School of Economics and Finance

Behaviour and Performance of Key Market Players in the US Futures Markets

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

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Abstract

This study gives an insight into the behaviour and performance of large speculators and large hedgers in 29 US futures markets. Using a trading determinant model and priced risk factors such as net positions and sentiment index, results suggest hedgers (speculators) exhibit significant positive feedback trading in 15 (7) markets. Information variables like the S&P500 index dividend yield, corporate yield spread and the three months treasury bill rate were mostly unimportant in large players' trading decisions. Hedgers had better market timing abilities than speculators in judging the direction of the market in one month. The poor market timing abilities and poor significance of positive feedback results suggest higher trading frequency intervals for speculators. Hedging pressures, which measure the presence of risk premium in futures markets, were insignificant mostly in agricultural markets. As a robust test of hedging pressures, price pressure tests found risk premium to be still significant for silver, crude oil and live cattle. The positive feedback behaviour and negative market timing abilities suggest hedgers in heating oil and Japanese yen destabilize futures prices, and points to a need to check CFTC's (Commodity Futures Trading Commission) position limits regulation in these markets. In fact, large hedgers in these two markets are more likely to be leading behaviour, in that they have more absolute net positions than speculators. Alternatively stated, positive feedback hedgers in these two markets are more likely to lead institutions and investors to buy (sell) overpriced (underpriced) contracts, eventually leading to divergence of prices away from fundamentals. Atlhought hedgers in crude oil had significant positive feedback behaviour and negative market timing skills, they would not have much of a destabilizing effect over remaining players because the mean net positions of hedgers and speculators were not far apart. While the results are statistically significant, it is suggested these could be economically significant, in that there have been no regulation on position limits at all for hedgers compared to speculators who are imposed with strict limits from the CFTC.

Further, mean equations were regressed against decomposed variables, to see how much of the futures returns are attributed to expected components of variables such as net

positions, sentiment and information variables. While the expected components of variables are derived by ensuring there are enough ARMA (autoregressive and moving average) terms to make them statistically and economically reliable, the unexpected components of variables measure the residual on differences of the series from its mean. When decomposing net positions against returns, it was found expected net positions to be negatively related to hedgers' returns in mostly agricultural markets. Speculators' expected (unexpected) positions were less (more) significant in explaining actual returns, suggesting hedgers are more prone in setting an expected net position at the start of the trading month to determine actual returns rather than readjusting their net positions frequently all throughout the remaining days of the month. While it important to see how futures returns are determined by expected and unexpected values, it is also essential to see how volatility is affected as well. In an attempt to cover three broad types of volatility measures, idiosyncratic volatility, GARCH based volatility (variance based), and PARCH based volatility (standard deviation) are used.

Net positions of hedgers (expected and unexpected) tend to have less effect on idiosyncratic volatility than speculators that tended to add to volatility, reinforcing that hedgers trading activity hardly affect the volatility in their returns. This suggest they are better informed by having a better control over their risk (volatility) measures. The GARCH model showed more reliance of news of volatility from previous month in speculators' volatility. Hedgers' and speculators' volatility had a tendency to decay over time except for hedgers' volatility in Treasury bonds and coffee, and gold and S&P500 for speculators' volatility. The PARCH model exhibited more negative components in explaining current volatility. Only in crude oil, heating oil and wheat (Chicago) were idiosyncratic volatility positively related to return, reinforcing the suggestion for stringent regulation in the heating oil market. Expected idiosyncratic volatility was lower (higher) for hedgers (speculators) as expected under portfolio theory. Markets where variance or standard deviation are smaller than those of speculators support the price insurance theory where hedging enables traders to insure against the risk of price fluctuations. Where variance or standard deviation of hedgers is greater than speculators, this suggest the motivation to use futures contracts not primarily to reduce risk, but by institutional characteristics of the futures exchanges like regulation ensuring liquidity. Results were also supportive that there was higher fluctuations in currency and financial markets due to the higher number of contracts traded and players present.

Further, the four models (GARCH normal, GARCH *t*, PARCH normal and PARCH *t*)[1] showed returns were leptokurtic. The PARCH model, under normal distribution, produced the best forecast of one-month return in ten markets. Standard deviation and variance for both hedgers' and speculators' results were mixed, explained by a desire to reduce risk or other institutional characteristics like regulation ensuring liquidity. Moreover, idiosyncratic volatility failed to accurately forecast the risk (standard deviation or variance based) that provided a good forecast of one-month return. This supports not only the superiority of ARCH based models over models that assume equally weighted average of past squared residuals, but also the presence of time varying volatility in futures prices time series.

The last section of the study involved a stability and events analysis, using recursive estimation methods. The trading determinant model, mean equation model , return and risk model, trading activity model and volatility models were all found to be stable following the effect of major global economic events of the 1990s[2]. Models with risk being proxied as standard deviation showed more structural breaks than where variance was used. Overall, major macroeconomic events didn't have any significant effect upon the large hedgers' and speculators' behaviour and performance over the last decade.

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[1] (GARCH normal) refers to the GARCH volatility model assuming a normal distribution. (GARCH *t*) refers to the GARCH model under a *t* distribution. (PARCH normal) refers to a PARCH volatility model under a normal distribution, and (PARCH *t*) refers to a PARCH model under a *t* distribution.

[2] Events analysed in this study were the US tightening interest rates after a long period of easing in 1994-1995, the Mexico crisis in 1994, the Asian Crisis in 1997-1998, the emerging markets slump and recovery in 1995-1996, the temporary revival from Japanese Recession in 1994-1996, the Russian crisis of 1998, Long Term Capital Management (LTCM) near financial collapse in 1998, and the introduction of the Euro currency in early 1999.

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Table of Contents *Page*

List of Tables

List of Graphs

List of Equations

Abbreviations and Acronyms

CUPSA	Curtin University Postgraduate Scholarship
ICBME	International Conference of Business, Management and Economics
BIS	Bank of International Settlements
CFTC	Commodity Futures Trading Commission
COT	Commitment of Traders
HDR	Higher Degree Research
US	United States
CEA	Commodity Exchange Act
SEA	Securities Exchange Act
CMFA	Commodity Modernization Futures Act
SPX	Share Price Index
FIA	Futures Industry Association
ARCH	Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
PARCH	Power Autoregressive Conditional Heteroscedasticity
RMSE	Root Mean Squared Error
CTO	Commodity Trading Operators
CTA	Commodity Trading Advisor
IMF	International Monetary Fund
IFC	International Finance Corporation
EMU	European Monetary Union
ECB	European Central Bank
OTC	Over the Counter
CBOT	Chicago Board of Trade
MMT	Money Market Traders
US	United States

Chapter 1
INTRODUCTION

"Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than mathematical expectations, whether moral or hedonistic or economic. Most probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as the result of animal spirits – a spontaneous urge rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities."
John Maynard Keynes (1883–1946) "The general theory of employment, interest and money" (1936, 161–162)

1.1 Background and Motivation for Study

Futures markets enable those who want to manage price risk (hedgers) to transfer that risk to those who are willing to accept it (speculators). Futures exchanges also provide price information as benchmarks in determining the value of a particular commodity or financial instrument on a given time and day. Benefits such as risk transfer and price discovery reach every sector where changing market conditions introduce economic risk, including areas like foreign exchange, imports and exports, financing, and agriculture (Pennings, 1998). Besides the benefits associated with risk reduction as important factors in motivating decisions to engage in futures trading, potential users are heavily influenced by their personal assessment of the performance and reliability of a futures market (Ennew et al., 1992). The biased assessment of the performance is essentially influenced by the information users have been exposed to about the hedging and speculation services of the futures contract. This is a consequence of the complex nature of the financial services provided by futures markets, which is also backed by regulation and macroeconomic events.

The trading game, like many other financial ventures, is biased in favour of the big money, the big traders, the money managers, the professionals, the commercials, the hedge funds, the mutual funds, the insiders and the politically connected. Whether legal or not, inside information is pervasive. Prosecutions or government policing will not stop this. It is a reality of the market. Recently, the Securities and Exchange Commission has taken a number of measures to slightly increase the odds for the public by making more information transparent. The SOES (Small Order Execution System), price decimalization and other measures have helped. However, in the futures industry, it seems that very little has been done to help the non-professional futures trader. Money rules, and the game is tilted decidedly in favour of the professional trader. For instance, the last few years have witnessed a mass entry of hedge funds into the commodity markets. Hedge funds control billions, if not trillions, of dollars. They trade big positions, collect large fees, and some of them even make big money for their clients. This is why, as a result of several well-known financial catastrophes, "herding[3]" has again become a critical term in the financial dictionary. Investors and fund managers are portrayed as herds that charge into risky ventures without adequate information and appreciation of the risk-reward trade-offs and, at the first sign of trouble, flee to safer directions. Some observers express concern that herding by market participants further increases volatility, destabilizes markets, and increases the fragility of the financial system.[4]

Recent financial research has laid emphasis on how individual trading behaviour relates to daily asset returns (for example, Goetzmann and Massa 2003). A remarkable factor behind this research is the prospective weight large players may have on the financial markets. In fact, several academic findings suggest that certain trading strategies can influence the returns and volatility of these markets. For instance, Grinblatt and Keloharju (2000) demonstrate that positive feedback behaviour is correlated with investor performance, and that both the behaviour and performance appear to be associated with the level of sophistication of the investor, i.e. foreign

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[3] One common form of herding is positive feedback trading.
[4] See, for example, Persaud (2000) for an analysis of how the interaction of herding and institutional risk management strategies may further increase volatility; and Council on Foreign Relations (1999) for the role hedge funds may have played in the Asian crisis.

investors like investment banking houses pursue positive feedback strategies and achieve superior performance. Conversely, Odean (1998) finds that the investors at a US discount brokerage house are unwilling to realise losses, and presents evidence which is consistent with contrarian behaviour. This motivates a need to investigate how positive feedback and contrarian behaviour relates to the trading determinants of the large and most influential players in the US futures markets, i.e, large hedgers and large speculators as defined by the CFTC.

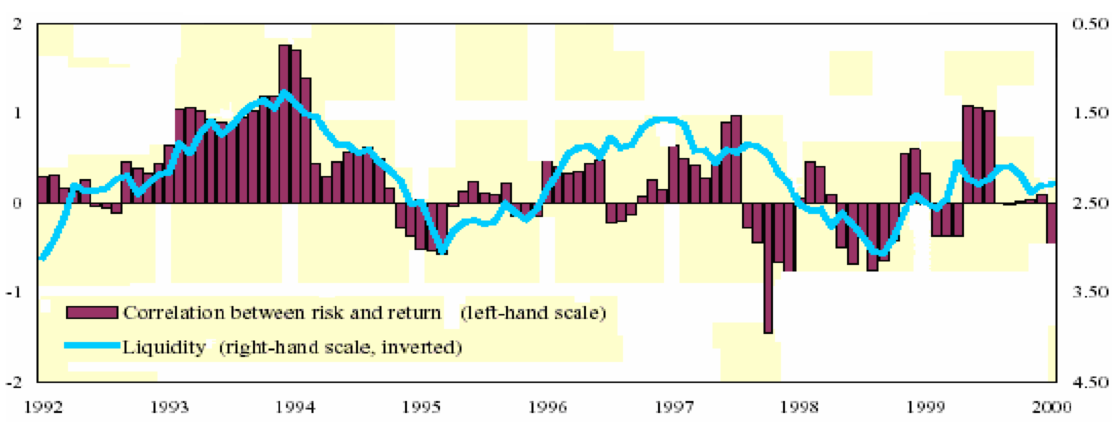
Significant research has also discussed whether speculation is beneficial or harmful[5]. Legislatures shared a negative view about speculators well into the twentieth century with both the Securities Exchange Act (SEA) of 1934 and the Commodity Exchange Act (CEA) of 1936 being passed largely to tackle the perceived problems of "excessive" speculation in corporate stocks and in commodities futures and options. More recently, the idea that speculation is harmful has lost favour. The conservative economic understanding now is that speculation, whether in derivatives or equities, is reasonably efficient because it transfers risk to those who can bear it most easily and facilitates market prices to better reflect underlying forces of supply and demand. However, the CEA still imposes margin requirements, position limits, short sales restrictions, capital gains rules, and other technical regulations that have both the purpose and the effect of discouraging speculative trading[6]. On the other hand, large hedgers are left mostly unregulated once they pass the test of being defined as commercials through the CEA[7]. Recent findings from Haigh et al. (2005) and NYMEX (2005) both find significant effect of rebalancing activities of large hedgers upon returns volatility. Lukken (2006) also find that when hedgers readjust their current positions to optimise their net positions, they significantly influence the market as well as influencing the volatility of returns. Alternatively stated, on one hand there are regulatory bodies imposing strict control on speculators, while on the other hand, hedgers who can

[5] See Chapter 2, section 2.5 for more insights on their effects on markets.
[6] See Stout (1999) for more on regulation imposed on speculators. Furthermore, exchanges are required by CFTC rule 150.5 to adopt speculative limit rules for certain other contracts not subject to CFTC speculative limits.
[7] The CMFA even allows Bona Fide Exemptions to encourage agricultural hedging positions (section 121 of the Act).

influence significantly markets are left wandering. This motivates further study where the issue of whether speculation or hedging is beneficial or destabilizing. The plan is to investigate whether large hedgers and/or large speculators have some destabilizing effect on the futures markets, by moving prices away from their fundamental values. This is important, as stated above, current legislation support that speculators are destabilizers, and hence the presence of position limits upon their trading and not hedgers'. Simultaneous positive feedback behaviour and market timing ability tests would allow to check whether these influential players are market destabilizers.

Investors' perceptions about risk also change with time, as shown in Graph 1.1. This graph shows investors' attitude towards risk and liquidity in the 1990s. While the correlation between risk and return (left-hand scale of graph) is measured by the slope coefficient of a cross-sectional regression of realized returns on historical volatility for a number of asset classes, liquidity is obtained as a GDP-weighted average of overnight real rates in the eurocurrency market for the US dollar, yen, euro and sterling. A rise in the coefficient indicates greater tolerance for risk; a decline indicates more risk aversion. Interestingly, the bond market turmoil during 1994 and the Asian crisis in mid-1997 interrupted extended periods of a relaxed market attitude towards risk. Also, the market strains following the Russian default and the near-collapse of LTCM took place against a background of a prolonged period captured by a cautious investor attitude.

Graph 1.1
Investors' attitude towards risk and liquidity



Sources: Datastream; national data; BIS (2000) estimates.

Further, as defined by the Basel Committee (2001), the control of risk by management[8] is the fourth and final most important part of the risk management process. While the benefits of risk dispersion are attainable without holding massive positions in the underlying financial instruments, too often in a monetarily plaid past the access to such leverage has motivated speculative excesses that have led to financial spasm. Moreover, while it is unlikely to reform the underlying human behaviour that lead to excess, there is a need to reinforce risk-management capabilities to restrict such detours from the road to balanced growth. Alternatively stated, in line with Daniel, Hirshleifer and Subrahmanyam (1998), it is believed that a good finance theory is to be grounded on evidence about how people actually behave and perform. That is why the understanding of risk and return becomes highly critical in understanding behaviour and performance of any rational player. This leads to the third motivation which looks at the "return and risk" relationship under different volatility models such as standard deviation, variance, and idiosyncratic volatility. By decomposing priced risk variables like three months treasury bill rates, dividend yield, corporate yield spread into expected and unexpected values, the plan is also to investigate how much of these expected values help in determining return and volatility. This is important to test whether large hedgers and/or large speculators are better informed by making use of more expected values than unexpected values in determining their risk and return.

The changing nature of the 'risk and return' relationship (see graph 1.1) in the 1990s introduces the fourth motivation factor of this study, where an event analysis is undertaken. More specifically, as mentioned earlier, major economic events like the Russian and Asian crisis seemed to have led to changing risk attitudes. In an attempt to bring all the motivations in line, the last part of this study investigate the effect of eight major economic events over the trading determinant, risk and return relationship model, and, trading activity and volatility relationship of large hedgers and speculators in the US

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[8] Management can be generalized to investors, firms and government bodies, where each of these are concerned about the policy implications of this study.

futures markets. This is important in that it helps in understanding if such players are, if at all, affected by major economic events.

In sum, existing research has mostly analysed the behaviour and performance of institutional investors in equity markets[9], especially mutual funds. Yet not much is known about the behaviour of futures traders, and more specifically large hedgers and large speculators in futures markets. The scope of this study extends from analysing the behaviour of large speculators and large hedgers, to the performance of these key market players, by looking at volatility and forecasting models, and the risk and return relationship over ten-years window events in the 1990s for large hedgers and large speculators. What makes this research really challenging and significant is the usage of the Commitment of Traders data. This research reduces the gap in further understanding the largest players' trading determinants, effect of hedgers and speculators' trading over markets and regulation, risk and return attitudes, and their changing reactions over major economic events. This study is supported by the use of market risk factors, regulatory issues, and event analysis in the US Futures markets in the 1990s.

Why US Futures markets?

The US Futures market is studied for various reasons, such as its history, the industry's growth, sector growth and uniqueness of its data. For example, the US is still a significant part of the global activity in terms of interest rate, currency and equity index futures markets, as can be seen in Graph 1.2.1. Panel A clearly shows that the interest rate futures markets are the most actively traded futures instruments globally. More importantly, the US had highest market share (55–57%) in terms of locations of interest rate, currency and equity index contracts still outstanding. European markets rank second with 29–32% of market share. Panel B further supports the US as a leader in futures markets, where interest rates, currency and equity index futures contracts have the highest market share over the 2003–2006 period. Graph 1.2 in Appendix 6.3 shows that US was

[9] See Chapter 2 for a detailed literature review on behaviour and performance in equity markets.

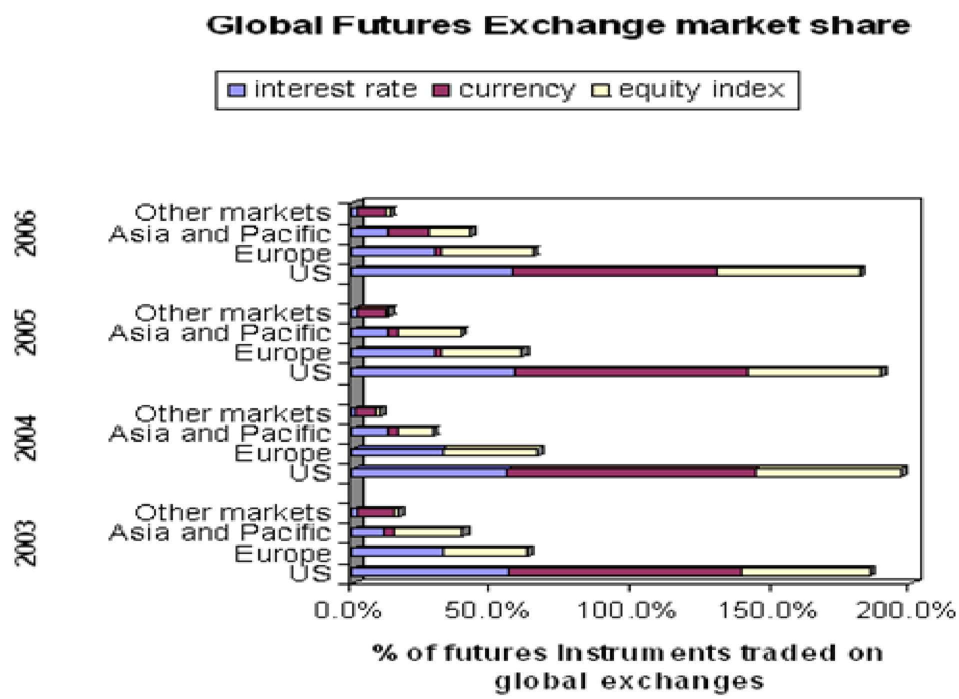
still leading in terms of futures contracts traded in the 1990s. Table 1.1 below also shows that US Futures derivatives have been among the top international futures contracts and also that US Futures Exchanges have been leaders on a global basis.

Graph 1.2.1
Futures instruments traded on global exchanges by location (notional principal in US billions)

Panel A

	Amount outstanding (in billions of US dollars)			
Instrument/location	2003	2004	2005	2006
All markets	13752	18903	21619	25824
Interest rate	13123	18164	20708	24699
Currency	79	103	107	140
Equity index	549	635	802	986
US	56%	55%	57%	57%
Europe	32%	32%	29%	29%
Asia and Pacific	11%	12%	12%	13%
Other markets	1%	1%	1%	1%

Panel B



Source : BIS

Table 1.1
Top international contracts (volume) and Top 5 exchanges (volume)

Top International Contracts*

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
U.S. T-bonds (CBOT)	84	99	112	90	78	71	69	63	72	86
3-Month Eurodollar (CME)	88	99	109	93	129	184	202	208	297	410
Euro-Bund (Eurex)	77	112	248	378	178	191	244	239	299	173

Top Five Exchanges

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
CBOT, USA	222	242	281	254	189	201	276	373	489	561
LIFFE, UK	170	209	194	105	135	160	238	311	343	101
CME, USA	177	200	226	200	195	222	444	530	684	883
BM&F, Brazil	134	122	87	63	80	95	113	173	187	132
Eurex**	77	112	248	378	289	312	536	668	684	784

* FIA volume figures include futures, options on futures, and options on stock indexes (no individual stock exchanges. options are included), interest rate, and currencies traded on the world's futures, options, and securities exchanges

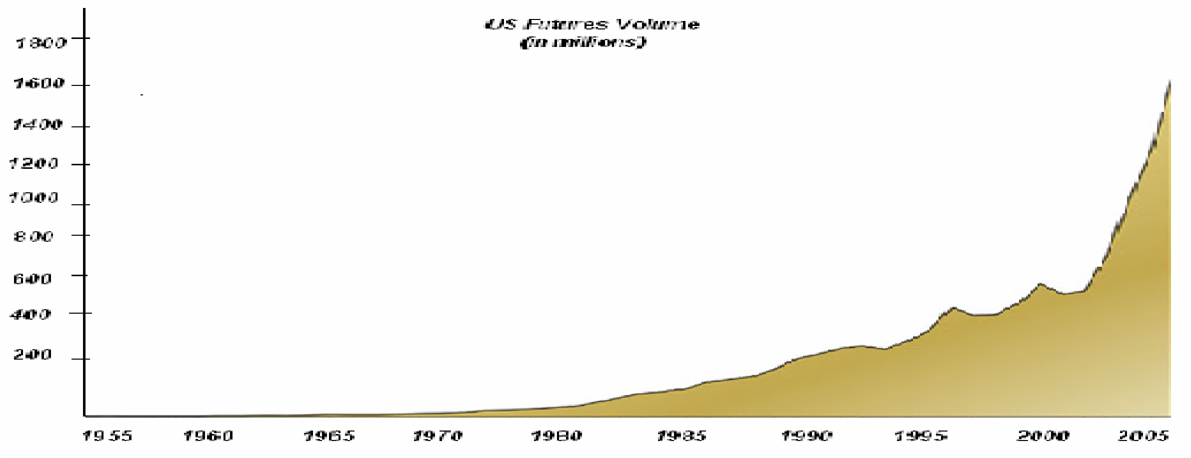
** Before 1998, it was DTB & SOFFEX combined

Source: FIA

Why the 1990s set as the data frame?

1990–2000 has been chosen as the timeframe for study, as this is the decade that provided the most swings in the US Futures market (1955—2005). This can be observed in Graph 1.3, which shows that, in 2005, US futures volume peaked at 1652 millions. The opportunity of studying the '1990-2000' period is supported from the graph, where it can be seen there were ups and downs in the total number of US futures trading volume, compared to the rest of the 2000-2005. This is also supported by the fact that, most of the largest US futures markets have also witnessed an increase in activity during the 1990–2000 timeframe (see Appendix 6.2 and 6.3). Interest rate derivatives have been the most actively traded contracts. The US Treasury bond and the Eurodollar are the top two international most traded contracts globally. US futures markets are also chosen as trading in them is more important for price discovery and release of information (Dhillon, Lasser, and Watanabe, 1997). More importantly, they are the only provider of the unique Commitment of Traders (COT) data about speculators and hedgers. The 1990s is set as the timeframe due to its events and excellent US performance (economic and regulatory), making it a good framework and a benchmark for pursuing this research[10].

Graph 1.3 US Futures Volume (in millions)
(1955-2005)



Source: FIA

1.2 Contribution to Literature:

This study contributes to the literature in that it provides evidence on the behaviour and performance of major types of traders in 29 commodities futures using CFTC's COT data. A unique specification of the COT database is that it gives a nice defragmentation of futures positions by key market players—hedgers and speculators[11].

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[10] See Chapter 2, section 2.17.1 for more details on the success of the 1990s.

[11] ***Commercial and Non-commercial Traders***: When reporting to the Commission, an individual trader is classified either as "commercial" or "non-commercial." Reported futures positions are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined in the Commission's regulations (1.3(z)). A trading organisation gets classified as a "commercial" by filing a statement with the Commission (on CFTC Form 40) that it is commercially "...engaged in business activities hedged by the use of the futures or option markets." To ensure accuracy and consistency, the Commission may exercise judgment in re-classifying a trader if it has more information about the trader's use of the markets. See Appendix 6.8.2 for information regarding classification among different entities.

That is done on the basis of whether a reportable position[12] is taken primarily for hedging purposes as defined by the CFTC regulations.

Two critical parts are focussed on in this study. The first one relates to behaviour, and more specifically is concerned with the relation between net futures position by traders' type, futures returns, market sentiment and information risk variables. Contrarians and positive feedbacks behaviour for each trader type are analysed. In fact, by including priced risk factors (information variables) they help in understanding whether they do influence hedgers/speculators in their positive feedback or contrarian behaviour. Similarly, the inclusion of a sentiment index reveals whether large players do use sentiment in determining monthly decisions. Most importantly, the usage of net positions shows its importance compared with well-used variables like volume and open interest. Hedging pressure effect tests are carried out to determine to existence of the transfer of risk from hedgers to speculators. Cross-hedging pressure effect tests help in reducing the scarce evidence of whether other futures contracts' hedging pressures might affect one particular futures contract. Further, by looking simultaneously at the behaviour (trading determinant) and possession of superior information (market timing ability) of large players, this study is the first one enlightening if large hedgers and speculators do destabilize futures prices. For instance, evidence of feedback trading does not entail market destabilization if these traders incorporate fundamental information into prices. Positive feedback trading together with negative market timing ability of a trader type suggest that the trader type tends to push away futures prices from their fundamental value, and thus destabilizes the market (Lakonishkok et al., 1992). This section of the study helps to shed further light in the area of policy implications, in helping regulatory bodies like CFTC to decide whether speculators/hedgers should have more tightened limit positions imposed to avoid disturbance in market flow.

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[12] See Appendix 6.8.1 for more information on reportable positions.

The second critical part of this study relates to performance. The main contributions cover the decomposed mean (return) model, volatility models, forecasting and a stability based event analysis. Firstly, the decomposition into expected and unexpected components of variables like net positions, sentiment, and priced risk factors helps to better understand how decomposed variables significantly affect the futures actual mean return. Essentially, the decomposition of variables into expected and unexpected components is to ensure the expected component (conditional mean of individual series) contain enough terms to make it still significant and reliable, while the unexpected component measures the residual on differences of the series from its mean. More significant expected components help in suggesting that large hedgers or large speculators are well informed players in using specific expected variables to affect their return at the start of the trading month. Besides, this is the first study including a lagged hedging pressure variable in the mean equation, which adds value whether the existence of risk premium or non-marketable risk is significant after taking into account priced risk factors like market dividend yield and three months Treasury bill yield. The regression of decomposed variables against idiosyncratic volatility is also carried out and helps in knowing how significant expected and unexpected components of variables contribute to idiosyncratic volatility. Idiosyncratic volatility, itself, is also decomposed into expected volatility and unexpected volatility to aid in knowing whether speculators' volatility (risk) is higher than hedgers'. The reason behind decomposing idiosyncratic volatility into expected volatility and unexpected volatility is to know how much of this volatility measure is determined by expected volatility (at the start of the trading month) and how much is determined by unexpected values of volatility (durig the rest of the trading month). It would be expected that hedgers' expected volatility would be less than speculators' expected and unexpected volatility since hedgers are in the market to reduce risk, and hence have an expected volatility (set at the start of the month) which is less than speculators'. Speculators' expected volatility and unexpected volatility (during the rest of the month) would be expected to be higher in affecting total volatility, in that speculators are in the market to bear more risk and also more induced to change their risk levels all during the trading month.

The return/ risk relationship is also the first to be tested with actual return being regressed against expected and unexpected volatility. This helps to gain a better understanding in how significant expected risk and unexpected risk explain hedgers' and speculators' futures return. As laid out by the literature on portfolio theory, higher risk is compensated with higher return, and speculators normally bear more risk. The relationship between "expected risk" and return for specific players in a specific market can provide an important foundation for futures trading models, in that, it provides an assumption that expected risk can be used as a proxy measure of risk in determining futures returns. For example, a lower value of expected risk in a market where hedgers are non-predominant can be explained by their lower expectancy of a higher return. Hence, the lower the risk, the lower the return, as supported by portfolio theory.

Further, this study integrates the use of GARCH/PARCH volatility models, which help not only to support the existing usage of these conditional variance models. The issue of why this study uses GARCH and PARCH volatility models is supported chiefly because one is standard deviation based and the other one is variance based. It is of interest to know whether standard deviation or variance provides a better proxy of risk for each player in determining actual returns. For instance, Davidian and Carroll (1987) argue that standard deviation specifications are more robust than variance specifications. Evidence is rare for models containing information variables, sentiment index, hedging pressures and net positions. The performance evaluation of GARCH and PARCH models, under both normal and *t* distribution, is a first one in explaining whether the conditional variance or standard deviation-based volatility model better explain the actual futures return. The decomposition of forecast errors into mean, variance and covariance proportions tells us how far the mean return of our model is from the mean of the actual series, how far the variation of the volatility model is from the variation of the actual series, and the remaining unsystematic errors from the volatility model. The use of different error distribution assumption such as normal and *t* is also the first one to check whether hedgers' and speculators' return follow a normal distribution. Due to the PARCH model being based on standard deviation rather than variance, it is expected the PARCH model to exhibit more skewness due to more outliers. A PARCH model, under a *t* distribution, would be expected to exhibit less skewness since the *t* distribution would lead to smaller conditional errors as explained in Bollerslev (1987). Further, by checking skewness and kurtosis measures, this study is the first to look at whether hedgers' probability functions would have a lower (flatter) kurtosis in more futures markets than speculators, due to hedgers entering the market to reduce risk and speculators entering the market to bear that risk.

The section on forecasting (static) reveals whether the GARCH and PARCH based volatility can accurately help in forecasting one-month futures return. Supporters of superior forecasting ability from large traders are Chang (1985) and Leuthold, Garcia, and Lu (1994).[13] This is also the first study to compare GARCH and PARCH model specifications under both normal and t distribution. Further, this study checks for the suitability of idiosyncratic volatility as a good proxy of risk, by testing whether idiosyncratic volatility can match the volatility measure (standard deviation or variance) that accurately forecasted one-month futures return.

The last section of this study, which relates to a stability and event study, brings a further contribution since it is the first to look at the stability of the trading determinant model, the mean return model, the risk and return relationship model, and the trading activity and volatility relationship model of hedgers and speculators over eight specific macroeconomic events in the 1990s. Briefly, the trading determinant model is important in that it relates to the behaviour of hedgers and speculators in how they would change their net positions for next month, based on today's returns, sentiment, and priced risk factors like treasury bill rates, corporate yield spread and dividend yield. The mean return model, in turn, examines the effect of net positions, sentiment, information variables have on existing futures return, after adjusting for stationarity and misspecification of variables. This model, while basic, is essential to see how these variables are related to return in a specific month period on average. The risk and return

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[13] Chang (1985) finds superior forecasting ability of large traders in the wheat contract for the 1951–1980 interval, and Leuthold, Garcia, and Lu (1994) demonstrate that elite traders earn significant net dollar returns in the frozen pork bellies market.

relationship model investigates the relationship between return and risk, where risk is proxied as standard deviation and variance. The trading activity and volatility model investigates the relationship between net positions and risk, where risk is proxied as standard deviation and variance. All these four models are of interest, in that they essentially form important models underlying the motivations of this study. They are robust tested to see whether they are still stable after accounting for major global events over the US futures markets. Alternatively stated, the use of recursive estimates also tests for the robustness of these models over the long run. For instance, it is possible to see whether hedgers or speculators continue to exhibit significant positive feedback or contrarian behaviour over the whole ten years. Similarly, the risk and return relationship of hedgers and speculators can be tested if stable over the last decade. More importantly, recursive estimates of independent variables in each of the models over the ten-year period help to find any significant structural break which matches a major macroeconomic event listed in this study. This helps in knowing whether hedgers/speculators significantly change their net positions during major events, whether their returns are affected during major events, and whether their attitude to risk changes during major events of the 1990s (May 1990–Dec 2000)[14]. For instance, there was a decline in the foreign exchange and commodity contract (by 4% and 8%), much of which can be attributed to the financial turbulence that followed the Russian debt moratorium and near collapse of the Long Term Capital Management (LTCM) (BIS, 1998). Similarly, the commodity and equity-linked segments expanded the most rapidly of all underlying risk categories, with increases of 20% and 24% (to \$1.8trn and \$0.5trn). This followed the aftermath of the introduction of the Euro earlier in the year (BIS, Dec 1999). Events looked at are: effect of US Federal Reserve tightening up interest rates for a duration of 20 months after a long time of easing; effect of Mexico crisis; effect of Emerging Markets slump and rebound; effect of temporary revival of Japanese recession in the mid-1990s; effect of Asian crisis; effect of LTCM near default & Russian crisis; and the introduction of the Euro currency. Finally, but not least, the relationship between trading activity and volatility for hedgers and speculators is tested in this study over a

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[14] So far, in previous literature, there is no underlying model or theory that suggest hedgers or speculators net positions or returns should change following an announcement or event.

ten-year period for the first time, where volatility is both proxied as standard deviation and variance.

These are the direct contributions to the existing literature and regulatory bodies. The non-availability of CFTC COT data in all the 29 futures markets before made such an analysis an impossible one. With the defragmentation of the market into hedgers/speculators, this study is also a guide to small traders (who form the residual of the futures market) to be able to know how the influential players (large hedgers and/or large speculators) change their monthly net positions for next month based on current returns, which players bear more or less risk in specific markets, and how they are affected after specific major economic events.

1.3 Organisation of the study

This study is organized into five main chapters as follows:

Chapter 1:
This chapter starts by giving a brief layout of the benefits of futures markets, followed by the ever-changing risk and return relationship of investors during the 1990s due to events. The reasons behind choosing the US Futures markets are then explained, in relation to the top five globally traded futures contracts and futures exchanges leaders. The reasons of setting the data sample to be the 1990s are further explained with some history of futures markets in the US over the 1955-2005 periods. Finally, the contributions of this study are laid out.

Chapter 2:
The existing literature is reviewed in this chapter, by starting with the notion of zero-sum game in the futures market. Previous research about investor sentiment and information variables are covered. Then, all the theoretical backgrounds about contrarian/ positive

feedback behaviour, volatility, forecasting, and a detailed synopsis of each event to be analysed are laid out.

Chapter 3:

The data and research methodology used are presented in this chapter. Efforts have been made to clarify the role of the CFTC in the US Futures markets, and its unique data, the COT. This chapter discusses the research objectives of this study. For consistency and ease of readability, a data classification and coding page, together with some flowcharts are presented in this chapter.

Chapter 4:

All empirical evidence from this study are provided in this chapter. The analysis is first made up of time series properties like stationarity, followed by the behaviour and performance sections. The behaviour section looks at contrarian/ positive feedback behaviour of hedgers/speculators, followed by market timing and hedging pressure effects tests. The performance sections initially deal with GARCH/PARCH/idiosyncratic volatility models, and then proceed to forecasting, stability and event analysis. The emphasis is on the trading determinant model, mean return model, risk and return relationship of hedgers/ speculators over the sample period. Finally, the relationship between trading activity and volatility is looked at.

Chapter 5:

This final chapter concludes this study, by giving a summary of findings, policy implications and practical significance, and some notes about generalization of results. The limitations of this study are discussed with directions for future research. Some concluding remarks end the chapter.

Chapter 2
LITERATURE REVIEW

2.1 Introduction

This chapter starts by giving us an understanding that futures trading is a zero-sum game and that investor behaviour differs. Both mainstream hedging and speculation theories are looked at, before giving an insight about large speculators and large hedgers in futures markets. Issues relating to regulation are laid out, with particular emphasis on speculative position limits imposed in futures markets. Further, investor sentiment, information variables, assumption for excluding volume, and implication of changing horizon are discussed since they form critical components of this study.

Once the literature reviews on these important areas are looked at, this chapter then considers all behaviour models that are specifically being tested. Models based on contrarian behaviour, positive feedback behaviour and hedging pressure effects are laid out, with particular emphasis on short run/long run perspectives of hedgers/speculators and robustness of each model. Models based on the performance section of the study are then discussed. In particular, volatility models such as GARCH and PARCH are discussed with relation to the symmetry assumption, forecasting, policy implications and error distributions under each model. The final part of the chapter relates to events analysis, where the success of the 1990s in the US are first looked at, before looking at each event in detail.

2.2 The Zero-sum game

Above all, one must contemplate that futures trading, unlike stock trading, is a *zero-sum game*. This means that capital changes hands, for every $1 won by one trader there is exactly $1 lost by another trader. If one wants to buy a futures contract, someone else has to be willing to sell it to the person and take the offsetting position. Therefore, at any given time, the number of long futures contracts exactly equals the number of short futures contracts. That's very different from the equity world, where essentially everyone can win or lose at once and winning does not require an opposite trader to realize an identical loss. Eventually, if one is not a superior trader to the traders on the opposite end of his futures trades, he will lose. Unlike stocks, futures don't create or destroy wealth, but rather shuffle it around speculators and hedgers mainly[15] (Harris, 1993). Alternatively stated, this study is challenging in that it relates specifically to distribution of contracts among hedgers and speculators.

2.3 Investors and Behaviour

Common views are investors trade to rebalance portfolios (for risk sharing or liquidity requirements) and speculate on private information (Llorente et al., 2001). Systematic irrational responses to sentiments and fads from investors are also present (Shiller, 1984; De Long et al., 1990). More critical is that different trading motives predict different performance across investor types. If for hedging purposes, asset prices must decrease (increase) to attract speculators to buy (sell) (Merton, 1987; Llorente et al., 2001). If for speculative purposes, the investor will buy (sell) the asset, reflecting the positive (negative) private information about the asset's future payoff and the eventual price will rise (fall) (Llorente et al., 2001). Furthermore, when a trader underreacts (overreacts) to news, the consequential asset prices reveal momentum (reversals) (Hong and Stein, 1999). Although various empirical tests have been performed on equity investor behaviour and performance, evidence about the behaviour and performance of the largest hedgers and speculators in major futures market is rare.

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[15] http://www-rcf.usc.edu/~lharris/ACROBAT/Zerosum.pdf

2.4 Hedging Revisited

Theories regarding futures price behavior or price information have been well reviewed by Carter (1999) and Leuthold and Pennings (2000). Of particular interest to our study is the price insurance, earnings returns, and liquidity theories.

2.4.1 Price Insurance Theory

While Hoffman (1932) states that hedging is shifting risk, Smith (1922) says that hedging enables hedgers to insure against the risk of price fluctuations. Previously, Marshall (1919) disseminates this view by stating that the hedger does not speculate, but, he insures. Hicks (1939) and Kaldor (1939) discuss hedging in terms of risk avoidance and insurance. In this line of thought, any loss made by the hedger on the transaction represents an insurance premium paid to the risk taking speculator. Prior to 1940's, this price risk motivation argument was the theoretical reason of why firms used futures exchanges, or as Blau (1944) statement that commodity futures exchanges are market organisations specially developed for facilitating the shifting of risks due to unknown future changes in commodity prices; i.e, risks which are of such a nature that they cannot be covered by means of ordinary insurance…".

