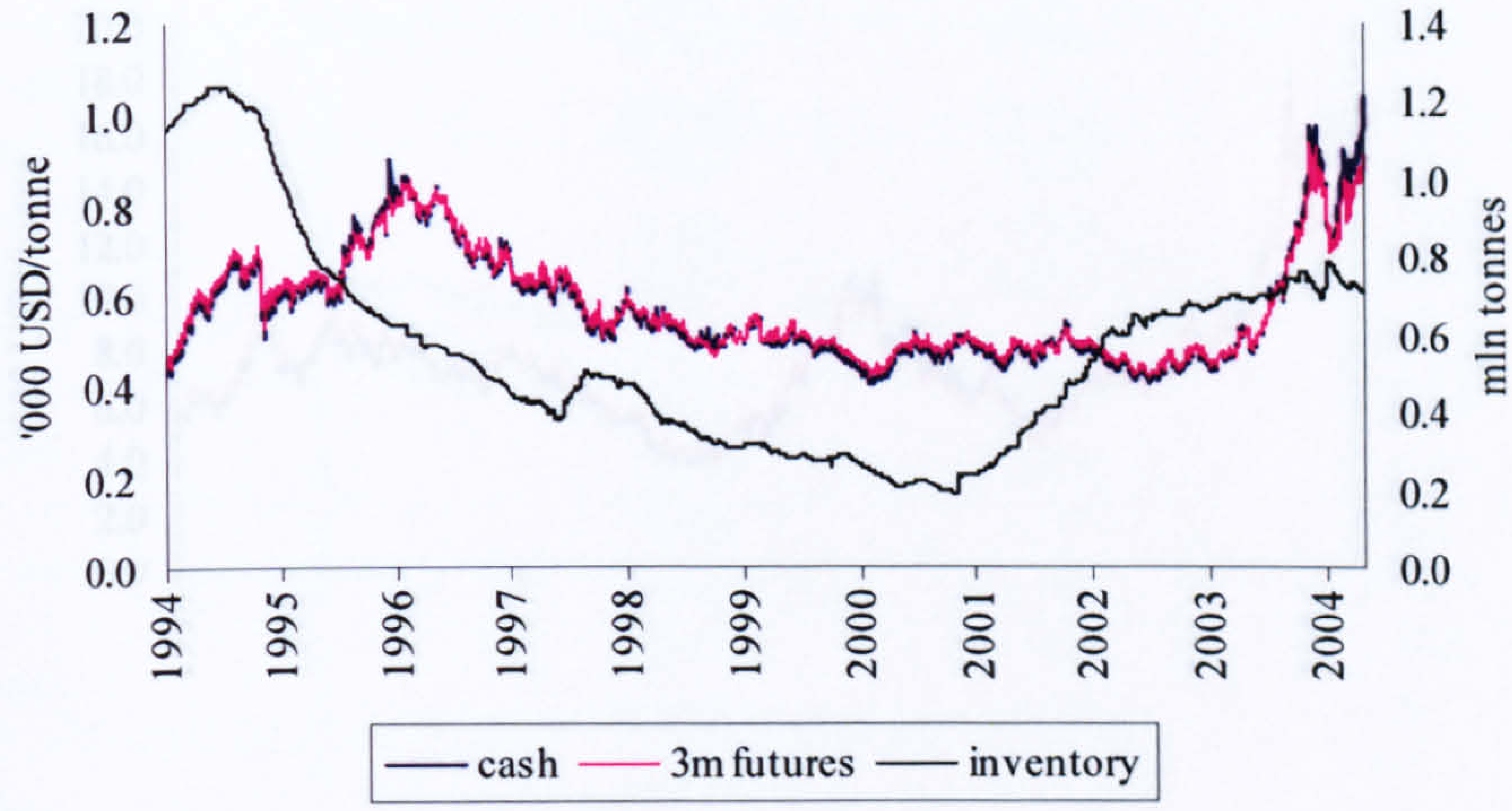


Figure 8 Lead 3m futures contract trading volume

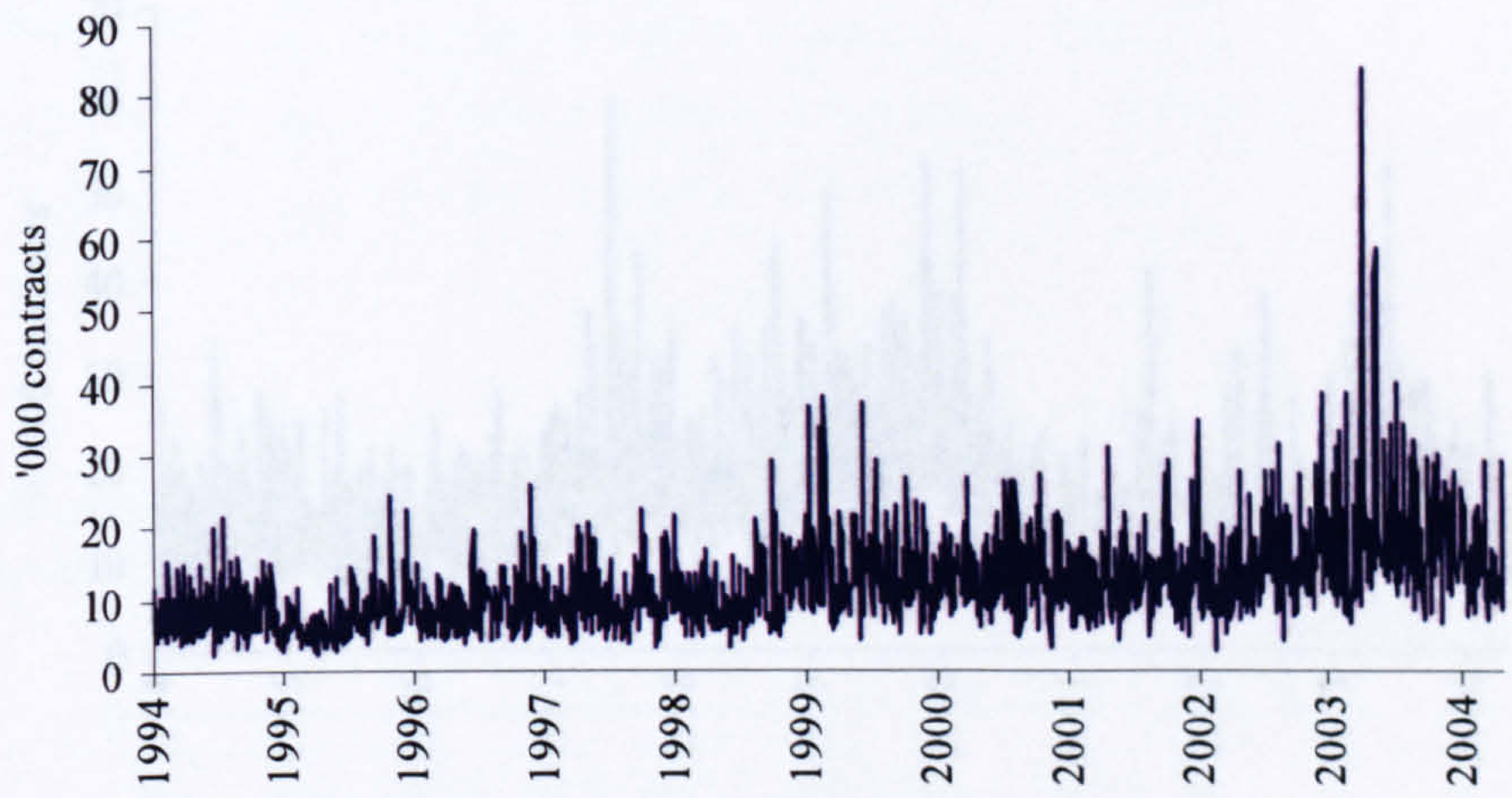


Figure 9 Nickel cash, futures price and inventory level

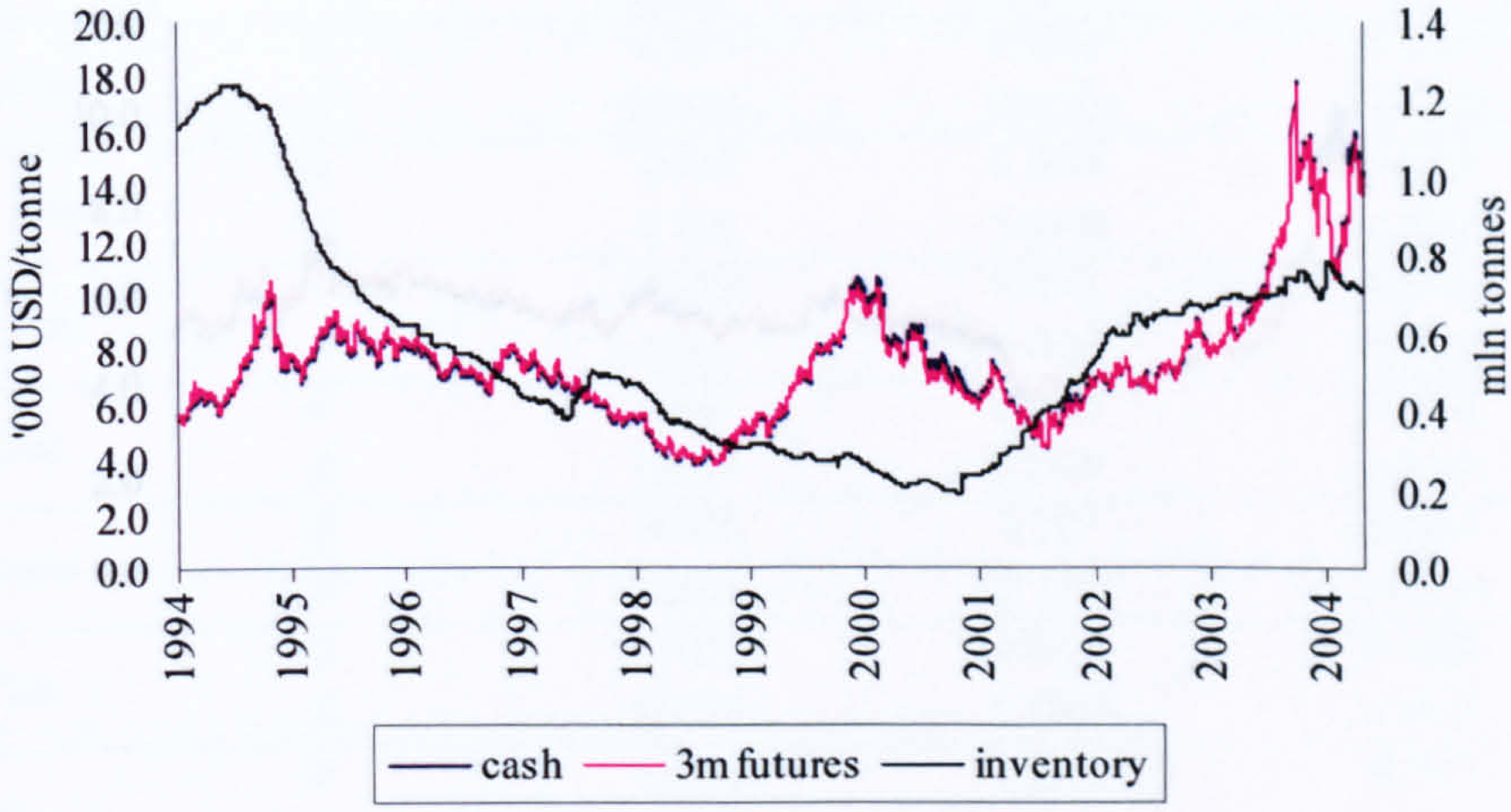


Figure 10 Nickel 3m futures contract trading volume

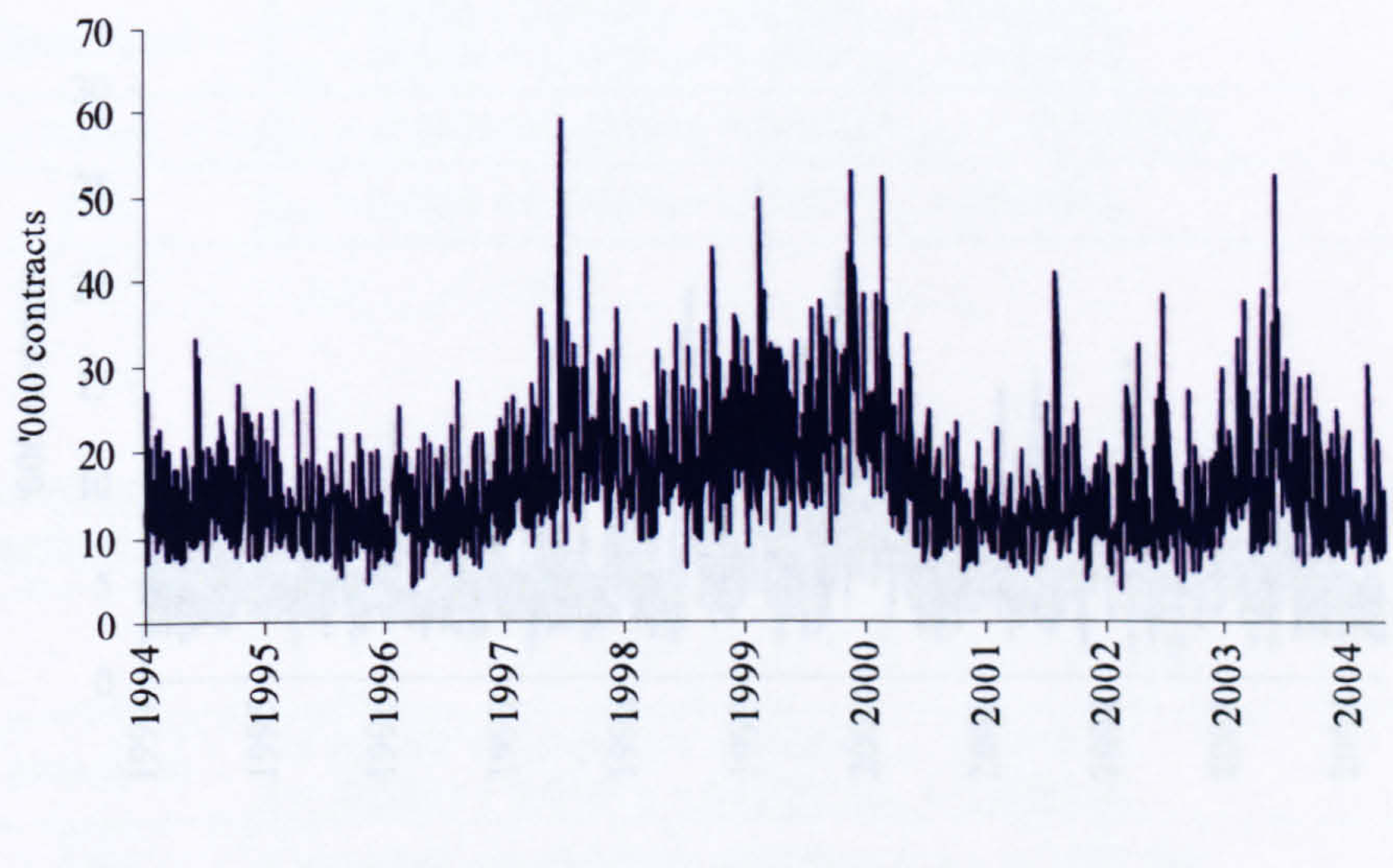