2.4.2 Earnings Returns Theory

Working (1953) challenges the idea of risk insurance by stating that hedging is the pursuit of profit through the exploitation of (expected) changes in the basis, that is, the exploitation of opportunities for profit presented by the prospective movement of prices in the futures market relative to the movement in the cash market. In this view, hedging is primarily a sort of *arbitrage*, to be engaged in only when the hedger perceives a promising opportunity for profit.[16] Later, Working renounces his earlier position when

[16] In the view of Working (1953), hedging in futures consists of making a standard contract to buy or sell, established and controlled by a commodity exchange, as a temporary substitute for an intended later contract to buy or sell on other terms. Working (1962) differentiates between several categories of hedging:

he assertes that (short) hedgers tend to lose money to speculators and they do so even in times where futures prices have fallen. The explanation is the "dips" or "bulges" that tend to occur when hedgers sell or buy futures contracts. Hence, Working's hedgers have to pay a price to speculators, i.e., they incur execution costs for the prompt carrying out of their sale or purchase transaction. This explanation links back to the price insurance theory: the reason for hedgers to have their orders executed expeditiously is to reduce the interval in which their inventories are left uncovered, exposed to the risk of price change. The adoption of the portfolio theory approach in the 1960's to decisions in futures markets rehabilitated the risk reduction notion in hedging theory.

2.4.3 Liquidity Theory

Telser (1981) argues that organized futures markets exist because they are superior to informal forward markets. An organized futures market has well structured rules, standing committees for arbitrating disputes, and a limited membership. In contrast to futures contracts, forward contracts rely on the good reliance of parties. Also, compared to standardized futures contracts, a typical forward contract crops up after ample negotiations between the individual parties. Therefore, they cannot be offset by identical contracts, and there is no scope for the advantages of clearinghouses and settlement by the payment difference. Through their rules and standardization, futures provide liquidity and eliminate counter-party risk. Telser (1981) states that an organized market *facilitates* trade among strangers. Also in Telser's view the use of futures exchanges helps to reduce risk, but he also acknowledges that there are other 'risk-reducing' instruments available to the firm. Telser argues that even if one accepts the price insurance theory, it does not explain why an organized futures market is necessary in order to accommodate hedging. Telser argues that a merchant who wishes to avoid the price risks of holding inventories can do so without an organized futures market, namely by entering into forward transactions in the cash market. In this view the motivation to

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carrying charge hedging, operational hedging, selective hedging, anticipatory hedging and pure risk avoidance hedging.

use futures contracts is not essentially driven by the firm's want to reduce risk, but by the institutional characteristics of the futures exchange itself like regulation ensuring liquidity.

2.5 Speculation revisited

A study from CBOT in 1983 revealed an increasing relationship between the number of years a speculator had traded and his transaction volume during a particular quarter; 51% of traders with ten or more transactions in the quarter studied had more than five years trading experience. However, Peck (1981) arrives at the alarming conclusion that in spite of the tremendous overall growth in commodity markets, speculation has in fact declined significantly on the three largest agricultural futures markets over a fifteen year period. Peck's work calls for us to learn more about the speculator's motivations in order to effectively assess their continuing role in the markets. In spite of their large share in market volume, the profile and motivation of the habitual speculator are not well understood. On the one hand, the traditional regulatory literature views the public futures trader as unsophisticated, uninformed and undercapitalized (Draper, 1985); such a profile is used to justify calls for strict regulation. On the other hand, most economic theory models the speculator's behavior as rational (i.e., they are assumed to be risk averse, profit-motivated investors) (Baker et al., 1977). Canoles et al. (1998) findings contradict both these profiles: one the one hand, their sample appears to be financially sophisticated, well-educated, and well-capitalized; on the other, their sample does not appear to be especially risk averse, and is probably not trading solely for profit.

Over the past five decades much more research attention has been directed toward the returns of speculators than towards their behaviour and motivation. A series of studies since the 1940's has yielded a consistent picture of speculative account performance. Beginning with Stewart's (1949) pioneering study and continuing through Hartzmark's (1991) article, four general conclusions have come into view: 1) when transaction costs are included, total net losses substantially exceed total net gains; 2) the average trade loss consistently exceeds the average trade profit; 3) there are a significant number of one time (or near one time) traders. (Hieronymus (1971) finds that 37% of all accounts surveyed are one time traders); 4) losses are constantly allowed to run while profits are cashed out. Ross (1975) finds that losing positions are held on average twice as long as winning positions.

2.5.1 Recreational utility of speculators

A number of earlier studies have suggested aspects of recreational utility in speculators' behaviour. Rockwell (1967) notes that speculators do not require an ex post history of profits in order to continue trading. He explains that speculators are possibly are risk seekers and are consequently willing to lose money for the privilege of speculating. Smidt (1965) discovers that 45% of respondents who indicated they thought of themselves as being unsuccessful traders were not ready to change their trading approach. Further, only 12% of all respondents indicate they would stop trading due to losses. Smidt concludes that these unusual findings suggest non profit-seeking economic behaviour. Draper (1985), in noting that 41.5% of commodity speculators in a Barron's Magazine survey said they were "seeking excitement," suggests that in addition to the investment aspects of futures markets, there are also significant consumption features. These propositions of recreational consumption are also proponed by psychologists studying habitual gamblers. For instance, Hyde (1978) argues that for the habitual gambler, gambling is an "end" rather than a "means to an end." The pleasure of betting or risk taking and the sense of being chief in the action are more critical than the winning or losing of money. Research by psychologists has found many clinically defined gamblers to be trading in the financial markets. In general, Murrell (1979) contends they can be divided into three categories: 1) profit motivated, 2) obsessive, or 3) leisure consumers, with the vast majority falling into the "leisure consumption" category. Murrell's categories might be used to classify habitual speculators as well.

2.6 Large hedgers and speculators: an insight

There is powerful support in early literature for the assumption that hedgers are less well-informed about market expectations than speculators[17]. Large speculators have been the most profitable group of traders in the 1980s and 1990s according to Chatrath et al., 1997). Also, large numbers of speculators will enter the market any time there is a risk premium, so that the futures price must equal the expected future spot price, if the costs of storage are ignored.[18] It also happens, as shown by Chang (1985) and by Leuthold, Garcia, and Lu (1994), that some large traders, particularly in some commodities in the United States, are as well informed as speculators.[19]

The effects of speculation in futures markets have been the topic of a long-lasting debate. It is argued that speculation has a number of desirable features (Kawaller et al., 1990). Briefly, they can be summarized as (a) by buying low and selling high, speculators stabilize prices and (b) by making future economic expectations, speculators smooth the time-series behaviour of the long-run equilibrium of the economy. In contrast, Hart (1977) shows that a sophisticated speculator could make money by exploiting the naive forecasting rules of less sophisticated agents and thereby destabilizing the future price. Also, Bessembinder (1992) finds that hedging activity has only minor effects on the pricing of Eurodollar futures contracts. Other critics suggest that large speculators have distorted commodity prices, so that the "commodity futures markets no longer accurately reflect the economic realities of supply and demand" (Taylor and Behrmann, 1994)[20]. Newbery (1987) also points out that a producer with

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[17] In regards to hedgers, Hawtrey (1940) says that "… they regard the making of price as a whole time occupation for experts, and, in general, will not pit their fragmentary information against the systematic study at the disposal of the professional dealers…" See also Johnson (1960).

[18] Hartzmark (1987) suggests that these traders may be risk lovers, or may simply enjoy dealing in futures markets.

[19] However, Chang et al. (2000) show the increased use of S&P 500 futures contracts by large hedgers over the sample period. The increased importance of hedgers in the stock index futures market may be due to the increased investment in mutual and pension funds over the same period, the increased supply of customized over-the-counter financial products or to an increased understanding and acceptance of futures contracts as a financial instrument.

[20] Note that Dalvi et al. (1997) find that speculation declined significantly in all three speculative measures in two of the three currency markets (Japanese yen and Swiss francs), in two of three financial markets (the S&P 500 and municipal bonds), and in heating oil #2. Furthermore, speculation declined or remained unchanged in at least two of the three speculative measures in eleven of the remaining commodity markets. These declines occurred in agricultural (oats, soybeans, and wheat), financials (NYSE Stock Exchange

market power may, even under rational expectations, advantageously destabilize the cash market through speculation (Kocagil, 1997). Alternatively stated, an increase in well-informed speculative trade has two opposite effects on measured volatility. It increases volatility due to new fundamental information since the information is impounded into prices more quickly and decreases volatility due to order flow imbalances caused by uninformed traders because informed traders provide liquidity in such events (Harris, 1989).

2.7 Investors, market and liquidity

It is important to note that while the market as whole may be operating efficiently, significant subsets ,i.e, individuals in that market may not. Beaver has argued:

"…it is important to distinguish between securities market and individual investors, because the role of information can vastly be different in each context. To a certain extent, the distinction is artificial, in that aggregate actions of individuals determine market behaviour. However, the process of aggregation is often deceptive, and if we fail to make the distinction, we may be subject to any one of a number of fallacies of composition…" (Winsen, 1976). Furthermore, (Caginalp and Laurent, 1998) find traders are reacting to expectations involving strategies and resources of other participants. In a similar fashion, uninformed traders over react to another's trades, thereby exaggerating price movements (Daigler and Wiley, 1999).

Moreover, although futures markets are highly liquid compared to commodity spot markets, the failure of investors to take advantage of commodity futures as investments indicates that there remain effective barriers (Hirshleifer, 1988). For instance, few non-commercials (speculators) investors take positions in commodities markets (futures, forwards, spots), which suggest that there exist barriers to participation,

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Composite Index and Eurodollars), livestock (live hogs and live cattle), and in the coffee, crude oil, and platinum markets.

possibly arising from fixed set up costs required to learn about these markets, or alternatively because of taking small positions (as with minimum contract sizes)[21]. On the other hand, Chang (1985) and Marcus (1984), find commodity futures prices changes are correlated with hedging positions taken previously by producers.

2.8 Speculative Position limits

Section 4a of the Commodity Exchange Act (CEA) provides limits on speculative trading on the premise that excessive speculation may lead to excessive price volatility. This section directs the Commodity Futures Trading Commission (CFTC) to set speculative position limits on futures. The CFTC directly sets limits on futures contracts and mandates the exchanges to adopt and enforce limits where the Commission has not established speculative position limits. For instance, (Dutt et al., 1997) provide justification for regulators to set tighter speculative position limits and exchanges to set higher margin requirements for inter-crop year spread positions relative to intra-crop-year spread positions. There are three basic elements to the regulatory framework for speculative position limits. They are:

(1) the size (or levels) of the limits themselves;

(2) the exemptions from the limits (for example, for hedge positions); and

(3) the policy on aggregating accounts for purposes of applying the limits[22]

2.9 Investor sentiment

Investor sentiment is studied in that it teaches us about biases in stock market forecasts of investors, and about the opportunities to earn extra returns by exploiting those biases. For instance, Bernstein and Prahuman (1994) find that the sentiment of

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[21] The set up costs may be interpreted as the time investment required to avoid being at a severe informational disadvantage in the commodity market. Therefore, it includes the effort required to understand the mechanism of trading, principles of futures pricing, and the complex factors influencing demand supply conditions (Hirshleifer, 1988).
[22] http://www.cftc.gov/opa/backgrounder/opaspeclmts.htm

Wall Strategists is a useful contrary indicator. Arthur Levitt, chair of the US Securities and Exchange Commission, warned day traders that they should trade only “with funds they afford to lose” (Wessel, 1999).

While sentiment levels of individual investors and strategists are reliable contrary indicators of future S&P500 returns (Fisher and Statman, 2000), Clarke and Statman (1998) find no statistically significant relationship between the level of sentiment of newsletter writers and DJIA or S&P500 returns in the following 4, 26, or 52weeks. In addition, some researchers have suggested that the returns to large (small) cap stocks are related to the sentiment of large (small) investors. For instance, Lee, Shleifer and Thaler (1991) conclude that small investors concentrate their holdings in small-cap stocks, thus creating such a link. Arguably, Fisher and Statman (2000), find no support for the argument that the sentiment of small investors follow the performance of small-cap stocks more closely than the performance of large-cap stocks.

Among major factors that affect investor sentiment are stock returns. While De Bondt (1993) finds consistent positive and significant relationships between S&P500 returns and future changes in the sentiment of individual investors, Wang (2003), further finds after controlling for market risk factors, that speculators respond positively to market sentiment and hedgers against market sentiment. Clarke and Statman (1998) and Fisher and Statman (2000) find that newsletter writers form their sentiments with the expectation of short term returns to continue and eventual reversals of long-term returns.

2.10 Information variables

To introduce market risk into models, De Bondt and Thaler (1985) and Harvey (1989) use the following information variables:

1. Monthly dividend yield of the S&P500 index, which tends to be higher during periods of slow economic growth or recessions (Fama and French, 1989) is regarded as a signal for the risk premium.

2. 3-Month T-bill yield, representing the short-term discount rate or expected inflation[23].

3. Corporate bond default yield spread, i.e., Moody's Baa-rated corporate bond yield less Aaa-rated corporate bond yield, represents a premium of default risk.

Bessembinder and Chan (1992), and Bjornson and Carter (1997) show that these above factors are priced risk factors in futures markets. Information variables also play an important role in the volatility spillover across markets (Chatrath and Song, 2003). Easley and O'Hara (2002) find information risk is a determinant of asset returns. Campbell and Shiller (1988) present evidence that dividend yields forecast stock returns. Chan et al. (1985) find that changes in short term interest rates can explain the equilibrium pricing of equities, and Chen (1991) shows that the cyclical behaviour of T-bill rates (low during economic contractions) captures the cyclical variation in equity risk premiums. Stock index dividend yield and the bond default and term spreads in the US markets help forecast the risk premium component of the foreign currency futures basis (Baum and Barkoulas, 1996). It is of interest to examine how these priced risk factors influence traders' trading decisions and how traders perform after controlling for risk.

In a study of fifteen US futures markets, coefficient estimates for information variables for hedgers have opposite signs to those of speculators (Wang, 2003). This tends to be in line with the "hedging demand" argument of Merton (1973). Because the available investment opportunities change as the information variables vary, Merton shows that investors may hedge these changes by investing in a way that gives them higher wealth precisely when investment opportunities are unattractive, i.e, expected returns are low. Therefore, hedgers adjust their positions as a way of hedging against movements in expected returns, as contrasted with the behaviour of speculators[24].

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[23] When non stationary, differencing of dividend yield is carried upon (Wang, 2003).

[24] Lynch (2001) provides evidence on the impact of return predictability on investors' multiperiod equity portfolios choices. He shows that return predictability of information variables can tilt equity investors' portfolios away from high book-market and small-size stocks. Thus, hedging demands provide an explanation for the size and book-market effects.

Furthermore, French, Schwert, and Stambaugh (1987) extend Merton's work by dividing market volatility variables into expected and unexpected components using ARMA models.

2.13 Market implications of monthly horizons

Because perceived risk varies inversely with time horizon, required returns vary directly with perceived risk. Furthermore, with market liquidity varying directly with distribution of investor horizons, changes in distribution of investor horizons might affect the level and volatility of market returns, i.e, if average horizons shrink, perceptions of risk should increase, therefore, higher returns (Olsen and Khaki, 1998). In addition, because horizon length is bounded by zero, a reduction of dispersion of horizons created by shortening of horizons (say from monthly to weekly data) should lead to poorer liquidity and greater volatility in market prices (Greezy, 1997). Finally, but not least, Peter (1994) supports that prices exhibit a pattern of volatility consistent with time horizons.

Moreover, Holmes (2006) reports that the rise in commodity prices is partly due to the more diversified types of financial investors and investment strategies, particularly, passively managed investments. In that line of thought, Beenen (2005) supports that such fund investors (large speculators) often pursue a fully collateralized long-only futures strategy with a longer term investment horizon. Investing in such longer term horizon (e.g monthly) include benefits such as diversification at a relatively low cost. Historically, commodity prices have had a relatively low correlation with prices in other asset classes and a high correlation with inflation (Gorton and Rouwenhorst, 2004). These academics also showed that historically, the return on a diversified basket of long commodities futures has been comparable with return on other asset classes with similar risk characteristics such as equity.

BIS (2007) also supports that non-commercials were dominated by managed money traders (MMT). In a seminal paper, Haigh et al. (2005) suggest that MMT participants do not change their positions as frequently as other participants. Wang (2004) further examines the relation between trading activity by trader type and futures returns over different horizons and found results were consistent on average. Similarly, he found negative conditional betas using weekly returns which are consistent with Bessembinder (1992) who used monthly data. These add support to the use of monthly CFTC data. Lastly, but not least, Wang (2003) supports it is less likely for traders' perception of risk to be changed over a short interval. The choice of monthly data interval not only makes the results comparable to the previous studies on backwardation or hedging pressure theories, but allow for consistency with monthly macroeconomic variables included in regression models.

2.13 Contrarians

2.13.1 Contrarians v/s naïve strategies

For decades, scholars and investment professionals have argued that value strategies outperform the market Dreman (1977). These value strategies generally looks upon buying stocks that have low prices relative to earnings, dividends, historical prices, book assets, or other measures of value. De Bondt and Thaler (1987) argue that extreme losers outperform the market over the subsequent several years. While it is argued that value strategies have produced superior returns, the interpretation of why they have done so is more of a debate. Value strategies might produce higher returns because they are contrarians to "naïve"[25] strategies followed by other investors. These naïve strategies might vary from forecasting using old earnings data, to overreaction to information, or equating a good bargain with a well-run company's year irrespective of price. Anyhow, some investors tend to get overly excited[26] about stocks that have done very well in the past and buy them up, so that these "glamour" stocks become overpriced. Likewise, they overreact to stocks that have done very badly, oversell them, and these out-of-favour "value" stocks become under priced. In brief, contrarians bet against these naïve

[25] "naïve" strategies are also sometimes referred as "popular" models (Shiller, 1984) and "noise" (Black, 1986)

[26] See overreaction hypothesis

strategies (Lakonishok et al., 1994). Because contrarian strategies invest disproportionately in stock that are under priced and under invest in stocks that are overpriced, they outperform the market (DeDondt and Thaler, 1985; and Haugen, 1994). In that line of thought, while Levis and Liodakis (2001) find biases in analysts' earnings forecasts, Dechow and Sloan (1997) find that naïve reliance on analysts' forecasts of future earnings growth can explain over half of the higher returns to contrarian strategies.

2.13.2 Over reaction hypothesis: short-run and long-run perspectives

2.13.2.1 Long-run perspective

The long-run perspective, which suggests that stock prices momentarily digress from their fundamental values due to swings of optimism and pessimism, has been examined using monthly returns by researchers including De Bondt and Thaler (1985) and Chopra, Lakonishok and Ritter (1992). Evidence from the long run perspective is generally not consistent with the hypothesis. As Bowman and Iverson (1998) argue, the overreaction event comes from basic human biasedness in processing information, so if it is authenticated, it should manifest itself in other markets. Kryzanowski and Zhang's (1992) long-term over-reaction findings in Canadian markets seem to contradict those of De Bondt and Thaler (1985) in US markets and those of Alonso and Rubio (1990) in the Spanish market[27]. Notwithstanding, Jegadeesh (1990) reports that a contrarian strategy, based on information from the previous month, yields statistically significant abnormal returns of 1.99% per month over 1934-1987 period in US markets, and 1.75% outside January. This result is quite outstanding, as these abnormal returns are nearly double those resulting from De Bondt and Thaler's long term contrarian strategies. There is no out-of-sample evidence to support Jegadeesh's (1990) one-month contrarian findings[28].

[27] Kryzanowski and Zhang's (1992) find significant continuation behaviour for winners and losers in the subsequent one and two years, and insignificant reversal over long test periods. Cleary and Inglis (1998) also find performance continuation over the medium term in Canadian markets.

[28] Lehmann (1990) finds that one-week winners and losers experience significant return reversals the next week, thereby reflecting arbitrage profits that persist after corrections for bid-ask spreads. However, Conrad, Gultekin, and Kaul (1997) argue that Lehmann's (1990) results are largely attributable to the bid-ask bounce of transaction prices.

2.13.2.2 Short-run perspective

The short-run perspective, which focuses on biases in the stock market reaction to the arrival of unexpected information, has also been analysed using daily returns by researchers such as Akhigbe, Gosnell and Harikumar (1998). Bowman and Iverson (1998) perform a similar analysis using weekly returns. Evidence on the short-run perspective favors the overreaction hypothesis. Alternatively stated if investor over-reaction/under-reaction is real, then the price correction process should primarily occur over a very short-term period since it is difficult to justify that any arbitrage opportunity arising from these deviations persists over a long period (Daniel, Hirshleifer, and Subrahmanyam, 1998).

2.13.3 Anatomy of a contrarian strategy

There is much support from behavioural finance that individuals form their predictions of the future without a full understanding of mean reversion. In other words, individuals tend to base their expectations on past data for the individual case they are considering without appropriately weighting data on what psychologists call the “base rate” or the class average. Kahneman and Tversky (1982, p.417) explain:

> “…One of the basic principles of statistical prediction, which is also one of the least intuitive, is that the extremeness of predictions must be moderated by considerations of predictability… Predictions are allowed to match impressions only in the case of perfect predictability. In intermediate situations, which are of course the most common, the prediction should be regressive, i.e, it should fall between the class average and the value that best represents one’s impression of the case at hand. The lower the predictability the closer the prediction should be to the class average. Intuitive predictions are typically non-regressive: people often make extreme predictions on the basis of information whose reliability and predictive ability are known to be low…”

To make the most of this defect of intuitive forecasts, contrarian investors should sell stocks with high past growth as well as high expected future growth and buy stocks with low past growth as well as low expected future growth. Prices of these stocks are most likely to reflect the failure of investors to impose mean reversion on growth forecasts (La Porta, 1995).

2.13.4 Are contrarian strategies riskier?

Two alternative theories explain why value strategies have produced higher returns in the past. The first one saying that they have done so because they exploit the mistakes of naïve investors, is backed by the fact that investors appear to extrapolating the past too far into the future, even though the future does not warrant such extrapolation. As to value stocks being fundamentally riskier than glamour stocks, these would be so if they underperform glamour stocks in some states of the world, and second, those are on average "bad states" (in which the marginal utility of wealth is high, making value stocks unappealing to the risk-averse investor). Interestingly, the reward for bearing fundamental risk does not seem to explain higher average returns on value stocks than on appealing stocks (Lakonishok et al., 1994).

2.13.5 Performance of contrarians

Contrarians buy stocks that performed poorly over the past two to five years (prior losers) and sell short stocks that performed well over the same period (prior winners). This approach earns subsequent excess returns of about 8 per cent per year (DeBondt and Thaler, 1985). However, the profits may be partly misleading, a product of methodological and measurement problems (Ball, Kothari, and Shanken, 1995). It may also be that the excess returns are "real" but rational reward for time-varying risk (Fama, 1991). Nonetheless, other academics like (Schiereck et al., 1999) find contrarian strategies to beat a passive approach invested in the market index. Odean (1998) supports that the investors at a US discount brokerage house are reluctant to realize losses, and presents evidence which are consistent with contrarian behaviour. Moreover, using Finland's data, domestic investors, particularly households, tend to be contrarians (Grinblatt and Keloharju, 2000). Evidence from the US, Japan, U.K., and other European countries suggests that over long time intervals, contrarian strategies generate significant abnormal returns (Arshanapali, Coggin, and Doukas, 1998; Fama and French, 1998[29]). Finally but not least, Jegadeesh (1990) observes a seasonality pattern in contrarian profits and document a significantly different return pattern in January.

Importantly too, many researchers attribute the performance of contrarian strategies to investor behaviour. De Bondt and Thaler (1985) also mention that past performance can provide a proxy for investor sentiment, and since prices are initially biased either by unnecessary optimism or pessimism; prior losers would make more attractive investments than prior winners over the long-term. Their argument is consistent with the hypothesis of long-term over-reaction by investors to information – a hypothesis documented in several other markets (e.g, Gunaratne and Yonesaaw (1997) in Japan, Schiereck, De Bondt, and Weber (1999) in Germany).

2.13.6 Robustness in contrarian investing

We must be vigilant in drawing conclusions about the relative importance of each horizon from a cross-horizon comparison of the share of positive buy ratio differences. While it is fair to conclude that uneven large magnitudes for the more recent horizons imply that the more recent horizons are more important, the converse need not apply. Larger magnitudes for the more distant horizons, can be simply be due to larger return inconsistencies between winning and losing stocks for the more distant horizons than for the more recent horizons. This is because the more distant horizons identify winners and losers over a larger number of days (Grinblatt and Keloharju, 2000). Also, it's worth encompassing the fact that the contrarian strategy almost inevitably leads to initial losses as an undervalued stock continues to go down. People are very averse to losses

[29] Note that the out performance of such strategies has declined and even reversed in the most recent years.

(Kahneman and Tversky, 1979). Likewise, Chopra, Lakonishok, and Ritter (1992) find that the overreaction phenomenon is considerably stronger for smaller firms than for larger firms. Similarly, Odean (1998) finds that small investors are reluctant to realize their losses, and they sell winners “early”. That’s critical for small investors’ decisions (Bange, 2000).

2.14 Positive feedbacks

Positive feedback investors buy stocks when prices rise and sell when prices fall. Many forms of behaviour common in financial markets can be described as positive feedback trading. It can result from extrapolative expectations about prices (Frankel and Froot, 1988), or trend chasing (De Long et al., 1990). It can also be a consequence of stop loss orders, which in effect prompt selling in response to price declines. Similarly, positive feedback trading can result from the liquidation of the positions of investors incapable to meet margin calls. Positive feedback trading is also displayed by buyers of portfolio insurance, who might use this practice because their willingness to bear risk rises sharply with wealth (Black, 1988).

2.14.1 Destabilizing feature of positive feedback trading

With positive feedback traders, rational speculation can be destabilizing. When rational speculators receive good news and eventually trade, they recognize that the initial price increase will stimulate buying by positive feedback traders tomorrow. In expectation of these purchases, informed rational speculators buy more today, driving prices up today higher than their fundamental values. Tomorrow, positive feedback traders react by buying due to today’s price increase and so keep prices above fundamentals even as rational speculators are selling out and stabilizing prices. The critical issue is that, although part of the price rise is rational, part of it is an outcome from rational speculators’ anticipatory trades and from positive feedback traders’ reaction to such trades. Trades from rational speculators destabilize prices because they prompt positive feedback trading by other investors (DeLong et al., 1990). Furthermore, it might pay a large speculator to destabilize prices (Hart, 1977).

In addition, the interaction of informed rational speculators and positive feedback traders leads to price destabilization which has several plausible empirical implications. DeLong et al. (1990) model generates a positive correlation of stock returns at short horizons, as positive feedback traders responds to past price increases by entering into the market, and negative correlations of stock returns at long horizons as prices eventually return to fundamentals. Such an attribute of realized returns has found also empirical support in Poterba and Summers (1988).

Managed futures trading are also purported to be guided by similar, positive feedback systems (Brorsen and Irwin, 1987). This may cause unwarranted futures price movements as managed funds and pools attempt to simultaneously buy after a price increase or sell after a price decrease[30]. Captivatingly, the concentration of commodity pool trading in financial futures markets is high, as these are the largest and most liquid markets. Commodity pool trading is not intense in smaller futures markets, such as livestock futures. This substantiates the observation that CPOs[31] and CTAs are aware of the possible market impacts of their trading and seek to curtail the impacts by limiting the size of their trading in smaller markets (Irwin and Yoshimaru, 1999).

2.14.2 Horizons of positive feedbacks

Importantly, positive feedback trading can occur at many horizons. Investment pools buy stock and then sell the stock slowly as positive feedback demand picks up rely on extrapolative expectations over a horizon of a few days. Frankel and Froot's (1988) forecast have a horizon of several months, which is also relevant for bubbles like those

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[30] Positive feedback trading systems also are known as technical trading systems. These systems are based on historical price patterns, and include moving average, price channel, and momentum systems. Previous research indicates technical systems tend to generate similar futures trading signals (Lukac, Brorsen, and Irwin, 1988).

[31] Commodity Pool Operators (CPOs)

that may have occurred in 1929 and 1987. Provided people anticipate a price rise over specific horizons on which they focus to continue, they structure extrapolative expectations that may support positive feedback trading patterns. Furthermore, De Long et al. (1990) suggest that that application to longer horizons is the most appropriate, since in that case learning is less likely to prevent positive feedback traders from repeating their mistakes.

2.14.3 Under-reaction hypothesis of positive feedbacks

Jegadeesh and Titman (1993) and others have documented the seeming profitability of such strategies. Over short periods of 3-12 months, there is a considerable degree of stock return persistence[32]. Also, observations that (1) positive feedbacks seem profitable, (2) that the volume of profits is linked to the "slow" adjustment of prices to earnings surprises as well as to (3) the "slow" revision of analyst earnings forecasts- all point to the conclusion that the market under reacts to information, especially news about company income (Chan, Jegadeesh, and Lakonishok, 1996). In a similar fashion, (Schiereck et al., 1999) using Frankurt Stock Exchange (FSE) find that positive feedback strategies appear to beat a passive approach[33] that invests in the market index.

2.14.4 Performance of positive feedback trading

Sirri and Tufano (1998) find that mutual fund managers tend to pursue such strategies. Brennan and Cao (1997) present evidence supporting the analysis that foreign investors should pursue such strategies and achieve inferior performance because they are less informed than domestic investors. Choe et al. (1999) find that foreign investors tend to be feedback traders, the latter paper focusing on short past-return horizons. Cutler et al. (1990) find evidence of positive correlation of returns at horizons of a few weeks or

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[32] Positive feedbacks in 12-month returns are also reported in De Bondt and Thaler (1985). The findings were not emphasized, however, since long-horizon price reversals were the focus of the paper.

[33] The passive approach would be similar to a buy-and-hold (excess) return, which combines the return for each stock multiplicatively, $[(1+R_j,1)(1+R_j,2)\ldots(1+R_j,n)]$, and subtracts the compounded market return, $[(1+R_m,1)(1+R_m,2)\ldots(1+R_m,n)]$ (Barber and Lyon, 1997).

months. Grinblatt and Keloharju (2000) analyzing the Finnish market, also demonstrate that positive feedback behaviour is correlated with investor performance, and that both the behaviour and performance appear to be associated with the level of sophistication of the investor, i.e, foreign investors (professionally managed funds or investment banking houses), pursue positive feedback strategies and achieve superior performance. More importantly, after removing feedback investing's contribution to performance, Grinblatt and Keloharju (2000) find that the feedback-adjusted performance of foreigners is highly significant[34]. Lakonishok et al. (1994) show how the positive feedback strategy of uninformed traders is directly associated with trend following and higher volatility. Finally, Jegadeesh and Titman (1993) show that following a positive feedback strategy over the previous six months will generate returns of approximately 1% per month over the six subsequent months in US markets.

2.14.5 Do positive feedbacks persist in long run?

Following market under reaction and over reaction hypotheses, one could argue feedback trading to be successful over short-time periods (six to twelve months). That's because market participants who share a positive sentiment about an asset will continue to buy even when negative information starts to build up. However, this negative information will eventually result in an over enthusiastic price revision, which does not take into account factors such as the probability that firms with bad results will turn themselves around, and that very few actually go out of business (Hilton, 2001). Despite these arguments, however, positive feedbacks might persist in the long run.

Firstly, every episode might look different to positive feedback traders, and so their learning from past mistakes might be limited. Learning might be particularly restricted if each episode of divergence of price from fundamentals takes several years, as might have been the case with conglomerates and real estate investment trusts (Soros,

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[34] The feedback-adjusted return for a stock over say (*t* to *t*+*x*) is the stock's actual return from *t* to *t*+120 less the average of the *x* days (that begin on day *t*) of the alternative stock(s) in the feedback class portfolio to which the stock belongs on day *t* (Grinblatt and Keloharju, 2000).

1987). Alternatively stated, by the time the new bubble emerges, many investors have forgotten the old one or have been replaced by younger investors who have never experienced the old one at all. Secondly, even if noise traders exit the market with losses now, they may save and return to the market later, especially if several years pass between bubbles. Finally, if traders' mistakes cause them to take positions that carry more market risk than rational investors' positions, they can earn higher returns in the market even if they make judgment errors. As such, positive feedback trading may well persevere in the long run (De Long et al., 1990). However, Frankel and Froot (1988) find market participants expect recent price changes (short run) to trigger others in the same direction, while they also expect prices to return to their fundamental values in the long run. Similarly, De Bondt and Thaler (1987), and De Long et al. (1990) find that extreme actions in prices of individual assets eventually revert, as long as part of these movements is accounted for by positive feedback trading.

2.14.6 Robustness in positive feedbacks

First, positive correlations of returns on a stock market index at short horizons can come in part from non-synchronous trading (De Long et al., 1990). In this case, the positive serial correlation is a fabrication of the construction of the market index and not a fact about the prices at which trades in individual securities can be carried out. However, Cutler et al. (1990) find significant positive serial correlations at short horizons in bond, gold, and foreign exchange market, where non-trading problems are not likely to be serious.

2.14.7 Feedback trading and herding

Extant evidence suggests that individual investors' herding is related to lag returns, i.e, individual investors feedback trade. Patel, Zeckhauser, and Hendricks (1991) demonstrate that flows into mutual funds are an increasing function of recent market performance. Similarly, Sirri and Tufano (1998) present evidence that individual investors invest disproportionately in funds with strong prior performance. Alternatively, consistent with the disposition effect, Odean (1998) support that individual investors are more likely to sell past winners than losers. As for institutional investors, studies like Wermers (1999) and Lakonishok et al. (1992) present strong evidence that these investors engage in some positive feedback trading and also document a strong relation between mutual fund herding and quarterly returns, i.e., they herd and exhibit positive feedback trading.

2.15 Hedging pressure effects

Futures prices are acknowledged to diverge from expected future spot prices because of risk premia in futures markets. The existence of a risk premium is fundamental in that it affects the transaction costs and benefits of hedging, including the benefits of including futures in a portfolio. Important research about how futures risk premia relates to systematic risk and hedging pressure can be found in Jagannathan (1985). In fact, hedging pressure is derived from risks that parties, do not, or cannot, want to trade because of market frictions such as information asymmetries and transactions costs. Using CFTC data for 20 futures markets, Roon et al. (2000) find own-hedging and cross-hedging pressures variables from within the futures own group are crucial in explaining futures returns[35]. Hirshleifer (1988) also shows that futures prices can be affected by hedging activity, containing a positive (negative) risk premium if hedgers are net short (long). Changes in the degree of net long or short hedging activity should therefore result in a change in the level of the expected risk premium. The total risk premium is the compensation expected by speculators for taking positions that offset hedgers' excess supply or demand. Empirical evidence found by Chang (1985) and Bessembinder (1992) also generally identify non-zero premia in futures prices.

[35] A rollover strategy is created for the return series. For the nearest-to-maturity series a position is taken in the nearest-to-maturity contract until the delivery month, at which the position changes to the following contract, which then becomes the nearest-to-maturity contract.

2.15.1 Own hedging pressure variable and effect

Positions of large traders in futures markets as reported by CFTC are used as proxies for hedging pressures. For each futures contract, Roon et al. (2000) create a variable that is based on reported positions of hedgers for each futures market as follows:

$$Q_t = \frac{\textit{Number of short hedge positions} - \textit{number of long hedge positions}}{\textit{Total number of hedge positions}} \qquad (2.1)$$

Assuming that Q_t is created from positions that by definition occur from hedge demand, it seems practical that this variable can be used as a proxy for the total non-marketable risks (Roon et al., 2000). By regressing futures returns against the hedging pressure variable and adjusting for heteroskedasticity consistent standard errors, they find significant relation between futures return and their own hedging pressure. Their results support Bessembinder (1992) who find that the average futures returns are considerably larger when hedgers are net short rather than when they are net long. Insignificant hedging pressure effects are found for index futures.

2.15.2 Cross hedging pressure variable and effect

In order to analyse the effects of hedging pressure from other futures markets on the futures risk premia, Roon et al. (2000) study each group of futures contracts and analyse the effect of hedging pressure variables within each group on future returns. Cross-hedging pressure regression used is as follows[36]:

$$R_{i,t+1}^{(j)} = \alpha_i + \beta_i R_{m,t+1}^{(j)} + \sum_{s=1}^{n} \theta_{s,i} Q_{s,t}^{(j)} + e_{i,t+1}^{(j)} \qquad (2.2)$$

[36] Note that $\beta_i R_{m,t+1}^{(j)}$ (market risk) implements the S&P500index returns within the model for the Wald tests, but is initially omitted for the hedging pressure effects.

, where *i* refers to futures contract *i* in market *j* (financial, agricultural, etc) and *m* refers to S&P500 market returns. The variables $Q_{s,t}$ are the *n* hedging pressure variables within the group. Therefore, $\theta_{s,i}$ measures how responsive the futures return is against hedging pressure variables within its own group.

Using semi-monthly data, Roon et al. (2000) reveal that, except for the S&P500 index futures and live cattle futures, for each contract at least one of the hedging pressures within the group resulted in an estimated coefficient $\theta_{s,i}$ that is significantly different from zero. In addition, numerous contracts have significant coefficients for hedging pressures other than their own. For instance, metal futures show coefficients that are notably different from zero for the silver and platinum hedging pressure variables. Similarly, the hedging pressure variable of Deutsch mark futures has a significant effect on all other currency futures, consistent with cross-hedging effects. The Wald test hypothesis $\theta_{s,i}=0$ being rejected, shows the relevance of own hedging pressures in explaining futures returns. As for the hypothesis that only, own-hedging pressure is relevant, it was rejected at 5% significant level, implying the importance of cross-hedging pressures as well.

2.15.2 Robustness of hedging pressure effects

To test, the robustness of such hedging pressures, the *price pressure* hypothesis should be accounted for. The price pressure hypothesis suggests that an increase in demand (supply) in the number futures contracts will result in an upward (downward) temporary change in the future price, and will in due course reverse out (Roon et al., 2000). As such, due to the reversal of the futures price change, an unexpected demand (supply) of futures contracts will be related with negative (positive) futures returns. Alternatively stated, while hedging pressure theory states that expected futures returns will be high whenever the level of hedging pressure is high, the price pressure hypothesis suggests that expected futures returns will be high, following a sizable increase in hedging pressure. To show whether futures returns are affected by price and/or hedging pressures, a price pressure effects test is used in Roon et al. (2000), where the pressure variables are divided by their own standard deviation. Results reported in Roon et al. (2000) show significant hedging pressure effects, even after controlling for price pressure.

2.16 Volatility, Error distribution and Forecasting

2.16.1 Volatility

There is a widespread perception in the financial press that volatility of asset returns has been changing (Maheu and Mccurdy, 2004). The new economy is introducing more uncertainty. Indeed, it can be argued that volatility is being transferred from the economy at large into the financial markets, which bear the necessary adjustment shocks[37]. Market volatility as a whole has not become more volatile, but uncertainty on the level of individual firms has increased substantially over a 35-year period (Campbell et al. 2001).

2.16.1.6 Volatility persistence

Merton (1980) states: "However, from the work of Rosenberg (1972) as well as many others, the hypothesis that the variance rate on the market remains constant over any appreciable period of time can be rejected at almost any confidence level". A number of papers (Haque et al., 2000; and Kim and Singal, 1999) examine the return-volatility behavior of a number of emerging market economies. Schwert (1989) shows weak evidence that macroeconomic volatility provides incremental information about future stock return volatility, and also that volatility is higher during recessions. Roth et al. (2003) show a positive relation between volatility and open interest for both hedgers and speculators, suggesting that an increase in volatility motivates both hedgers and speculators to engage in more trading in futures markets.

[37] "Coping with the market's mood swings," *Financial Times*, London, September 27, 2000.

Other previous studies in the finance literature suggest that investors may increase their participation in futures trading when volatility increases. For instance, in Shalen's (1993) noisy rational expectations model of a futures market, speculators determine the size of their trading position on futures contracts based on the dispersion of beliefs among traders about the equilibrium price of futures. Shalen further suggests that the dispersion of expectations is closely related to volatility. In addition, a higher volatility may induce investors to increase trading in futures because futures contracts constitute a convenient means to amend their investment positions (Chen, Cuny, and Haugen, 1995). The Chen et al. model shows that when the stock market volatility increases, investors wishing to reduce risk exposure would sell stocks and stock index futures, thereby stimulating futures trading. The analyses of both Shalen and Chen et al. suggest that volatility is positively related with trading demand. Easley and O'Hara (1987) argue that informed traders may choose to break up their trade such that they don't trade quickly on information. Chang, Chou, and Nelling (2000) also show that open interest of hedgers increases when volatility is higher. Finally, Peck (1981) studies the role of speculation and price volatility and found that speculation is closely related to trading volume. Even if the study of price volatility can be performed without reference to volume, as in Streeter and Tomek (1992), most often these two variables are linked together, as in Cornell (1981). Finally, but not least, currency futures volatility seems to have a less-persistent memory than commodity futures' volatility (Crato and Ray, 2000).

2.16.1.7 Information variables and volatility

The literature also points to the importance of considering economic variables in addition to the information variables (Kenyon et al., 1987); and Goodwin & Schnepf, 1998). For e.g., Kenyon et al. (1987) find a direct relationship between the level of futures prices and price volatility. That is, as price increased, price volatility also tended to increase. Streeter and Tomek (1992) supports that price level may be reflecting the effects of supply and demand on volatility. Consequently, it may be difficult to ascertain the effects of supply and demand variables when the price level is included in a model of volatility. A nonlinear relationship between price and volatility was shown by Hudson and Coble (1999). Other economic variables have shown to be imperative to price volatility. For example, Goodwin and Schnepf (1998) find that variables such as private stocks, market concentration, and exports were significant determinants of price volatility in grains.

2.16.1.8 Policy and volatility

CFTC and exchanges regulatory policy has the potential to affect price volatility. For instance, some evidence from Ray et al. (1998) supports that movement toward more "market oriented" policy is expected to increase price volatility, whereas others like Collins and Glauber (1998) argue that this is not inevitably true. For e.g., an important agricultural policy variable is the non-recourse or Commodity Credit Corporation (CCC) loan rates. Other thing being equal, the loan rate is expected to reduce volatility because it limits the downward movement in price. Hudson and Coble (1999) reject the idea of heading towards more "market-oriented" policies. This is in line with the idea of no real increase in volatility for cotton with the functioning of the FAIR 1996 Act as put forward in Ray et al. (1998). In other words, the specification of the policy variable effects constraint the possibility of a broad conclusion about which policy components affect volatility. For instance, certain components of policy such as acreage set asides have been shown to affect farm income volatility (Zulauf, 1998). Predominantly in the most recent market-oriented market environment after the FAIR 1996 Act, six out of eight storable commodity futures markets provided both an unbiased forecast signal of cash prices. This shows the economic significance of using futures markets to guide the production of storable commodities because it results in optimal resource allocation in the welfare sense (Stein, 1981) – more hedging since 1996.

2.16.1.9 GARCH model

Traditional time-series analysis makes the assumption that current price is a linear function of historical prices. In autoregressive integrated moving average (ARIMA) models, price changes are assumed to be drawn independently from an identical normal distribution. Yet, non-constant volatility of price leads to autocorrelation patterns in the conditional variance of price innovations where the variance is conditional on the information set available at the time forecasts are being formed.

Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model help explain conditional variance movements and capture part of the excess kurtosis in commodity prices (Bollerslev, 1986; Engle, 1982). Yang and Brorsen (1992) examining daily cash prices of seven agricultural commodities, support the non-normality of daily returns. Beck (2001) derives that Muth's (1961) rational-expectations model of commodity markets implies an ARCH process in spot prices of storable commodities. Her analysis of 19 different commodity prices, using yearly data, finds significant ARCH processes for most storable commodity price series.

In fact, Bollerslev (1986) extends the ARCH model by including past variances as well as past forecast errors. Due to past variances, this model is referred to as generalized ARCH (GARCH). A GARCH (1, 1) model is employed and expressed as:

$$\sigma_t{}^2 = \varphi_0 + \varphi_1 \, \xi_{t-1}{}^2 + \varphi_2 \, \sigma_{t-1}{}^2 + \varepsilon_t \qquad (2.3)$$

, where the restrictions $\varphi_0 > 0$ and φ_1 and $\varphi_2 \geq 0$ are imposed to insure a positive variance. Both ARCH and GARCH impose the restrictions on coefficients to ensure a positive variance. An extra restriction is that both ARCH and GARCH models assume symmetry in the distribution of asset returns. The GARCH model has the benefit of including heteroscedasticity into the estimation process. All GARCH models are martingale difference implying that all expectations are unbiased (Bollerslev, 1986). Moreover, the GARCH models allow the capture of volatility clustering in financial data. Volatility clustering in stock returns implies that large (small) price changes follow large (small) price changes of either sign. Also, conclusions regarding predictability of returns based on the significance of autocorrelation coefficients are valid only after controlling for the ARCH effects (Errunza et al., 1994). Chou (1988) and Bollerslev, Chow and Kroner (1992) show that the persistence of shocks to volatility depends on the sum of the ($\varphi_1 + \varphi_2$) parameters. Values of the sum lower than one suggest the volatility response tends to decay over time. Otherwise, values of the sum equal (or greater) than one suggest indefinite (or increasing) volatility persistence to shocks over time. Nonetheless, a significant impact of volatility on the stock prices can only occur if shocks to volatility persist over a long time (Poterba and Summers, 1986).

Hardouvelis and Kim (1996) study the volatility of copper futures contracts as it relates to margin requirements. Chang, Chen, and Chen (1990) find copper, silver and platinum futures bear more risk (as measured by their standard deviations) than equity stocks. After examining the volatility of copper futures prices, Bracker and Smith (1999) concludes that this volatility was more suitably modelled as a Generalized Autoregressive Conditional Heteroscedastic (GARCH) process of time-varying volatility. Urich (2000) presents hedging models in which spot and futures prices are cointegrated in their logs and return disturbances are GARCH. Yang and Brorsen (1993) find GARCH effects in 13 of the 15 futures markets studied. Najand and Yung (1991) find that GARCH effects persist for Treasury bond futures. Ragunathan and Peker (1997) produce similar results for Australian financial futures.

2.16.1.10 Symmetry: an important assumption

The assumption of symmetry, i.e, that all traders have the same starting variance of information, same cross covariance between signals and the same covariance between signals and true value is *critical* for the analysis (Foster and Viswanathan, 1996). Suominen (1996) and Karpoff (1988) suggest that the observed positive correlation between volume and returns in equity markets can be explained by the presence of differential costs in acquiring short and long positions. As a result, one should not observe any asymmetry in futures markets since the costs of taking short and long positions in such markets are symmetric, which can be verified by calculating the contemporaneous correlation coefficients between the two variables (Karpoff, 1988). Furthermore, Kocagil and Shachmurove's (1998) volume-return correlations support Karpoff's (1988) hypothesis that the absence of trading cost asymmetry assures symmetric trading volume in futures markets like copper, corn, crude oil, gasoline, gold, heating oil, live cattle, orange juice, palladium, platinum, silver, soybeans, sugar (world), wheat, S&P 500 index and Treasury bond. Further, Merton (1995) argues generally that the introduction of futures trading and derivative markets can improve efficiency by reducing asymmetric responses to information[38]. Dadalt et al. (2002) also support the conjectures of Breeden and Viswanathan (1998) who argue that hedging reduces noise related to exogenous factors and hence decreases the level of asymmetric information.[39] Finally, large players are likely to have less asymmetric information due to higher institutional ownership and greater analysis (see Atiase, 1985)[40].

2.16.2 Error distribution

Research on probability distributions often use changes in the logarithms of prices. The evidence is mixed on whether price changes are well approximated by the log normal distribution. For example, Hudson, Leuthold, and Sarassoro (1987) find that the log normal distribution is a good approximation for wheat, soybeans, and live cattle for daily prices for the years 1976 through 1982, but not if earlier years are included. Similarly, Hilliard and Reis (1999) observe on every price intraday change for soybeans for the period July 1990 to June 1992, and they conclude that the logarithmic changes are not distributed normally. It is not infrequent that agricultural futures prices, like many other financial series are distributed nonnormally with the fat tails. (Yang and Brorsen, 1993; and Hall, Brorsen, and Irwin, 1989) suggest that the distribution of commodity price changes is not normal, but is leptokurtic. For six agricultural futures, Corazza et al. (1997) find returns are not log-normally distributed, due to fatter tails and instability in

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[38] Academics argue that asymmetries occur due to the effect of price falls on operating and financial leverage (see, for example, Nelson, 1991). However, the extent to which these explanations can account fully for the observed asymmetric effect is debatable. In particular, see Braun, Nelson, and Sunier (1991), who argue that these explanations are insufficient in explaining the extent of the observed asymmetries. Thus, the market dynamics argument may well explain, at least in part, the observed asymmetries in volatility.

[39] Brown (2001) provides further support of the asymmetric information mitigation hypothesis. In an examination of the risk practices of a large multinational, he reports that its hedging decisions are in part motivated by attempts to reduce informational asymmetries.

[40] Dadalt et al. (2002) examine the relationship between derivatives usage and information asymmetry using a structural model in which they simultaneously model derivatives usage as a function of information asymmetry and vice versa (see Graham and Rogers, 1999). Coefficients on the asymmetric information variables were generally negative and statistically insignificant.

the variance level (accounting for the relatively many outliers). Bera and Garcia (2002) and Manfredo et al. (1999) propose a *t* distribution after the normal distribution being left with excess kurtosis. Similarly, Bailey and Myers (1991) use a conditional *t* distribution and find strong evidence of persistent shocks to the volatility. Finally, Poitras (1990) conclude that more "normal" distributions are produced by increasing the differenced data interval from daily to weekly.

An understanding of the probability distributions of futures prices is important to decision makers. First, optimal hedges in futures depend on the parameters of the underlying probability distributions, and the estimates of these parameters depend, in turn, on the analyst's assumed model of the distribution (McNew and Fackler, 1994). Second, models of options prices make assumptions about the nature of the probability distribution of the underlying asset. In the case of traded agricultural options, the underlying asset is a position in a futures contract (Tomek and Peterson, 2001). In addition, these authors suggest that changes in volatility can pressure the margin level for futures contracts and hence influence the cost of hedging. Moreover, one might expect that with normally distributed data the symmetric GARCH model would exhibit the lowest RMSE. Bracker and Smith (1999) show that the GARCH model rank first compared to the asymmetric EGARCH, AGARCH, and GJR for some futures market.

2.16.3 Forecasting

It is well known that successful hedging and speculative activities in futures markets depend critically on the ability to forecast price movements (Girma and Mougoue, 2002). The econometrics literature is full of studies comparing the forecasting ability of various time-series models.[41] For instance, Poon and Granger (2003) list 39 studies comparing the out-of-sample forecasting abilities of the GARCH (1, 1) model and the historical variance. Factors influencing the supply and demand of inventories provide critical information towards making expectation about the value of the month price at

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[41] For an excellent review of existing studies in this area see Poon and Granger (2003). Notable examples include Loudon et al. (2000) and Hansen and Lunde (2001).

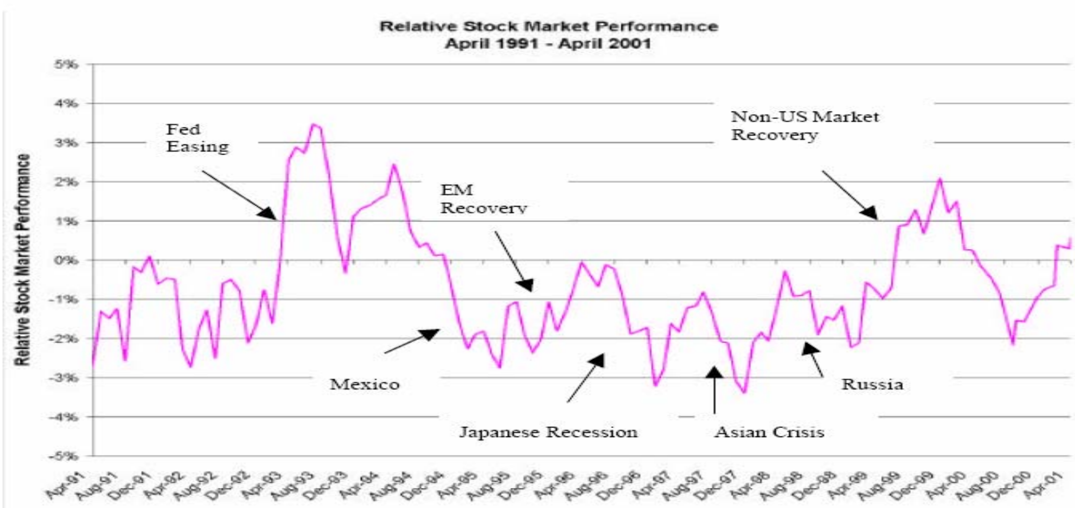
maturity. As time passes, new information comes, and both the price level and the price differences can alter. However, in an efficient market, truly new information is a surprise and is incorporated rapidly into price changes making arbitrage opportunities disappear quickly. Indeed, most traders cannot profit from price forecasts if markets are efficient. Put another way, econometric models in the public domain cannot outperform efficient futures markets as forecasts of the maturity price (Tomek, 1997). Also, consistent with the existing volatility forecasting literature, Manfredo et al. (1999) confirm the difficulty in finding a "best" volatility forecasting method across different horizons and data intervals. Yet, markets may not be strong form efficient, and some traders may profit by having better (private) data and models (Bessler and Brandt, 1992). Moreover, price-forecasting models can have statistical, but not economic significance, that is, returns from using the forecasts are less than transaction costs (Peterson, 2001). Overall, the literature suggests that no one particular method for forecasting the volatility of asset returns performs best over a wide array of data series and alternative forecast horizons. The sensitivity of the forecasts and the forecastibility of volatilities to diverse techniques depend very much on the return series in question (Jackson, Maude and Perraudin, 1997).

One issue addressed by Poon and Granger (2003) is whether volatility forecast errors are best measured in terms of the standard deviation or variance. As they point out, when the RMSFE is measured in terms of the variance, a few outliers tend to dominate the results. In addition, derivative prices are roughly proportional to the standard deviation. Consequently, they define RMSFE in terms of the standard deviation, and find that the GARCH model puts too much weight on recent observations relative to those in the past. This is consistent with prior evidence showing that asset market volatility has a long memory, such as Ding and Granger (1996). They also make mention of the inability of other models to forecast very well out-of-sample due to the cost of added complexity underscoring the argument of Dimson and Marsh (1990).

2.17 Events Analysis

For a proper event study, it is worthwhile to take a look at the following diagram, depicting all the important events in the US during the 1990s[42].

Table 3.1
Major macroeconomic events during the period April 1991- April 2001



Sources: MSCI, Bloomberg Financial Markets and Citibank Analysis

2.17.1 Success of 1990s

In the late 1990s, many policymakers agreed that there have been fundamental changes in the US economy, of which remarkable economic performance has been the subject of so much analysis (for example see Baily, 2001; DeLong and Summers, 2001; Claussen and Staehr, 2001). Food and energy prices were stable, the volatility of growth, unemployment, and inflation was stable and the push for fiscal and monetary policies made interest rates more responsive to inflation than was the case in previous periods (Mankiw, 2001). As Friedman said "…I'm baffled. I find it hard to believe..What I'm puzzled about is whether, and if so how, they suddenly learned how to regulate the

[42] Adapted from Chafkin (2002).

economy. Does Alan Greenspan have an insight into movements in the economy and the shocks that other people don't have?…" (Taylor, 2001)

New Economy proponents argued that the use of new information and communication technology (ICT) has reformed the economy in important ways. Furthermore, many economies have become more integrated into the world economy with increased openness for trade and human capital (Mankiw, 2001). Other forces were also at work including the earlier deregulation of key US industries, financial innovation and a more intense pressure of competition. Up till 1999, the US stock market was just remarkable (Temple, 2002). Price-earning ratios for the aggregate US market were at the highest levels ever observed in the Twentieth Century. For example, the market value was a mere $7.4 trillion in January 1996, and the market value of publicly held company stock reached $17.5 trillion, in December 1999, hit a monthly peak in August of 2000 at $18.9 trillion, and had fallen to $15.5 trillion in April of 2001 (Baily, 2001). Temple (2002) also suggests that the US experience is exceptional, and have used it to criticise the apparent lack of progress in other countries, particularly of Europe. Governments outside the US are routinely blamed for presiding over sluggish economies that are overregulated and slow to innovate (Savag, 2004). Other factors behind the success of 1990s like stable food and energy price shocks, good performance of stock market, and macroeconomic policy can be found in found in Appendix 6.6.

2.17.2 Events and volatility

The way futures markets respond to important macroeconomic variables depends on how information in these variables change expectations of different parties. This, in turn, depends on the historical experiences of parties and on the anticipated reactions of policy makers and thus, may vary across countries and across policymaking regimes (Hakkio and Pearce, 1985). Some researchers concentrated their efforts into the investigation of the effects of news on various measures of volatility of asset returns. These include Bonser-Neal and Tanner (1996) and Hung (1997) who utilised option price implied volatilities for the US dollar exchange rates to look at the effet of news on volatility. Kim (1998) uses the GARCH methodology to analyse the news effects on the Australian dollar exchange rate volatility. In general, these studies report an increase in volatility of asset returns in response to new information. For instance, it has been found that the bond volatility significantly rose in response to the surprise component of each announcement suggesting that when the market is presented with new information relevant for bond pricing, there are elevated trading activities with the result of higher price volatility (Kim, 1999).

Turbulence in financial markets over recent years gave birth to many propositions to restructure the international financial system to improve stability (Eichengreen, 1999; and Kenen, 2000). In fact, structural breaks have been identified for several futures contracts, implying that the volatility increase is in some cases due to upward shifts and not due to continuous changes (Menkhoff and Frommel, 2003). They also show that volatility has been increasing until the introduction of Euro in January 1999. Others like Flood and Rose (1999) demonstrate that exchange rate volatility can not be linked to changes in underlying fundamentals but rather to an influence by the regime in the sense that the float is related to higher volatility than the former Bretton Woods regime. Similarly, there is evidence in favour of the recent floating regime, indicating the usefulness of economic variables in explaining longer-term exchange rate movements (see Rogoff, 1996). Cheung (2001) argues that macroeconomic announcements have a smaller impact on the gold market than on the Treasury bond or foreign exchange markets. Patterson and Fung (2001) find that the Eurodollar, although influenced substantially by domestic US news, is an international asset that is traded globally. Thus, price changes in the Eurodollar may more readily reflect both world news and changes in risk premiums among different Eurocurrency rates in the international financial market. Conversely, the 3-month US Treasury bill is a prima facie domestic asset that may be less affected by offshore information Patterson and Fung (2001). While it is outside the scope of this study to look at all events of the last decade, an attempt is made with 8 macroeconomic global events namely:

- US tightening interest rates after a long period of easing in 1994-1995.
- Mexico crisis in 1994
- Asian Crisis in 1997-1998

- Emerging markets slump and recovery in 1995-1996
- Temporary revival from Japanese Recession in 1994-1996.
- Russian crisis of 1998
- Long Term Capital Management (LTCM) near financial collapse in 1998
- The introduction of the Euro Currency in early 1999.

Details for each of these events can be found in Appendix 6.9

2.18 Conclusion

The emphasis of most empirical studies on the behaviour and performance of key market players has been to look at either some really specific groups of traders like floor merchants, CTOs, CTAs and hedge funds, or some groups based on their behavioural features like contrarians, positive feedback traders, noise traders and herds. Very few studies have attempted to distinguish between the two key market players of the futures markets, namely large hedgers and large speculators. There is scarce evidence of the trading determinants of these key market players: their reliance on variables like dividend yield, sentiment data, three-month Treasury bill, corporate yield spread, and most importantly net positions in determining their actual returns; the existence of their superior market timing ability as opposed to significant risk premium in futures markets; their destabilizing features in futures markets; the betterment of standard deviation or variance as a proxy of risk in explaining these players' actual return and forecasting one-month return under different error distribution assumptions; the relationship between risk and return for these players; the relationship between trading activity and risk; and the effect of major macroeconomic events upon the behaviour and performance of these key players in the US futures industry. By making use of the CFTC COT data and quantitative econometric models, this study fills in the gap in these areas to promote a better understanding of how the giants of the US futures industry behaved and performed during the Clinton era.

Chapter 3:
DATA AND RESEARCH METHODOLOGY

3.1 Introduction

This chapter deals with the data and research methodology used in this study. An overview of the CFTC in the futures markets is provided, followed by a brief introduction about the COT unique data reports and its usage by key market players. This chapter then discusses the research objectives of this study, followed by the statement of problems and econometric steps taken to achieve these objectives. For consistency and ease of readability, a data classification and coding page, together with some flowcharts, are presented in this chapter.

3.2 Data

An analysis of CFTC and its COT database is essential before moving to the statement of hypotheses.

3.2.2 CFTC

The mission of the CFTC is to protect public users and the market players from abusive practices and manipulation related to the sale of commodity and financial futures and options, and to promote competitive, open, and financially well structured futures and option markets. The US Congress introduced the CFTC in 1974 as an independent organization with the endorsement to implement rules on commodity futures and option markets in the United States. The organization's mandate has been renewed and extended several times since then, most recently by the Commodity Futures Modernization Act of 2000 (CFMA). Today, the CFTC ensures the proper functioning of the futures markets by enhancing their efficiency and competitiveness, building their integrity and protecting market players through the clearing process. Through effective management and control, the CFTC enables the futures markets to serve the important function of providing a means for price discovery and offsetting price risk[43].

3.2.2 COT

The first COT report was in 1962, reporting only thirteen agricultural commodities. However, it was declared as "another step forward in the policy of providing the public with current and basic data on futures market operations". Those monthly reports were always published on the 11th or 12th calendar day of the following month. However, in forthcoming years, COT report was published more often, changing to mid-month and month-end in 1990 to weekly since October 1992[44]. The COT report is published quicker, i.e, on the 6th business day after the "as of" date (1990) and then to the 3rd business day after the "as of" date (1992). It includes more data on the number of traders in each category, a crop-year breakout, concentration ratios (early 1970s) and data on option positions (1995).

Principally, COT reports provide defragmented data on each Tuesday's open interest for markets traders who hold positions equal to or above the reporting levels established by the CFTC. The weekly reports for *Futures-Only Commitments of Traders* and for *Futures-and-Options-Combined Commitments of Traders* are released every Friday at 3:30 p.m. Eastern time. Reports are accessible in both short and long formats. For reportable positions, further data are made available for commercial and non-commercial holdings, spreading, changes from the previous report, percentage of open interest by category and numbers of traders. The short report shows open interest individually by reportable and non-reportable positions. In addition, the long reports also collection the data by crop year, where appropriate, and shows the focus of positions held

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[43] See http://www.cftc.gov/cftc/cftchome.htm

[44] See previous footnote to access more information on COT and CFTC.

by the largest four and eight traders.[45] There are roughly 41 scholarly works that have used the COT data up to now (Haigh et al., 2005). For this study, data from Pinnacle Data Corp., Webster, New York, which was extracted from CFTC magnetic tapes, was used. Since 10/16/1992, the CFTC has compiled the data weekly (as per market close on Tuesday) and releases two weekly reports on alternating Fridays. Although COT is still only weekly data, its quality more than makes up for its quantity: it is the only source of the actual holding of these three key groups by having inside information on the trading activities of the "savvy Commercials", the "too shrewd Non-Commercials" and the "unsuspecting Small Traders".[46]

3.2.2.1 Use of COT

The NGFA (National Grain and Feed Association) provided to CFTC 2006 Review Commission[47] the most comprehensive list of traders who use the COT reports: "farm marketing advisors/brokers; commercial hedging advisors; FCMs, IBs, and CTAs; cash merchandiser/hedgers or similar decision makers, including end-users, exporters, processors, merchants; and OTC dealers or other trading desks." For instance, there may be situations when speculators are more likely to have an indication of the hedging imbalances. First, extraordinary surges in the level of hedging imbalances will likely attract speculators. For instance, sudden increases of short hedgers in agricultural futures may be noticed early when there are harvest revisions, or later, in the trading pits. Second, several commodities pursue evident patterns of hedging imbalances. For instance, coffee has historically had an excess of short hedgers over long hedgers, with some exceptions in 1984, and oats has had an excess of short hedgers since 1987 (Chatrath et al., 1997). For the purpose of this study, monthly net positions of commercials and non-commercials are used[48]. Product specifications like reporting levels for each of the 29 futures markets are provided in Section 3.2.5.

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[45] See http://www.cftc.gov/cftc/cftccotreports.htm for more on COT data.
[46] See http://pinnacledata.com/cot.html for more on Pinnacle data.
[47] See http://cftc.gov/files/cftc/cftcnoticeonsupplementalcotreport.pdf for the CFTC 2006 review.
[48] See Section 2.12 for implications of choosing monthly data interval.

3.2.3 Sentiment Index

The sentiment data used in the study is the Consensus bullish sentiment index provided by Investors Co-op & Consensus Inc[49]. The exclusive Consensus Sentiment Index is the premium measure of positions and outlook of major professional brokerage firms and advisors as interpreted and recorded by Consensus Inc. By drawing from a diversified mix of both brokerage house analysts and independent advisory services, Consensus ensures a strong and reliable system when compiling the index. The data covers a wide range of ways players approach the market, including the fundamental, technical, and cyclical. Consensus makes no attempt to distinguish among these approaches and considers only opinions which have been committed to publication and therefore have an influence on the trading public, and does not consider opinions which brokers or advisors may hold but do not disclose publicly. The data has been published since May 1983, and is available through Consensus Research as early as 8:00 p.m. Central Time on Tuesdays. These are matched with the net positions and return series in this study.

3.2.4 Return Series and Information Variables

Continuous series of futures returns is created for each market. The return is measured as the percentage change in settlement prices of the contract with the nearest delivery date using a rollover strategy (Chatrath et al., 1999). The use of sequential rollovers of short-term futures hedges is helpful as it might serve as a long-term hedge (Gardner, 2001)[50]. Also, the Samuelson "maturity effect" hypothesis[51] is avoided with rollover, in that the selected futures prices are not biased at the maturity dates. For example, a position is taken in the nearest-to-maturity contract until the delivery month in which the position switches to the second-nearest contract. To match the COT data, we construct a monthly return series, which is the holding period return over one-month interval (Tuesday–

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[49] See http://www.consensus-inc.com/hotline.htm for more on the Consensus sentiment data.
[50] See also Roth et al. (2003).
[51] Samuelson (1976) argued that we 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.

Tuesday).[52] Data on futures prices and information variables are sourced from Datastream[53].

A sample of 29 actively traded US futures contracts over the May 1990–Dec 2000 interval is chosen[54]. The sample consists of four currencies (British pounds, Swiss francs, Canadian dollars, Japanese yen), three financials (Eurodollars, T-bonds, S&P500), sixteen agriculturals (soybean, soybean oil, soybean meal, pork bellies, hogs (frozen), cattle (live), feeder cattle, wheat—Chicago, wheat—Kansas, wheat—Minn (Minnesota), corn, sugar #1, cocoa, coffee, cotton, lumber), and six minerals (silver, gold, copper, platinum, crude oil, light sweet heating oil #2).[55] The sample of markets chosen are from ten different US exchanges, thereby allowing for enough market characteristics and cross-sectional differences in the underlying assets.

[52] In the same line as Wang (2003), return is measured as the percentage change in settlement prices of a futures contract over 4-week interval (see also Sorensen, 2002).
[53] Corporate bond yields are those from Lehman Brothers. (see Athanassakos and Carayannopoulos, 2001)
[54] See section 1.1 for reasons behind choosing 1990–2000 data interval.
[55] For each futures product specification details, see section 3.2.5, Data classification and coding section.

3.2.5 Data Classification and Coding

	Symbol	Market*	Reporting levels (contracts)
Minerals			
Silver	SI	CE	150
Gold	GC	CE	200
Copper	HG	CE	100
Platinum	PL	NYMEX	50
Crude Oil, light sweet	CL	NYMEX	350
Heating Oil #2	HO	NYMEX	250
Financials			
Eurodollars	ED	IMM	1000
T-bonds	US	CBOT	1000
S&P500	SP	IMM	1000
Currencies			
British Pounds	BP	IMM	400
Swiss Francs	SF	IMM	400
Canadian dollar	CD	IMM	400
Japanese Yen	JY	IMM	400
Agriculturals			
Soybean	S	CBOT	500,000 bushels, 100 contracts
Soybean Oil	BO	CBOT	200
Soybean Meal	SM	CBOT	200
Porc Bellies, frozen	PB	CME	25
Hogs	LH	CMM	100
Cattle (live)	LC	CME	100
Feeder cattle	FC	CME	50
Wheat - Chicago	W	CBOT	500,000 bushels, 100 contracts
Wheat - Kansas	KW	KCBOT	500,000 bushels, 100 contracts
Wheat - Minn	MW	MGE	500,000 bushels, 100 contracts
Corn	C	CBOT	750,000 bushels, 150 contracts
Sugar #1	SB	CSCE	400
Cocoa	CC	CSCE	50
Coffee	KC	CSCE	100

***CE**	**Commodity Exchange Inc.**
NYMEX	**New York Mercantile Exchange**
IMM	**International Money Market**
CBOT	**Chicago Board of Trade**
CME	**Chicago Mercantile Exchange**
CMM	**Chicago Mercantile Market**
KCBOT	**Kansas City Board of Trade**
MGE	**Minn. Grain Exchange**
CSCE	**Coffee, Sugar & Cocoa Exchange**
NYCE	**New York Cotton Exchange**

3.3.1 Primary Objectives

The research objectives concentrate on providing contribution to three particular areas related to the behaviour and performance of large hedgers and large speculators in 29 US Futures markets. The first area of concentration relates to the *behaviour section* (see graph 3.1). In particular, behavioural models are tested for positive feedback/contrarian behaviour, market timing abilitiy, existence of risk premium, destabilizing features of large players over futures prices and the need to reconsider CFTC's regulation.

The second part of the study looks at the *performance theme* and *event analysis theme* (see graph 3.1). In particular, performance is related to the effect of expected and unexpected components of variables like net positions on return and volatility of large speculators and hedgers; and the suitability of standard deviation and/or variance in explaining actual returns. The ability of standard deviation or variance in forecasting one-month return under different error distribution assumptions, and the suitability of idiosyncratic volatility as an accurate proxy of risk in forecasting one- month return under different error distribution assumptions also form the basis for the performance section. In regards to the *event analysis theme* (see graph 3.1), the use of recursive estimates over the trading determinant model, the mean return model, the return and risk relationship model, and trading activity and volatility relationship model are looked at. The effect of eight major macroeconomic events of the 1990s is tested for structural breaks in these models. Structural breaks are potentially important in the events section due to the fact that there is huge evidence documenting the instability of many important relationships among economic variables.[56] The use of a ten-year period regression helps in asserting the long-run properties of these models, and whether large hedgers and large speculators continue to exhibit stable relationships between independent and dependent variables of the models in this study.

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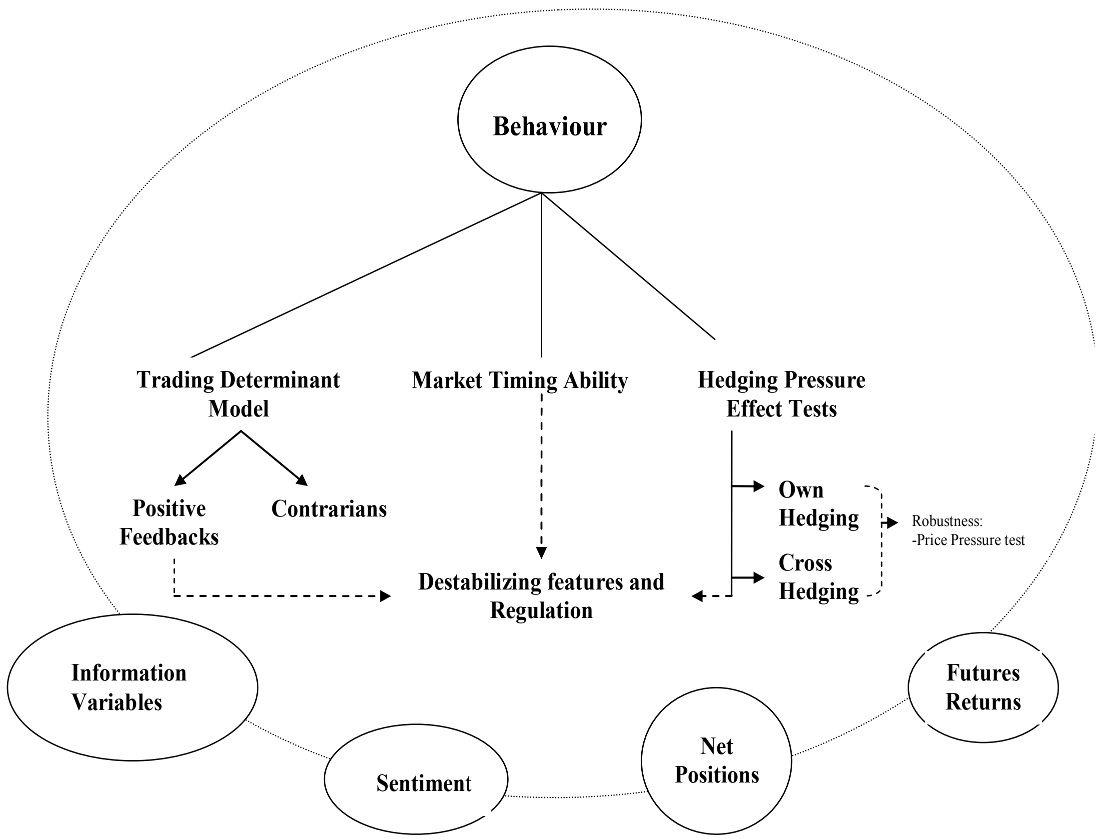
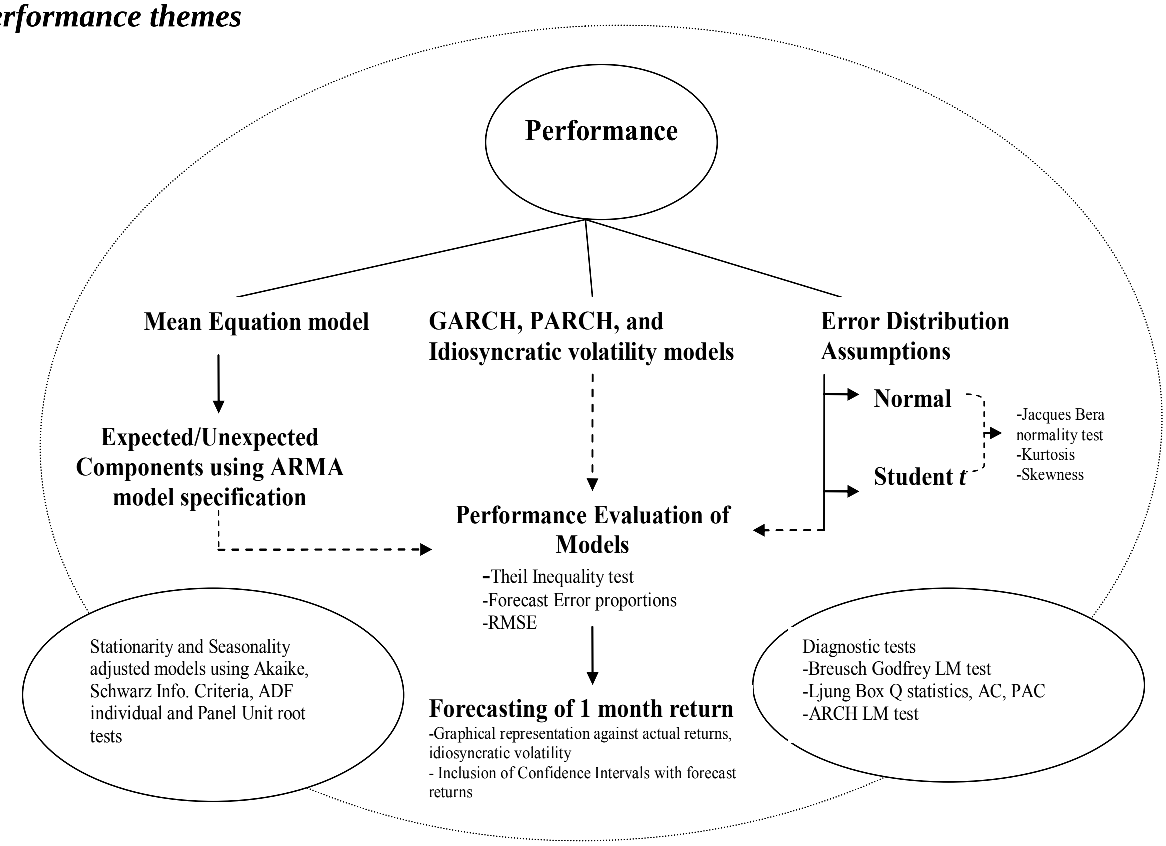
[56] For instance, Stock and Watson (1996) suggest that the laws of motion governing the evolution of many important macroeconomic time series appear to be unstable. See also Frommel and Menkhoff (2003).

Graph 3.1
Themes of study and econometric methods

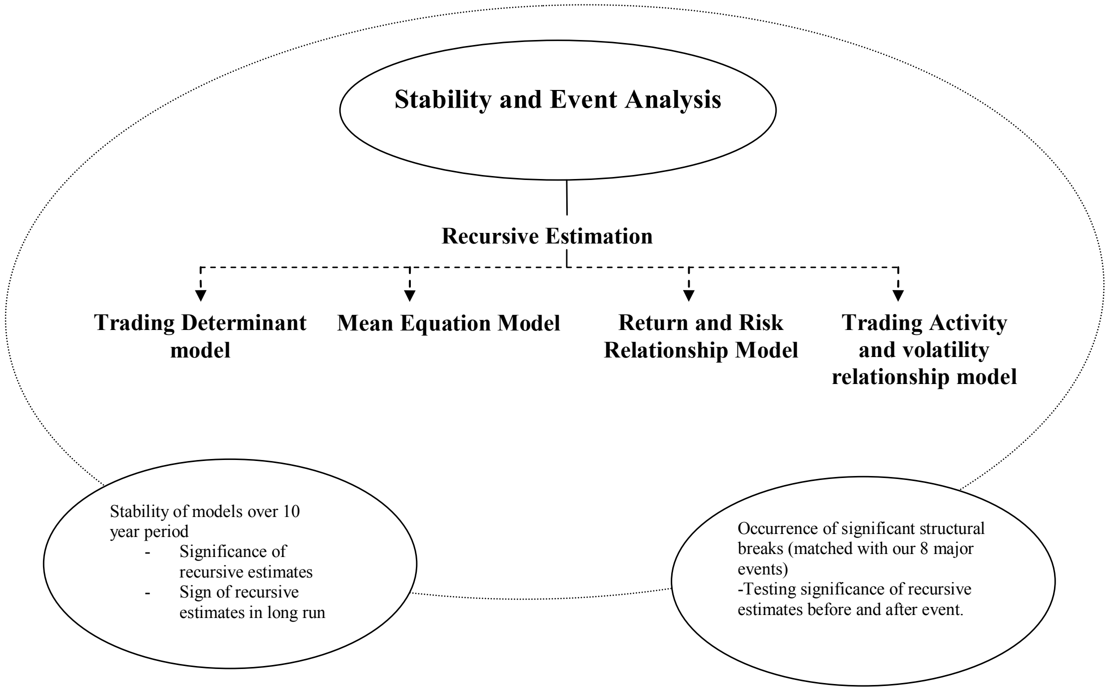
Behavioural themes



Performance themes



Events Analysis themes



For the purpose of this study, econometric software Eviews 5.0 is used to conduct Ordinary Least Squares (OLS) regressions such as trading determinant model, market timing test, hedging pressure tests and mean equation models; GARCH and PARCH volatility models under Autoregressive Conditional Heteroskedasticity (ARCH) models; ARMA model specification and diagnostic tests for variables and models; stability tests (recursive estimates), static in-sample performance evaluation and out-of-sample forecasting. Specification details of each test used can be found in the Appendix. All results are reported 10% significance level except for the initial unit root reported at 1%, 5% and 10% level. Throughout Chapter 4 and appendices, only significant *t* ratios are shown due to high number of markets being analysed.

3.3.2 Statement of Hypotheses:

BEHAVIOUR

Hypothesis 1: Large speculators exhibit contrarian behaviour, and large hedgers exhibit positive feedback trading.