Figure 11 Tin cash, futures prices and inventory level

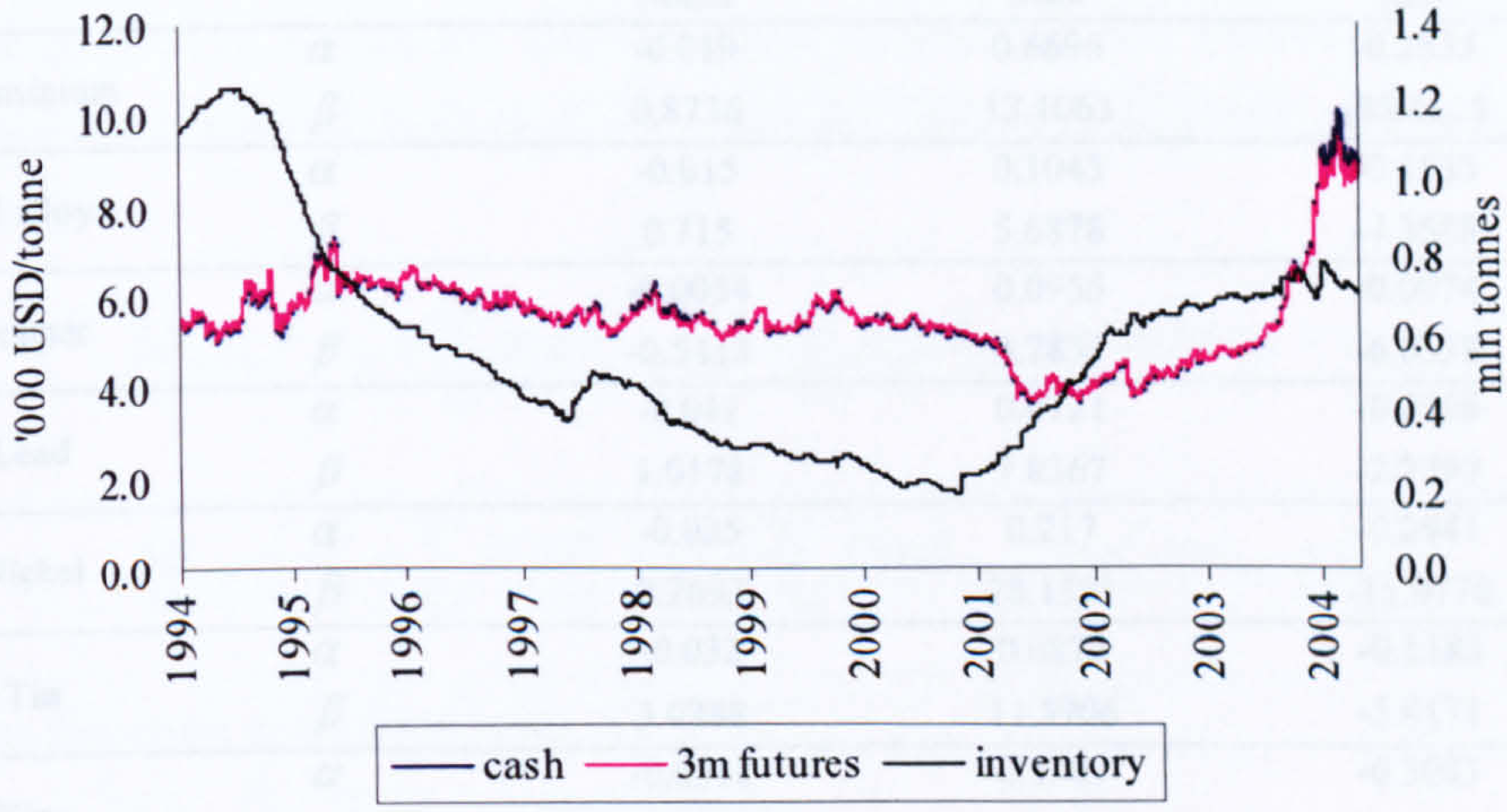


Figure 12 Tin 3m futures contract trading volume

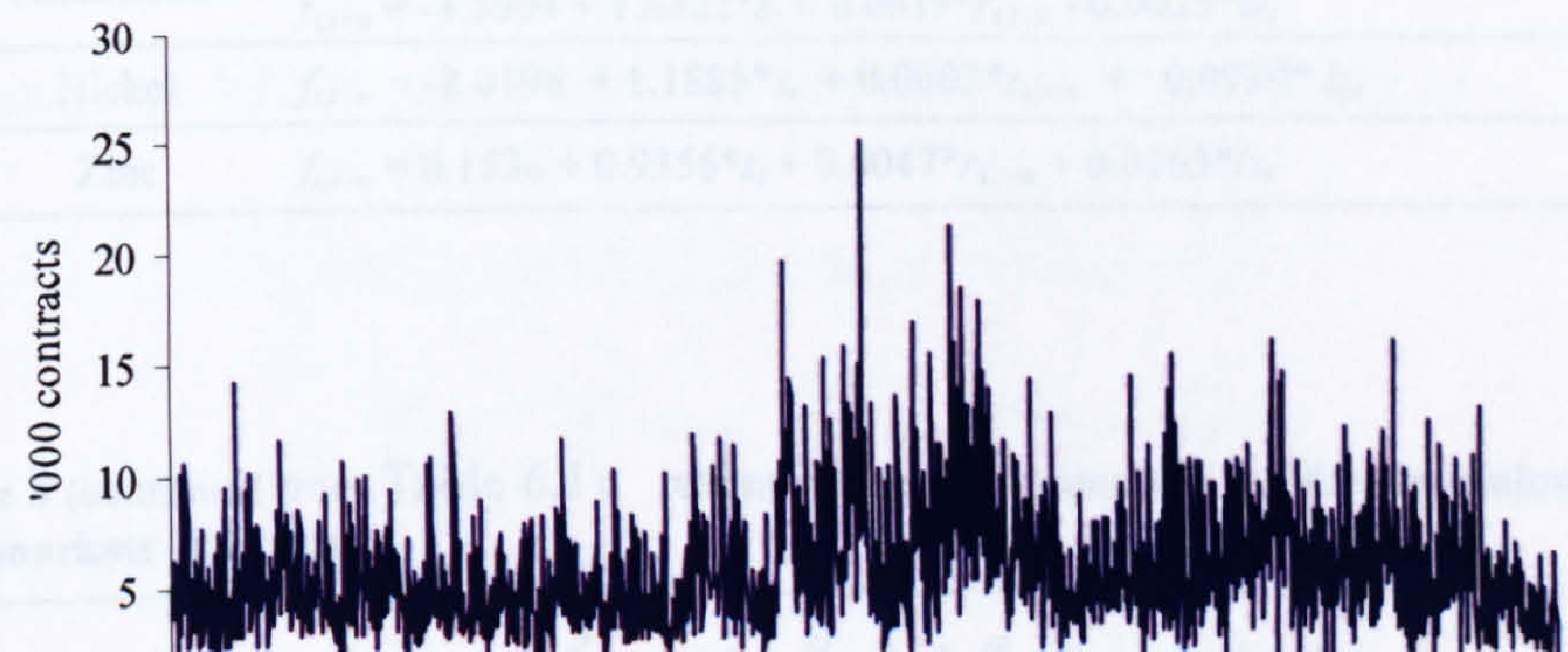


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Table 1 Rolling estimates of the UH coefficients

$$\Delta_n S_{t+n} = \alpha + \beta B_{t,t+n} + \eta_{t,t+n}$$

		Mean	Max	Min
Aluminium	α	-0.019	0.6696	-0.2555
	β	0.8736	13.1063	-35.4615
Al alloy	α	-0.015	0.1045	-0.1535
	β	0.715	5.6878	-4.3505
Copper	α	-0.0054	0.0955	-0.0974
	β	-0.5413	4.7837	-6.0338
Lead	α	-0.041	0.0721	-0.2108
	β	1.0178	7.8367	-2.7797
Nickel	α	-0.025	0.217	-0.2941
	β	0.2693	28.1581	-15.9774
Tin	α	-0.032	0.0876	-0.1188
	β	3.0288	11.5906	-5.4171
Zinc	α	-0.0558	0.1307	-0.3081
	β	3.1887	14.9869	-3.5819

- Weekly data over the period 04/1994 and 06/2004. The regression is run with the rolling window length as two years. The number of estimated α and β coefficients is 422.