As stated in Chapter 2 (section 2.13 and 2.14), there have been numerous studies regarding positive feedback and contrarian behaviour trading in equity markets. Very few studies like Brorsen and Irwin (1987), Grinblatt and Keloharju (2000) and Wang (2003) looked at behaviour over futures markets. While the first two studies find significant positive feedback trading in managed futures trading (where speculators are predominant), Wang (2003) find hedgers (speculators) to exhibit positive feedback (contrarian hehaviour) trading in 15 futures markets. Hedgers would normally be expected to be contrarians, due to the presence of hedging pressure effects, which necessitates a negative relationship between net position and subsequent returns. This hypothesis, fills in the gap by adopting Wang (2003) trading determinant model over 29 futures markets. If the changes in net positions of one trader type (at time $t+1$) is negatively related to returns (at time t), this would suggest that the trader is pursuing a contrarian strategy. If the changes in net positions of one trader type (at time $t+1$) is positively related to returns (at time t), this would suggest the trader is pursuing a positive feedback strategy. Sentiment index and information variables are also included to test for their significance in each player's trading determinant behaviour.

H_0: There is no significant contrarian (positive feedback trading) behaviour for speculators (hedgers).

H_1: There is significant contrarian (positive feedback trading) behaviour for speculators (hedgers) and/or there is significant contrarian (positive feedback trading) behaviour for hedgers (speculators).

Methodology: Ordinary Least Squares (OLS) regression of the following trading determinant model. Check for sign and significance of φ_2 to determine contrarian or positive feedback behaviour.

$$\Delta NP_{t+1} = \varphi_0 + \varphi_1 \, \Delta \, SI_t + \varphi_2 \, R_t + \varphi_3 \, \text{Tbill yield}_t + \varphi_4 \, \text{BAA - AAA}_t + \varphi_5 \, \text{Divyield}_t + \xi_{t+1} \quad (3.1)$$

$\Delta \, NP_{t+1}$ is the change in net positions of large speculators in month $t+1$. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. $\Delta \, SI_t$ denotes the change in the Consensus index in month *t*. R_t is the futures return in month *t*, in percent. Tbillyield_t, BAA-AAA_t, Divyield_t are the three information variables included in the model.

Hypothesis 2: Large speculators have superior market timing ability compared to large hedgers in judging correctly the direction of the market.

Backed by Wang (2003) behaviour models who find speculators outperform hedgers and Keynes (1930) theory of normal backwardation, this second assumption is critical in that it shows whether large speculators have superior market timing ability than large hedgers. Due to the fact that hedgers are motivated essentially in taking positions to insure their business , and that speculators are essentially in the market to take risk and get a higher return, their different motives would guide them towards different market timing abilities. More importantly, there is huge debate that hedgers pay a premium to speculators like suggested in Keynes's (1930) theory of normal backwardation, where two important assumptions are made - hedgers are net short, and speculators do not have forecasting ability. While it could be found that hedgers are mostly net short, the second assumption about large speculators having no forecasting or market timing ability is yet to be tested in this study to support the existence of risk premium in the futures markets. This hypothesis fills the gap by using Wang (2003) market timing ability test, for comparison purposes, over 29 futures markets. If the changes in net positions of one trader type (at time *t*) is negatively related to the futures returns (at time *t+1*), this would suggest that the trader has incorrectly judged the direction of the market and is getting negative returns in the next period (*t+1*). However, if the changes in net positions of one trader type (at time *t*) is positively related to the futures returns (at time *t+1*), this would suggest that the trader has correctly judged the market direction and is getting positive returns in period *t+1*. Large speculators and large hedgers can both possibly also correctly judge the market direction, showing that these players are informed players. The purpose of this hypothesis is to find support for the existence of risk premium, where following Keynes (1930) theory of normal backwardation, large speculators would be generally net long and would not be expected to have good market timing ability. Information variables are implemented to know if hedgers and speculators have good market timing abilities, after controlling for priced risk factors.

H_0: There is no significant market timing ability of large speculators and/or large hedgers in the futures markets.

$H_{1:}$ There is significant positive (negative) market timing ability of large speculators and/or large hedgers in the futures markets.

Methodology: Perform OLS regression of the following regression. Check for positive sign and significance of φ_1 to determine superior market timing ability and vice versa.

$$R_{t+1} = \varphi_0 + \varphi_1 \Delta NP_t^i + \varphi_2 \text{ Tbill yield}_t + \varphi_3 \text{ BAA - AAA}_t + \varphi_4 \text{ Divyield}_t + \xi_{t+1} \tag{3.2}$$

R_{t+1} is the futures return in one month time, in percent. ΔNP_t^i is the change in net positions of large hedgers and large speculators in the current month. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. Tbillyield$_t$, BAA-AAA$_t$, Divyield$_t$ are the three information variables included in the model.

<u>Hypothesis 3</u>: Significant own-hedging pressure and cross-hedging pressure effects exist in the futures markets.

Important studies reveal that findings regarding outperformance of hedgers or speculators over each other is mixed. While, Hartzmark (1997) find hedgers to earn consistent profits in several futures markets, Wang (2001) find speculators to outperform hedgers in six agricultural futures markets. Others like Roon et al (2000) (see section 2.15), support that futures markets have significant own- and/or cross-hedging pressure effects within certain groups of commodities like agriculturals and minerals, such that any outperformance can be explained by hedging pressure theories rather than market timing abilities. This hypothesis, backed by the previous one, supports the existence of risk being transferred from large hedgers to large speculators in the US futures markets. Significant own- and cross- hedging pressure effects are expected in the agricultural group, particularly where hedgers are mostly net short.

H_0: There is no significant own- and/or cross-hedging pressure effect(s) in the futures markets.

H_1: There is significant own- and/or cross-hedging pressure effect(s) in the futures markets.

Methodology:

1. Calculate own-hedging pressure variable (λ) as follows:

$$\lambda_t = \frac{\textit{Number of short hedge positions} - \textit{number of long hedge positions}}{\textit{Total number of hedge positions}} \qquad (3.3)$$

2. For own-hedging pressure test, perform the following OLS regression and check for sign and significance of φ_1 to determine existence of risk premium in own futures markets.

$$R_{t+1} = \varphi_0 + \varphi_1 \lambda_t + \xi_{t+1} \tag{3.4}$$

3. For cross-hedging pressure test, perform the following OLS regression and check for sign and significance of φ_1 to determine existence of risk premium spilling from other futures markets.

$$R_{i,t+1}^{(j)} = \varphi_0^{(j)} + \sum_{n=1}^{N} \varphi_{i,n}^{(j)} \lambda_{n,t}^{(j)} + \xi_{t+1}^{(j)} \tag{3.5}$$

where i (i = 1, 2, 3…, n) refers to the futures market and j (j=1,..,4) refers to the specific group the futures market belong to. $\sum_{n=1}^{N}\varphi$ represent the coefficients of own- and cross-hedging pressure variables for each futures market within each of the four groups. For comparison with Roon et al (2000), the 29 futures markets are grouped into four groups as financials, currencies, minerals, and agriculturals.

4. For price-pressure test, perform the following OLS regression and check for sign and significance of φ_1 and φ_2 to determine the existence of risk premium in futures markets, after accounting for price pressures effects on returns.

$$R_{i,t+1} = \varphi_0 + \varphi_1 \frac{\lambda_{i,t}}{\sigma(\theta_{i,t})} + \varphi_2 \frac{\Delta\theta_{i,t}}{\sigma(\Delta\theta_{i,t})} + \xi_{i,t+1} \tag{3.6}$$

where: $\lambda_{i,t}$ is the own-hedging pressure variable, $\Delta\theta_{i,t}$ is the change in hedging pressure variable (price pressure), $\sigma(\theta_{i,t})$ is the standard deviation of own-hedging pressure variable, and $\sigma(\Delta\theta_{i,t})$ is the standard deviation of change in hedging pressure variable.

<u>Hypothesis 4</u>: The large speculators and/or large hedgers are destabilizing the futures markets.

This hypothesis shows whether large speculators and/or large hedgers have a destabilizing force over the futures markets. As supported in Chapter 2 (sections 2.5 and 2.8), large speculators have in some cases been heavily regulated due to their destabilizing nature in markets. On the other hand, large hedgers have not been imposed with strict regulations like position limits and higher margin requirements. Based on the results from hypothesis 1 and 2, if one trader type exhibits positive feedback trading, together with negative performance in judging the market direction, this would suggest that the trader is moving away prices from their fundamentals, i.e. they are destabilizing the futures market, and vice versa.

H_0: There is no significant positive feedback trading and negative performance of large speculators and/or large hedgers.

H_1: There is significant positive feedback trading and negative performance of large speculators and/or large hedgers.

Methodology:

1. Check both for the significant positive feedback behaviour from hypothesis 1, and negative market timing abilities from hypothesis 2. The existence of both simultaneously suggests destabilizing features of hedgers or speculators in futures markets.

2. This can be further supported with the two following tests:

   (i) Firstly, with the decomposition of volatility into expected and unexpected volatility. Before proceeding further, there is a need of a volatility measure. In line with Lopez (2001), it can shown $\xi_t^{\ 2}$ is an unbiased estimator of $\sigma_t^{\ 2}$ as follows:

$$R_t = \mu_t + \xi_t, \quad \xi_t = \sqrt{\sigma_t}\, z_t, \quad z_t \sim N(0,1) \tag{3.7}$$

, where the conditional mean $\mu_t = \mathrm{E}\left[R_t \mid \Omega_{t-1}\right]$

, Ω_{t-1} is the information set available at time t-1,

, ξ_t is the innovation term,

, σ_t is its conditional variance,

$$\begin{aligned} \xi_t^{2} &= \mathrm{E}\left\lfloor \xi_t^2 \mid \Omega_{t-1} \right\rfloor \\ &= \sigma_t^{2}.\mathrm{E}\left\lfloor z_t^2 \mid \Omega_{t-1} \right\rfloor \\ &= \sigma_t^{2} \end{aligned}$$

Then, volatility is decomposed using ARMA model specification, where it is ensured that there are no autocorrelation in the individual time series[57]. Perform the following OLS regression and check for sign and significance of φ_1 and φ_2.

$$\sigma_t^{2} = \varphi_0 + \varphi_1 \ Exp \ \sigma_t^{2} + \ \varphi_2 Un\exp \ \sigma_t^{2} + \varepsilon_t \tag{3.8}$$

The decomposition of volatility into expected and unexpected volatility allows for determining how much expected volatility contributed to the volatility measure. For instance, if hedgers expected volatility is higher, this would support NYMEX (2005) and Haigh et al (2005) that their trading activity is volatile, and would further warrant a need to recheck such large players position limits in terms of regulation in the futures markets.

(ii) Secondly, with the effect of expected and unexpected volatility on futures returns.

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[57] This is done by checking for autocorrelation properties of ARMA model, by using correlograms (AC, PAC, Ljung-Box Q-statistics). If autocorrelations have a seasonal pattern, include SAR (Seasonal Autoregressive) and SMA (Seasonal Moving Average) terms. Choose appropriate number of lags (up to 10 lags) in the ARMA model by using Akaike and Schwarz Information Criteria. The whole procedure is repeated using different terms and number of lags until series is free of autocorrelation.

Perform the following OLS regression of risk/return using expected and unexpected volatility as independent variables and futures returns as dependent variable, and check for sign and significance of φ_1 and φ_2.

$$R_t = \varphi_0 + \varphi_1 \; Exp \;\; \sigma_t^{\;2} + \varphi_2 Un\exp \;\; \sigma_t^{\;2} + \varepsilon_t \tag{3.9}$$

Hedgers' expected volatility would be expected to be negative or insignificant, since they are in the market with a view of minimizing risk as laid out in Hoffman (1932). Any finding or a positive and significant expected risk coefficient in determining returns would add further support of a need to recheck regulation for specific players in specific futures markets. The link between expected return and volatility has implications for the relation between hedging demand and volatility. With a higher expected volatility at the start of the month, hedgers are expected to adjust their portfolios accordingly. A rise in unexpected volatility, however, may cause hedgers to raise their future expectations in estimates of expected volatility, and hence increase the demand for hedging. That's why, one might expect the relation between return and expected volatility to be weaker than for unexpected volatility.

PERFORMANCE

<u>Hypothesis 5</u>: There is some significant expected component for variables like hedgers' and speculators' net positions, sentiment and information variables in explaining returns and idiosyncratic volatility.

Many studies analysed the relation between extent of futures participation and price volatility. For instance, Chang et al (2000) find no strong relationship between open interest, expected and unexpected volatility. Others like Ward (1974) and Peck (1981) find a negative relation between the degree of market participation (open interest) by speculators and volatility. Despite the potential link between returns, volatility and speculation, much less attention has been given to how volatility and returns depend on the expected (ex ante) value of independent variables such as net position, sentiment and information variables. This hypothesis also fills the gap where market participation is proxied by net positions for the first time, and not by open interest or volume as used extensively in previous literature (see Karpoff (1987) for a review).

Following French, Schwert and Stamburgh (1987) work on decomposing market volatility variables into expected and unexpected components, the aim of this hypothesis is to determine, using ARMA specifications, how each each decomposed variable affect the return and volatility of hedgers and speculators. Alternatively stated, the purpose in doing so is to assess whether traders' reactions to returns or volatility depend upon the predictability of variables they use. If there are relatively more significant expected components of variables in determining hedgers' or speculators' returns, this suggests the specific player is more reliant upon expected values of variables in determining their returns. Alternatively stated, the expected component of a variable reflect the value of that variable as of the beginning of the trading month, where as the unexpected component captures unanticipated changes during the month. For instance, with a higher expected net position at the start of the month, hedgers would readjust their portfolios accordingly. However, a rise in unexpected net position may cause the large players to increase their future expectations in estimates of expected net positions, and hence increasing their future returns. This is supported in Chang et al (2000) who find the expected open interest is less than unexpected open interest, such that hedgers respond more to surprises in open interest and open they can predict. That's why, one might also expect the relation between return and expected net positions to be weaker than for unexpected positions. Further, the decomposition of net positions against volatility can also help to justify whether there is a positive relationship between trading demand and volatility as supported in Karpoff (1987). The decomposition of information variables would add further support in testing whether large players in US futures markets use these priced risk factors in determining their returns, and also whether they affect current volatility levels.

H_0: There is no significant expected and/or unexpected component of each variable determining the returns and risk of each trader type.

H_1: There is a significant expected and/or unexpected component of each variable determining the returns and risk of each trader type.

Methodology:

1. Check for stationarity of each individual time series.
2. Check for autocorrelation properties of ARMA model, by using correlograms (AC, PAC, Ljung-Box Q-statistics). If autocorrelations have a seasonal pattern, include SAR (Seasonal Autoregressive) and SMA (Seasonal Moving Average) terms. Choose appropriate number of lags (up to 10 lags) in the ARMA model by using Akaike and Schwarz Information Criteria.
3. Check for no autocorrelation in the individual time series using Q-statistics and Breusch-Godfrey LM test. Otherwise repeat step 2 using different terms and number of lags until series is free of autocorrelation.
4. Carry an ARCH LM test to ensure equations below are uncorrelated with past residuals and efficient
5. Perform the following OLS regressions of mean equation and idiosyncratic volatility equation, using decomposed components of sentiment, net positions,information variables, and a lagged hedging pressure variable to control for hedging pressure effect.

Mean equation

$$\begin{aligned} R_t = \varphi_0 &+ \varphi_1 \text{Exp}\, SI_t + \varphi_2 \text{Unexp}\, SI_t + \varphi_3 \text{Exp}\, NP_t + \varphi_4 \text{Unexp}\, NP_t \\ &+ \varphi_5 \text{HP}_{t-1} + \varphi_6 \text{Exp Tbill yield}_t + \varphi_7 \text{ Unexp Tbill yield}_t \\ &+ \varphi_8 \text{Exp BAA - AAA}_t + \varphi_9 \text{ Unexp BAA - AAA}_t \\ &+ \varphi_{10} \text{Exp Divyield}_t + \varphi_{11} \text{ Unexp Divyield}_t + \xi_t \end{aligned} \tag{3.10}$$

Volatility equation

$$\begin{aligned} \sigma_t^2 = \varphi_0 &+ \varphi_1 \text{Exp}\, SI_t + \varphi_2 \text{Unexp}\, SI_t + \varphi_3 \text{Exp}\, NP_t + \varphi_4 \text{Unexp}\, NP_t \\ &+ \varphi_5 \text{HP}_{t-1} + \varphi_6 \text{Exp Tbill yield}_t + \varphi_7 \text{ Unexp Tbill yield}_t \\ &+ \varphi_8 \text{Exp BAA - AAA}_t + \varphi_9 \text{ Unexp BAA - AAA}_t \end{aligned}$$

$$+ \ \varphi_{10}\,\text{Exp Divyield}_t + \varphi_{11}\ \text{Unexp Divyield}_t + \ \xi_t \qquad (3.11)$$

6. Repeat step 2 for mean equation and also.
7. Check for sign and significance of expected and unexpected components (φ_1 - φ_{11})

<u>Hypothesis 6</u>: The GARCH and/or PARCH volatility models accurately reflect(s) the volatility in determining actual returns for each player.

Following Engle (1982), the innovation in the mean, ξ_t, of the monthly close-to-close futures prices of the most active contracts, is assumed to be serially uncorrelated with mean zero, hence justifying the use of ARCH processes such as GARCH and PARCH. Instead of using models where the variance of tomorrow's return is an equally weighted average of the squared residuals from the last month, the GARCH and PARCH models allow the weights to be self-determined. Finally but not least, commodity price volatility is known to have a time-varying pattern as documented in Yang and Brorsen (1993). In markets, where speculators trade actively, prices are subject to lots of speculative trades, which increases the volatility in prices. Consequently, this leads to more speculation and hence even more volatility. This is why time-varying volatility models, particularly ARCH, are widely used to model the behaviour of commodity prices (Beck, 2001).

While, the GARCH model is well documented in existing literature (see section 2.16.1.9), the PARCH model is less commonly used. If any series is normally distributed, one can characterize its distribution by its first two moments or the common use of a squared term (Mckenzie et al 2001). Hence the use of variance models. However, for non-normal error distribution, the use of a squared term is less appropriate. The same authors suggest that by imposing such a structure on the data, it may drastically lead to sub-optimal models. Introduced by Ding et al (1993), the PARCH model, allows the optimal power term to be estimated rather than imposed. See Brooks et al (2000) and Ding et al (1993) for a review of PARCH models. Denoting one to the power of term result in a standard deviation based volatility model.

This purpose of this hypothesis is to be the first to contribute as to whether the variance measure (GARCH) or the standard deviation measure (PARCH) more accurately reflects the risk of each trader type. Following empirical support of the extensive usage of ARCH (particularly GARCH models) and non-constant variance (see section 2.16.1.9), this study makes use of GARCH (variance based) and PARCH (standard deviation based) volatility models to reduce the gap in better understanding the risk of each trader type. The GARCH model will show how lagged volatility and news of volatility from the previous period impact on current players' volatility. This provides the possibility to check for persistence of volatility to shocks for hedgers and speculators during the last decade. The difference between conditional standard deviation (PARCH) and conditional variance (GARCH) models shows which model captures more significant negative variables like lagged volatility and news of volatility from the previous period. This hypothesis is complemented with the robust check of the in-sample model performance of hypothesis 8.

H_0: The 'variance' (GARCH model) and/or the 'standard deviation' (PARCH model) are indifferent in measuring the risk of each trader, in determining actual returns.

H_1: The 'variance' (GARCH model) or the 'standard deviation' (PARCH model) is a better measure of the risk of each trader, in determining actual returns.

Methodology:

1. Set up of *mean equation* as follows:

$$R_t = \varphi_0 + \varphi_1\, SI_t + \varphi_2\, NP_t + \varphi_3\, \mathrm{HP}_{t-1} + \varphi_4\, \text{Tbill yield}_t \\ + \varphi_5\, \text{BAA - AAA}_t + \varphi_6\, \text{Divyield}_t + \xi_t \tag{3.12}$$

where R_t is the monthly returns, SI_t is the sentiment index, HP_{t-1} is the hedging pressure effect variable; Tbill yield_t, BAA - AAA_t, Divyield_t are the three information variables. Note that Gannon (1996) and McKenzie (1999) find the mean model specification has little impact on the ARCH models estimated in both discrete and continuous time.

2. OLS regression of the GARCH and PARCH volatility equations as follows:

GARCH volatility equation

$$\sigma_t^{\ 2} = \varphi_0 + \varphi_1 \xi_{t-1}^{\ 2} + \varphi_2 \sigma_{t-1}^{\ 2} + \varepsilon_t \qquad (3.13)$$

PARCH volatility equation

$$\sigma_t^{\delta} = \varphi_0 + \sum_{i=1}^{p} \varphi_i \left(\left|\xi_{t-i}\right| - \gamma_i \xi_{t-i}\right)^{\delta} + \sum_{j=1}^{q} \varphi_j \sigma_{t-j}^{\delta} + \varepsilon_t \qquad (3.14)$$

where: δ>0, $|\gamma_i| \leq 1$ for $i = 1, \ldots, r$, and $\gamma_i = 0$ for all $i > r$, $r \leq p$.

Substituting δ=1, i=j=1 and $\gamma_i = 0$ in equation 4.14.1, results in a symmetrical PARCH model as follows:

$$\sigma_t = \varphi_0 + \varphi_1 \xi_{t-1} + \varphi_2 \sigma_{t-1} + \varepsilon_t \qquad (3.15)$$

Note that if δ=2, and $\gamma_i = 0$ for all i, the PARCH model is simply a standard GARCH specification.

3. Ensure both volatility models are white noise by calculating the correlograms of squared residuals and probability (observed r-squared) from an ARCH LM test.
4. Check for sign and significance of φ_1 and φ_2 in volatility equations to determine the effect of lagged volatility and news about volatility from the previous period.

5. Check for sum of φ_1 and φ_2 in volatility equations to determine persistence of shocks in specific markets.

<u>Hypothesis 7</u>: The error distribution of each trader type is tested in reference to whether they are normally distributed.

Based on the previous hypothesis, it has been assumed that the series are normally distributed. While it might work well with the GARCH model where second moments or squared terms are used, the PARCH model might not be the best optimal model where the series are not normally distributed (see McKenzie et al, 2001 for example). Also, if the error term in the mean equation mostly contains outliers, the Gaussian normal distribution is inappropriate. To deal with such leptokurtosis, the model(s) can be estimated, assuming conditional errors are drawn from a conditional t-distribution (Bollerslev, 1987).

The purpose of this hypothesis is to check the error distribution of the GARCH and PARCH models used. Based on the assumption that the mean equation and the variance equation have been arrived at, the Jacques-Bera normality test is critical in knowing which error distribution the series tends to follow. Earlier empirical support from section 2.16.2 showed that most agricultural and metals display right skewness and excess kurtosis under normal distribution. Testing normality of the PARCH and GARCH models, under *t* distribution, is a first one assessed under this hypothesis. Due to the PARCH model being based on standard deviation rather than variance, it is expected the PARCH model to exhibit more skewness due to more outliers. A PARCH model, under a *t* distribution, would be expected to exhibit less skewness since the t-distribution would lead to smaller conditional errors as explained in Bollerslev (1987). A lower kurtosis is expected particularly where for hedgers since hedgers are in the market to reduce risk and speculators to bear that risk as supported by hedging and speculators theories in section 2.4 and 2.5.

H_0: The distribution of each commodity for each trader type departs from normality.

H_1: The distribution of each commodity for each trader type is normally distributed.

Methodology: Perform normality test for GARCH and PARCH models, under both normal and *t* distribution, using Jarque-Bera statistics, skewness and kurtosis measures.

<u>Hypothesis 8</u>: The models used (GARCH / PARCH) have good forecasting abilities for each trader type.

Following massive support from literature reviews like Poon and Granger (2003) (see section 2.16.3), this hypothesis carries weight in that it is the first one where the forecasting abilities of the GARCH and PARCH models are assessed. Forecast evaluation and model performance tools commonly used in empirical support include bias proportions, covariance proportions, Theil inequality and root squared mean error (RMSE). All these are tested to reveal whether the GARCH or PARCH model is better specified in explaining actual returns. Out-of-sample forecasting for one month return is also tested for each model using graphical representations. The out-of-sample forecasting helps not only to find which volatility model(s) accurately predict one-month return, but whether idiosyncratic volatility can accurately serve as a proxy to volatility in matching the volatility in one month's time.

H_0: The GARCH and/ or PARCH model are indifferent in predicting the performance of each trader type.

H_1: The GARCH or the PARCH model better predicts the performance of each trader type.

Methodology:

1. Perform in-sample model evaluation using Theil inequality test, proportions (bias, variance and covariance) and RMSE.
2. Carry out-of-sample forecasting with graphical representation of one-month forecast return from GARCH and PARCH models against actual returns.
3. Include 95% confidence intervals to ensure actual returns are within range of forecasted returns.
4. Check for accuracy of idiosyncratic volatility in forecasting one-month return with graphical representation of actual volatility (from GARCH and PARCH model) against idiosyncratic volatility.

<u>Hypothesis 9</u>**: The large hedgers/large speculators changed their behaviour and performance during specific events in the 1990s.**

This final hypothesis relates to both an event and stability analysis of whether large hedgers and/or large speculators changed their behaviour and performance during specific events in the 1990s, or if they were indifferent to these events. The purpose of this hypothesis also add further support to earlier hypotheses in regards to how large hedgers or speculators change their future trading positions based actual returns, how their returns are affected by net positions, how the risk and return relationship varies over time, and what relationship exist between trading activity and volatility. All these models are tested before and after important global events. Hence the use of an event and stability test.

The Fed easing interest rates in the early 1990s, the Mexico crisis, the Japanese crisis, the temporary slump of emerging markets in the mid-1990s, the Asian crisis, the Russian crisis and Long Term Capital Management (LTCM) are chosen as events in that they are international in nature with different backgrounds, making the analysis a more comparable and distinct one. The trading determinant model, mean equation model, and return/risk relationship model are tested for stability and structural breaks. A fourth model and last model within this hypothesis tests the relationship between net positions and volatility, where volatility is proxied as standard deviation and variance.

H_0: Large hedgers and/or large speculators did not significantly change their behaviour and performance during one or more of the events of the 1990s.

H_1: Large hedgers and/or large speculators significantly changed their behaviour and performance during one or more of the events of the 1990s.

Methodology:

1. Recursive estimates regression of the trading determinant model, mean equation model, risk and return relationship model, and trading activity and volatility model as follows:

Trading determinant model

$$\Delta NP_{t+1} = \varphi_0 + \varphi_1 R_t + \xi_t \tag{3.16}$$

Mean equation model

$$R_t = \varphi_0 + \varphi_1 NP_t + \xi_t \tag{3.17}$$

Risk and return relationship model

$$R_t = \varphi_0 + \varphi_1 \sigma_t + \varepsilon_t \tag{3.18}$$

$$R_t = \varphi_0 + \varphi_1 \sigma_t^2 + \varepsilon_t \tag{3.19}$$

Trading activity and volatility model

$$NP_t = \varphi_0 + \varphi_1 \sigma_t + \varepsilon_t \tag{3.20}$$

$$NP_t = \varphi_0 + \varphi_1 \sigma_t^2 + \varepsilon_t \tag{3.21}$$

where: $\Delta\ NP_{t+1}$ is the change in net positions in one month time, R_t is the actual monthly returns, NP_t is the actual net positions, σ_t is the standard deviation based on the PARCH volatility model, and $\sigma_t^{\ 2}$ is the variance based on the GARCH volatility model. Other variables such as sentiment index and information variables are excluded due to the small sample size of some events and non-significant effect of some variables in as found in earlier hypotheses (see Gurrib, 2008).

2. Check for sign and significance of φ_1 in each model over whole sample period to determine significance of independent variable, hence stability, in the long run.
3. Check for structural breaks in each model. Match any structural break with one of the eight macroeconomic events. Check for significance of break before and after event to determine if event has affected recursive estimates of model.

3.4 Conclusion

This chapter starts by laying out details about the uniqueness and broad use of the COT data, some features of the CFTC as a regulatory body in the US, the sentiment index data, calculation of futures returns, a data coding and classification list, the primary objectives of this study, and the statement of hypotheses to be analysed in the next chapter. Graph 3.1 is also provided to help in gaining a better understanding of the behaviour, performance and event analysis sections of this study. The main econometric tests are laid out in this graph to ease follow-up in Chapter 4.

Chapter 4:
RESEARCH OUTPUT AND FINDINGS

4.1 Introduction

This section encapsulates the research output and findings of this study. Initially, time series properties tests such as unit root test are performed to test for stationarity in the futures returns, sentiment index, net positions (for hedgers and speculators), and information variables. The individual Augmented Dick-Fuller (ADF) unit root test and panel unit root tests (ADF Fisher test and Im, Perasan and Chin test) are performed to avoid spurious regressions.

This chapter further provides the analysis of the behaviour and performance sections of the study. The behaviour section looks at positive feedback and contrarian behaviour for both large speculators and large hedgers. A market timing test follows to assess whether speculators perform better than hedgers. To test for robustness of superior performance of speculators, own- and cross-hedging pressure effects tests are carried out.

In the performance sections, the mean equation is first regressed against decomposed variables together with a lagged hedging pressure variable. Volatility equations (derived from ARMA models) are also regressed in relation to expected and unexpected volatility components. GARCH and PARCH volatility models are then assessed, and commodity return series under both models are tested to see if they are normally distributed. Further, the return and risk relationship is looked at where risk is decomposed into expected and unexpected volatility. Static forecasting of one-month futures return is then carried out, both under normal and *t* distributions for GARCH and PARCH models. The ability of the idiosyncratic volatility to accurately match standard deviation or variance in forecasting one-month returns is then looked at. Diagnostic and model specification tests are carried out on all the models used before making any comment.

Finally but not least, events analysis is carried out for the eight named events. The robustness or stability of the behaviour and performance models is re-looked at when faced with structural breaks. The trading determinant model (behaviour), mean equation (performance), return/risk relationship model, and trading activity and volatility relationship model are tested for robustness with recursive stability tests. The purpose of this section is to further analyse the concept of risk (standard deviation and variance) and return relationship at different time intervals and how the relationship is affected by specific macroeconomic events. This chapter ends with a conclusion of all the findings of this study.

4.2 Time Series Properties and Descriptive Statistics

The first couple of things examined under descriptive statistics is whether the mean of futures returns are "near zero" values as expected in efficient markets[58]. The mean of hedgers' net positions would reveal whether hedgers are net short as expected[59], and the mean of speculators' net positions would reveal whether speculators are net long on average. The mean of each trader type should also be negatively related due to the concept of futures trading being a zero-sum game. The mean of hedgers is also expected to be of greater magnitude than the mean of speculators, showing that hedgers are the main players in the futures market as expected, and that the difference between the mean of the two players' net positions is attributed to the existence of small traders. The standard deviation of hedgers and speculators should reveal not only whether hedgers or speculators change their net positions more often, but also which group exhibits more swings in its average returns, e.g. highly-traded currency and financials compared with agriculturals. Further, the mean of sentiment index should be almost the same over the different commodities due to the trend-chasing behaviour of the 1990s. The standard deviations in one particular group will reveal which consumers have more volatile sentiment. The mean and standard deviation of information variables would also reveal

[58] See Fama (1991) Efficient Market Hypothesis and three factor model for an example.
[59] Most hedgers, particularly in commodity markets, are producers or manufacturers who face the risk of falling prices when selling their goods in the future. Hence, they short to reduce that risk.

whether these priced risk factors are significant in the decision-making process by players, by being significantly different from zero at 1%, 5%, and 10% level. Finally, but not least, it is also of interest to see how each variable relate to each other, and correlations between important variables such as net positions, changes in net positions, sentiment and returns will be laid out.

Before carrying out any regression analysis throughout the whole study, all data series are tested for stationarity in levels or after differencing[60]. Both individual (ADF) and panel unit root tests (ADF Fisher and Im, Perasan and Chin) are performed using both Akaike and Schwarz information criteria. Results for individual unit root tests are reported in tables 4.1–4.3. An ADF test with trend and no intercept has been included as per ADF model specification in Appendix 6.5.1[61]. The ADF test statistic used in the test is a negative number. The more negative it is, the stronger the rejection of the hypothesis of a unit root at 1%, 5% and 10% significance levels. Table 4.6 reports the descriptive summary statistics.

As can be seen from Table 4.1, ADF test futures returns and market sentiment are stationary at levels. Both Akaike and Schwarz information criteria results confirm that there is no need for differencing, i.e. $I(0)$. This is also observed in other studies where futures returns are used instead of futures prices (Wang, 2003). Table 4.2, however, shows that net positions for hedgers are not stationary at levels, for Eurodollars, t-bonds, soybeans, S&P500, feeder cattle, wheat (Kansas), cocoa and coffee. Net positions for speculators are not stationary at levels for Swiss francs, Japanese yen, feeder cattle, wheat (Chicago), wheat (Kansas), cocoa, lumber, soybeans, and soybean oil. Further, Table 4.3 reports that the corporate yield spread, the dividend yield, and the Treasury bill yield are non-stationary at levels. All non-stationary series become stationary at $I(1)$[62], i.e. after differencing one time. ADF Fisher test and Im, Perasan and Chin panel unit root tests

[60] See Working (1953) for more details on futures trading and stationary processes.
[61] An intercept is not included due to restricted sample size and Eviews software specifications. A trend component is included however due to hedgers and speculators reversing most of the positions after a point of time. However, future research might further robust the variables with a trend and intercept component.
[62] Appendix 6.10, Graph 4.1 and Graph 4.2 provide tabular and graphical representations that all series are stationary after differencing one time.

also support the above findings of individual unit root tests and can be found in Appendix 6.10.

The descriptive summary statistics in Table 4.6 are divided into three panels. Panel A shows that the mean returns in the 29 futures markets are significantly not different from zero. This supports the Efficient Market Hypothesis that, on average, no superior returns can be achieved in futures markets. The high positive mean values of sentiment data support the fact that US futures markets moved with bullish events in the 1990s. The mean values of net positions of hedgers were negative in 21 of the 29 futures markets, suggesting that large hedgers were mostly net short during the 1990s. In fact, out of the 16 agricultural futures markets, only corn and feeder cattle markets of large hedgers were net long. Large hedgers being net short is backed by Keynes (1930). Large speculators, on the other hand, are net long for 21 of the 29 futures markets. More importantly, the mean net positions of speculators are less than hedgers for most markets. This can be explained by the existence of effective barriers to participation, like those proposed by Hirshleifer (1988). These barriers might arise from fixed set-up costs required to learn about these markets. This suggests why large hedgers are the market players that were mostly followed by investors in decision-making in futures markets.[63] The difference in mean values between large speculators and large hedgers can be attributed to small speculators', small hedgers' and small traders' mean as defined by the CFTC, where small speculators, small hedgers and small traders are the rest of the market.

Panel B shows the correlation between returns, net positions at levels of hedgers (speculators), changes in net positions of hedgers (speculators), and market sentiment. The correlation between changes in net positions of hedgers (speculators) with market sentiment appears to be negatively (positively) related. Futures returns and changes in net positions of hedgers (speculators) appear to be also negatively (positively) correlated. The correlation coefficient between return and hedgers' change in net positions tends to be greater than those between return and speculators', in absolute values. This is supported by Marcus (1984) and Chang (1985) who found that commodity futures price

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[63] Several studies like Khouris and Perrakis (1998) and Chang et al. (2000) suggest that large hedgers generally pick the right direction of futures markets.

changes are negatively correlated with hedging positions taken previously by producers. Net positions of hedgers appear to be negatively correlated with net positions of speculators, with the soybean oil futures market exhibiting the highest negative correlation (0.975) between these large players. This finding supports the fact that trading in futures markets is a zero-sum game. Panel C results show that all the information variables are significantly different from zero at 1%, 5%, and 10% level.

Table 4.1
Stationarity of sentiment index and futures returns

This table shows the test for unit root for investors' sentiment data and futures returns, using Augmented Dickey-Fuller (ADF) test. Investor sentiment is proxied by the Consensus Index, in percent. The futures returns is measured as the percentage change in settlement prices of a futures contract over 1 month period. *(**)(***) denotes significance of ADF test at 1%(5%)(10%) level. Both Akaike and Schwarz information selection criteria are used. Specification of ADF test, Akaike and Schwarz information criteria can be found in appendices. An ADF test with a trend, but no intercept is being used as follows:

$$\Delta y_t = \alpha y_{t-1} + x_t{'}\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \dots + \beta_p \Delta y_{t-p} + v_t$$

Stationarity of sentiment index & futures returns (level series)

	Sentiment index		*Futures returns*	
	ADF test result under Information Criteria		ADF test result under Information Criteria	
	Akaike	Schwarz	Akaike	Schwarz
Metals				
SI	-6.059	-6.990	-24.842	-24.842
GC	-6.729	-6.729	-23.037	-23.037
HG	-7.645	-7.348	-15.734	-25.769
PL	-3.627	-8.621	-19.302	-27.620
Financials				
ED	-6.192	-7.427	-4.049	-14.877
US	-7.320	-7.320	-26.837	-26.837
Currencies				
BP	-8.192	-7.806	-5.414	-24.172
SF	-7.192	-7.192	-23.827	-23.827
CD	-8.323	-8.323	-13.634	-26.353
JY	-5.378	-7.488	-25.267	-25.267
Soybean complex				
S	-7.598	-7.598	-26.179	-26.179
BO	-6.840	-8.670	-24.690	-24.690
SM	-3.790	-8.093	-26.820	-26.820
Stock Index				
SP	-6.688	-6.688	-26.938	-26.938
Meats				
PB	-8.660	-8.660	-23.940	-23.940
LH	-8.575	-8.575	-5.107	-21.951
LC	-8.889	-8.889	-26.304	-26.304
FC	-9.676	-9.676	-28.246	-28.246
Grains				
W	-6.919	-6.919	-24.880	-24.880
KW	-6.919	-6.919	-10.004	-24.309
MW	-6.919	-6.919	-10.363	-24.220
C	-6.386	-6.258	-7.373	-25.532
Foods				
SB	-5.090	-6.885	-23.760	-23.760
CC	-8.709	-8.709	-24.844	-24.844
KC	-8.662	-8.352	-12.545	-24.751
Fibres				
CT	-7.878	-7.878	-7.023	-23.260
LB	-9.992	-9.678	-22.358	-22.358
Energy complex				
CL	-7.314	-6.965	-12.346	-26.533
HO	-8.070	-8.070	-6.968	-26.395

Table 4.2
Stationarity of large hedgers and large speculators

This table shows the test for unit root for net positions of large hedgers and large speculators, using Augmented Dickey-Fuller (ADF) test. Net positions (NP) are defined as the long positions less the short positions of a trader type on the basis of the CFTC's COT reports, in units of 1,000 contracts. *(**) (***) denotes significance of ADF test at 1%(5%)(10%) level. Both Akaike and Schwarz information selection criteria are used. Specification of ADF test, Akaike and Schwarz information criteria can be found in appendices. An ADF test with a trend, but no intercept is being used as follows:

$$\Delta y_t = \alpha y_{t-1} + x_t{}'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + v_t$$

		Hedgers NP			***Speculators NP***	
		ADF test result under Information Criteria			**ADF test result under Information Criteria**	
		Akaike	Schwarz		Akaike	Schwarz
Metals						
SI		-5.136	-5.136		-4.749	-4.749
GC		-4.766	-4.766		-3.841	-4.817
HG		-5.044	-5.044		-5.256	-5.256
PL		-5.468	-5.468		-5.563	-5.563
Financials						
ED	*,**,***	-1.806	-1.806		-3.519	-3.519
US	*,**	-2.456	-4.515		-4.420	-4.420
Currencies						
BP		-7.417	-7.417		-7.012	-7.012
SF		-6.752	-6.797	*,**,***	-1.818	-6.544
CD		-5.668	-5.668		-6.257	-6.390
JY		-4.937	-4.937	**,***	-2.535	-5.324
Soybean complex						
S	***	-3.280	-2.882	***	-3.239	-3.239
BO		-4.109	-4.109	***	-3.117	-3.967
SM		-4.169	-4.169		-4.563	-4.563
Stock Index						
SP	*,**,***	-0.059	-0.926		-4.108	-4.108
Meats						
PB		-4.563	-4.283		-4.346	-4.346
LH		-3.665	-3.808		-3.899	-3.899
LC		-4.766	-4.766		-4.552	-4.552
FC	*,**,***	-1.207	-4.088	***	-2.749	-3.867
Grains						
W		-4.870	-5.925	*,**,***	-1.827	-4.593
KW	*,**,***	-0.033	-2.514	***	-2.919	-5.529
MW		-5.511	-5.511		-4.842	-4.842
C		-3.919	-3.919		-3.642	-3.642
Foods						
SB		-5.046	-5.046		-4.463	-4.463
CC	*,**,***	-2.297	-2.739	*,**,***	-2.100	-2.937
KC	**,***	-2.728	-5.767		-3.771	-7.104
Fibres						
CT		-4.897	-4.897		-4.540	-4.315
LB		-3.540	-4.669	***	-3.347	-5.116
Energy complex						
CL		-5.444	-5.444		-5.486	-5.486
HO		-4.445	-5.735		-3.518	-6.589

Table 4.3
Stationarity of information variables

This table shows the test for unit root for the corporate yield spread, dividend yield and 90-day T-bill yield, using Augmented Dickey-Fuller (ADF) test. Corporate yield spread is the monthly yield on the Lehman's BAA-rated bonds less the yield on AAA-rated bonds. Dividend yield is the monthly yield on the S&P500index. 90-day T-bill is the monthly yield on the 3-month Treasury bills. *(**) (***) denotes significance of ADF test at 1%(5%)(10%) level. Both Akaike and Schwarz information selection criteria are used. Specification of ADF test, Akaike and Schwarz information criteria can be found in appendices. An ADF test with a trend, but no intercept is being used as follows:

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + v_t$$

<u>Stationary of information variables</u>

		Level series	
		ADF test result under Information Criteria	
		Akaike	Schwarz
Corporate Yield Spread	*,**,***	-0.758	-0.362
Dividend yield	*,**,***	-0.492	-0.818
90-day T-bill yield	*,**,***	-2.716	-2.632

Test critical values:	1% level	-3.483
	5% level	-2.885
	10% level	-2.579

Table 4.6
Descriptive summary statistics

This table is divided into three panels. Panel A shows the summary statistics for futures returns, net positions of hedgers and speculators, and sentiment index. Panel B shows the correlation between all futures returns, sentiment index, net positions of hedgers (speculators), and changes in net positions of hedgers (speculators). Panel C shows the summary statistics for information variables. Net positions (NP) are defined as the long positions less the short positions of a trader type on the basis of CFTC's COT reports, in units of 1,000 contracts. The return is measured as the percentage change in settlement prices of a futures contract over 1 month interval. Corporate yield spread is the monthly yield on the Lehman's BAA-rated bonds less the yield on AAA-rated bonds. Dividend yield is the monthly yield on the S&P500index. 90-day T-bill is the monthly yield on the 3-month Treasury bills. Investor sentiment is proxied the Consensus Index, in percent SI Ω $\Delta NP^{S(H)}$ denotes the correlation between sentiment index and changes in net positions of speculators (hedgers). R Ω $\Delta NP^{S(H)}$ denotes the correlation between returns and changes in net positions of speculators (hedgers). ΔNP^{H} Ω ΔNP^{S} denotes the correlation between changes in net positions of speculators and hedgers.

Panel A: Summary statistics for Returns, Sentiment, and Net Positions

	Returns (%)		**Sentiment (%)**		**Speculator**		**Hedger**	
	Mean	*Std. dev.*	*Mean*	*Std. dev.*	*Mean*	*Std. dev.*	*Mean*	*Std. dev.*
Metals								
SI	0.098	5.566	50.463	18.756	18.206	14.504	-39.746	14.375
GC	-0.181	3.373	47.980	18.665	-12.187	32.076	5.366	39.932
HG	-0.089	6.017	45.239	19.476	3.330	8.610	-8.761	12.037
PL	0.271	4.653	49.263	21.261	3.592	4.145	-6.251	4.756
Financials								
ED	0.026	0.305	47.412	20.846	9.116	89.114	116.503	175.776
US	0.118	2.817	42.726	15.902	9.880	25.800	-14.834	37.501
Currencies								
BP	-0.041	2.854	45.683	21.905	0.175	12.372	0.921	18.023
SF	-0.030	3.605	40.223	21.703	-5.402	13.995	9.268	21.061
CD	-0.184	1.250	39.867	19.026	-0.706	11.593	-2.805	16.924
JY	0.321	3.437	41.916	19.267	-9.418	19.647	14.145	30.423
Soybean complex								
S	0.019	5.248	52.636	17.201	12.258	21.934	-22.400	28.583
BO	-0.138	5.076	45.700	21.194	3.253	15.518	-11.715	21.476
SM	0.228	5.887	46.122	21.390	3.275	10.331	-14.060	16.273
Stock Index								
SP	1.087	3.941	44.075	14.095	-15.690	9.656	11.250	21.807

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Meats								
PB	1.023	13.776	40.698	18.947	-0.347	1.745	-0.359	0.892
LH	0.386	9.473	43.059	15.222	2.580	5.916	-0.837	4.848
LC	0.089	3.822	49.659	15.109	5.348	9.582	-3.582	8.552
FC	0.121	3.274	47.737	18.275	1.443	2.426	0.811	1.803
Grains								
W	0.024	6.617	48.753	19.659	5.342	10.093	-11.886	10.920
KW	0.126	6.475	48.753	19.659	1.139	3.500	-1.085	6.152
MW	0.094	5.996	48.753	19.659	-0.088	1.049	-0.447	1.995
C	0.010	6.123	51.155	19.421	23.667	43.289	0.724	50.876
Foods								
SB	0.027	8.523	50.438	20.612	15.504	28.381	-25.751	35.622
CC	-0.170	7.279	46.287	17.420	4.310	10.127	-10.928	12.416
KC	0.481	12.141	44.234	20.642	3.236	5.437	-7.761	7.005
Fibres								
CT	0.149	6.514	47.505	18.638	-3.023	11.354	-0.315	12.664
LB	0.506	9.046	42.695	22.872	0.120	0.529	-0.298	0.701
Energy complex								
CL	0.759	8.927	46.528	19.158	6.581	24.324	-7.297	33.617
HO	0.851	9.186	45.334	21.760	2.655	8.706	-15.478	13.844

Panel B : Correlations

	$SI\ \Omega\ \Delta NP^S$	$SI\ \Omega\ \Delta NP^H$	$R\ \Omega\ \Delta NP^S$	$R\ \Omega\ \Delta NP^H$	$\Delta NP^H \Omega \Delta NP^S$	$NP^H\ \Omega\ NP^S$
Metals						
SI	0.155	-0.362	-0.083	-0.666	0.050	-0.448
GC	0.064	-0.412	-0.040	-0.609	0.115	-0.570
HG	0.178	-0.445	-0.011	0.026	-0.025	-0.429
PL	-0.049	-0.504	-0.087	-0.610	0.254	-0.642
Financials						
ED	-0.066	-0.315	-0.159	-0.110	0.044	-0.619
US	0.115	-0.249	0.189	-0.086	0.047	-0.504
Currencies						
BP	0.069	-0.444	0.027	-0.109	0.166	-0.186
SF	0.087	-0.406	-0.088	-0.121	0.038	-0.177
CD	0.070	-0.477	0.032	0.052	-0.061	-0.384
JY	0.083	-0.367	0.087	-0.627	-0.021	-0.276
Soybean complex						
S	0.213	-0.506	0.165	-0.743	-0.123	-0.764
BO	0.462	-0.459	0.667	-0.674	-0.968	-0.975
SM	0.145	-0.444	0.074	-0.658	0.100	-0.521

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Stock Index						
SP	0.068	-0.191	0.022	-0.325	-0.159	-0.494
Meats						
PB	0.112	-0.146	0.078	0.002	-0.050	-0.094
LH	0.130	-0.380	0.039	-0.202	-0.031	-0.486
LC	0.226	-0.306	0.031	-0.340	0.020	-0.348
FC	0.046	-0.237	0.005	-0.441	0.076	0.207
Grains						
W	0.201	-0.375	0.183	-0.540	-0.175	-0.349
KW	0.134	-0.317	0.126	-0.389	-0.056	-0.155
MW	0.127	-0.243	0.166	-0.319	-0.034	-0.013
C	0.177	-0.443	0.144	-0.646	-0.072	-0.569
Foods						
SB	0.175	-0.480	-0.004	-0.582	0.098	-0.402
CC	-0.086	-0.319	-0.240	-0.530	0.309	-0.589
KC	0.158	-0.474	0.033	-0.577	-0.170	-0.450
Fibres						
CT	0.145	-0.511	0.057	-0.591	0.007	-0.409
LB	0.071	-0.179	0.038	-0.236	-0.139	-0.310
Energy complex						
CL	-0.028	-0.297	-0.028	-0.297	0.137	-0.422
HO	0.123	-0.440	0.083	-0.441	0.060	-0.286

Panel C: Summary Statistics and Description for Information Variables

	Mean	Std. Dev.	t-statistics	
90 day Treasury bill Yield	5.004	1.177	50.139	***
BAA-AAA Lehman's Corporate spread	2.067	3.321	7.337	***
Dividend yield	2.322	0.802	34.160	***

*** denotes that parameter is significantly different from zero at 1%,5%,10% level.

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4.3 BEHAVIOUR

4.3.1 Positive Feedback and Contrarian Behaviour

Nofsinger and Sias (1999) and Grinblatt and Keloharju (2000) showed that investors are most likely to condition their trades on past returns, exhibiting contrarian or positive feedback trading behaviour. Further, Bessembinder and Chan (1992) and Bjornson and Carter (1997) showed that common information variables like T-bill yield, equity dividend yield and default premium have forecasting power in futures markets. To test how lag investor sentiment, returns, and these information variables influence trading decisions by type of trader, the behaviour model used by Wang (2003) is adapted over the 29 futures markets as follows:

$$\Delta NP_{t+1} = \varphi_0 + \varphi_1 \Delta SI_t + \varphi_2 R_t + \varphi_3 \text{Tbill yield}_t + \varphi_4 \text{BAA - AAA}_t + \varphi_5 \text{Divyield}_t + \xi_{t+1} \quad (4.1)$$

ΔNP_{t+1} is the change in net positions of large speculators in month $t+1$. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. ΔSI_t denotes the change in the Consensus index in month t. R_t is the futures return in month t, in percent.[64] Tbillyield$_t$, BAA-AAA$_t$, Divyield$_t$ are the three information variables included in the model.[65]

[64] To match with COT reporting dates, a month represents a 4-week interval (Tuesday–Tuesday).
[65] See Chapter 2, section 2.10 for more on information variables' relevance to futures markets.

Table 4.7.1
Trading behaviour of large hedgers

This table shows the results for testing the determinants of trading decisions for large hedgers. ΔNP_{t+1} represents the changes in net positions of large hedgers in month $t+1$. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. ΔSI_t denotes the change in the Consensus index in month t. R_t is the futures return in month t, in percent. Tbillyield$_t$, BAA-AAA$_t$, Divyield$_t$ are the three information variables included in the model. The numbers in parentheses are t-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated behaviour type equation is

$$\Delta NP_{t+1} = \varphi_0 + \varphi_1 \Delta SI_t + \varphi_2 R_t + \varphi_3 \text{Tbill yield}_t + \varphi_4 \text{BAA - AAA}_t + \varphi_5 \text{Divyield}_t + \xi_{t+1}$$

Changes in Net Positions, lag changes in Sentiment, Returns, and Information variables

	Intercept	*ΔSI_t*	*R_t*	*Tbillyield$_t$*	*BAA-AAA$_t$*	*Divyield$_t$*
Panel A: Hedger						
Metals						
SI	-5.417	-0.230	0.544	0.767	-0.202	0.958
		(-3.203)	(2.387)			
GC	2.469	-0.544	2.973	-1.241	-1.130	2.884
		(-3.029)	(3.307)			
HG	-2.109	-0.034	-0.304	0.224	-0.222	0.636
			(-2.203)			
PL	-2.137	-0.039	0.336	0.274	0.004	0.304
		(-2.576)	(4.020)			
Financials						
ED	23.633	-0.208	-24.229	-7.845	1.292	4.382
US	9.747	-0.084	0.153	-2.898	-1.023	2.800
Currencies						
BP	-4.653	0.124	-1.933	0.415	-0.293	1.439
SF	-1.332	0.016	-1.617	-1.021	-0.667	3.328
			(-3.227)			
CD	-2.017	-0.094	-4.690	0.523	-0.075	-0.525
		(-1.697)	(-4.866)			
JY	0.887	-0.219	1.762	1.172	0.892	-3.717
		(-1.982)	(2.638)			
Soybean complex						
S	0.379	-0.179	-0.005	-0.807	-0.629	2.055
		(-2.380)				
BO	-2.734	-0.086	0.375	0.179	-0.521	1.357
SM	-0.350	-0.112	0.561	-0.468	-0.289	1.242
		(-2.365)	(2.825)			

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Stock Index						
SP	-1.013	0.080	-0.076	0.019	0.554	-0.365
Meats						
PB	-0.230	-0.007	0.003	0.050	0.013	-0.014
		(-2.795)				
LH	-0.103	0.001	-0.115	0.078	0.022	-0.126
			(-3.915)			
LC	-0.863	-0.058	-0.084	0.430	0.265	-0.728
FC	-0.144	-0.022	0.060	0.031	0.019	-0.026
		(-4.551)	(1.889)			
Grains						
W	2.396	-0.137	0.393	-0.603	-0.181	0.356
		(-2.828)	(2.822)			
KW	0.057	-0.035	0.046	-0.202	0.018	0.293
		(-1.846)				
MW	-0.013	-0.014	0.058	-0.060	-0.062	0.180
		(-1.745)	(2.248)			
C	0.144	-0.525	0.988	-0.371	-0.197	0.902
		(-3.072)	(1.942)			
Foods						
SB	-13.001	-0.356	0.684	1.981	-0.201	1.645
		(-2.766)	(2.221)			
CC	-0.806	-0.111	0.386	0.224	-0.136	0.037
		(-2.847)	(3.720)			
KC	-1.932	-0.018	0.180	0.728	0.259	-0.956
			(3.495)			
Fibres						
CT	-0.753	-0.153	0.377	-0.016	0.022	0.278
		(-3.203)	(2.476)			
LB	-0.186	-0.003	0.003	0.071	0.040	-0.109
		(-1.977)			(1.744)	
Energy complex						
CL	4.085	-0.140	0.802	-0.753	0.003	-0.525
			(2.982)			
HO	1.211	-0.185	0.407	-0.611	-0.270	0.850
		(-4.557)	(3.579)			

Note: Only significant t ratios are reported.

Table 4.7.2
Trading behaviour of large speculators

This table shows the results for testing the determinants of trading decisions for large speculators. ΔNP_{t+1} represents the changes in net positions of large speculators in month *t+1*. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. ΔSI_t denotes the change in the Consensus index in month *t*. R_t is the futures return in month *t*, in percent. Tbillyield_t, BAA-AAA_t, Divyield_t are the three information variables included in the model. The numbers in parentheses are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated behaviour type equation is

$$\Delta NP_{t+1} = \varphi_0 + \varphi_1 \Delta SI_t + \varphi_2 R_t + \varphi_3 \text{Tbill yield}_t + \varphi_4 \text{BAA - AAA}_t + \varphi_5 \text{Divyield}_t + \xi_{t+1}$$

Changes in Net Positions, lag changes in Sentiment, Returns, and Information variables

	Intercept	ΔSI_t	R_t	$Tbillyield_t$	$BAA\text{-}AAA_t$	$Divyield_t$
Panel B: Speculator						
Metals						
SI	0.982	0.155	0.608	-0.065	0.097	-0.431
		2.613	*3.234*			
GC	2.185	0.743	-0.241	0.244	0.197	-1.627
		5.548				
HG	0.811	0.098	0.118	0.165	0.181	-0.808
		3.509				
PL	0.160	0.040	0.149	0.043	0.133	-0.298
		3.086	*2.112*			
Financials						
ED	-20.546	0.515	-29.123	5.454	2.211	-4.506
		2.641	*-1.888*			
US	-3.332	0.071	0.211	0.097	-0.346	1.549
Currencies						
BP	1.559	0.079	0.415	-0.133	0.109	-0.505
		1.706				
SF	0.804	0.054	0.423	-0.082	-0.115	-0.057
CD	-0.048	0.187	-0.694	-0.062	-0.084	0.170
		4.387				
JY	2.843	0.022	1.254	-0.176	0.223	-1.328
			2.774			
Soybean complex						
S	-0.616	0.130	0.628	0.214	0.132	-0.337
		2.133	*2.949*			
BO	1.104	0.055	-0.171	-0.014	0.300	-0.776
SM	-0.413	0.132	0.050	0.102	0.012	-0.034
		4.661				

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Stock Index						
SP	-0.112	-0.047	0.373	0.112	-0.031	-0.278
Meats						
PB	0.178	0.015	-0.002	0.003	0.044	-0.124
		2.937				
LH	0.830	0.028	0.047	-0.123	0.066	-0.184
LC	1.063	0.010	0.415	-0.396	-0.088	0.412
FC	0.344	-0.006	0.184	-0.075	-0.006	0.017
Grains						
W	-0.985	0.056	0.196	0.023	-0.075	0.444
			1.849			
KW	-0.041	0.011	0.036	-0.047	-0.052	0.178
MW	-0.026	-0.002	0.014	-0.008	0.000	0.021
C	-0.804	0.330	0.543	-0.598	-0.178	1.565
		2.448				
Foods						
SB	4.353	0.110	0.376	-0.884	-0.117	0.114
CC	0.990	0.068	0.285	0.104	0.220	-0.868
		2.154	*3.399*			
KC	0.344	0.050	-0.008	-0.011	0.021	-0.148
		2.171				
Fibres						
CT	1.005	0.056	0.341	-0.102	0.061	-0.319
			2.972			
LB	0.167	0.002	0.004	-0.036	-0.011	0.009
Energy complex						
CL	3.195	0.259	0.305	-1.171	-0.358	1.414
		3.141				
HO	1.142	0.091	0.093	-0.212	-0.008	-0.036
		3.021				

Note: Only significant t ratios are reported.

Panel A shows that in 25 futures markets, hedgers will decrease their current net positions if the change of market sentiment is positive in the previous period. The negative coefficients of ΔSI_t are significantly different from zero, for 18 of these 25 markets at 10% significance level. This can be intuitively explained by the fact that hedgers were mostly net short as shown previously in panel B of table 4.6. On the other hand, large hedgers increase their current net positions if the futures prices have risen in the previous period in 20 markets. Results are significant for 15 of these 20 markets at 10% significance level. Large hedgers significantly decrease their current net positions if the futures prices have risen in the previous period for gold, copper, Swiss francs, Canadian dollars, and live hogs only. These findings are similar to Wang (2003) suggesting that large hedgers tend to exhibit positive feedback trading in US Futures markets.

While hedgers tend to reduce (increase) their current net positions, if market sentiment is bullish (bearish) in the previous period, Panel B shows that large speculators tend to increase (decrease) their current net positions if market sentiment is bullish (bearish) in the previous period. Results are significantly positive for 15 markets at 10% significance level. This result is also supported by De Bondt (1993) and Wang (2003) who found hedgers (speculators) respond negatively (positively) to market sentiment, after controlling for market risk. Speculators also tend to increase their current net positions if futures prices have risen in the previous month, for 23 markets. This is consistent with Brorsen and Irwin (1987) who argued that managed funds and pools attempt to buy after a price increase or sell after a price decrease using positive feedback trading systems, mainly in highly liquid financial and currency futures. This is further supported by Grinblatt and Keloharju (2000) who found that sophisticated institutional investors pursue positive feedback strategies and achieve superior performance in the Finnish market. However, results are significantly positive for only seven futures markets[66], and significantly negative only for Eurodollars.[67] Overall, the mixed findings

[66] Japanese yen has the highest coefficient in explaining the effect of actual returns on one-month future net position. This supports why the concentration of commodity pool trading (CPOs and CTAs) is not concentrated in smaller futures markets like livestock futures.

regarding the behaviour of large speculators in Panel B suggest that the monthly data interval is not synchronous enough to determine speculators' trading decisions or that they are not momentum traders.

Among the 29 markets, only the corporate spread coefficient for the lumber market is significantly different from zero at 10% significance level. On average, the coefficient estimates for changes in T-bill yield and default premium are more likely to be negative than positive. This finding is consistent with Bessembinder and Chan (1992) and Bjornson and Carter (1997) that expected inflation and default premium are associated with negative expected premiums, and therefore speculators cut back net positions. The negative coefficients for changes in T-bill yield for T-bond futures and Eurodollars futures suggest that these assets provide a natural hedge to the types of risk.[68] Moreover, the effect of information variables on the trading decisions of speculators is larger in magnitude in T-bond, Eurodollars[69], currency, and crude oil futures than in the other markets. The effect of information variables on the trading decisions of hedgers in gold futures is also quite distinct, compared to other markets. Overall, however, insignificant coefficients of information variables in both panels suggest that large hedgers and large speculators do not use these monthly yields in their trading decisions. This finding is inconsistent with Easley and O'Hara (2002) who supported that information variables help in determining returns. One possible explanations for this inconsistency are that the authors of Easley and O'Hara (2002) rely on private information rather than public information, and that the method differs in that these authors supported private information affects returns and not changes in net positions.

4.3.2 Market Timing Test

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[67] Our trading determinant model fails to explain hedgers' and speculators' return effect on future net positions. This can be explained due to the highly traded and most liquid Eurodollars market. Since our model uses a monthly data interval, abnormal coefficient figures are obtained and disregarded for analysis.

[68] For example, Bodie and Rosansky (1980) showed that substantial benefits were available to investors by combining portfolios of commodities and stocks, because of their negative correlation arising from opposite inflation sensitivities.

[69] Eurodollars are one of the most actively traded contracts in the futures markets, and information variables (in both Panel A & B) like T-bill yield and dividend yield tend to have a larger effect in magnitude on these fixed income derivatives.

While Chatrath et al. (1997) showed that large speculators have been the most profitable group of traders in the 1980s and 1990s, Khoury and Perrakis (1998) argued that some large hedgers, particularly in some commodities in the United States, are as well informed as speculators.[70] Both studies, while significant, fail to take the full decade as timeframe before concluding. More importantly, there is huge debate that hedgers pay a premium to speculators like suggested in Keynes's (1930) theory of normal backwardation, where two important assumptions are made - hedgers are net short, and speculators do not have forecasting ability. While it has been found that hedgers are mostly net short, the second assumption about large speculators having no forecasting or market timing ability is yet to be tested in this study to support the existence of risk premium in the futures markets. To test for market timing ability of large speculators or hedgers, Equation 4.2 is used as follows:

$$R_{t+1} = \varphi_0 + \varphi_1 \, \Delta \, NP_t^i + \varphi_2 \text{ Tbill yield}_t + \varphi_3 \text{ BAA - AAA}_t + \varphi_4 \text{ Divyield}_t + \xi_{t+1} \qquad (4.2)$$

Results for the possible market timing ability are laid out in Table 4.8.1 for hedgers and Table 4.8.2 for speculators. Table 4.8.1 results show that $\Delta \, NP_t^i$ is positive and significant for silver, corn, cocoa and coffee; and negative and significant for copper, T-bonds, Japanese yen, soybean oil, crude oil and heating oil at 10% significance level. This suggests that any change in net positions of hedgers in the current period will increase the futures return of hedgers for silver, corn, cocoa and coffee, and decrease the futures return in copper, T-bonds, Japanese yen, soybean oil, crude oil and heating oil. The results are consistent with Wang (2003) only in cocoa, coffee, and Japanese yen. The non-significance in Eurodollars is also found in Bessembinder (1992) where hedging activity has only minor effects on the pricing of Eurodollar futures contracts. Table 4.8.2, on the other hand, shows that $\Delta \, NP_t^i$ is significant and positive only for wheat (Minnesota) and cocoa for large speculators. The considerable inflows from managed futures funds and hedge funds in the 1990s can help explain the positive performance of

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[70] Refer to Chapter 2, section 2.6 (Large hedgers and speculators: an insight), section 2.4 (Hedging revisited) and section 2.5 (Speculators revisited) for detailed theories regarding these players roles and performance in markets.

speculators in the cocoa market, where these funds usually were net long. (Mitchell and Gilbert, 1997 and Table 4.6). Overall results of $\Delta\ NP_t^i$ from Table 4.8.2 support findings in Table 4.7.2 that speculators do not depend significantly on changes in net positions in the current month, for future monthly returns. More importantly, it relates back to the normal backwardation theory where one of the assumption of risk premium rely on speculators not having any forecasting or market timing ability.

Findings of $\Delta\ NP_t^i$ from both Table 4.8.1 and 4.8.2 support Khoury and Perrakis (1998) that hedgers in silver, corn, and coffee properly change their net positions to increase their futures return in one-month timeframes, and hence better judge the direction of these markets than speculators. More importantly, this reflects the fact that any existence of risk premium in those markets are highly reduced in that hedgers have market timing abilities and might act upon those to reach higher returns. For copper, T-bonds, Japanese yen, soybean oil, crude oil and heating oil, where $\Delta\ NP_t^i$ of hedgers were significant and negative, the poor market timing ability is supported by Working (1953) who asserted that short hedgers tend to lose money to speculators on their hedge transactions in the futures market.[71] Due to the non-significance of $\Delta\ NP_t^i$ for speculators, a higher frequency data interval is recommended to test the market timing ability of speculators, who, by definition, change their net positions more frequently than hedgers to benefit from short-term fluctuations in price. Further, the coefficients of T-bill yield for Eurodollars and T-bonds contracts are significantly positive (both for hedgers and speculators), supporting the previous findings that the T-bill yield affects fixed income derivatives more than other derivatives.

[71] All these markets were net short as shown in Table 4.6 except Japanese yen.

Table 4.8.1
Market timing ability of large hedgers

This table provides the results for the market timing ability of large hedgers, over a one month period. $\Delta\ NP_t^i$ is the change in net positions of hedgers at time *t*, $\sum\ \theta_t$ represents the 3 information variables used, and R_{t+1} is the futures return in one month time. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated behaviour type equation is

$$R_{t+1} = \varphi_0 + \varphi_1\ \Delta\ NP_t^i\ + \varphi_2\ \text{Tbill yield}_t + \varphi_3\ \text{BAA - AAA}_t + \varphi_4\ \text{Divyield}_t + \xi_{t+1}$$

Market timing ability

	Intercept	ΔNP^H	*Tbillyield* $_t$	*BAA-AAA* $_t$	*Divyield* $_t$
Panel A: Hedger					
Metals					
SI	4.028	0.080	-0.682	0.026	-0.260
		1.995			
GC	-0.619	0.008	-0.001	0.014	0.188
HG	0.930	-0.108	-0.530	-0.356	1.040
		-2.006			
PL	4.273	0.047	-0.465	-0.155	-0.593
	2.027				
Financials					
ED	-0.427	0.000	0.097	0.025	-0.035
	-3.189		*3.703*	*1.899*	
US	-1.809	-0.015	0.457	0.226	-0.359
		-1.655	*1.873*	*1.823*	
Currencies					
BP	-1.952	-0.001	0.395	0.077	-0.106
SF	-1.699	-0.003	0.236	0.078	0.134
CD	-0.996	-0.005	0.099	-0.059	0.190
	-1.749				
JY	-0.268	-0.025	-0.337	-0.254	1.199
		-2.047		*-1.665*	*2.051*
Soybean complex					
S	-0.681	-0.027	0.242	0.256	-0.455
BO	1.160	-0.050	-0.184	0.296	-0.454
		-1.659			
SM	-1.011	-0.020	0.365	0.166	-0.401

/pto

Stock Index					
SP	2.024	-0.001	-0.387	-0.239	0.623
Meats					
PB	5.102	-0.703	-0.683	0.033	-0.387
LH	3.076	0.089	-0.362	-0.103	-0.317
LC	0.127	0.044	0.134	0.032	-0.332
FC	0.906	0.092	0.121	0.093	-0.694
Grains					
W	-0.295	0.020	-0.423	-0.327	1.367
KW	-0.081	0.048	-0.485	-0.422	1.543
MW	0.605	-0.375	-0.566	-0.332	1.305
C	0.091	0.057	-0.006	0.071	-0.095
		1.971			
Foods					
SB	5.675	-0.029	-1.038	-0.236	0.056
CC	-0.103	0.237	-0.275	0.057	0.490
		2.977			
KC	5.346	0.406	-2.691	-1.295	4.838
		2.544	*-2.592*	*-2.455*	*2.391*
Fibres					
CT	0.779	0.068	-0.482	-0.304	1.007
LB	4.685	1.238	-1.311	-0.065	1.059
Energy complex					
CL	-3.713	-0.122	1.559	0.309	-1.674
		-4.867	*2.141*		
HO	-4.217	-0.112	1.897	0.559	-2.359
		-1.739	*2.376*		

Note: Only significant t ratios are reported.

Table 4.8.2
Market timing ability of large speculators

This table provides the results for the market timing ability of large speculators, over a one month period. $\Delta\ NP_t^i$ is the change in net positions of speculators at time *t*, $\sum\ \theta_t$ represents the 3 information variables used, and R_{t+1} is the futures return in one month time. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated behaviour type equation is

$$R_{t+1} = \varphi_0 + \varphi_1\ \Delta\ NP_t^i + \varphi_2\ \text{Tbill yield}_t + \varphi_3\ \text{BAA - AAA}_t + \varphi_4\ \text{Divyield}_t + \xi_{t+1}$$

Market Timing Ability

	Intercept	**ΔNP^S**	***Tbillyield*** $_t$	***BAA-AAA*** $_t$	***Divyield*** $_t$
Panel B: Speculator					
Metals					
SI	3.771	-0.018	-0.637	0.016	-0.231
GC	-0.600	0.019	-0.024	-0.002	0.245
HG	1.084	0.087	-0.535	-0.321	0.949
PL	4.247	0.045	-0.470	-0.166	-0.562
	2.015				
Financials					
ED	-0.429	0.000	0.098	0.026	-0.038
	-3.218		*3.756*	*1.961*	
US	-1.968	0.002	0.503	0.242	-0.401
			2.051	*1.939*	
Currencies					
BP	-1.976	-0.023	0.398	0.076	-0.101
SF	-1.691	-0.001	0.233	0.077	0.136
CD	-1.002	0.014	0.096	-0.063	0.203
	-1.769				
JY	-0.274	-0.012	-0.343	-0.266	1.224
				-1.719	*2.065*
Soybean complex					
S	-0.659	0.030	0.246	0.259	-0.473
BO	1.238	0.053	-0.188	0.305	-0.488
SM	-1.002	-0.024	0.379	0.174	-0.438

/pto

Stock Index					
SP	1.998	-0.018	-0.372	-0.234	0.599
Meats					
PB	5.115	0.450	-0.693	0.024	-0.368
LH	3.256	-0.307	-0.375	-0.103	-0.363
LC	0.162	0.043	0.133	0.033	-0.343
FC	0.951	-0.178	0.126	0.104	-0.734
Grains					
W	-0.242	0.031	-0.431	-0.322	1.355
KW	-0.089	0.315	-0.470	-0.381	1.460
MW	0.643	1.275	-0.534	-0.321	1.228
		2.067			
C	0.345	-0.004	-0.071	0.039	-0.035
Foods					
SB	6.444	-0.038	-1.168	-0.244	-0.001
CC	-0.696	0.235	-0.219	-0.032	0.725
		2.513			
KC	4.958	0.002	-2.617	-1.313	4.880
			-2.462	*-2.430*	*2.355*
Fibres					
CT	0.673	0.047	-0.476	-0.308	1.046
LB	4.725	-0.477	-1.300	-0.047	0.999
Energy complex					
CL	-3.848	-0.031	1.494	0.244	-1.399
			1.892		
HO	-4.273	-0.126	1.951	0.589	-2.464
			2.435		

Note: Only significant t ratios are reported.

4.3.3 Hedging Pressure Effects

In line with Bessembinder (1993) and De Roon et al. (2000), who found that futures risk premia[72] are usually related with futures own-hedging pressure, an own-hedging pressure effect test is performed on the 29 futures markets. For each futures

[72] See Chapter 2, section 2.15 for more hedging pressure effects and risk premia in futures markets.

contract, a variable λ is created, based on CFTC's reportable positions of hedgers in each market. Assuming that λ is constructed from positions that by definition arise from hedge demand, it appears fair that this variable will proxy for the aggregate non-marketable risks. A similar model to De Roon et al. (2000) is used as follows:

$$R_{t+1} = \varphi_0 + \varphi_1 \lambda_t + \xi_{t+1} \qquad (4.3.1)$$

where R_{t+1} refers to the futures return, futures contract and φ_1 measures the sensitivity of the futures return to the hedging pressure variable in its own group. λ_t is the hedging pressure variable and is calculated as follows:

$$\lambda_t = \frac{\textit{Number of short hedge positions} - \textit{number of long hedge positions}}{\textit{Total number of hedge positions}}$$

To allow for comparisons with previous studies[73] and within this study, four groups are set up (financial, currency, minerals, and agricultural)[74]. Results are reported in Table 4.9.1.

[73] De Roon's data range from January 1986 to December 1984.
[74] From now on, all tables will be grouped into these four groups for consistency and comparison purposes.

Table 4.9.1
Own Hedging Pressure Effects

This table shows the results for the own hedging pressure effects of the 29 Futures markets. θ_1 is the own hedging pressure variable and $t(\theta_1)$ is the t ratio of own hedging pressure variable. R_{t+1} is the futures return in one month time, in percent. Significant t ratios are shown in bold at 10% significance level. Estimated equation used is $R_{t+1} = \varphi_0 + \varphi_1 \lambda_t + \xi_{t+1}$, where

$$\lambda_t = \frac{\textit{Number of short hedge positions} - \textit{number of long hedge positions}}{\textit{Total number of hedge positions}}$$

Own hedging pressure effects

		θ_1	$t(\theta_1)$
Financial	sp	-6.330	-1.200
	ed	1.311	**2.999**
	us	0.809	0.186
Mineral	gc	-0.835	-0.662
	si	-7.245	**-2.527**
	hg	2.895	1.120
	pl	-0.243	-0.151
	cl	43.008	**3.618**
	ho	9.235	1.010
Currency	bp	-0.016	-0.027
	sf	-0.335	-0.506
	cd	0.336	1.053
	jy	1.142	1.434
Agricultural	w	4.308	1.300
	kw	3.524	0.690
	mw	2.196	0.454
	corn	1.467	0.465
	s	0.666	0.315
	bo	0.507	0.245
	sm	-0.607	-0.195
	pb	2.382	0.805
	lh	2.147	0.671
	lc	-5.752	**-2.542**
	fc	-1.322	-1.257
	sb	0.865	0.244
	cc	6.279	1.180
	kc	-7.051	-1.042
	ct	0.068	0.024
	lb	3.036	1.617

Note: Only significant t ratios are reported.

Eurodollars, silver, crude oil, and live cattle futures markets exhibit significant own-hedging pressures at 10% significance level. The positive hedging pressure for Eurodollars can be attributed to hedgers being net long, and also to the non-significant market timing ability for speculators as shown in Table 4.8.2[75]. The own-hedging pressure effect test being negative for silver and live cattle can be explained from Table 4.6 where hedgers are net short on average. Speculators in the silver market who are long bear the risk and would be awarded for the risk premium as supported in Table 4.8.2 where speculators exhibit no significant market timing ability. For the crude oil market, while hedgers have been net short on average, as shown in Table 4.6, the hedging pressure variable is positive in Table 4.8.1. This is similar to Chang (1985) who showed that futures prices on average rise when hedgers are short. The significant risk premium is also supported by the poor market timing ability of speculators, which is one of the main assumption of the theory of normal backwardation. Overall, the findings of own-hedging pressures are inconsistent with De Roon et al. (2000) in most agricultural, interest and financial futures markets, but consistent with Bessembinder (1993) in these markets; that hedging pressure does not affect the risk premia, hence the futures returns at least on a monthly basis. The findings are similar with the index futures market reporting insignificant own-hedging pressures in affecting risk premia.

To analyse the effects of hedging pressure from other futures markets on the futures risk premia, a cross-hedging pressure effect test is performed on the 29 futures markets[76]. Assuming market betas of futures contracts being close to zero,[77] four groups are set up (financial, currency, minerals, and agricultural). An extension of Equation 4.3.1 gives the following[78]:

---

[75] One likely explanation is missing variables in equation 4.3.1. Since it appears that the coefficient of information variables in equation 4.2 are quite significant, these are included in the hedging pressure effect test for ED. With the introduction of the variable Tbillyield_{t+1} in equation 4.3.1, the significance of φ_1 disappear.

[76] See Anderson and Danthine (1981) for more on cross-hedging pressure theories.

[77] See De Roon et al. (2000) where cross-hedging pressures within each group and not between the four groups were found.

[78] Similar to equation 2.2, but excluding the market return variable R_m. See also footnote 34 and 35.

$$R_{i,t+1}^{(j)} = \varphi_0^{(j)} + \sum_{n=1}^{N} \varphi_{i,n}^{(j)} \lambda_{n,t}^{(j)} + \xi_{t+1}^{(j)} \quad (4.3.2)$$

where i (i = 1, 2, 3 …, n) refers to the futures market and j (j=1,..,4) refers to the specific group the futures market belong to. $\sum_{n=1}^{N} \varphi$ represent the coefficients of own- and cross-hedging pressure variables for each futures market within each of the four groups. Full results are reported in Appendix 4.9.2.

In the financial group, the Eurodollar is again found to have significant own-hedging pressure effect, but disappears after accounting for Tbill yield_{t+1} in equation 4.3.2. In the minerals group, silver again has significant own-hedging pressure, but also significant cross-hedging pressure from the copper market. Similarly, platinum has significant cross-hedging pressures from the gold market. In the crude oil market, significant cross-hedging pressures come from the heating oil, silver and gold market. For the currency markets, only Japanese yen has significant cross-hedging pressures from the Swiss francs. For agricultural futures markets, 13 out of 16 markets have at least one cross-hedging pressure within the agricultural group[79]. Similar findings were obtained in previous studies by De Roon et al. (2000) who investigated 20 futures markets, with different groups of markets.

Taking into account that the above results might also be explained by the traditional price pressure hypothesis, i.e. a shock in demand or supply causes a temporary price change, a price pressure effect test is carried out to show if the hedging pressures coefficients are still significant after controlling for price pressure. To make the coefficient of hedging pressures variables and price pressure variables comparable, the hedging pressure and price pressure variables are normalized by scaling them down by their own standard deviation. This is shown as follows:

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[79] Further Wald test statistics that only the own-hedging pressure is relevant are rejected in 13 of the 16 markets at ten per cent significance level.

$$R_{i,t+1} = \varphi_0 + \varphi_1 \frac{\lambda_{i,t}}{\sigma(\theta_{i,t})} + \varphi_2 \frac{\Delta\theta_{i,t}}{\sigma(\Delta\theta_{i,t})} + \xi_{i,t+1} \quad (4.4)$$

where $\lambda_{i,t}$ is the own-hedging pressure variable, $\Delta\theta_{i,t}$ is the change in hedging pressure variable (price pressure), $\sigma(\theta_{i,t})$ is the standard deviation of own-hedging pressure variable, and $\sigma(\Delta\theta_{i,t})$ is the standard deviation of change in hedging pressure variable. Results are reported in Table 4.9.3. After controlling for price pressures, the coefficients for own-hedging pressures for Eurodollars, silver, crude oil, and live cattle are still significant[80] at 10% significance level. Lumber also has a significant own-hedging pressure variable after controlling for price pressures. Noticeably too, markets like copper, heating oil, soybean oil, cocoa, and coffee exhibit significant price pressures, suggesting that the relation between returns and hedging pressure variables should be limited to futures markets, and should not be present in the spot markets. Even though futures prices and the underlying values are related through the cost-of-carry relation, particularly in the case of commodities, it is unlikely to observe this effect in spot markets because price pressure is a temporary effect caused by shocks in demand and supply in the futures markets.