Table 2 (continued from Table 5.1). **Cointegration relationships for the aluminium, nickel and zinc markets –weekly data**

$$f_{t,t+n} = c + \beta_1 \cdot s_t + \beta_2 \cdot r_{t,t+n} + \beta_3 \cdot ls_t$$

Aluminium	$f_{t,t+n} = 0.3986 + 0.8946*s_t + 0.0023*r_{t,t+n} - 0.0511*ls_t$ $f_{t,t+n} = -4.5904 + 1.6302*s_t + 0.0019*r_{t,t+n} - 0.0035*ls_t$
Nickel	$f_{t,t+n} = -2.0196 + 1.1885*s_t + 0.0002*r_{t,t+n} + 0.0939*ls_t$
Zinc	$f_{t,t+n} = 0.1836 + 0.9356*s_t + 0.0047*r_{t,t+n} + 0.0363*ls_t$

Table 3 (continued from Table 6.1) **Cointegration relationships for the aluminium, lead, nickel and zinc markets –daily data**

$$f_{t,t+n} = c + \beta_1 \cdot s_t + \beta_2 \cdot r_{t,t+n} + \beta_3 \cdot ls_t$$

Aluminium	$f_t = 0.3892 + 0.9505*s_t + 0.0005*r_{t,t+n} - 0.0017*ls_t$ $f_t = -0.6811 + 0.964*s_t + 0.0029*r_{t,t+n} + 0.0665*ls_t$
Lead	$f_t = 2.6746 + 0.5896*st + 0.0158*rt,t+n + -0.0171*lst$
Nickel	$f_t = 2.8279 + 0.7564*s_t - 0.0009*r_{t,t+n} - 0.0566*ls_t$ $f_t = 0.5656 + 0.9776*s_t + 0.0008*r_{t,t+n} - 0.0398*ls_t$
Zinc	$f_t = 17.9878 + -1.4141*s_t + 0.0562*r_{t,t+n} - 0.1447*ls_t$

Appendix II VECM and UH

In the context of testing the Unbiasedness Hypothesis, the unrestricted VECM with basis as the error correction term (see, for instance, Kellard *et al*, 1999) can be expressed as:

$$\Delta F_{t,t+n} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta F_{t-i,t+n-i} + \sum_{j=1}^{q} \beta_j \Delta S_{t+n-j} + \gamma \cdot ect_{t-1} + \varepsilon_{t+n} \tag{1}$$

$$\Delta S_{t+n} = \alpha_0' + \sum_{i=1}^{p} \alpha_i' \Delta F_{t-i,t+n-i} + \sum_{j=1}^{q} \beta_j' \Delta S_{t+n-j} + \gamma' \cdot ect_{t-1} + \zeta_{t+n} \tag{2}$$

where the error correction term $ect_t = F_{t,t+n} - S_t$.

It is argued that the restricted version of the VECM does not lead to the original relationship between $F_{t,t+n}$ and S_{t+n} under the UH. The proof is as follows.

Restrictions are imposed on the intercepts and coefficients of α and β of model (1) and (2), i.e. $\alpha_0(\alpha_0') = 0,\ \alpha_1(\alpha_1') = \alpha_2(\alpha_2') = \cdots = \alpha_p(\alpha_p') = 1$,

$\beta_1(\beta_1') = \beta_2(\beta_2') = \cdots = \beta_q(\beta_q') = 1$ and $\gamma(\gamma') = 1$ are imposed on model (1) and (2). Thus the restricted VECM can be written as: (for simplicity let $p = 1$, $q = 1$).

$$\Delta F_{t,t+n} = \Delta F_{t-1,t+n-1} + \Delta S_{t+n-1} + ect_{t-1} + \varepsilon_{t+n} \tag{3}$$

$$\Delta S_{t+n} = \Delta F_{t-1,t+n-1} + \Delta S_{t+n-1} + ect_{t-1} + \zeta_{t+n} \tag{4}$$

By expanding (3) and (4), we get:

$$(F_{t,t+n} - F_{t-1,t+n-1}) = (F_{t-1,t+n-1} - F_{t-2,t+n-2}) + (S_{t+n-1} - S_{t+n-2}) + (F_{t-1,t+n-1} - S_{t-1}) + \varepsilon_{t+n} \tag{5}$$

$$(S_{t+n} - S_{t+n-1}) = (F_{t-1,t+n-1} - F_{t-2,t+n-2}) + (S_{t+n-1} - S_{t+n-2}) + (F_{t-1,t+n-1} - S_{t-1}) + \zeta_{t+n} \tag{6}$$

which can be reduced to:

$$F_{t,t+n} = 3F_{t-1,t+n-1} - F_{t-2,t+n-2} + S_{t+n-1} - S_{t+n-2} - S_{t-1} \tag{7}$$

$$S_{t+n} = 2F_{t-1,t+n-1} - F_{t-2,t+n-2} + 2S_{t+n-1} - S_{t+n-2} - S_{t-1} \tag{8}$$