[80] The introduction of the T-bill yield variable (*t+1*) gets rid of the significance of the own-hedging pressure variable for ED as previously supported.

Table 4.9.3
Price Pressure Effect test

This table shows the results for the robustness of the hedging pressure effects tests of the 29 Futures markets. δ_1 represents the normalized own hedging pressure variable $(\theta/\sigma(\theta))$. δ_2 represents the normalized change in hedging pressure variable $(\Delta\theta/\sigma(\Delta\theta))$, where θ is the own hedging pressure variable, and $\Delta\theta$ is the change in hedging pressure variable. $\sigma(\theta)$ is the standard deviation of own hedging pressure variable, $\sigma(\Delta\theta)$ is the standard deviation of change in hedging pressure variable, $t(\delta_1)$ is the t ratio of own hedging pressure variable, and $t(\delta_2)$ is the t ratio of change in hedging pressure variable. R_{t+1} is the futures return in one month time, in percent. Significant values of t ratios are shown in bold at 10% significance level. Estimated equation used is

$$R_{i,t+1} = \varphi_0 + \varphi_1 \frac{\lambda_{i,t}}{\sigma(\theta_{i,t})} + \varphi_2 \frac{\Delta\theta_{i,t}}{\sigma(\Delta\theta_{i,t})} + \xi_{i,t+1}$$

Price Pressure Effects

		δ_1	$t(\delta_1)$	δ_2	$t(\delta_2)$
Financial	sp	-0.281	-0.784	-0.044	-0.127
	ed	0.085	**3.213**	-0.026	-0.992
	us	0.003	0.012	0.279	1.064
Mineral	gc	-0.150	-0.469	-0.132	-0.413
	si	-1.082	**-2.084**	-0.099	-0.192
	hg	0.252	0.442	0.759	**1.333**
	pl	-0.108	-0.244	0.166	0.376
	cl	1.601	**2.018**	2.372	**2.989**
	ho	-0.053	-0.061	1.671	**1.922**
Currency	bp	-0.136	-0.466	0.255	0.875
	sf	-0.125	-0.356	0.028	0.079
	cd	0.049	0.400	0.129	1.047
	jy	0.306	0.939	0.208	0.643
Agriculturals	w	0.695	1.124	-0.015	-0.023
	kw	0.284	0.459	-0.004	-0.007
	mw	-0.107	-0.188	0.623	1.081
	corn	0.205	0.369	0.307	0.554
	s	0.084	0.184	0.318	0.693
	bo	-0.195	-0.432	0.958	**2.126**
	sm	-0.108	-0.193	0.087	0.156
	pb	0.654	0.513	0.832	0.646
	lh	0.637	0.710	-0.237	-0.264
	lc	-0.693	**-2.004**	-0.099	-0.286
	fc	-0.376	-1.259	0.086	0.288
	sb	-0.051	-0.064	0.915	1.153
	cc	1.186	**1.867**	-1.744	**-2.755**
	kc	0.205	0.169	-2.535	**-2.117**
	ct	0.206	0.339	-0.734	-1.208
	lb	1.930	**2.341**	-1.623	**-1.972**

Note: Only significant t ratios are reported.

4.3.4 Destabilizing Features

By complementing behaviour and market timing abilities of large players, this study can shed some further light in terms of policy implications upon stringent regulation[81] imposed upon speculators in the futures markets[82]. For instance, evidence of feedback trading does not imply market destabilization if these traders incorporate fundamental information into prices. Positive feedback trading together with negative performance of a trader type suggests that the trader type tends to push prices away from fundamental value, and thus destabilizes the market (Lakonishkok et al., 1992).

Earlier findings in this study show that hedgers exhibit positive feedback trading in silver, gold, platinum, Japanese yen, soybean meal, wheat, cocoa, sugar, coffee, cotton, crude oil and heating oil. Speculators, on the other hand, exhibit similar behaviour for silver, platinum, Japanese yen, soybean, wheat, cocoa, and cotton. Further findings also support poor market timing ability of hedgers for the copper, Treasury bonds, Japanese yen, soybean oil, crude oil and heating oil. Significant positive market timing ability was displayed from speculators in wheat (Minnesota) and cocoa. Adapting Lakonishkok et al. (1992), the above results suggest a need to reconsider the position limits imposed upon speculators in the crude oil, heating oil, and Japanese yen futures markets in the US. In fact, positive feedback hedgers would be destabilizing if they lead institutions or investors to jump on the bandwagon and buy overpriced contracts and sell underpriced contracts, thereby contributing to a further divergence of prices away from fundamentals. Potentially, this means that large hedgers can have massive influence by holding relatively larger positions than other parties like speculators and small traders. This is also substantiated where positive feedback trading behaviour is particularly driven by a belief of continuing trends as explained in the behaviour literature. Particular emphasis should be made on the heating oil and Japanese yen futures market, since there is no significant risk premium (after controlling for price pressures) which are borne by

[81] See Commodity Futures Modernization Act 2000 (CFMA) for more details.
[82] See Chapter 2, section 2.8.2 regarding speculation position limits in the US

speculators[83]. Hedgers are the positive feedback players with negative market timing abilities in the heating oil and Japanese yen markets, and as such there is a need for a review of the regulation regarding position limits imposed on speculators. This is inconsistent with Taylor and Behrmann (1994) who suggested that large speculators have distorted commodity prices such that commodity futures markets no longer accurately reflect the economic realities of supply and demand. The need for stringent regulation upon hedgers in these markets is further supported due to the decline in speculation in these markets (Dalvi et al., 1997). This is also supported from Table 4.6, where net positions of speculators were less than net positions of hedgers, both for the mean and standard deviation figures. Finally, but not least, the findings are further supported by Haigh et al. (2005) who found that hedgers' rebalancing activities have a positive effect on the volatility of futures returns in energy markets like crude oil.

So far, the above sections have helped to shed light regarding the relationship of net positions, sentiment, information variables and returns; the trading determinants of large hedgers and large speculators; their market timing ability, and existence of risk premium in futures markets. The following sections deal with the performance issues regarding returns, volatility, forecasting and, finally the events analysis section.

4.4 PERFORMANCE

4.4.1.1 Mean Equation

There is huge support of the use of mean equations from Grinblatt and Keloharju (2000), Grundy and Martin (2001), De Bondt and Weber (1999), Arshanapali, Coggin, and Doukas (1998), Fama and French (1998), and Wang (2001, 2003). Their usage extends from understanding relationships between returns and other variables, to

[83] The existence of risk premium for crude oil suggests the risk-bearing potentials of speculators at some higher frequency data intervals. This is also supported by the fact that speculators' mean net positions are net long and hedgers' mean net positions are net short. The two mean (absolute) values are not far apart, suggesting a convergence towards equilibrium rather than disequilibrium of the effect of risk premium on expected prices.

volatility and forecasting models. In line with Wang (2001, 2003), the study makes use of the following model:

$$R_t = \varphi_0 + \varphi_1\, SI_t + \varphi_2\, NP_t + \varphi_3\, \mathrm{HP}_{t-1} + \varphi_4\, \text{Tbill yield}_t + \varphi_5\, \text{BAA - AAA}_t + \varphi_6\, \text{Divyield}_t + \xi_t \tag{4.10.1}$$

where R_t is the monthly returns, SI_t is the sentiment index, HP_{t-1} is the hedging pressure effect variable; Tbill yield_t, BAA - AAA_t and Divyield_t are the three information variables. A one-month lagged own-hedging pressure variable is added to the mean equation for the first time in the literature to account for the existence of risk premium in futures markets[84]. The full results are reported in Table 4.10.1 and Table 4.10.2.

[84] The lagged hedging pressure variable has been obtained after manipulating the return in Equation 4.3.1.

Table 4.10.1
Mean equation of large hedgers

This table shows the results for the mean equation for large hedgers. R_t is the futures return in month t, in percent. NP_t represents the net positions of large hedgers in month t. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. SI_t denotes the Consensus index in month t. HP_{t-1} is the lagged own hedging pressure variable. Tbillyield_t, BAA-AAA_t, Divyield_t are the three information variables included in the model. All variables are differenced until they are stationary. The numbers in italics are t-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated mean equation is

$$R_t = \varphi_0 + \varphi_1\, SI_t + \varphi_2\, NP_t + \varphi_3\, HP_{t-1} + \varphi_4 \text{ Tbill yield}_t + \varphi_5 \text{ BAA - AAA}_t + \varphi_6 \text{ Divyield}_t + \xi_t$$

	Intercept	*NP $_t$*	*SI $_t$*	*HP $_{t-1}$*	*Tbillyield $_t$*	*BAA-AAA $_t$*	*Divyield $_t$*
Panel A : Hedger							
Minerals							
GC	-4.338	-0.040	0.075	-8.219	0.126	-0.011	-0.045
	-2.870	*-4.850*	*3.742*	*-5.682*			
SI	-3.477	-0.147	0.132	-15.399	0.453	0.093	-1.809
		-3.555	*4.770*	*-5.676*			*-1.951*
HG	-1.652	0.000	0.042	1.473	-0.582	-0.422	1.404
PL	-4.893	-0.234	0.129	-5.564	0.388	0.092	-1.252
	-2.798	*-2.086*	*4.935*	*-3.872*			*-2.196*
CL	-8.943	-0.055	0.055	25.257	1.391	0.513	-0.607
		-2.144		*2.496*			
HO	-16.063	-0.282	0.140	-20.934	1.383	0.268	0.286
	-2.490	*-4.592*	*3.930*	*-2.177*			
Financials							
SP	-2.123	-0.065	0.145	-37.600	-0.307	0.156	-1.417
		-2.683	*6.147*	*-4.887*			
ED	-0.358	0.000	0.004	-0.095	0.027	0.003	0.032
	-2.732		*3.290*				
US	-3.033	-0.010	0.028	-6.073	0.431	0.194	-0.245
	-2.375		*1.826*		*1.862*	*1.998*	
Currencies							
BP	-5.331	0.050	0.077	-0.338	0.292	-0.015	0.123
	-3.277	*3.120*	*4.403*				
SF	-4.493	0.035	0.067	-0.836	-0.013	-0.119	0.688
	-2.554	*1.800*	*3.318*				
CD	-1.053	0.016	0.017	0.456	0.035	-0.031	0.038
	-1.970	*1.724*	*2.401*				

/pto

JY	-0.720	-0.074	0.056	-3.873	-0.221	-0.136	0.244
		-6.469	*4.109*	*-4.327*			
Agriculturals							
W	-13.035	-0.199	0.191	-9.808	0.023	-0.093	1.412
	-5.349	*-4.142*	*8.162*	*-3.281*			*1.647*
KW	-12.637	-0.177	0.214	-12.180	0.312	-0.091	0.384
	-5.120	*-1.936*	*8.658*	*-2.209*			
MW	-10.809	-0.909	0.176	-7.312	0.164	0.063	0.445
	-4.320	*-3.835*	*7.474*				
C	-5.723	-0.074	0.143	-23.429	-0.269	0.041	-0.241
	-2.642	*-5.176*	*5.209*	*-6.595*			
S	-8.442	-0.203	0.105	-27.585	0.219	0.171	0.796
	-3.873	*-7.410*	*4.541*	*-8.909*			
BO	-4.703	-0.133	0.120	-14.068	-0.260	0.076	0.196
	-2.584	*-5.345*	*6.889*	*-6.487*			
SM	-7.008	-0.207	0.133	-18.726	-0.681	-0.215	2.059
	-3.083	*-5.441*	*5.511*	*-6.566*			*3.201*
PB	-3.671	2.168	0.252	2.554	-1.358	-0.096	0.701
	-0.596		*3.799*				
LH	-8.673	0.209	0.343	1.361	-1.197	-0.381	0.490
	-2.115		*7.066*		*-1.779*		
LC	-6.800	-0.044	0.107	-12.427	0.519	0.277	-0.370
	-4.004		*6.036*	*-3.495*	*1.818*	*1.646*	
FC	-4.291	-0.590	0.094	-5.511	0.369	-0.019	-0.855
	-2.806	*-3.341*	*7.204*	*-4.405*	*1.580*		*-1.933*
SB	-7.045	-0.113	0.200	-19.184	-0.442	0.044	-0.365
	-2.033	*-3.908*	*5.434*	*-4.635*			
CC	-16.105	-0.211	0.263	-31.505	0.463	-0.014	1.034
	-5.027	*-2.676*	*5.243*	*-5.458*			
KC	-17.695	-0.721	0.289	-21.982	0.870	-0.528	0.169
	-4.862	*-4.231*	*6.044*	*-4.481*			
CT	-9.709	-0.204	0.176	-14.002	0.131	-0.088	0.480
	-3.927	*-3.712*	*7.287*	*-4.660*			
LB	-7.067	-0.079	0.235	0.500	-0.447	0.156	-0.293
	-1.716		*9.272*				

Table 4.10.2
Mean equation of large speculators

This table shows the results for the mean equation for large speculators. R_t is the futures return in month t, in percent. NP_t represents the net positions of large speculators in month t. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. SI_t denotes the Consensus index in month t. HP_{t-1} is the lagged own hedging pressure variable. Tbillyield_t, BAA-AAA_t, Divyield_t are the three information variables included in the model. All variables are differenced until they are stationary. The numbers in italics are t-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated mean equation is

$$R_t = \varphi_0 + \varphi_1 SI_t + \varphi_2 NP_t + \varphi_3 HP_{t-1} + \varphi_4 \text{Tbill yield}_t$$
$$+ \varphi_5 \text{BAA - AAA}_t + \varphi_6 \text{Divyield}_t + \xi_t$$

	Intercept	***NP*** $_t$	***SI*** $_t$	***HP*** $_{t-1}$	***Tbillyield*** $_t$	***BAA-AAA*** $_t$	***Divyield*** $_t$
Panel B : Speculator							
Minerals							
GC	-7.892	-0.002	0.129	-5.303	0.201	0.012	0.131
	-5.395		*6.683*	*-4.065*			
SI	-5.242	-0.122	0.201	-3.060	-0.156	-0.326	0.127
	-2.149	*-3.051*	*10.576*				
HG	-2.114	-0.092	0.044	4.091	-0.565	-0.460	1.533
			1.654			*-1.734*	
PL	-5.028	-0.081	0.156	-3.195	0.157	0.048	-0.830
	-2.752		*9.580*	*-2.671*			
CL	-10.708	-0.045	0.100	47.531	1.463	0.388	-0.577
	-1.531		*3.484*	*3.145*			
HO	-15.149	-0.007	0.228	-1.721	1.260	0.111	-0.306
	-2.288		*7.418*				
Financials							
SP	-3.434	0.006	0.149	-18.700	-0.104	0.111	-1.154
			6.195	*-2.055*			
ED	-0.374	0.000	0.005	0.621	0.028	0.005	0.022
	-2.840		*3.752*				
US	-2.945	0.000	0.034	-2.345	0.433	0.197	-0.381
	-2.087		*2.520*		*1.931*	*2.111*	
Currencies							
BP	-4.018	-0.012	0.051	-0.649	0.274	-0.029	0.147
	-2.681		*3.647*				
SF	-3.491	-0.015	0.047	-1.047	0.054	-0.068	0.509
	-2.194		*3.101*				*/pto*

CD	-1.036	0.001	0.010	0.110	0.055	-0.041	0.111
	-1.757		*1.684*				
JY	-4.728	-0.033	0.113	-0.091	-0.233	-0.021	0.512
	-3.582	*-1.677*	*8.840*				
Agriculturals							
W	-14.512	-0.021	0.241	-3.286	0.412	-0.047	0.670
	-5.848		*10.616*				
KW	-13.493	0.032	0.226	-6.972	0.415	-0.156	0.380
	-5.442		*9.543*				
MW	-10.458	0.310	0.192	0.498	0.227	-0.011	0.050
	-4.047		*8.464*				
C	-11.308	0.009	0.238	-11.249	-0.187	0.088	-0.105
	-5.053		*10.902*	*-4.233*			
S	-13.291	-0.012	0.218	-4.754	0.172	0.027	0.802
	-5.790		*10.529*	*-1.723*			
BO	-2.979	0.151	0.135	-12.399	-0.454	0.056	-0.041
	-1.573	*4.646*	*8.354*	*-5.747*			
SM	-8.015	0.013	0.204	-8.600	-0.561	-0.266	1.451
	-3.434		*10.479*	*-2.748*			*1.850*
PB	-4.530	-0.741	0.246	0.513	-1.111	-0.288	0.502
	-0.734		*3.628*				
LH	-7.221	-0.313	0.329	3.602	-1.154	-0.424	0.320
	-1.587		*7.723*		*-1.709*		
LC	-7.105	-0.013	0.115	-10.250	0.551	0.315	-0.474
	-4.371		*6.942*	*-3.643*	*1.922*	*1.811*	
FC	-4.855	-0.158	0.107	-2.786	0.476	0.044	-1.149
	-3.550		*9.318*	*-3.395*	*2.047*		*-2.303*
SB	-12.805	-0.061	0.297	-4.191	0.574	0.293	-1.734
	-3.786	*-2.347*	*9.738*	*-1.329*	*1.134*	*1.285*	*-1.996*
CC	-16.859	-0.034	0.322	-16.008	0.248	-0.062	1.063
	-5.321		*9.076*	*-2.462*			
KC	-16.772	0.029	0.406	-13.951	-0.057	-0.301	1.089
	-4.044		*10.308*	*-3.232*			
CT	-14.023	0.008	0.245	-7.732	0.284	-0.100	0.631
	-5.965		*10.413*	*-3.149*			
LB	-7.418	-0.997	0.239	1.070	-0.373	0.194	-0.391
	-1.806		*9.618*				

Note: Only significant t ratios are reported.

Tables 4.10.1 and 4.10.2 report the regression of the mean equation for hedgers (Panel A) and speculators (Panel B). In minerals, agriculturals and currencies, hedgers' returns are more significantly associated with the level of net positions. Twenty-two out of these 26 markets have significant net positions variables after having regressed the mean equation at 10% significance level. Eighteen out of these 22 net positions variables have a negative coefficient. This is consistent with the early findings of negative correlations between returns and changes in positions of hedgers ($R\ \Omega\ \Delta NP^{H}$). As for speculators, only four out of the 29 markets show significance in net position variables. This is also consistent with the low correlation between returns and changes in positions of speculators ($R\ \Omega\ \Delta NP^{S}$), and also supports the highly negative correlation between hedgers' and speculators' net positions. Soybean meal, for instance, has a high negative correlation of -0.975 between its hedgers' and speculators' net positions. While its hedgers exhibit a significant negative sign of -0.133 in its NP variable, a positive sign is observed for speculators (0.151) when regressing the mean equation.

As for the sentiment index, both hedgers' and speculators' returns are highly associated with the level of sentiment index. For hedgers, 27 out of 29 markets exhibit a significant positive sign, while for speculators, all markets exhibit a significant positive sign at 10% significance level. This is inconsistent with Clarke and Statman (1998) who found no statistical significance between sentiment and S&P500 returns. However, the results can be explained by the herding behaviour of speculators (Corsetti et al., 2001), but also with the fact that 1990s have been scheduling significant bullish behaviour in the US. In relation to the hedging pressure effects, significance is observed mainly in agricultural markets, and these support earlier findings of own- and cross-hedging pressures by De Roon et al. (2000) and Keynes (1930). Information variables, however, do not have much significance in affecting hedgers' and speculators' returns. Only 11 and 12 markets have significant information variables for hedgers and speculators. These findings are inconsistent with Chatrath et al. (1997) and Easley and O'Hara (2002) who support that information variables like dividend yield, corporate spread and Treasury bill yield help in determining returns. This suggests that such large players do not take much consideration of information variables in determining their returns.

4.4.1.2 Decomposed Mean Equation

Important ARMA models (Schwert, 1989; Jiang and Chiang, 2000; and Chatrath et al., 1999) have helped to get expected and unexpected components of market volatility, trading activity and returns. In line with Schwert (1989), this study makes use of an ARMA model to decompose the mean equation variables into expected and unexpected components. Variables decomposed are net positions of hedgers and speculators, sentiment index and information variables. An extension of Equation 4.10.1 gives the decomposed mean equation as follows:

$$
\begin{aligned}
R_t = \varphi_0 &+ \varphi_1 \text{Exp}\, SI_t + \varphi_2 \text{Unexp}\, SI_t + \varphi_3 \text{Exp}\, NP_t + \varphi_4 \text{Unexp}\, NP_t \\
&+ \varphi_5 \, \text{HP}_{t-1} + \varphi_6 \text{Exp Tbill yield}_t + \varphi_7 \text{Unexp Tbill yield}_t \\
&+ \varphi_8 \text{Exp BAA - AAA}_t + \varphi_9 \text{Unexp BAA - AAA}_t \\
&+ \varphi_{10} \text{Exp Divyield}_t + \varphi_{11} \text{Unexp Divyield}_t + \xi_t \qquad (4.10.2)
\end{aligned}
$$

Similar to Thomakosi and Wang (2003) and Daigler and Chen (1999), autocorrelations (AC) and partial autocorrelations (PAC) are used in selecting an ARIMA specification[85]. The Akaike information criteria (AIC) provides a guide for the appropriate lag order selection[86]. In line with Tam and Reinsel (1998), if autocorrelations appear to have a seasonal pattern[87], SMA (Seasonal Moving Average) and SAR (Seasonal Autoregressive) are included in the ARMA model structure. Diagnostic tests using correlograms and Breusch-Godrey LM test[88] help to assess the structure of the ARMA model (Sadorsky, 2003; Yang et al., 2001). Results for optimal lag selection (including seasonal variables), Q statistics and Breusch-Godrey LM test support an optimized model structure of the mean equation, without autocorrelation in variables. Ljung-Box Q test statistics and Breusch-Godfrey LM tests are again used, together with ARCH LM test, to check if the residuals from the mean equation are uncorrelated with

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[85] See Appendix 6.5.7 for more details.

[86] R-squared values are also initially looked at, but, as expected, give too low values to be considered for inferencing.

[87] See Appendix 6.5.8 for estimating ARMA models (differencing and ARMA terms (including seasonal))

[88] See Appendix 6.5.10 for Breusch-Godfrey LM test.

past residuals[89] (McKenzie and Holt, 2002). Results for these residuals tests support the series have white noise properties and can be found in Appendix 6.11 (Table 4.10.6). Full results of the decomposed mean equation are provided below in Table 4.10.3 and Table 4.10.4[90]. Results are reported at 10% significance level.

Table 4.10.3
Decomposed mean equation for large hedgers

This table shows the results for the decomposed mean equation for large hedgers. R_t is the futures return in month *t*, in percent. NP_t represents the net positions of large hedgers in month *t*. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. SI_t denotes the Consensus index in month *t*. HP_{t-1} is the lagged own hedging pressure variable. $Tbillyield_t$, $BAA\text{-}AAA_t$, $Divyield_t$ are the three information variables included in the model. All variables are differenced until they are stationary. NP_t, SI_t, $Tbillyield_t$, $BAA\text{-}AAA_t$, and $Divyield_t$ are decomposed using ARMA model specifications. Autocorrelations (AC) and partial autocorrelations (PAC) are used in selecting an ARIMA specification. The Akaike information criteria (AIC) is used to select the appropriate lag order. SMA (Seasonal Moving Average) and SAR (Seasonal Autoregressive) variables are included in the ARMA model if autocorrelations appear to have a seasonal pattern. Diagnostic tests using correlograms and Breusch- Godrey LM test are used to assess the structure of the ARMA model. Ljung-Box Q test statistics are again used to check if the residuals from the model are nearly white noise, i.e, no serial correlation left in the residuals. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated mean equation is

$$R_t = \varphi_0 + \varphi_1 \,\mathrm{Exp}\, SI_t + \varphi_2 \,\mathrm{Unexp}\, SI_t + \varphi_3 \,\mathrm{Exp}\, NP_t + \varphi_4 \,\mathrm{Unexp}\, NP_t + \varphi_5 \,\mathrm{HP}_{t-1} +$$
$$\varphi_6 \,\mathrm{Exp\,Tbill\ yield}_t + \varphi_7 \,\mathrm{Unexp\,Tbill\ yield}_t + \varphi_8 \,\mathrm{Exp\,BAA - AAA}_t + \varphi_9 \,\mathrm{Unexp\,BAA - AAA}_t +$$
$$\varphi_{10} \,\mathrm{Exp\,Divyield}_t + \varphi_{11} \,\mathrm{Unexp\,Divyield}_t +$$

	Intercept	*NP t*		*SI t*		*HP t-1*	*Tbillyield t*		*BAA-AAA t*		*Divyield t*	
		Exp	*Unexp.*	*Exp*	*Unexp.*		*Exp*	*Unexp.*	*Exp*	*Unexp.*	*Exp*	*Unexp.*
Panel A : Hedger												
Minerals												
GC	-9.68	-0.02	-0.02	0.19	-0.03	-5.90	4.24	1.46	0.90	0.50	-11.46	0.52
	-5.36		*-1.98*	*5.06*		*-3.95*				*1.88*		
SI	-13.43	-0.11	-0.02	0.28	-0.05	-9.54	5.13	0.99	1.54	1.76	4.46	-1.51
	-5.87	*-2.23*		*6.52*	*-2.14*	*-3.97*				*3.89*		
HG	-8.60	0.11	-0.01	0.21	0.14	3.88	27.37	-2.65	0.90	-0.13	-2.02	-18.71
	-2.16			*2.22*	*3.79*		*1.72*					*-3.83*
PL	1.05	0.11	-0.04	0.15	0.16	-0.80	-4.18	3.22	-0.85	0.08	-18.55	1.00
				2.52	*8.00*							
CL	-17.27	0.03	-0.02	0.35	0.00	33.02	16.84	-0.33	-1.37	-1.48	-104.97	13.18
	-4.77			*4.49*		*3.38*					*-2.50*	*2.30*
HO	-29.06	-0.30	0.11	0.55	0.07	-9.19	-23.91	-0.67	-0.07	-0.81	-37.45	6.21
	-6.33	*-2.71*		*4.65*								*/pto*

[89] See Appendix 6.5.9 for Ljung-Box Q statistics specification, Appendix 6.5.12 for ARCH LM test.
[90] Since, standard inference procedures do not apply to regressions that contain an integrated dependent variable or integrated regressors (like in ARMA), stationary testing is also performed on the mean equations, and residuals were found stationary.

Financials												
SP	-9.39	-0.07	-0.02	0.24	0.02	-27.43	2.24	2.10	-0.97	-0.08	64.81	2.21
	-4.06	*-2.11*		*5.84*		*-3.28*					*2.56*	
ED	-0.65	0.00	0.00	0.01	0.00	-0.26	-3.06	-0.18	0.05	0.01	-1.48	0.08
	-3.43			*3.46*			*-2.92*	*-2.02*				
US	-3.54	0.00	-0.01	0.08	0.07	-0.93	-12.25	-0.46	-0.40	-0.17	-6.51	2.31
	-2.46			*2.53*	*3.97*							
Currencies												
BP	-11.23	0.00	0.06	0.24	0.05	-1.07	-1.29	-1.68	0.16	-0.19	-14.51	5.87
	-5.05		*3.62*	*5.07*	*4.28*							*3.13*
SF	-5.58	-0.03	-0.06	0.14	0.05	-1.57	-3.81	-1.89	0.83	-0.10	-3.77	4.65
	-2.52		*-4.07*	*2.90*	*2.46*	*-2.37*						
CD	-1.49	-0.02	-0.01	0.03	0.03	-0.07	2.78	-0.09	0.67	-0.14	-1.71	-1.30
	-2.26	*-2.45*		*2.07*	*4.69*			*-0.20*				
JY	-7.50	-0.05	0.00	0.20	-0.02	-1.11	-4.91	3.51	0.93	0.32	10.86	-0.45
	-4.37	*-2.86*		*5.51*				*3.41*				
Agriculturals												
W	-9.21	-0.58	0.01	0.08	-0.04	-7.33	-18.30	0.68	0.43	0.05	33.27	-0.69
	-3.45	*-6.38*				*-2.31*						
KW	-4.44	2.85	0.12	0.11	-0.01	8.97	-21.86	-0.57	0.87	0.41	40.94	5.29
	-1.74	*5.00*		*2.18*								
MW	-7.43	-2.09	0.50	0.14	0.00	-8.75	-12.24	-2.81	1.36	0.48	22.84	2.14
	-2.77	*-5.06*	*1.75*	*2.68*								
C	-5.01	-0.09	0.00	0.08	0.16	-21.35	-14.05	-1.24	-1.14	-0.46	-22.90	-0.25
	-1.73	*-5.05*			*5.57*	*-4.93*				*-1.50*		
S	6.34	-0.19	-0.03	-0.15	-0.01	-13.84	0.85	-1.29	-2.02	-0.07	13.14	0.53
	2.18	*-7.89*		*-2.79*		*-5.05*						
BO	-21.14	-0.10	0.00	0.45	-0.04	-7.92	-9.34	-1.10	-1.85	0.69	1.48	1.67
	-10.09	*-3.78*		*9.45*	*-1.74*	*-4.44*				*1.74*		
SM	-10.32	-0.38	0.07	0.18	-0.03	-21.50	0.95	-0.97	1.28	0.32	-0.71	3.86
	-4.79	*-9.43*	*2.00*	*3.75*	*-1.71*	*-7.35*						
PB	-24.31	2.04	1.99	0.63	0.22	1.77	-11.14	0.28	10.47	0.13	-44.02	4.67
	-3.44			*3.65*	*3.07*				*2.09*			
LH	-11.86	-0.99	-0.25	0.25	-0.14	-4.74	-44.85	6.17	6.24	1.28	-27.08	7.85
	-1.74	*-5.04*			*-2.43*		*-1.85*	*2.24*	*1.94*			
LC	-13.74	-0.10	-0.01	0.28	0.02	-10.23	-0.44	-1.30	0.94	-0.03	-6.26	4.99
	-4.78			*4.91*		*-2.84*						*1.80*
FC	-13.50	1.28	-0.25	0.28	-0.03	-2.20	4.31	0.67	-1.85	-0.18	9.73	-1.58
	-6.98	*1.93*		*6.69*	*-1.68*	*-1.97*						
SB	-4.96	-0.13	0.03	0.08	0.02	-6.66	-5.77	1.97	1.70	1.55	58.68	9.39
		-3.13								*2.13*		
CC	-8.52	-0.37	0.21	0.15	0.01	-24.73	-21.43	-4.54	3.82	0.17	-7.77	12.56
	-1.65	*-3.39*	*2.28*			*-3.14*		*-1.79*				*1.66*
KC	-33.64	-0.17	0.03	0.86	0.05	-14.48	14.51	-0.73	3.77	0.81	60.19	-10.59
	-4.86			*6.10*		*-2.32*						
CT	-9.67	-0.58	0.04	0.22	-0.04	-19.07	1.85	-1.37	-1.35	0.29	43.11	10.08
	-2.08	*-6.68*		*2.27*		*-5.21*						*1.87*
LB	-65.83	-1.29	0.41	1.54	0.01	-0.28	-7.79	-4.81	-9.67	-1.05	23.29	1.74
	-6.60			*6.52*					*-1.70*			

Table 4.10.4
Decomposed mean equation for Large speculators

This table shows the results for the decomposed mean equation for large speculators. R_t is the futures return in month t, in percent. NP_t represents the net positions of large speculators in month t. A net position is defined as the long position less the short position of a trader type, in units of 1,000 contracts. SI_t denotes the Consensus index in month t. HP_{t-1} is the lagged own hedging pressure variable. Tbillyield_t, BAA-AAA_t, Divyield_t are the three information variables included in the model. All variables are differenced until they are stationary. NP_t, SI_t, Tbillyield_t, BAA-AAA_t, and Divyield_t are decomposed using ARMA model specifications. Autocorrelations (AC) and partial autocorrelations (PAC) are used in selecting an ARIMA specification. The Akaike information criteria (AIC) is used to select the appropriate lag order. SMA (Seasonal Moving Average) and SAR (Seasonal Autoregressive) variables are included in the ARMA model if autocorrelations appear to have a seasonal pattern. Diagnostic tests using correlograms and Breusch- Godrey LM test are used to assess the structure of the ARMA model. Ljung-Box Q test statistics are again used to check if the residuals from the model are nearly white noise, i.e, no serial correlation left in the residuals. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated mean equation is

$$R_t = \varphi_0 + \varphi_1 \text{Exp}\, SI_t + \varphi_2 \text{Unexp}\, SI_t + \varphi_3 \text{Exp}\, NP_t + \varphi_4 \text{Unexp}\, NP_t + \varphi_5 \text{HP}_{t-1} + \varphi_6 \text{Exp Tbill yield}_t + \varphi_7 \text{Unexp Tbill yield}_t + \varphi_8 \text{Exp BAA - AAA}_t + \varphi_9 \text{Unexp BAA - AAA}_t + \varphi_{10} \text{Exp Divyield}_t + \varphi_{11} \text{Unexp Divyield}_t + \xi_t$$

	Intercept	NP_t		SI_t		HP_{t-1}	Tbillyield_t		BAA-AAA_t		Divyield_t	
		Exp	Unexp.	Exp	Unexp.		Exp	Unexp.	Exp	Unexp.	Exp	Unexp.
Panel B : Speculator												
Minerals												
GC	-11.05	0.00	0.00	0.22	-0.01	-5.19	2.57	1.12	0.50	0.45	-11.29	1.03
	-3.72			*3.86*		*-4.51*				*1.67*		
SI	-12.36	0.00	0.04	0.32	-0.05	-7.70	5.88	1.32	1.42	1.83	-0.89	-1.27
	-5.35			*7.58*	*-1.87*	*-2.88*				*4.05*		
HG	-6.47	-0.08	0.13	0.15	0.13	3.29	22.11	-3.33	1.59	-0.23	1.03	-18.39
	-1.95			*2.04*	*4.04*							*-3.91*
PL	-4.79	-0.02	-0.19	0.12	0.16	-3.08	-6.81	3.53	-1.09	0.12	-13.26	2.41
	-1.83		*-2.33*	*1.98*	*9.18*	*-2.27*						
CL	-17.11	0.10	-0.25	0.33	0.02	28.49	16.71	0.96	-2.30	-1.37	-115.01	11.35
	-4.49		*-2.68*	*3.85*		*2.77*					*-2.91*	*1.96*
HO	-33.19	0.04	0.04	0.73	0.05	-0.93	-17.04	0.65	-0.79	-0.79	-32.03	4.67
	-6.16			*5.54*								
Financials												
SP	-9.25	0.04	-0.06	0.25	0.03	-13.66	3.42	1.50	-0.33	-0.21	62.00	1.14
	-3.95			*6.11*		*-1.99*					*2.27*	
ED	-0.68	0.00	0.00	0.01	0.00	-0.02	-3.05	-0.17	0.03	0.01	-1.52	0.10
	-4.61			*4.39*			*-2.84*	*-1.92*				
US	-3.54	-0.01	0.01	0.08	0.07	-0.47	-11.91	-0.38	-0.54	-0.13	-6.76	1.68
	-2.49			*2.67*	*4.36*							

/pto

Currencies												
BP	-6.83	-0.05	0.01	0.15	0.05	-0.41	-1.77	-2.50	-0.35	-0.24	-7.05	6.12
	-4.06			*4.06*	*4.30*			*-1.94*				*3.02*
SF	-6.10	-0.07	-0.03	0.14	0.06	-1.49	-7.79	-2.40	0.14	0.30	-8.01	6.09
	-3.35			*3.23*	*4.19*	*-2.29*		*-1.91*				*2.11*
CD	-1.80	0.01	-0.01	0.04	0.03	-0.06	3.82	-0.05	0.70	-0.11	-1.42	-1.79
	-2.35			*2.31*	*6.01*							*-1.84*
JY	-10.34	0.06	0.05	0.26	0.00	-0.21	-13.25	3.94	1.29	0.48	12.59	1.04
	-8.13	*1.74*	*2.67*	*8.71*				*3.54*				
Agriculturals												
W	-5.97	0.69	-0.16	0.12	-0.01	2.11	-24.50	-0.45	-0.79	0.15	49.33	-1.31
	-2.26	*2.47*	*-1.98*	*2.32*							*1.77*	
KW	-3.72	-1.22	-0.05	0.09	-0.02	-1.01	-22.25	-1.55	-0.15	0.19	53.74	2.71
		-2.41									*1.96*	
MW	-4.33	1.38	0.85	0.10	-0.01	0.90	-6.36	-1.96	1.59	0.38	35.06	1.52
				1.81								
C	-10.49	0.00	0.02	0.19	0.26	-9.11	-19.64	-1.90	-1.56	-0.44	-22.84	-0.28
	-3.63			*3.34*	*9.33*	*-2.47*						
S	1.24	0.05	0.20	-0.03	-0.02	1.56	3.48	0.42	-3.45	0.39	29.70	1.07
			5.29									
BO	-24.40	-0.43	-0.03	0.54	0.01	-4.80	-8.58	-1.47	-1.37	0.73	6.24	1.84
	-11.30			*11.85*		*-2.48*				*1.75*		
SM	-8.64	0.05	0.19	0.20	-0.02	-5.20	-1.42	0.18	-2.35	0.37	-0.03	2.59
	-3.71		*2.77*	*4.06*								
PB	-28.24	-0.83	-1.39	0.71	0.20	-0.42	-9.48	0.85	8.38	0.17	-40.02	2.19
	-3.50			*3.62*	*2.81*				*1.63*			
LH	-21.40	-0.43	0.61	0.51	-0.09	6.63	-37.71	9.04	6.27	1.48	-38.22	9.77
	-3.31		*2.80*	*3.24*		*1.65*		*2.81*		*1.79*		
LC	-15.03	0.02	0.00	0.31	0.02	-7.37	-1.31	-1.37	0.93	-0.01	-8.08	4.73
	-5.83			*6.07*		*-3.07*						*1.69*
FC	-12.61	0.34	0.61	0.26	-0.02	-1.18	-0.78	0.73	-1.50	-0.16	13.52	-2.18
	-6.97		*3.03*	*6.84*								
SB	-10.79	-0.07	0.06	0.24	-0.01	3.11	-10.15	2.13	0.61	1.71	61.22	9.56
	-3.29			*3.97*						*2.52*		
CC	-18.95	0.61	-0.17	0.43	0.02	-14.42	-29.00	-3.20	2.46	0.03	-11.67	17.52
	-4.49	*2.57*		*4.28*								*2.45*
KC	-27.28	0.79	0.27	0.68	0.03	-19.14	22.53	0.19	4.01	0.95	63.86	-12.39
	-3.61	*1.82*		*4.29*		*-3.06*						
CT	-13.84	0.27	-0.12	0.32	-0.02	-7.98	-15.07	-3.14	-4.10	-0.33	42.60	11.37
	-3.70	*3.57*		*4.32*		*-2.24*						*1.67*
LB	-68.64	2.48	4.48	1.61	0.01	-0.05	-1.90	-4.43	-9.71	-1.02	14.61	0.57
	-7.32		*2.51*	*7.36*					*-1.86*			

Findings from Table 4.10.3 show that in 17 markets, expected components of net positions of hedgers are significantly related to the actual futures returns at 10% significance level. Importantly, 15 of these 17 markets are from the agricultural group, and exhibit a significant negative sign. Expected components of net positions are positive and significant only in feeder cattle and wheat (Kansas). The presence of significant negative signs on expected net positions is consistent with earlier findings in Table 4.6 where net positions of hedgers exhibit a negative relationship towards returns. Unexpected components of net positions for hedgers are significant only in six cases, where gold and Swiss francs exhibit a negative sign. The difference in significance between expected and unexpected components for net positions of hedgers suggest that hedgers are informed players by adjusting their net positions more often at the start of the trading month rather than in a noisy way all throughout the month[91]. This result can be compared with Table 4.10.4, where the unexpected component of net positions of speculators is significant in 10 futures markets[92] at 10% significance level. Six out of these 10 markets exhibit a significant positive sign, supporting the finding in Table 4.6 that speculators' net positions and returns are positively related. This tends to be also the case for the expected component of net positions of speculators, where in five out of six markets a positive significant sign is displayed. The mere positive significance of the expected component for net positions for speculators suggests that these players are less informed than hedgers. This is further supported by more significance (both negative and positive) of unexpected net positions for speculators compared to hedgers, suggesting speculators are traders who change their net positions more often than hedgers all throughout the month to get higher returns. These findings also support Canoles et al. (1998) that both hedgers and speculators are financially sophisticated, well-educated, well-capitalized, and that hedgers are better informed in setting better expected net positions to determine actual returns. The poor significance of expected net positions, and the greater significance of unexpected net positions of speculators in determining

[91] This is in contrast to uninformed noisy traders or small traders who tend to lose in futures markets.
[92] Note again that some of the net positions of speculators are differenced series. See Appendix 4.10 for more details.

returns, support Murrell (1979) and Hyde (1978) that speculators can be in the market for recreational utilities and not only higher returns or profits.