The restricted VECM form of model (7) and (8) obviously has no similarity with the appropriate relationship between the futures price and the realised spot price under the UH, which is:

$$F_{t,t+n} = S_{t+n} \tag{9}$$

Sometimes researchers (for instance, Yang, Bessler and Leatham, 2001) also use the difference between futures price and the realised spot price as the error correction term in the VECM. In turn, in model (1) and (2), the error correction term $ect_t = F_{t,t+n} - S_{t+n}$. In such a VECM, the restricted version is:

$$(F_{t,t+n} - F_{t-1,t+n-1}) = (F_{t-1,t+n-1} - F_{t-2,t+n-2}) + (S_{t+n-1} - S_{t+n-2}) + (F_{t-1,t+n-1} - S_{t+n-1}) + \varepsilon_{t+n} \tag{10}$$

$$(S_{t+n} - S_{t+n-1}) = (F_{t-1,t+n-1} - F_{t-2,t+n-2}) + (S_{t+n-1} - S_{t+n-2}) + (F_{t-1,t+n-1} - S_{t+n-1}) + \zeta_{t+n} \tag{11}$$

To simplify, this becomes:

$$F_{t,t+n} = 3F_{t-1,t+n-1} - F_{t-2,t+n-2} - S_{t+n-2} - S_{t-1} \tag{12}$$

$$S_{t+n} = 2F_{t-1,t+n-1} - F_{t-2,t+n-2} + S_{t+n-1} - S_{t+n-2} - S_{t-1} \tag{13}$$

which again is not the form of (9) under the UH.

Appendix III Markov Chain

The construction of a Markov chain requires two basic ingredients, namely a transition matrix and an initial distribution. We start with the definition of the transition matrix. Assume a finite set $S = \{1,\ldots,m\}$ of states. Assign to each pair $(i,j) \in S^2$ of states a real number p_{ij} such that the properties (14) and (15) are satisfied.

$$p_{ij} \geq 0 \qquad \forall (i,j) \in S^2 \tag{14}$$

$$\sum_{j \in S} p_{ij} = 1 \qquad \forall i \in S \tag{15}$$

Define the transition matrix **P** by

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{pmatrix} \tag{16}$$

Let $\{Y_t\}_{t \in \mathrm{N0}}$ be a sequence of random variables with values in S. Here, t denotes the time at which the state Y_t occurs.

Definition (Markov Chain): the sequence $\{Y_t\}_{t \in \mathrm{N0}}$ is called a homogeneous Markov chain with discrete time, state space S, and transition matrix P, if for every $t \in \mathrm{N0}$ the condition Meyn, and Tweedie (1993):

$$P\left(Y_{t+1} = j \middle| Y_0 = i_0, \cdots, Y_t = i_t\right) = P\left(Y_{t+1} = j \middle| Y_t = i_t\right) = p_{i_t, j} \tag{17}$$

is satisfied for all $(i_0, \cdots, i_t, j) \in S^{t+2}$, for which $P(Y_0 = i_0, \cdots, Y_t = i_t) > 0$.

The first identity in (17), which is also called "Markov property", defines the "memory" or "order" of the chain. In this case, the order equals one since the transition probabilities are entirely determined by the preceding state. The transition probability in the Hamilton (1989) Markov Regime Switching model follows a first-order Markov process. The second identity in (17) is called homogeneity condition. It assures that the transition probabilities do not vary with time t.

To complete the construction of a Markov chain we need to specify an initial distribution. Hence denote by D_S the set of discrete distributions on S,

$$D_S = \left\{ P = (p_i)_{i \in S} : p_i \geq 0, \sum_{i \in S} p_i = 1 \right\} \tag{18}$$

We call $P_0 = (p_{0i})_{i \in S} \in D_S$ the *initial distribution* of the chain $\{Y_t\}_{t \in N0}$ if $P[Y_0 = i] = P_{0\,i}$ for all states $i \in S$.

Appendix IV The LME Metal Futures Market

1. The London Metals Exchange

The London Metals Exchange was founded in 1877 and it is a major contributor to UK's financial markets, being the second largest exchange in the United Kingdom, after the London International Futures Exchange (LIFFE). The exchange has a strong link with the metal industry. The main function of LME is hedging, representing 75-85% of turnover. Only a small percentage (around 2%) of LME contracts result in delivery. Annual trading volume on the LME is consistently around 60 million lots. The LME provides a 24-hours trading system to facilitate trading activities around the world. LME futures contracts specify a certain delivery date (prompt date) by which time either the position must be closed or delivery will take place. The US dollar is the major currency used in the LME, in which transactions on the floor are made and used as official price quotation. The LME permits contracts in sterling, Japanese yen, and Euro and provides official exchange rates from US Dollars for each of them.

The London Metal Exchange provides futures and options contracts for the six major primary non-ferrous metals: copper, aluminium, nickel, tin, zinc, and lead. The Exchange also offers futures and options contracts for secondary aluminium (aluminium alloy) and from 4th March 2002, the North American Special Aluminium Alloy (NASAAC). In addition the LME operates futures and traded options contracts based on an index (LMEX) of the six primary contracts. Table 1 summarises when the products started trading and when the current contract specifications were introduced in the LME.

Table 4 LME contracts introducing time

	First traded on LME:	Current specification introduced:
Copper (grade A)	1877	April 1986
Aluminium (High Grade Primary)	1978	June 1987
Nickel (Primary)	1979	April 1979
Tin	1877	June 1989
Lead (Standard)	1903	1968
Zinc (Special high grade)	1915	Sept. 1988
Aluminium Alloy	1992	October 1992
NASAAC	4 March 2002	4 March 2002
LMEX	10 April 2000	10 April 2000

Besides the futures and options contract on the seven metals and LMEX index, the exchange also offers the London Metal Exchange Traded Average Price Options (TAPOs) for copper grade A, high grade primary aluminium, standard lead, primary nickel, special high grade zinc, aluminium alloy, NASAAC and tin. The TAPOs are Exchange cleared contracts based on the LME Monthly Average Settlement Price (MASP).