Moreover, expected sentiment variables are positive and significant for both players in most markets. Unexpected sentiment variables are significant for hedgers in 13 markets and significant for speculators in 10 markets. In eight similar markets, unexpected sentiment is significantly positive for both hedgers and speculators[93]. Live hogs, soybean meal, soybean oil, feeder cattle and silver display a significant negative unexpected sentiment variable for hedgers, while only live hogs and silver have a significant negative unexpected sentiment variable for speculators. Overall, findings of sentiment over returns showing a positive relationship are consistent with the herding behaviour of speculators, and bullish trend in the 1990s. Also, consistent with Table 4.10.1 and 4.10.2, the lagged hedging pressure variable is significant and negative mostly in agricultural markets.

Results for information variables were mixed. Only live hogs (Eurodollars) exhibited a significant and negative expected T-bill yield coefficient for hedgers (speculators). Unexpected T-bill yield had a significant and positive effect for hedgers and speculators in Japanese yen and live hogs. Unexpected T-bill yield had a negative effect on hedgers' return in Eurodollars and cocoa, and a negative effect on speculators' return in Eurodollars, British pounds and Swiss francs. It can be observed that T-bill yield not only has more effect on financial and currency groups, but also that speculators' returns are more affected by unexpected changes in T-bill yield. This supports the fact that speculators are more reliant on adjusting their returns all throughout the month based on changing variables like T-bill yield.

Expected corporate spread had a significant positive effect only on hedgers' return in pork bellies and live hogs, and a significant negative effect only on both

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[93] Since the same sentiment data is used for both hedgers and speculators, the relationship between sentiment and return should normally be the same when regressing the mean equation. Any difference is due to net positions being different, which eventually affect sentiment variables differently.

hedgers' and speculators' return in lumber. Unexpected corporate spread has had a positive effect on both players' return in gold, silver, soybean oil and sugar. Interestingly too is that the expected dividend yield has had a negative effect on crude oil, and a positive effect on S&P500 futures for both players. This is consistent with crude oil and market dividend yield bearing a negative relationship, and that the market dividend yield has been increasing over the 1990–2000 period resulting in higher returns. Further, unexpected dividend yield has had a significant positive effect for hedgers in crude oil, British pounds, live cattle and cotton; and a significant positive effect for speculators in crude oil, British pounds, Swiss francs, live cattle, cocoa and cotton. Unexpected dividend yields were negative, however, for copper for hedgers; copper and Canadian dollars for speculators. Results not only support that dividend yield tends to affect crude oil, major financials and currencies more than agriculturals, but that speculators' returns are more positively affected by unexpected dividend yield changes. Mainly to financials, minerals and currencies, findings of decomposed information variables suggest that unexpected T-bill yield appears to be more significant to returns for speculators, and unexpected corporate spread and dividend yield appears to be more positively significant to returns of speculators. These again support that speculators' returns are based also on changing (unexpected) components of information variables all throughout the month, hence, their volatile trading habits.

4.4.2 Volatility

4.4.2.1 Idiosyncratic Volatility and Decomposed Variables

While studies such as Roth et al. (2003) show a positive relation between volatility and open interest for both hedgers and speculators, Foster (1995) found that volume and volatility are positively related and that these variables are endogenous to the system. Others like Chatrath et al. (1999) found that information variables also play an important role in the volatility spillover across markets[94]. In line with Lopez (2001), it

[94] See Chapter 2, section 2.16 for more details on volatility.

can be shown by using Equation 4.10.2, that $\xi_t^{\,2}$ is an unbiased estimator of $\sigma_t^{\,2}$ as follows:

$$R_t = \mu_t + \xi_t, \quad \xi_t = \sqrt{\sigma_t}\, z_t, \quad z_t \sim N(0,1)$$

, where the conditional mean $\mu_t = \mathrm{E}\left[R_t \mid \Omega_{t-1}\right]$

, Ω_{t-1} is the information set available at time t-1,

, ξ_t is the innovation term,

, σ_t is its conditional variance,

$$\begin{aligned} \xi_t^{\,2} &= \mathrm{E}\left[\xi_t^2 \mid \Omega_{t-1}\right] \\ &= \sigma_t^2 .\mathrm{E}\left[z_t^2 \mid \Omega_{t-1}\right] \\ &= \sigma_t^{\,2} \end{aligned} \tag{4.11.1}$$

To know the relationship between net positions of players, sentiment index, hedging pressure, information variables and idiosyncratic volatility, Equation 4.11.2 is regressed as follows, and full results are reported in Table 4.11.1 and 4.11.2[95].

$$\begin{aligned} \sigma_t^{\,2} = \varphi_0 &+ \varphi_1 \mathrm{Exp}\, SI_t + \varphi_2 \mathrm{Unexp}\, SI_t + \varphi_3 \mathrm{Exp}\, NP_t + \varphi_4 \mathrm{Unexp}\, NP_t \\ &+ \varphi_5 \mathrm{HP}_{t-1} + \varphi_6 \mathrm{Exp\,Tbill\,yield}_t + \varphi_7 \mathrm{Unexp\,Tbill\,yield}_t \\ &+ \varphi_8 \mathrm{Exp\,BAA - AAA}_t + \varphi_9 \mathrm{Unexp\,BAA - AAA}_t \\ &+ \varphi_{10} \mathrm{Exp\,Divyield}_t + \varphi_{11} \mathrm{Unexp\,Divyield}_t + \xi_t \end{aligned} \tag{4.11.2}$$

Table 4.11.1 shows the volatility equation for hedgers. Expected net positions are negative and significant for S&P500 and wheat (Chicago), and positive and significant for soybean oil and wheat (Minnesota); while unexpected net positions are significantly negative for S&P500 and Swiss francs and significantly positive for Canadian dollars and sugar only. This supports the results earlier that hedgers are informed players in the

[95] All results are reported at 10% significance level. Only significant t ratios are showed.

futures markets, where unexpected net positions add to volatility in Canadian dollars and sugar only. Expected sentiment is negative and significant only for platinum; while unexpected sentiment is significantly negative for British pounds and positive for feeder cattle. The lagged hedging pressure variable is significant and positive for platinum and soybean meal; and significant and negative for Japanese yen and sugar. While Japanese yen did not exhibit significant risk premium in the decomposed mean equation (Table 4.10.3), the lagged hedging pressure variable tends to reduce the volatility for hedgers when looking at the volatility equation. Therefore, the negative coefficient for Japanese yen supports the claim made earlier in the destabilizing feature section where there is a need to reconsider the position limits of speculators in that market.

Expected Treasury bill yield is negative and significant for British pounds and positive for corn and soybean oil. Unexpected Treasury bill yield is significant and negative only for British pounds and heating oil. Expected corporate spread is significant and positive for copper, wheat (Minnesota) and corn; while unexpected corporate spread is significant and positive for Treasury bonds, soybean oil, and negative for Canadian dollars. Expected dividend yield is significant and negative for S&P500 futures and positive for feeder cattle futures. Unexpected dividend yield have no significance to volatility in any market. This not only suggests that the market (S&P500) overall trend was predictable at the start of the month[96], but also that dividend yield does not have significant effect upon the volatility of informed players like hedgers.

In contrast, Table 4.11.2 shows that expected net positions for speculators are significant and positive for Swiss francs, wheat (Chicago, Minnesota) and coffee; and significant and negative for cocoa only. Unexpected net positions are significant and positive for Canadian dollars and lumber; and negative for wheat (Kansas) and live hogs. This suggests that net positions of hedgers (expected and unexpected) tend to have less effect on volatility compared to speculators' net positions (expected and unexpected)

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[96] This is also supported by the fact that the expected dividend yield was significant and negative in reducing the volatility in S&P500 futures market.

which tend to add to volatility[97]. This is consistent with the Shalen (1993) and Chen et al. (1995) models, where speculators' volatility is positively associated with trading demand (measured as net positions). The negative impact of trading demand on volatility for hedgers in S&P500 and wheat (Chicago) can be explained due to hedgers' net positions having a negative impact over returns in both markets (as shown in Table 4.6), and also due to the fact that volatility is measured as the squared residual from the mean equation, where net position is a significant variable in determining returns, as seen in Table 4.10.1.

Expected sentiment for speculators has significant positive effects on the volatility of silver, copper and Japanese yen; and significant negative effects on the volatility of platinum and soybean. Unexpected sentiment is significant and positive for live hogs and feeder cattle, and negative for Treasury bonds and British pounds. Comparing the expected and unexpected sentiment for both players, it appears that expected sentiment has led to an increase in volatility of speculators. This can be explained by trend-chasing behaviour in the 1990s which resulted in an increase in trading activity and thus volatility levels (Wang, 2003). Further, the number of significant expected and particularly unexpected variables affecting volatility can be found within the currencies group for both players, supporting the fact the foreign exchange markets are among the most actively traded contracts in the US[98].

Expected Treasury bill yield is negative and significant for feeder cattle and British pounds, and positive for soybean oil and pork bellies. Unexpected Treasury bill yield is negative and significant for heating oil and pork bellies. Expected corporate yield spread is not significant in any market for speculators, while unexpected corporate yield spread is significant and negative only in Japanese yen and soybean oil. This contrasts with hedgers, where expected corporate yield spread tends to have a positive effect on volatility. Expected dividend is positive and significant only in wheat (Kansas),

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[97] However, it is important to understand that idiosyncratic volatility is always a positive number since it is the squared residual from the mean equation. Regressing positive values of volatility against net positions of hedgers (which are net short overall) would lead to a negative net position coefficient.
[98] See Appendix 6.2 for 25 largest trading US Exchange Traded contracts.

and unexpected dividend was significant and positive for sugar and soybean. This again contrasts with hedgers where unexpected dividend yield is not significant in any market. The above overall findings support that information variables do not significantly affect volatility of large hedgers and large speculators.

Table 4.11.1
Volatility equation for large hedgers

This table shows the volatility equation for large hedgers. Volatility is the squared residuals obtained from the mean equation, as shown below. Net positions of hedgers, sentiment data, treasury bill yield, corporate spread, dividend yield are decomposed into expected and unexpected variables using ARMA specifications. A lagged hedging pressure variable is also regressed against volatility. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated idiosyncratic volatility equation is

$$\sigma_t^{\,2} = \varphi_0 + \varphi_1 \text{ Exp } SI_t + \varphi_2 \text{ Unexp } SI_t + \varphi_3 \text{ Exp } NP_t + \varphi_4 \text{ Unexp } NP_t + \varphi_5 \text{ HP}_{t-1} +$$
$$\varphi_6 \text{ Exp Tbill yield}_t + \varphi_7 \text{ Unexp Tbill yield}_t + \varphi_8 \text{ Exp BAA - AAA}_t + \varphi_9 \text{ Unexp BAA - AAA}_t +$$
$$\varphi_{10} \text{ Exp Divyield}_t + \varphi_{11} \text{ Unexp Divyield}_t + \xi_t$$

, where the volatility measure $\sigma_t^{\,2}$ is derived from the following mean equation:

$$R_t = \mu_t + \xi_t, \quad \xi_t = \sqrt{\sigma_t}\, z_t, \quad z_t \sim N(0,1)$$

, where the conditional mean $\mu_t = \mathrm{E}\left[R_t \mid \Omega_{t-1}\right]$

, Ω_{t-1} is the information set available at time t-1,

, ξ_t is the innovation term,

, σ_t is its conditional variance,

$$\xi_t^{\,2} = \mathrm{E}\left[\xi_t^2 \mid \Omega_{t-1}\right] = \sigma_t^2 . \mathrm{E}\left[z_t^2 \mid \Omega_{t-1}\right] = \sigma_t^{\,2}$$

Volatility Equation:

	Intercept	***NP$_t$***		***SI$_t$***		***HP$_{t-1}$***	***Tbillyield$_t$***		***BAA-AAA$_t$***		***Divyield$_t$***	
		Exp	*Unexp.*	*Exp*	*Unexp.*		*Exp*	*Unexp.*	*Exp*	*Unexp.*	*Exp*	*Unexp.*
Panel A : Hedger												
Minerals												
GC	-5.435	0.212	0.024	0.211	0.502	1.794	-35.591	21.151	-1.649	0.473	-21.310	-22.982
SI	-12.785	-0.083	-0.022	0.533	0.006	-2.646	13.249	0.448	-12.365	0.594	82.526	-21.001
HG	9.351	-0.337	-0.991	0.496	-0.110	-22.237	67.733	-13.398	27.236	-5.977	82.134	43.229
									2.054			
PL	41.158	1.011	-0.112	-0.580	0.112	13.709	-3.824	-9.961	-6.810	0.055	44.499	-24.164
	2.363			*-1.844*		*1.759*						

/pto

CL	-265.195	-0.064	-0.490	5.390	-0.478	-547.545	-1313.354	-48.780	-93.662	-51.468	-3529.056	396.573
HO	-40.956	0.723	1.220	1.521	0.102	-26.033	-752.937	-114.887	-99.405	-27.615	-1251.436	93.661
								-2.089				
Financials												
SP	22.882	-0.279	-0.362	-0.306	-0.009	-12.283	-32.269	-4.459	2.872	1.307	-143.906	4.389
	2.171	*-2.457*	*-2.583*								*-1.731*	
ED	1.149	0.147	0.012	0.141	-0.084	14.382	-1.006	-5.290	-2.046	-0.638	-55.348	12.406
US	0.023	0.000	0.000	0.001	0.000	0.173	0.394	0.081	0.043	0.014	-0.596	0.012
										1.649		
Currencies												
BP	-0.897	0.227	-0.001	0.126	-0.102	2.470	-40.694	-12.975	2.779	-2.101	10.508	-4.853
					-1.667		*-1.656*	*-1.655*				
SF	-12.087	0.080	-0.113	0.514	-0.054	-6.530	15.762	-2.055	4.091	-0.601	108.333	-20.898
			-1.730									
CD	2.464	-0.007	0.020	-0.036	0.001	-0.572	1.414	-0.804	-0.074	-0.522	-4.474	0.064
	2.600		*1.772*							*-2.617*		
JY	-9.144	0.056	0.002	0.310	0.106	-7.353	-54.576	-4.704	-5.324	-1.138	30.519	-18.315
						-1.850						
Agriculturals												
W	27.092	-2.099	-0.489	-0.150	-0.395	-21.124	-10.537	-2.147	36.178	3.553	444.922	51.812
		-2.326							*1.721*			
KW	13.536	-1.926	-0.389	0.517	-0.370	107.565	-138.352	-29.707	34.725	3.282	375.077	41.696
MW	2.165	9.412	5.040	0.814	-0.872	37.098	-61.942	-25.037	44.828	-1.282	430.909	-9.287
		1.828							*1.996*			
C	-11.565	0.200	0.183	0.567	0.336	15.857	117.768	-10.067	12.393	3.494	-87.750	-41.905
							1.695		*1.668*			
S	5.834	0.063	0.263	0.166	-0.051	4.785	-38.973	13.046	-3.698	-2.155	-95.563	39.004
BO	2.826	0.261	0.031	0.314	0.003	-8.741	86.490	-0.034	1.184	2.278	47.383	10.515
		2.392					*2.040*			*2.262*		
SM	2.894	0.174	0.066	0.166	-0.158	36.367	-0.584	10.909	-29.149	-3.073	-113.805	-22.794
						2.066						
PB	382.897	-20.169	-5.743	-5.660	1.504	63.992	928.344	-50.260	76.568	-15.878	3.544	-39.070
	1.998											
LH	-3.547	5.299	-2.964	1.545	0.881	28.742	276.368	-1.837	53.782	9.064	-1064.175	76.672
LC	-12.264	-0.099	0.274	0.485	-0.113	4.012	-10.356	0.331	3.551	2.816	80.026	17.201
FC	9.882	-2.748	-1.875	-0.017	0.095	7.095	-24.234	-2.767	3.527	0.703	86.853	4.630
					1.790						*1.829*	
SB	54.348	0.026	0.632	0.442	0.645	-113.082	-187.005	18.093	24.332	-5.556	135.696	74.024
			2.241			*-2.363*						
CC	-0.301	-1.818	1.286	1.049	-0.052	-238.856	192.605	2.866	35.015	-2.912	-87.923	4.800
KC	-23.937	-0.401	1.087	3.368	-0.443	-23.232	413.284	212.959	14.690	13.719	546.731	39.920
CT	36.309	-0.377	0.095	-0.210	0.155	34.549	-122.693	6.426	27.446	-3.093	106.348	-22.697
									1.726			
LB	-140.664	15.009	-1.665	4.646	0.065	25.137	87.658	13.335	27.161	8.935	-2.802	41.511

Table 4.11.2
Volatility equation of large speculators

This table shows the volatility equation for large speculators. Volatility is the squared residuals obtained from the mean equation, as shown below. Net positions of speculators, sentiment data, treasury bill yield, corporate spread, dividend yield are decomposed into expected and unexpected variables using ARMA specifications. A lagged hedging pressure variable is also regressed against volatility. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated idiosyncratic volatility equation is

$$\sigma_t^2 = \varphi_0 + \varphi_1 \text{Exp}\, SI_t + \varphi_2 \text{Unexp}\, SI_t + \varphi_3 \text{Exp}\, NP_t + \varphi_4 \text{Unexp}\, NP_t + \varphi_5 \text{HP}_{t-1} +$$
$$\varphi_6 \text{Exp Tbillyield}_t + \varphi_7 \text{Unexp Tbillyield}_t + \varphi_8 \text{Exp BAA-AAA}_t + \varphi_9 \text{Unexp BAA-AAA}_t +$$
$$\varphi_{10} \text{Exp Divyield}_t + \varphi_{11} \text{Unexp Divyield}_t + \xi_t$$

, where the volatility measure σ_t^2 is derived from the following mean equation:

$$R_t = \mu_t + \xi_t, \quad \xi_t = \sqrt{\sigma_t}\, z_t, \quad z_t \sim N(0,1)$$

, where the conditional mean $\mu_t = \mathrm{E}\left[R_t \mid \Omega_{t-1}\right]$

, Ω_{t-1} is the information set available at time t-1,

, ξ_t is the innovation term,

, σ_t is its conditional variance,

$$\xi_t^2 = \mathrm{E}\left\lfloor \xi_t^2 \mid \Omega_{t-1} \right\rfloor = \sigma_t^2 . \mathrm{E}\left\lfloor z_t^2 \mid \Omega_{t-1} \right\rfloor = \sigma_t^2$$

Volatility Equation

	Intercept	*NP$_t$*		*SI$_t$*		*HP$_{t-1}$*	*Tbillyield$_t$*		*BAA-AAA$_t$*		*Divyield$_t$*	
		Exp	*Unexp.*	*Exp*	*Unexp.*		*Exp*	*Unexp.*	*Exp*	*Unexp.*	*Exp*	*Unexp.*
Panel B: Speculator												
Minerals												
GC	-24.417	-0.519	-0.371	0.483	0.608	14.797	-82.531	15.158	-1.601	1.049	-45.841	-3.690
SI	-15.514	-0.139	-0.252	0.662	0.066	2.985	7.901	-2.328	-7.068	0.576	75.333	-17.806
				2.110								
HG	-14.278	-0.863	-0.808	1.108	0.216	-14.952	185.876	-14.038	14.339	-5.728	27.231	18.558
				2.495								
PL	43.044	1.022	-0.069	-0.624	0.108	14.199	-5.029	-9.604	-7.398	0.220	47.865	-18.972
	2.343			*-1.883*		*1.757*						

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CL	-324.699	-5.338	-1.523	7.011	-0.161	-637.533	-1014.352	-45.498	-97.082	-48.698	-3545.714	388.938
HO	-61.578	-3.400	-2.219	2.106	-0.289	13.672	-709.652	-139.631	-50.586	-29.394	-1070.650	125.594
								-2.144				
Financials												
SP	23.042	-0.004	-0.082	-0.312	0.003	39.347	-48.943	-5.349	4.616	1.787	-119.030	-7.806
ED	0.048	0.002	0.000	0.000	0.000	-0.035	0.342	0.076	0.053	0.015	-0.629	0.001
US	4.277	-0.100	-0.152	0.051	-0.103	5.256	3.075	-5.192	0.676	-0.023	-48.386	5.673
					-1.840							
Currencies												
BP	-2.089	-0.143	0.005	0.166	-0.113	-0.014	-50.075	-15.092	4.356	-2.133	13.739	-4.353
					-1.750		*-1.859*	*-1.694*				
SF	-17.397	0.481	0.112	0.672	-0.057	-9.769	51.706	-2.995	5.557	0.140	72.855	-10.551
		2.189				*-1.651*						
CD	2.882	0.026	0.022	-0.043	-0.003	-0.537	3.283	-1.043	-0.053	-0.594	-1.498	-0.298
	2.276		*1.700*									
JY	-3.982	-0.187	0.011	0.202	0.045	-9.716	-38.409	-6.700	-1.040	-1.677	30.519	-10.745
				2.134		*-2.393*				*-2.853*		
Agriculturals												
W	39.017	4.688	-1.156	0.312	-0.425	-26.907	-104.566	-14.656	16.204	5.004	697.312	-23.677
	1.747	*1.683*									*2.136*	
KW	-1.869	7.235	-5.788	0.997	-0.644	166.607	-121.909	-22.273	48.202	1.780	440.535	-42.827
			-1.655									
MW	25.675	14.921	2.891	0.302	-0.447	-44.918	-112.938	-13.564	27.712	2.735	330.196	-10.267
		1.855										
C	-2.881	-0.002	-0.029	0.449	-0.004	-13.373	117.107	-4.109	11.684	2.154	-85.901	-29.619
S	53.011	0.348	0.056	-0.556	-0.098	-15.295	-2.035	6.313	-17.846	-5.054	88.276	71.243
	2.897			*-1.669*								*2.569*
BO	15.252	9.701	0.028	0.045	-0.123	-18.164	90.097	4.372	-0.180	3.159	37.393	10.277
							1.767			*3.075*		
SM	28.317	-1.093	0.620	-0.098	-0.156	57.732	64.244	-2.434	-31.785	-9.981	237.944	-8.023
						1.740						
PB	428.541	-24.089	18.211	-6.732	0.976	100.079	1250.519	-3.276	62.971	-4.393	518.192	-96.832
	2.072						*1.775*					
LH	77.765	-5.266	-3.526	-0.197	1.658	69.451	207.248	8.438	26.548	6.087	-1082.530	107.844
			-1.746		*1.952*							
LC	-10.511	-0.195	-0.029	0.479	-0.107	11.269	7.247	2.206	3.090	2.982	94.307	14.641
FC	9.164	1.341	-0.243	-0.032	0.110	5.424	-46.236	-0.640	2.019	-0.327	70.345	0.811
					2.147	*1.775*	*-1.988*					
SB	65.351	0.103	-1.173	0.285	0.392	-126.700	-2.628	6.234	44.742	-2.094	-66.825	120.731
						-1.931						*1.830*
CC	-15.929	-5.891	-0.863	1.785	-0.116	-169.390	260.965	19.956	16.047	-7.817	76.029	-33.352
		-1.816										
KC	19.033	17.744	-1.433	1.763	-0.733	-163.552	546.021	224.628	22.571	13.808	895.653	31.666
		2.247										
CT	19.702	0.002	-1.097	0.409	-0.052	68.151	-5.524	12.831	-2.918	-7.470	419.045	-74.944
LB	-50.977	-33.365	28.217	2.466	-0.199	4.431	69.095	23.479	26.490	9.736	-22.215	40.359
			1.721									

4.4.2.2 Decomposed Volatility Equation

French, Schwert, and Stambaugh (1987) extended Merton's work by dividing market volatility variables into expected and unexpected components using ARMA models. In line with these authors, the volatility equation for each futures market is decomposed in expected and unexpected volatility. The idiosyncratic volatility σ_t^2 obtained from Equation 4.11.1 is regressed as follows:

$$\sigma_t^2 = \varphi_0 + \varphi_1 \; Exp \;\; \sigma_t^2 + \;\; \varphi_2 Un\exp \;\; \sigma_t^2 + \varepsilon_t \qquad (4.12.1)$$

The results in Table 4.12 are arrived at after decomposing the idiosyncratic volatility into an expected and unexpected component. ARMA model specification is used together with Ljung-Box Q statistics and Breusch-Godfrey serial correlation LM test to arrive at uncorrelated expected and unexpected volatility[99]. Results for Q statistics and LM test are provided in Appendix 6.12. Findings from Table 4.12 reveal that expected volatility for hedgers is significant in 21 markets, with 14 being positive and seven being negative at 10% significance level. All minerals like crude oil and heating oil have a positive expected volatility, suggesting that hedgers in these markets set a risk level at the start of the month, which will have a positive net effect of total risk for the whole month. This also supports previous findings like Haigh et al. (2005) and NYMEX (2005) that in these markets, hedgers' trading activity is volatile and requires more need of attention when it comes to CFTC's position limits. Regarding unexpected volatility, only soybean exhibits a significant unexpected volatility component. Speculators, on the other hand, have 22 markets with significant expected volatility. Seventeen out of these 22 markets exhibit positive expected volatility. While speculators also have significant positive expected volatility for crude oil and heating oil, the magnitude of the coefficients is larger for hedgers, suggesting more active trading, particularly at the start of the month.

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[99] An ARCH effect test is also performed on Equation 4.12.1. However, due to correct model specification using ARMA, the correlograms of squared residuals are invalid due to insufficient variation in the data. This can also be explained by the high R^2 value of Equation 4.12.1.

Table 4.12
Decomposed idiosyncratic volatility for hedgers and speculators

This table shows the decomposed idiosyncratic volatility equation for large hedgers and speculators. Volatility is the squared residuals obtained from the mean equations, as shown in equation 4.11.1. The idiosyncratic volatility is decomposed into expected volatility and unexpected volatility using ARMA specifications and tested for serial correlation using Ljung- Box Q statistics and Breusch Godfrey LM test. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated decomposed idiosyncratic volatility equation is

$$\sigma_t^{\,2} = \varphi_0 + \varphi_1 \; Exp \; \sigma_t^{\,2} + \; \varphi_2 Un\exp \; \sigma_t^{\,2} + \varepsilon_t \, ,$$

, where the volatility measure $\sigma_t^{\,2}$ is derived from the following mean equation:

$$R_t = \mu_t + \xi_t \, , \;\; \xi_t = \sqrt{\sigma_t} \, z_t \, , \;\; z_t \sim N(0,1)$$

, where the conditional mean $\mu_t = \mathrm{E}\left[R_t \mid \Omega_{t-1}\right]$

, Ω_{t-1} is the information set available at time t-1,

, ξ_t is the innovation term,

, σ_t is its conditional variance,

$$\xi_t^{\,2} = \mathrm{E}\left\lfloor \xi_t^2 \mid \Omega_{t-1} \right\rfloor \qquad = \qquad \sigma_t^{\,2} . \mathrm{E}\left\lfloor z_t^2 \mid \Omega_{t-1} \right\rfloor \qquad = \qquad \sigma_t^{\,2}$$

Volatility Equation:	***Hedgers***			***Speculators***		
	Intercept	***Expected*** σ_t^2	***Unexpected*** σ_t^2	***Intercept***	***Expected*** σ_t^2	***Unexpected*** σ_t^2
Minerals						
GC	-50.185	8.322	0.000	-44.351	7.288	0.000
	-208.976	*204.763*		*-164.916*	*171.218*	
SI	420.257	-25.397	0.008	-452.753	28.835	0.000
	11.937	*-11.652*				
HG	-83.024	4.036	0.000	-30.071	2.087	-0.051
	-16.591	*23.092*		*-2.122*	*3.882*	
PL	-166.120	16.403	0.000	-235.891	23.258	0.000
	-56.338	*63.198*		*-109.716*	*121.145*	
CL	-2149.937	35.211	0.000	-2208.169	37.519	0.000
	-5.650E+13	*5.750E+13*		*-1.710E+14*	*1.740E+14*	*-6.165*
HO	6.087	0.869	0.045	-107.013	2.895	0.002
		2.175		*-2.576*	*3.440*	

/pto

Financials						
SP	-19.264	3.240	0.000	-2.466	1.403	0.031
	-10.189	*12.234*				
ED	0.029	0.482	0.074	0.028	0.502	0.086
US	-12.735	3.033	0.001	-21.037	4.357	-0.013
Currencies						
BP	-28.531	6.542	0.000	-32.792	7.022	0.000
	-89.646	*97.364*		*-1.240E+15*	*1.350E+15*	
SF	723.904	-91.080	0.000	164.933	-18.396	0.000
	3.170E+13	*-3.140E+13*		*1.360E+14*	*-1.310E+14*	
CD	-10.093	10.445	-0.002	62.456	-19.976	0.264
	-34.349	*37.751*		*4.719*	*-1.720*	
JY	1.425	0.743	-0.038	-29.213	5.936	0.000
				-5.940E+14	*6.730E+14*	
Agriculturals						
W	-114.279	4.732	0.000	-116.986	4.080	0.000
	-2.600E+15	*3.250E+15*	*-2.079*	*-6.370E+14*	*7.900E+14*	
KW	1570.486	-47.443	0.000	-5210.247	141.731	0.000
	6.750E+13	*-6.650E+13*	*-1.841*	*-1.110E+13*	*1.120E+13*	
MW	564.163	-18.521	0.000	372.979	-10.412	0.000
	1.100E+14	*-1.070E+14*	*1.936*	*1.540E+15*	*-1.450E+15*	
C	217.767	-12.127	0.000	1861.842	-95.923	0.000
	2.920E+14	*-2.750E+14*		*7.150E+12*	*-7.090E+12*	
S	13.507	0.175	-0.197	22.843	-0.134	-0.086
			-2.897	*2.928*		
BO	14.241	-0.285	0.144	-31.486	3.643	0.001
	2.615			*-2.400*	*3.335*	
SM	-110.925	7.500	0.000	-138.621	6.298	0.000
	-5.470	*6.451*		*-516.004*	*790.672*	
PB	-766.399	5.998	0.010	-868.429	6.697	0.000
	-6.948	*8.303*		*-6.140E+14*	*6.910E+14*	
LH	39942.280	-586.142	0.000	-5272.522	74.291	0.000
	5.960E+10	*-5.950E+10*		*-7.030E+12*	*7.090E+12*	
LC	137.703	-11.477	0.001	136.214	-11.217	0.001
	50.675	*-50.773*		*32.953*	*-32.526*	
FC	26.508	-2.883	0.014	-15.005	3.396	-0.009
	2.781	*-2.159*		*-2.097*	*2.998*	
SB	-88.665	2.545	0.023	-65.441	2.097	0.000
	-2.643	*3.884*		*-2.095*	*3.460*	
CC	-1842.037	46.947	0.000	-4065.788	92.975	0.000
	-1.510E+13	*1.540E+13*		*-3.150E+12*	*3.180E+12*	
KC	-99.773	1.914	0.008	-99.323	1.941	0.010
	-6.289	*12.786*		*-4.586*	*8.874*	
CT	913.833	-36.873	0.011	6735.471	-204.139	0.002
				16.780	*-16.680*	
LB	-59.406	2.098	0.006	-30.869	1.604	-0.002
	-4.030	*6.368*		*-2.145*	*4.766*	

4.4.3.1 GARCH Volatility Model

In line with Bollerslev (1986), a GARCH (1, 1) model is employed and expressed as:

$$\sigma_t^{\,2} = \varphi_0 + \varphi_1\, \xi_{t-1}^{\,2} + \varphi_2\, \sigma_{t-1}^{\,2} + \varepsilon_t \qquad (4.13)$$

The GARCH process is analogous to an ARMA representation. Restrictions like $\varphi_0 > 0$ and φ_1 and $\varphi_2 \geq 0$ are usually imposed to ensure a positive variance (see Bollerslev (1986). These restrictions in GARCH models are relaxed, since any model can have a positive and negative coefficient attached to any variable. This is supported by Nelson and Cao (1992) and Hwang and Pereira (2006) who supported that Bollerslev (1986) non-negative restrictions are too restrictive and negative estimates can be found in practice. An additional restriction is that both ARCH and GARCH models assume symmetry in the distribution of asset returns[100]. To ensure that the GARCH model is white noise and efficient, the correlograms of squared residuals and an ARCH LM test are carried out, and presented in Appendix 6.13. Full results for GARCH volatility models are reported in Table 4.13 at 10% significance level.

News about volatility from the previous period, measured as the lag of the squared residual from the mean equation $\xi_{t-1}^{\,2}$, is significant in 13 markets for hedgers, where nine out of the 13 markets are from the agricultural group. In 10 markets, news about volatility from the previous month is positive, suggesting that the ARCH term is quite important in determining current volatility levels for hedgers, particularly for agricultural futures markets. Only in Canadian dollars, live cattle and pork bellies, has previous news about volatility reduced current volatility levels. On the other hand, the GARCH term $\sigma_{t-1}^{\,2}$ is significant in 24 markets, where 14 markets are from the

[100] See Chapter 2, section 2.16.1.5 for more details on the assumptions behind symmetrical models such as GARCH and PARCH.

agricultural group. As expected, $\varphi_2 \geq 0$, except for soybean oil[101]. This is consistent with Yang and Brorsen (1993) who found GARCH effects in 13 out of 15 futures markets studied.

In contrast, speculators' volatility tends to be affected by news about volatility from the previous month. In fact, ${\xi_{t-1}}^2$ is significant for 18 of the markets, where all three financials, three currencies, three minerals and nine agriculturals volatility are affected by the previous month's news on volatility. Fifteen out of these 18 markets exhibit a significant positive effect on current volatility, whereas only Canadian dollars, Swiss francs and live cattle exhibit a negative effect on current volatility. This supports the fact that large speculators are more geared towards trend-chasing behaviour, and noise trading where news from previous period affects current volatility levels. Further, the GARCH term ${\sigma_{t-1}}^2$ is significant for speculators in 20 markets, where only wheat (Chicago) exhibits a negative effect on current volatility.

Further, in line with Bollerslev, Chow and Kroner (1992) who showed that the persistence of shocks to volatility depends on the sum of φ_1 and φ_2, the findings in Table 14.3 supports that hedgers' volatility in Treasury bonds and coffee; and speculators' volatility in gold and S&P500 futures, have experienced increasing volatility persistence to shocks over the 1990s. In contrast, in all the remaining markets, hedgers' and speculators' volatility has shown a tendency to decay over time in response to shocks over the 1990s[102]. This supports that both players are informed and react well to news volatility.

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[101] In addition, it is suspected higher GARCH (p,q) order models will lead to positive forecasted lagged variance. Testing for GARCH (2,1) confirms that hypothesis.

[102] However, a significant impact of volatility on the stock prices can only take place if shocks to volatility persist over a long time (Poterba and Summers, 1986).

Table 4.13
GARCH volatility equation for hedgers and speculators

This table shows the results of using a GARCH (1, 1) volatility model to estimate the conditional variance and mean equation for both hedgers and speculators. Only the intercept, ARCH and GARCH term of the volatility equation are provided below. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated symmetric GARCH volatility equation is

$$\sigma_t^{\ 2} = \varphi_0 + \varphi_1\, \xi_{t-1}^{\ 2} + \varphi_2\, \sigma_{t-1}^{\ 2} + \varepsilon_t$$

GARCH volatility equation

	Hedger			Speculator		
	Intercept	$\xi_{t-1}^{\ 2}$	$\sigma_{t-1}^{\ 2}$	***Intercept***	$\xi_{t-1}^{\ 2}$	$\sigma_{t-1}^{\ 2}$
Minerals						
GC	6.310	0.084	-0.088	0.356	0.533	0.605
						4.936
SI	2.910	0.190	0.645	9.942	0.455	0.013
		1.648	*3.630*	*3.125*	*3.515*	
HG	32.322	0.048	0.005	8.659	-0.001	0.744
PL	2.163	0.334	0.516	2.225	0.332	0.507
			3.530		*1.712*	*3.842*
CL	6.420	0.046	0.766	6.656	0.070	0.745
			5.192			*5.645*
HO	4.330	0.013	0.835	5.512	0.067	0.780
			6.688			*5.365*
Financials						
SP	2.031	0.308	0.530	0.157	0.159	0.848
	1.689	*1.740*	*3.051*		*2.008*	*11.147*
ED	0.008	0.090	0.819	0.007	0.088	0.821
		1.740	*10.227*		*1.764*	*9.814*
US	0.020	-0.035	1.040	4.231	0.610	-0.043
			10.086	*5.006*	*1.726*	
Currencies						
BP	0.005	-0.026	1.018	-0.006	-0.015	1.006
			8.585			*12.209*
SF	1.132	-0.044	0.947	2.826	-0.070	0.827
			20.392	*2.017*	*-3.193*	*5.950*
CD	0.074	-0.087	1.040	0.064	-0.083	1.046
	2.863	*-2.754*	*26.838*	*2.341*	*-2.586*	*24.536*
JY	4.302	0.312	-0.097	4.874	0.351	-0.002
	2.950			*2.950*	*1.862*	

/pto

Agriculturals						
W	6.650	0.092	0.590	41.534	0.062	-1.066
			2.026	*6.703*	*1.773*	*-9.246*
KW	2.149	0.126	0.781	2.957	0.129	0.749
			8.446		*1.781*	*5.847*
MW	2.192	0.070	0.818	2.673	0.138	0.742
			4.894			*4.471*
C	3.144	0.008	0.813	6.215	0.030	0.657
			2.702			
S	6.471	0.297	0.115	9.084	0.228	0.147
	2.976	*2.109*		*2.381*		
BO	11.847	0.343	-0.442	7.123	0.346	-0.082
	4.643	*3.308*	*-3.257*	*2.833*	*2.706*	
SM	3.193	0.175	0.585	3.159	0.113	0.700
		2.185	*3.364*			*4.129*
PB	8.402	-0.071	1.031	102.558	0.421	0.015
	3.346	*-1.840*	*20.220*	*3.748*	*1.997*	
LH	1.342	0.116	0.876	1.637	0.117	0.867
		1.645	*13.652*			*13.903*
LC	5.724	-0.072	0.544	5.817	-0.074	0.552
	1.792	*-5.385*	*1.706*	*1.865*	*-5.703*	*1.850*
FC	0.527	0.044	0.853	0.406	0.055	0.876
			6.362			*7.414*
SB	6.349	0.429	0.454	4.452	0.206	0.696
	2.129	*3.228*	*3.551*		*2.038*	*3.870*
CC	2.867	0.097	0.778	3.544	0.066	0.798
			2.954			*4.329*
KC	15.789	1.104	0.015	30.952	0.871	-0.045
	4.428	*3.269*		*4.090*	*2.847*	
CT	2.312	0.176	0.730	2.537	0.206	0.706
			5.283		*1.758*	*4.470*
LB	5.228	0.370	0.571	3.975	0.221	0.712
		1.923	*3.352*		*2.817*	*6.879*

4.4.3.2 Power ARCH (PARCH) Volatility Model

In line with Davidian and Carroll (1987) who argue that standard deviation specifications are more robust than variance specifications, a Taylor (1986) and Schwert (1989) standard deviation volatility model is constructed as follows:

$$\sigma_t^{\delta} = \varphi_0 + \sum_{i=1}^{p} \varphi_i (|\xi_{t-i}| - \gamma_i \xi_{t-i})^{\delta} + \sum_{j=1}^{q} \varphi_j \sigma_{t-j}^{\delta} + \varepsilon_t \qquad (4.14.1)$$

, where δ>0, $|\gamma_i| \leq 1$ for $i = 1,\ldots, r$, and $\gamma_i = 0$ for all $i > r$, $r \leq p$.