2. LME Trading Practices

The LME metal contracts run on a daily basis for a period of three months. The use of daily prompt dates is an important difference between the LME and other futures exchanges. Trade is conducted in lots rather than tonnes, with each lot of aluminium, copper, lead and zinc amounting to 25 tonnes. Nickel is traded in 6 tonne lots, tin in 5 tonnes and aluminium alloy and NASAAC in 20 tonne lots. The contract for each metal sets out the shapes, weights and methods of strapping. The contract specifications are for the quality and shape which are most widely traded and demanded by the industry.

There are three ways to trade on the LME -- ring trading, inter-office telephone market trading and LME select screen system trading.

2.1 Trading in the ring

The London Metal Exchange is still using the traditional way of trading – ring trading, as one of its trading methods. Ring trading is so called because the LME uses a "ring" with the traders sitting at fixed points around the circle. The ring sessions, and especially the second morning rings from which official prices emerge, concentrate liquidity because the physical trade requires prices as close as possible to the daily settlement prices. Table 7 shows the ring and kerb trading time segments for each of the metals during a working day.

2.2 Trading in the inter-office telephone market

The ring offers the traditional benefits of transparency which attach to a physical, open outcry marketplace, but it is only available for a part of the 24 hour working day. The Inter-Office telephone market offers a service to its customers that works for all of the working day. The market participants can see an indicative price on a screen as they contact a broker, and then complete a deal there and then. Brokers continually provide indicative prices which are available through vendor screens. Transactions done through the inter-office trading system are "real" LME contracts and pass on through the matching, clearing and settlements procedures.

2.3 LME select screen trading system

LME Select is the official exchange operated electronic trading platform, available in addition to open outcry ring trading and the telephone market. Member firms are connected to the system which allows accredited traders to execute trades via the screen. The system allows trading on all LME contracts, futures, options, and TAPOs. It also allows for straight-through processing whereby LME Select trades are automatically sent to the matching and clearing systems operated by the London Clearing House (LCH). LME Select operates between 07:00 and 19:00 (London Time).

Table 5 The London Metal Exchange ring trading time

First session		
Aluminium Alloy & NASAAC	11.45 to 11.50	35 minutes first morning ring (1st RING)
Tin	11.50 to 11.55	
Primary Aluminium	11.55 to 12.00	
Copper	12.00 to 12.05	
Lead	12.05 to 12.10	
Zinc	12.10 to 12.15	
Nickel	12.15 to 12.20	
Interval	12.20 to 12.30	
Copper	12.30 to 12.35	35 minutes second morning ring (2nd RING)
Aluminium Alloy & NASAAC	12.35 to 12.40	
Tin	12.40 to 12.45	
Lead	12.45 to 12.50	
Zinc	12.50 to 12.55	
Primary Aluminium	12.55 to 13.00	
Nickel	13.00 to 13.05	
Interval	13.05 to 13.15	
Kerb Trading	13.15 to 15.10	
Second session		
Aluminium Alloy & NASAAC	15.10 to 15.15	35 minutes first afternoon ring (3rd RING)
Interval	15.15 to 15.20	
Lead	15.20 to 15.25	
Zinc	15.25 to 15.30	
Copper	15.30 to 15.35	
Primary Aluminium	15.35 to 15.40	
Tin	15.40 to 15.45	
Nickel	15.45 to 15.50	
Interval	15.50 to 16.00	
Lead	16.00 to 16.05	35 minutes second afternoon ring (4th RING)
Zinc	16.05 to 16.10	
Copper	16.10 to 16.15	
Primary Aluminium	16.15 to 16.20	
Tin	16.20 to 16.25	
Nickel	16.25 to 16.30	
Aluminium Alloy & NASAAC	16.30 to 16.35	
Kerb Trading	16.35 to 17.00 *	

Note: at 16:45 Aluminium Alloy and NASAAC cease trading;
at 16:50 Lead and Tin cease trading;
at 16:55 Nickel and Zinc cease trading.

3. The LME Contracts

All LME contracts assume delivery of physical metal. To meet this need, large stocks of metal are held in a worldwide network of warehouses approved, but not owned, by the LME. Currently there are over 400 warehouses in some 32 locations covering the USA, Europe, the Middle East and the Far East. Very few LME contracts result in a delivery, the vast majority of contracts are bought or sold back before falling due. As a result, deliveries that do take place either in or out of a warehouse strongly reflect the demand-supply in the physical market. The LME approved warehouses where the physical delivery can take place are located in the following places. The United States (Baltimore, Chicago, Detroit, Long Beach, Los Angeles, New Orleans, and St. Louis), Sweden (Gothenburg and Helsingborg), UK (Avonmouth, Hull, Sunderland, Newcastle, Liverpool), Netherlands (Vlissingen and Rotterdam), Belgium (Antwerp), Germany (Bremen and Hamburg), Italy (Genoa, Leghorn, Trieste), Spain (Barcelona and Bilbao), Japan (Hakata, Moji, Nagoya, and Yokohama), Korea (Busan and Gwangyang) and Singapore.

Delivery of LME contracts is in the form of warrants, which are bearer documents. Each warrant entitles the holder to take possession of one lot of metal at a specific LME approved warehouse. In 1999, the LME introduced an electronic transfer system, SWORD, for the production and transfer of title of LME warrants. SWORD is a joint initiative between the LME and the London Clearinghouse. All LME warrants are produced to a standard format with a barcode. Warehouse companies issuing these warrants ensure that the details are known to SWORD, which acts as a central database, holding details of ownership and is subject to stringent security controls. The ownership of LME warrants can be transferred between SWORD members in a matter of seconds and all rent payments are automatically calculated.

3.1 Aluminium

Aluminium contracts were firstly traded on the LME in 1978 and the current contract specification was introduced in June 1987. Despite being the most prolific metal on earth, aluminium only began to be used extensively once an inexpensive method for distilling it by means of electrolytic reduction was discovered in the mid 19th century. Hence aluminium is considered to be a very young metal. It is extremely light and pliable, has high conductivity and is resistant to rust. It is widely used in motor vehicles, internal combustion engines and computer office equipment. Little wonder then that it has become the most extensively used metal and more recently the largest contract traded on the LME. In 2002 there were over 22 million futures contracts traded on the LME. Aluminium world production is around 23,624,000 tonnes per annum.

The LME futures contracts for aluminium are available for three-month, 15-month and 27-month maturities. The prices are quoted as USD/tonne. The LME aluminium contract specification restricts the minimum price movement to 50 cents per tonne. The delivery dates are daily for three months forward, then every Wednesday for the next three months and then every third Wednesday of the month for the next 57 months. (A total of 63 months forward).

3.2 Aluminium Alloy

The qualities that make the primary metal, aluminium, so successful have also led to the production of aluminium alloys, where various amounts of other metals are combined with aluminium to give strength and specific characteristics for a particular use. The world production of aluminium alloy is around 7,473,000 tonnes per annum.

Aluminium alloy cash and three-month futures contracts started trading on the LME in October 1992. The 15-month futures contract was introduced in January 1993 and the 27-month futures contract in April 2002. The prices are quoted in USD/tonne. The minimum price movement is 50 cents per tonne. The contracts are delivered daily for 3 months forward, then every Wednesday for the next 3 months and then every third Wednesday of the month for the next 21 months. (a total of 27 months forward).

3.3 Copper

Copper was firstly traded on the LME in 1877 and the current contract specification was introduced in April 1986. The world production is about 14,092,000 tonnes per annum. Copper was the first mineral that man extracted from the earth and it is an excellent conductor of electricity, and as such its main industrial usage is for the production of cable, wire and electrical products for both the electrical and building industries. The construction industry also accounts for copper's second largest usage in such areas as pipes for plumbing, heating and ventilating as well as building wire and sheet metal facings. The main producers of copper ore are Chile and USA followed by Canada, Russia, Kazakhstan, Zambia and Australia.

Copper futures contracts are available for three-month, 15-month and 27-month forward. The 27-month futures contracts started trading in July 1993. The prices are quoted in USD/tonne. The minimum price movement is 50 cents per tonne. Futures contracts are delivered daily for 3 months forward, then every Wednesday for the next 3 months and then every third Wednesday of the month for the next 57 months. (A total of 63 months forward).

3.4 Lead

Metal lead is very soft, pliable and highly resistant to corrosion. Batteries are the main outlets of lead consumption, accounting for 80%. Lead can also be found in computer screens, construction materials, and protective coatings. Environmental issues have brought about new uses for the metal, particularly in the housing of power generation units to protect against electrical charges or dangerous radiation. The world production is around 6,143,000 tonnes per annum. The US is the largest lead producer.

Lead started trading on the LME in 1903 and the current contract specification was introduced in 1968. Currently there are three-month and 15-month futures and cash settlement contracts available. The minimum price movement is 50 cents per tonne. The delivery dates are daily for 3 months forward, then every Wednesday for the next 3 months and then every third Wednesday of the month for the next 9 months. (A total of 15 months forward).

3.5 Nickel

In early years nickel was found in copper mines and it was not until the mid 18th century that primary nickel was first isolated as a separate metal. Nickel is used in the following industries: construction, infrastructure, chemical production, communications, energy supply, environmental protection, food preparation, water treatment, and transportation. The world's largest producer is Russia, followed by Canada and Australia.

Nickel contracts started trading on the LME in 1979 when the current contract specification was introduced as well. Now three-month, 15-month and 27-month futures contracts and cash contracts are available. (The 27-month futures price starts on 17 July 1995). The minimum price movement is $5USD per tonne. The delivery dates are daily for 3 months forward, then every Wednesday for the next 3 months and then every third Wednesday of the month for the next 21 months. (A total of 27 months forward).

3.6 Tin

Tin is one of the earliest metals known to mankind. Nowadays tin is utilized to coat other metals in order to prevent corrosion or other chemical reactions. Tin is also used to manufacture containers for the food industry (30% of annual consumption) where it is competing with aluminium and plastic. Tin is added as hardening agent to alloys with other metals. The world production is around 245,424 tonnes per annum. Most of the tin supply comes from Malaya, Bolivia, Indonesia, Zaire, Thailand, and Nigeria. Particularly liked for its fusion abilities in the making of alloys, notably bronze, and its non-toxic qualities, tin was soon traded in many parts of the world. Not surprisingly, it was traded on the LME from the market's outset in 1877. The current specification was introduced in June 1989.

Tin cash and futures prices for three-month and 15-month forward contracts are available on the LME. The minimum price movement is $5USD per tonne. The delivery dates are daily for 3 months forward, then every Wednesday for the next 3 months and then every third Wednesday of the month for the next 9 months. (A total of 15 months forward).

3.7 Zinc

Zinc is commonly mined as a co-product with lead and both metals have growing core markets for their consumption. For standard lead, this is its use in batteries and for zinc, the main market is galvanising, which accounts for almost half its modern-day demand. Zinc's electropositive nature enables metals to be readily galvanised, which gives added protection against corrosion to building structures, vehicles, machinery and household equipment. The zinc world production is about 8,220,000 tonnes per annum Zinc is mined mostly in Canada, FSU, Australia, Peru, Mexico and the US.

Zinc first traded on the LME in 1915 and the current contract specification was introduced in September 1988. Three-month, 15-month and 27-month futures contracts are available now in the LME. The minimum price movement is 50 cents per tonne. The delivery dates are daily for 3 months forward, then every Wednesday for the next 3 months and then every third Wednesday of the month for the next 21 months. (A total of 27 months forward).).

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