Substituting δ=1, i=j=1 and $\gamma_i = 0$ in equation 4.14.1, results in a symmetrical PARCH model as follows:

$$\sigma_t = \varphi_0 + \varphi_1 \xi_{t-1} + \varphi_2 \sigma_{t-1} + \varepsilon_t \qquad (4.14.2)$$

Note that if δ=2, and $\gamma_i = 0$ for all i, the PARCH model is simply a standard GARCH specification. The correlograms of squared residuals and an ARCH LM test supporting the model is white noise and efficient are presented in Table 4.16 of Appendix 6.13. Output for the Taylor-Schwert volatility model can be found in Table 4.14.

Table 4.14
PARCH volatility equation for hedgers and speculators.

This table shows the results of using a PARCH volatility model to estimate the conditional variance and mean equation for both hedgers and speculators. Only the intercept, lagged error residual and lagged volatility term of the volatility equation are provided below. The numbers in italics are t-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated symmetric PARCH volatility equation is

$$\sigma_t^{\delta} = \varphi_0 + \sum_{i=1}^{p} \varphi_i (|\xi_{t-i}| - \gamma_i \xi_{t-i})^{\delta} + \sum_{j=1}^{q} \varphi_j \sigma_{t-j}^{\delta} + \varepsilon_t$$

, where δ>0, $|\gamma_i| \leq 1$ for $i = 1,\ldots, r$, and $\gamma_i = 0$ for all $i > r$, $r \leq p$.

Substituting δ=1, i=j=1 and $\gamma_i = 0$ in the above equation, results in a symmetrical PARCH model as follows:

$$\sigma_t = \varphi_0 + \varphi_1 \xi_{t-1} + \varphi_2 \sigma_{t-1} + \varepsilon_t$$

PARCH volatility equation

	Hedger			Speculator		
	Intercept	$\lvert\xi_{t-i}\rvert$	σ_{t-1}	***Intercept***	$\lvert\xi_{t-i}\rvert$	σ_{t-1}
Minerals						
GC	3.083	-0.235	0.471	4.468	0.165	-1.055
				8.067		*-11.637*
SI	1.020	0.189	0.599	2.535	0.498	-0.011
		1.833	*2.632*	*3.883*	*5.766*	
HG	5.248	0.037	0.073	1.924	-0.020	0.685

/pto

PL	0.774	0.317	0.520	5.982	-0.087	-0.739
		2.190	*2.037*	*3.303*	*-2.069*	*-1.946*
CL	0.835	0.095	0.789	14.636	0.056	-1.026
			6.082	*4.600*		*-11.369*
HO	5.585	0.674	-0.276	0.662	0.095	0.818
	5.966	*4.010*	*-2.943*		*1.969*	*8.629*
Financials						
SP	0.557	0.274	0.615	1.490	0.571	0.113
		2.258	*4.002*	*2.700*	*4.454*	
ED	0.027	0.080	0.844	0.027	0.074	0.849
		1.824	*9.364*			*8.098*
US	2.068	-0.373	0.549	1.732	-0.441	0.716
	2.556	*-3.360*		*4.083*	*-3.782*	*3.414*
Currencies						
BP	0.152	0.187	0.796	0.030	0.063	0.936
		3.141	*10.266*			*24.347*
SF	1.628	0.190	0.373	1.428	0.246	0.391
	1.660			*1.805*	*1.842*	
CD	0.048	-0.084	1.031	0.051	-0.092	1.037
	2.256	*-2.164*	*24.531*	*1.989*	*-2.363*	*23.230*
JY	0.069	-0.082	1.034	2.294	0.420	-0.176
		-1.662	*45.221*	*3.047*	*3.326*	
Agriculturals						
W	8.404	0.084	-0.907	2.717	0.061	0.390
	4.279		*-3.164*			
KW	0.326	0.145	0.819	6.411	-0.355	-0.089
		2.085	*8.696*	*4.328*	*-10.839*	
MW	4.769	-0.280	0.047	0.671	0.183	0.715
	4.652	*-7.322*			*2.216*	*4.174*
C	4.260	-0.255	0.157	1.505	0.017	0.649
	2.363	*-8.276*				
S	1.802	0.261	0.237	2.134	0.213	0.265
	2.270	*2.802*		*1.640*	*1.662*	
BO	3.228	0.334	-0.286	2.523	0.363	-0.123
	3.390	*3.566*		*2.741*	*3.449*	
SM	6.515	-0.044	-0.693	6.801	-0.022	-0.597
	5.837		*-2.749*	*2.084*		
PB	7.101	0.319	0.198	0.641	-0.105	1.031
	3.095	*2.229*		*2.995*		*15.116*
LH	15.145	0.032	-1.061	15.137	0.093	-1.056
	6.617		*-5.787*	*9.787*		*-14.720*
LC	0.218	-0.114	1.025	3.078	-0.231	0.239
	2.007	*-2.531*	*34.308*	*2.851*	*-4.148*	
FC	0.032	-0.058	1.027	1.055	-0.031	0.607
			28.534			
SB	-9.967	-0.044	0.731	0.897	0.171	0.722
	-2.188				*1.901*	*3.760*
CC	9.909	-0.033	-0.924	2.060	0.064	0.551
	11.556		*-6.828*			
KC	3.455	0.773	-0.037	0.199	-0.060	1.028
	4.393	*4.596*		*1.782*		*25.818*
CT	7.900	-0.301	-0.417	6.578	-0.009	-0.359
	3.460	*-16.830*				
LB	1.117	0.401	0.527	1.478	0.588	0.349
		3.306	*3.231*	*2.210*	*4.879*	*2.522*

Volatility or the proxy measure of risk is measured as the standard deviation σ_t under the PARCH model. As expected, findings from Table 4.14 show that the effect of ξ_{t-i} on current volatility is much more mixed and significant than its counterpart $\xi_{t-1}{}^2$ in Table 4.13. News about volatility from the previous month is significant for 19 markets at 10% significance level. In seven markets, namely Treasury bonds, Canadian dollars, Japanese yen, wheat (Minnesota), corn, live cattle, and cotton, news about volatility from previous month has a significant negative effect on current volatility. On the other hand, in silver, platinum, heating oil, S&P500, Eurodollars, British pounds, wheat (Kansas), soybean, soybean oil, pork bellies, coffee and lumber markets, news about volatility from previous month has a significant positive effect on current volatility. Further, lagged volatility σ_{t-1} is significant in 17 markets, where in heating oil, wheat (Chicago), soybean meal, live hogs and cocoa, lagged volatility has a significant negative impact on current volatility. This compares with 24 markets which are significantly affected by $\sigma_{t-1}{}^2$ from the GARCH model.

Speculators also bear the significant effect of ξ_{t-i} on current volatility in 15 markets. In 10 out of these 15 markets, news about volatility from the previous month tends to add to current volatility levels. This result interestingly compares with 18 markets which were significantly affected by $\xi_{t-1}{}^2$ from the GARCH model. Further, lagged volatility of large speculators' trading activity is significant and positive for 10 out of 14 markets. Lagged volatility has a significant negative impact on current volatility only in wheat (Chicago). Hedgers' and speculators' current volatility (under GARCH) have significantly increased (decreased) by last month volatility in 23 (1) and 19 (1) markets respectively. More importantly, while speculators' current volatility (under GARCH) has significantly increased (decreased) in 14 (5) markets after accounting for news about volatility (under GARCH) from previous month, hedgers' current volatility (under PARCH) significantly increased (decreased) in 12 (7) markets after accounting for similar news about volatility from previous month. In sum, as expected, while the

PARCH model exhibits more significant negative variables, the GARCH model produces more significant positive variables. Further, it can be observed that the significance of ${\sigma_{t-1}}^2$ over σ_{t-1} is much higher for both hedgers and speculators. However, while ${\xi_{t-1}}^2$ is more significant than ξ_{t-i} for large speculators, that's not the case for hedgers, where ξ_{t-i} appears to have more impact than ${\xi_{t-1}}^2$. Although, ${\xi_{t-1}}^2$ is more significant than ξ_{t-i} for large speculators, it is important also to understand that the PARCH model has captured more significant negative impact of news about lagged volatility than in the GARCH model for speculators also. In that line of thought, findings suggests that the PARCH model, by capturing more significant negative impact of variables, is a more informative model than its counterpart GARCH model for speculators. Similarly, while the PARCH model for hedgers also captures more significant negative impact of variables like lagged volatility and news about volatility from previous month, the PARCH model also captures more significant positive impact of the news about volatility from previous month than its GARCH counterpart. However, to test whether the conditional standard deviation or variance model is a better model in reflecting actual volatility, in-sample model performance evaluations is suggested. This is carried out in section 4.4.5.

4.4.3.3 Return and Risk Relationship

Backed by authors such as De Long et al. (1990b), Lakonishok et al. (1994), and Daniel, Hirshleifer and Subrahmanyam (1998), who all studied trading behaviour, returns and volatility[103]—and due to the changing investors' attitude to risk and return as shown in graph 1.1—a simple risk and return equation is regressed to seek the relationship between futures return, expected volatility and unexpected volatility. Full output can be found in Table 4.15 and results are reported at 10% significance level. The risk/return equation is as follows:

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[103] Refer to Chapter 2 with particular reference to hedging and speculation theory, positive feedback, contrarian strategies, and volatility for more information.

$$R_t = \varphi_0 + \varphi_1 \; Exp \; \sigma_t^{\;2} + \varphi_2 Un\exp \; \sigma_t^{\;2} + \varepsilon_t \tag{4.15}$$

Hedgers' expected volatility (or risk) is theoretically expected to be low or insignificant due to the purpose of hedging in minimizing risk (Hoffman, 1932). Results from Table 4.15 shows that expected volatility of hedgers is significant in nine markets, where only crude oil, heating oil and wheat (Chicago) returns are significantly increased by expected volatility. These findings support earlier results in the study that there is a need to re-check CFTC regulation in regards to position limits of hedgers in crude oil and heating oil markets. Further, an increase in expected volatility tends to reduce futures returns in silver, Eurodollars, Japanese yen, wheat (Kansas, Minnesota) and pork bellies. On the other hand, unexpected volatility in hedgers' trading is significant for seven markets, where S&P500 and soybean oil futures' returns are reduced by an increase in unexpected volatility. Due to the informed characteristic of hedgers, unexpected volatility is also theoretically expected to be low and insignificant, in that hedgers will hardly readjust their risk levels throughout the month but rather set a tolerated risk level at the start of the month for a given return.

On the opposite side of the coin, speculators' expected volatility is theoretically expected to be high or significant, compensated by the higher returns. While expected volatility significantly adds to speculators' futures returns in crude oil, heating oil, and wheat (Kansas, Chicago), it significantly reduces returns in Eurodollars, Canadian dollars and pork bellies. Unexpected volatility also is theoretically assumed to be higher or more significant for speculators due to over-reaction towards noise information, and also due to the fact that speculators will usually readjust their risk levels during the month to affect their returns. While findings support that speculators' returns are significantly increased by unexpected volatility in gold, silver, Swiss francs and cotton, returns are significantly decreased by unexpected volatility in Japanese yen, pork bellies and wheat (Chicago). This supports theories propounded by Keynes (1930), Hicks (1939) and Kaldor (1939) that any loss made by the hedger in terms of risk avoidance and insurance represents an insurance premium paid to the risk-assuming speculators.

Table 4.15
Risk and return relationship for hedgers and speculators.

This table shows the relationship between futures return at time *t* and risk (which is proxied as volatility) for hedgers and speculators. Volatility is measured as the squared residuals obtained from the mean equations, as shown in below. The idiosyncratic volatility is decomposed into expected volatility and unexpected volatility using ARMA specifications and tested for serial correlation using Ljung- Box Qstatistics and Breusch Godfrey LM test. The numbers in italics are *t*-statistics relevant to the hypothesis that the relevant parameter is zero at 10% significance level. Estimated risk and return equation is

$$R_t = \varphi_0 + \varphi_1 \; Exp \; \sigma_t^{\,2} + \varphi_2 Un\exp \; \sigma_t^{\,2} + \varepsilon_t$$

, where the volatility measure $\sigma_t^{\,2}$ is derived from the following mean equation:

$$R_t = \mu_t + \xi_t, \quad \xi_t = \sqrt{\sigma_t}\, z_t, \quad z_t \sim N(0,1)$$

, where the conditional mean $\mu_t = \mathrm{E}\left[R_t \mid \Omega_{t-1}\right]$

, Ω_{t-1} is the information set available at time t-1,

, ξ_t is the innovation term,

, σ_t is its conditional variance,

$$\xi_t^{\,2} = \mathrm{E}\left\lfloor \xi_t^2 \mid \Omega_{t-1} \right\rfloor \quad = \quad \sigma_t^{\,2}.\mathrm{E}\left\lfloor z_t^2 \mid \Omega_{t-1} \right\rfloor \quad = \quad \sigma_t^{\,2}$$

Risk/Return Equation

	Hedgers			Speculators		
	Intercept	*Expected* σ_t^2	*Unexpected* σ_t^2	*Intercept*	*Expected* σ_t^2	*Unexpected* σ_t^2
Minerals						
GC	-0.078	-0.010	0.013	-0.100	-0.007	0.013
			3.587			*3.685*
SI	17.331	-1.080	0.033	-31.344	1.935	0.038
	2.005	*-1.991*	*1.724*			*2.053*
HG	-0.722	0.025	0.012	-0.998	0.035	-0.001
PL	1.202	-0.109	-0.007	1.762	-0.164	-0.006
CL	-11.389	0.193	0.000	-12.307	0.215	0.000
	-6.097	*8.453*		*-6.962*	*9.908*	
HO	-1.254	0.036	-0.004	-3.244	0.069	0.002
	-1.717	*4.197*		*-2.555*	*2.824*	

/pto

Financials						
SP	2.158	-0.117	-0.036	0.734	0.046	-0.013
	3.227		*-1.741*			
ED	0.218	-3.552	0.109	0.217	-3.566	0.117
	2.055	*-1.835*		*1.990*	*-1.775*	
US	-0.697	0.127	-0.007	-0.921	0.163	-0.007
Currencies						
BP	0.133	-0.032	0.011	-0.305	0.050	0.011
SF	3.318	-0.428	0.039	1.143	-0.139	0.032
			2.881			*2.538*
CD	0.872	-0.976	-0.061	1.454	-1.464	-0.072
				1.657	*-1.855*	
JY	1.529	-0.189	-0.003	0.949	-0.097	-0.039
	2.822	*-2.974*				*-2.010*
Agriculturals						
W	-4.133	0.135	-0.002	-3.240	0.085	-0.008
	-1.913	*1.873*		*-1.883*	*1.869*	*-1.692*
KW	18.539	-0.569	-0.001	-33.885	0.917	-0.004
	2.007	*-1.999*		*-1.718*	*1.722*	
MW	3.108	-0.104	0.000	2.059	-0.060	0.002
	1.908	*-1.737*				
C	-0.573	0.032	-0.006	-14.533	0.755	-0.005
S	-2.950	0.198	0.014	1.059	-0.050	0.007
BO	-0.975	0.090	-0.058	2.330	-0.200	-0.032
			-1.988			
SM	0.847	-0.037	-0.007	0.357	-0.006	-0.011
PB	19.004	-0.117	-0.003	11.971	-0.072	-0.005
	4.936	*-4.868*		*3.641*	*-3.772*	*-1.776*
LH	-129.067	1.905	-0.010	39.525	-0.542	-0.010
LC	-0.580	0.053	0.005	-1.120	0.101	0.004
FC	-2.521	0.384	-0.013	0.032	0.010	-0.013
SB	-1.767	0.030	-0.007	-3.221	0.053	-0.013
CC	5.371	-0.136	-0.012	12.394	-0.282	-0.013
KC	-1.187	0.016	0.007	-1.459	0.020	0.007
			1.727			
CT	-4.355	0.182	0.018	12.217	-0.371	0.013
			3.676			*2.850*
LB	-1.251	0.036	0.010	-0.763	0.028	-0.013

4.4.4 Error Distribution

In line with McNew and Fackler (1994) who underlined the importance of probability distributions, and backed by Bera et al. (1997) and Manfredo et al. (1999) who showed the relevance *t* distribution has over normal distribution[104], the GARCH and PARCH models used in this study are tested for normality in their probability distributions. Skewness, kurtosis and the Jarque-Bera statistics for both GARCH and PARCH models (under normal and *t* distribution) are provided in Table 4.17[105].

Findings from Table 4.17 show that the skewness for hedgers' returns (under the GARCH model), under normal distribution, is positive for 20 markets and negative for Eurodollars, Treasury bonds, British pounds, corn, feeder cattle, sugar, cotton, live cattle and silver. The fact that 20 markets have a probability distribution with long tail to the right is reflected also in the upward trend in the S&P500 returns in the 1990s, where many hedgers have had positive returns in their respective markets. The skewness values under *t* distribution are positive and negative as under the normal distribution. However, under *t* distribution, the probability distributions are as skewed or more skewed to the right if the skewness is positive and as skewed as or more skewed to the left if the skewness if negative. That's the case except for Canadian dollars where the positive skewness value is larger than under *t* distribution. The skewness for hedgers under (PARCH, normal) is negative for 12, where the nine markets under (GARCH, normal) are also reflected here in addition to gold, copper and Japanese yen. The skewness under (PARCH, normal) is less in value than under (GARCH, *t*) for 26 markets except for Swiss francs, Canadian dollars, and soybean where skewness under (PARCH, normal) was higher in value. The skewness under (PARCH, *t*) for hedgers' probability distribution returns is negative for 11 markets, which is the same as for (GARCH, normal) except for Japanese yen and soybean oil.

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[104] See Chapter 2, section 'Error distribution' for more information.
[105] See Appendix 6.5.11 and 6.5.16 for specification on the skewness, kurtosis and Jarque-Bera test.

The skewness for speculators' probability distributions returns under (GARCH, normal) is negative in 11 markets, which is the same as under (GARCH, normal) for hedgers in addition to soybean and copper. The negative skewness for Eurodollars and Treasury bonds for both hedgers and speculators can be attributed to introduction of the Euro currency that affected Eurodollars Treasury bonds (BIS, 1999). The skewness under (GARCH, *t*) is the same as under (GARCH, normal). However, under *t* distribution, the probability function is more skewed to the right if the skewness is positive and more skewed to the left if the skewness is negative. This similarity holds for 25 markets except for copper, wheat (Minnesota), corn and soybean oil. Under (PARCH, normal), the skewness for speculators' probability returns is negative for 13 markets. In fact, under (PARCH, normal), the skewness is less in value than the skewness under (GARCH, *t*) except for soybean oil, corn, wheat (Minnesota), Canadian dollars, crude oil and copper. In contrast, under (PARCH, *t*), the skewness is negative in 11 markets, which is the same as under (GARCH, normal) except for copper and soybean oil.

Having assumed symmetry in the GARCH and PARCH models, it is interesting to know which model (GARCH, PARCH) and under what error distribution (normal or *t*) do hedgers' and speculators' distribution returns appear to exhibit a greater tendency towards symmetry. Table 4.17 shows that the PARCH model, under normal distribution, ranks first in converging hedgers' returns towards symmetry[106]. This contrasts with speculators, where the GARCH model, under *t* distribution, ranks first in converging speculators' returns towards a skewness of zero[107].

In regards to kurtosis, a value less than three suggests that the probability function is flat (platykurtic) and a value greater than three suggests the probability function is peaked (leptokurtic). Hedgers' probability functions theoretically have a lower (flatter) kurtosis in more futures markets than speculators, due to hedgers entering the market to reduce risk and speculators entering the market to bear that risk. Table 4.17 shows that this is the case under (GARCH, normal), (GARCH, *t*), (PARCH, normal), but not under

[106] The (GARCH, normal) model ranks 2nd, followed by (PARCH, *t*) and lastly, (GARCH, *t*).
[107] The (PARCH, *t*) model ranks 2nd, followed by (PARCH, normal), and lastly, (GARCH, normal).

(PARCH, *t*)[108]. As such, the first three models help to support the fact that hedgers enter the market to reduce risk and has managed to do so in copper, crude oil, heating oil, soybean oil, sugar and Canadian dollars, relative to speculators. Speculators, however, also have a kurtosis lower than three in silver, copper, crude oil, Canadian dollars, sugar and soybean. Further, the kurtosis of hedgers is much smaller than speculators in copper, crude oil and sugar, but bigger than speculators in Canadian dollars.

The probability of the Jarque-Bera statistic is also reported under each model in Table 4.17. It appears that in four markets, hedgers' probability distribution returns converge to normality due to their high probability in the Jarque-Bera test. In fact, copper and soybean oil have the highest probability under (GARCH, normal), Canadian dollars under (PARCH, *t*), and sugar under (PARCH, *t*). Speculators' probability distribution returns also converge to normality in copper, soybean, soybean oil and soybean meal. Soybean and soybean meal have the highest probability under (PARCH, normal), copper under (GARCH, *t*), and soybean oil under (GARCH, normal). The high probability of the Jarque-Bera test is supported by low skewness and kurtosis not far from three. Overall, Table 4.17 supports the non-normal distribution in 25 markets for both hedgers' and speculators' probability distribution returns. This is consistent with Hilliard and Reis (1999) and Taylor (1986) who concluded non-normality in most futures markets. This is also supportive of studies by Mann and Heifner (1976), Blattberg and Gonedes (1984) and Houthakker (1961) where the distribution of large hedgers' and speculators' returns appear to be not normal, but rather leptokurtic.

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[108] In fact, hedgers (speculators) have a kurtosis in 3 (2) markets under (GARCH, normal), in 6 (3) markets under (GARCH, *t*), in 3 (2) markets under (PARCH, normal), and a kurtosis in 2 (3) in (PARCH, *t*).

Table 4.17
Normality test of error distribution under GARCH and PARCH volatility models for hedgers and speculators.

This table shows the values for skewness, kurtosis and Jarque-Bera statistics for the GARCH and PARCH volatility models. Panel A reports the results of hedgers under normal and t distribution, while Panel B reports the results for speculators. If the skewness value is positive (negative) that would indicate that error distribution is skewed to the right (left). A kurtosis value less than 3 indicates the distribution is flat (platykurtic) and peaked (leptokurtic) relative to the normal if it's greater than 3. The probability of the Jarque-Bera test is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed values under the null hypothesis of a normal distribution. A small probability rejects the null hypothesis. S denotes Skewness and K denotes Kurtosis.

	GARCH						PARCH					
	Normal dist.			*t dist.*			*Normal dist.*			*t dist.*		
	S	*K*	*Prob. (J-Bera)*	*S*	*K*	*Prob. (J-Bera)*	*S*	*K*	*Prob. (J-Bera)*	*S*	*K*	*Prob. (J-Bera)*
Panel A: Hedger												
Minerals												
GC	4.076	36.339	0.000	5.551	52.863	0.000	-0.254	3.094	0.463	3.312	30.844	0.000
SI	-0.225	3.171	0.515	-0.225	3.203	0.496	-0.460	3.491	0.044	-0.460	3.491	0.044
HG	0.010	3.138	0.946	1.003	0.013	0.938	-0.009	3.152	0.935	0.106	3.187	0.795
PL	1.027	6.081	0.000	2.232	14.846	0.000	1.166	6.985	0.000	2.090	14.127	0.000
CL	0.831	5.495	0.000	1.083	2.238	0.000	0.829	5.528	0.000	1.344	8.405	0.000
HO	0.792	5.575	0.000	1.018	1.390	0.000	0.954	5.577	0.000	1.285	10.661	0.000
Financials												
SP	0.749	4.782	0.000	0.950	5.496	0.000	0.706	4.628	0.000	0.864	5.452	0.000
ED	-0.563	3.872	0.003	-0.630	4.515	0.000	-0.560	3.939	0.002	-0.656	4.589	0.000
US	-0.390	3.353	0.122	-0.870	5.509	0.000	-0.742	5.611	0.000	-1.149	7.608	0.000
Currencies												
BP	-0.095	3.987	0.055	-1.151	10.942	0.000	-0.341	4.700	0.000	-0.676	5.929	0.000
SF	0.165	3.960	0.052	0.298	4.438	0.001	0.310	3.712	0.077	0.273	4.510	0.001
CD	0.021	2.633	0.675	0.020	2.614	0.649	0.029	2.642	0.685	0.025	2.648	0.695
JY	0.381	5.516	0.000	0.544	6.526	0.000	-0.184	4.214	0.010	-5.422	51.136	0.000

/pto

Agriculturals												
W	0.493	4.517	0.000	0.571	4.794	0.000	0.268	4.184	0.008	0.259	4.399	0.002
KW	0.732	5.259	0.000	0.873	6.911	0.000	0.593	4.532	0.000	0.143	5.351	0.000
MW	0.888	6.557	0.000	0.888	6.557	0.000	0.498	6.040	0.000	0.638	7.016	0.000
C	-0.640	5.997	0.000	-0.662	5.890	0.000	-0.451	4.977	0.000	-0.593	5.838	0.000
S	0.218	3.772	0.105	0.216	4.114	0.016	0.268	3.586	0.164	0.253	3.941	0.038
BO	0.125	2.813	0.756	0.136	2.825	0.742	0.028	2.856	0.934	-0.116	3.136	0.812
SM	0.300	3.582	0.134	0.466	5.062	0.000	0.200	3.241	0.534	0.380	4.457	0.000
PB	0.860	4.164	0.000	1.062	5.436	0.000	0.816	4.311	0.000	0.748	3.921	0.000
LH	1.080	5.217	0.000	1.263	7.005	0.000	1.251	6.623	0.000	0.477	5.084	0.000
LC	-0.736	4.105	0.000	-0.743	4.153	0.000	-0.568	3.373	0.016	-0.821	4.449	0.000
FC	-0.394	4.256	0.002	-0.475	5.073	0.000	-0.304	3.451	0.193	-0.109	4.288	0.007
SB	-0.269	2.784	0.380	-0.269	2.785	0.380	-0.058	2.698	0.740	-0.023	2.805	0.891
CC	0.448	4.980	0.000	0.589	6.509	0.000	0.517	4.801	0.000	0.830	5.317	0.000
KC	0.304	3.666	0.096	0.469	4.113	0.002	0.414	3.700	0.034	0.585	4.990	0.000
CT	-0.658	6.658	0.000	-1.439	11.948	0.000	-0.720	7.323	0.000	-1.069	10.198	0.000
LB	0.463	4.893	0.000	0.549	5.349	0.000	0.360	4.264	0.002	0.327	3.791	0.048

	Normal dist.			***t dist.***			***Normal dist.***			***t dist.***		
	S	***K***	***Prob. (J-Bera)***	***S***	***K***	***Prob. (J-Bera)***	***S***	***K***	***Prob. (J-Bera)***	***S***	***K***	***Prob. (J-Bera)***
Panel B: Speculator												
Minerals												
GC	1.543	11.677	0.000	3.893	33.207	0.000	1.123	12.157	0.000	2.849	25.705	0.000
SI	-0.375	3.211	0.175	-0.378	3.275	0.156	-0.320	2.957	0.306	-0.225	3.353	0.390
HG	-0.096	3.161	0.835	-0.091	3.171	0.836	-0.109	3.144	0.821	0.175	2.760	0.594
PL	0.739	4.755	0.000	1.698	11.363	0.000	1.281	8.296	0.000	1.683	10.864	0.000
CL	0.743	5.442	0.000	1.154	2.543	0.000	1.390	8.236	0.000	1.957	14.205	0.000
HO	0.770	5.546	0.000	1.057	7.227	0.000	0.728	5.298	0.000	0.803	8.902	0.000

/pto

Financials												
SP	0.477	4.242	0.000	0.638	4.680	0.000	0.510	4.196	0.001	1.040	5.392	0.000
ED	-0.644	4.009	0.000	-0.701	4.555	0.000	-0.660	4.282	0.000	-0.726	4.718	0.000
US	-0.594	3.845	0.000	-0.995	6.222	0.000	-0.632	4.963	0.000	-1.242	8.123	0.000
Currencies												
BP	-0.292	4.061	0.015	-0.941	8.451	0.000	-0.339	4.475	0.001	-0.837	6.154	0.000
SF	0.238	4.019	0.026	0.398	4.390	0.001	0.359	3.500	0.111	0.338	4.467	0.001
CD	0.044	2.509	0.488	0.046	2.511	0.490	0.054	2.567	0.564	0.071	2.581	0.569
JY	0.375	4.648	0.000	1.088	7.386	0.000	0.352	4.613	0.000	0.614	4.999	0.000
Agriculturals												
W	0.255	3.335	0.342	0.689	5.010	0.000	0.600	4.708	0.000	0.196	3.710	0.151
KW	0.743	5.098	0.000	0.877	6.232	0.000	-0.056	4.502	0.001	0.476	5.842	0.000
MW	0.635	4.569	0.000	0.373	6.566	0.000	0.558	4.519	0.000	0.343	5.803	0.000
C	-0.651	5.736	0.000	-0.639	5.886	0.000	-0.664	5.694	0.000	-0.507	5.168	0.000
S	-0.136	2.984	0.807	-0.137	2.984	0.806	-0.123	3.077	0.825	-0.165	3.533	0.323
BO	0.085	3.107	0.891	0.036	3.295	0.767	0.117	3.016	0.854	-0.224	3.244	0.474
SM	0.191	3.225	0.569	0.197	3.400	0.404	-0.010	3.188	0.903	0.041	3.530	0.437
PB	0.787	4.265	0.000	1.049	5.431	0.000	0.911	4.424	0.000	0.690	3.679	0.001
LH	1.050	4.946	0.000	1.294	7.504	0.000	0.942	5.175	0.000	0.518	5.353	0.000
LC	-0.722	4.006	0.000	-0.735	4.073	0.000	-0.551	3.850	0.004	-0.791	4.316	0.000
FC	-0.598	4.719	0.000	-0.618	5.777	0.000	-0.384	4.479	0.000	-0.336	4.628	0.000
SB	-0.417	3.462	0.073	-0.506	3.850	0.007	-0.399	3.378	0.107	-0.038	2.552	0.553
CC	0.363	3.551	0.092	0.433	3.930	0.010	0.389	3.475	0.091	0.700	4.252	0.000
KC	0.335	4.292	0.002	0.672	5.474	0.000	0.379	3.555	0.079	0.810	5.050	0.000
CT	-0.568	5.933	0.000	-1.385	11.935	0.000	-1.337	11.221	0.000	-1.337	11.306	0.000
LB	0.520	5.019	0.000	0.594	5.322	0.000	0.328	3.889	0.030	0.332	3.775	0.050

4.4.5 Performance Evaluation of Models

Backed by Poon and Granger (2003) who reviewed 39 studies[109] on the out-of-sample forecasting abilities of models such as GARCH (1, 1), this study validates the performance of the GARCH, PARCH and idiosyncratic models. To check in-sample and out-sample forecasting abilities, the 139 data sample is divided into two parts, where the first 126 data are used to test for actual model specification, and the remaining 13 data are used for out-of-sample forecasting[110]. Results for the actual model performance[111] are displayed in Table 4.18, with the root mean squared error (RMSE), and forecasting evaluation tools (bias proportions, variance proportions, covariance proportions, and Theil inequality test)[112].

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[109] See Chapter 2, section 2.16.3 for a review of studies on forecasting.

[110] The 126 data sample ends on December 1999, right before the burst occurred in early 2000. This helps to see whether models such as GARCH (1, 1) and PARCH forecast well the year 2000 burst.

[111] Actual model specification uses the data sample 1 126. Out-of-sample forecasting uses the data sample 127 139.

[112] Specifications of the RMSE, bias proportions, variance proportions, covariance proportions and Theil inequality can be found in Appendix 6.5.14 and 6.5.15.

Table 4.18
Performance evaluation for GARCH and PARCH models

This table shows the GARCH and PARCH model performance evaluation for the period 1990-2000, for hedgers and speculators, under normal and *t* distribution. The mean (bias) proportions, variance proportions, covariance proportions, and Theil inequality test results are displayed in Panel A-D, and the root mean squared error (rmse) is shown in Panel E. If the model is well specified, the mean and variance proportions should be small, and the covariance proportions should be near 1. A lower rmse also suggests a better specified model.

Panel A **Hedgers**

normal distribution

	GARCH				*PARCH*			
	Theil Ineq.	*Bias prop.*	*Variance prop.*	*Covariance prop.*	*Theil Ineq.*	*Bias prop.*	*Variance prop.*	*Covariance prop.*
Minerals								
GC	45.51%	0.05%	21.65%	78.31%	42.52%	0.01%	2.36%	97.63%
SI	44.31%	0.09%	23.84%	76.06%	43.62%	0.13%	20.86%	79.01%
HG	79.68%	0.00%	63.20%	36.80%	79.71%	0.00%	63.26%	36.74%
PL	41.46%	0.22%	18.80%	80.99%	41.95%	0.04%	20.85%	79.10%
CL	64.51%	0.90%	26.17%	72.93%	64.09%	1.02%	24.64%	74.34%
HO	49.87%	0.20%	23.35%	76.46%	52.53%	1.30%	33.27%	65.42%
Financials								
SP	47.15%	0.03%	29.51%	70.46%	47.66%	0.00%	30.34%	69.66%
ED	63.51%	0.13%	42.71%	57.16%	63.30%	0.13%	41.68%	58.18%
US	71.43%	0.04%	46.42%	53.54%	78.47%	1.11%	60.77%	38.13%
Currencies								
BP	73.21%	0.05%	62.12%	37.83%	71.89%	0.00%	59.61%	40.39%
SF	71.71%	0.02%	51.40%	48.58%	69.38%	0.01%	43.71%	56.28%
CD	74.00%	0.00%	59.06%	40.94%	73.72%	0.02%	56.62%	43.35%
JY	40.11%	0.11%	19.92%	79.97%	40.39%	0.27%	19.73%	80.01%
Agriculturals								
W	40.01%	0.19%	14.74%	85.07%	39.97%	0.02%	14.48%	85.50%
KW	42.90%	0.79%	15.76%	83.46%	42.86%	1.65%	13.96%	84.39%

MW	44.66%	0.66%	18.64%	80.70%	46.36%	0.18%	24.65%	75.17%
C	39.24%	0.02%	15.31%	84.68%	38.88%	0.70%	12.33%	86.97%
S	36.67%	0.05%	18.81%	81.14%	36.54%	0.04%	17.85%	82.11%
BO	36.70%	0.16%	14.44%	85.40%	37.34%	0.18%	17.79%	82.03%
SM	36.78%	0.24%	13.65%	86.11%	37.22%	0.58%	11.05%	88.37%
PB	69.04%	0.45%	46.15%	53.40%	66.63%	0.09%	40.46%	59.45%
LH	58.72%	0.54%	38.44%	61.02%	58.40%	1.26%	34.73%	64.02%
LC	56.46%	0.00%	31.50%	68.50%	57.03%	0.26%	33.48%	66.27%
FC	44.35%	0.09%	22.01%	77.90%	44.85%	0.36%	24.60%	75.04%
SB	44.46%	0.80%	31.46%	67.74%	40.42%	0.01%	16.86%	83.13%
CC	41.29%	0.00%	22.95%	77.05%	39.82%	0.00%	16.43%	83.56%
KC	44.72%	0.69%	37.01%	62.30%	43.81%	0.61%	34.02%	65.38%
CT	42.06%	0.55%	19.86%	79.59%	40.31%	0.44%	12.18%	87.37%
LB	51.72%	0.31%	30.30%	69.39%	51.12%	0.55%	29.36%	70.09%

Panel B **Hedgers**

t distribution

	GARCH				***PARCH***			
	Theil Ineq.	***Bias prop.***	***Variance prop.***	***Covariance prop.***	***Theil Ineq.***	***Bias prop.***	***Variance prop.***	***Covariance prop.***
Minerals								
GC	50.36%	0.05%	39.52%	60.44%	46.01%	1.46%	24.05%	74.50%
SI	44.47%	0.14%	24.56%	75.30%	43.35%	0.35%	20.61%	79.04%
HG	79.61%	0.00%	63.02%	36.97%	68.98%	46.43%	18.56%	35.01%
PL	42.40%	0.75%	20.51%	78.74%	42.04%	0.63%	21.66%	77.71%
CL	66.72%	0.43%	46.99%	52.57%	74.05%	4.93%	21.57%	73.51%
HO	51.57%	0.39%	31.73%	67.88%	63.82%	49.07%	22.42%	28.50%

Financials								
SP	48.62%	0.41%	31.77%	67.82%	45.95%	0.05%	22.16%	77.79%
ED	67.29%	0.02%	54.00%	45.98%	66.63%	0.02%	52.61%	47.36%
US	72.86%	0.86%	52.22%	46.92%	71.91%	1.46%	52.68%	45.86%
Currencies								
BP	72.84%	0.03%	59.58%	40.39%	62.61%	0.14%	39.10%	60.76%
SF	72.49%	0.04%	53.06%	46.90%	72.20%	0.18%	49.74%	50.08%
CD	73.47%	0.00%	57.70%	42.30%	73.75%	0.03%	56.46%	43.51%
JY	43.20%	0.16%	29.51%	70.34%	41.46%	0.23%	13.50%	86.26%
Agriculturals								
W	40.50%	0.00%	17.37%	82.63%	41.02%	17.84%	5.14%	77.02%
KW	44.54%	0.03%	23.40%	76.56%	43.79%	4.70%	14.62%	80.67%
MW	46.93%	0.22%	27.84%	71.93%	51.20%	32.13%	17.35%	50.52%
C	39.37%	0.10%	16.00%	83.91%	38.87%	3.18%	9.97%	86.85%
S	36.46%	0.02%	17.62%	82.36%	35.13%	1.22%	10.07%	88.71%
BO	36.78%	0.17%	14.72%	85.12%	35.77%	0.36%	9.46%	90.18%
SM	38.54%	0.05%	21.75%	78.19%	37.84%	0.09%	18.82%	81.09%
PB	72.70%	2.23%	54.66%	43.12%	79.22%	77.22%	3.21%	19.57%
LH	56.72%	0.00%	32.29%	67.71%	74.16%	77.42%	8.20%	14.39%
LC	56.58%	0.03%	31.91%	68.07%	57.47%	2.38%	31.15%	66.47%
FC	45.91%	0.00%	28.66%	71.33%	44.57%	0.02%	23.19%	76.79%
SB	44.46%	0.80%	31.47%	67.74%	41.77%	4.71%	16.45%	78.84%
CC	42.73%	0.13%	28.63%	71.23%	49.63%	2.45%	42.17%	55.37%
KC	44.07%	0.56%	34.90%	64.54%	55.22%	18.23%	50.39%	31.38%
CT	43.41%	0.14%	27.33%	72.54%	50.83%	32.84%	18.11%	49.05%
LB	50.95%	0.02%	30.54%	69.44%	67.15%	60.33%	25.23%	14.44%

Panel C **Speculators**

	normal distribution							
	GARCH				*PARCH*			
	Theil Ineq.	*Bias prop.*	*Variance prop.*	*Covariance prop.*	*Theil Ineq.*	*Bias prop.*	*Variance prop.*	*Covariance prop.*
Minerals								
GC	50.25%	0.02%	19.94%	80.04%	48.00%	0.02%	20.93%	79.05%
SI	41.45%	0.02%	11.67%	88.31%	40.71%	0.00%	7.76%	92.24%
HG	78.22%	0.00%	61.10%	38.90%	78.32%	0.00%	61.31%	38.69%
PL	42.10%	0.28%	17.26%	82.45%	42.06%	0.01%	18.75%	81.24%
CL	65.48%	0.90%	26.88%	72.21%	66.10%	0.00%	44.89%	55.10%
HO	54.92%	0.10%	28.39%	71.52%	54.80%	0.10%	26.49%	73.41%
Financials								
SP	50.32%	0.11%	32.04%	67.84%	51.74%	0.50%	36.75%	62.75%
ED	61.66%	0.15%	40.70%	59.15%	62.01%	0.08%	41.98%	57.94%
US	71.16%	1.55%	49.62%	48.83%	81.19%	1.39%	58.27%	40.34%
Currencies								
BP	79.05%	0.09%	70.68%	29.23%	80.10%	0.04%	75.20%	24.76%
SF	74.44%	0.02%	57.20%	42.77%	69.73%	0.01%	42.22%	57.77%
CD	76.38%	0.00%	63.18%	36.82%	75.65%	0.03%	58.54%	41.43%
JY	49.53%	0.01%	29.13%	70.86%	52.36%	0.03%	38.62%	61.34%
Agriculturals								
W	43.65%	0.31%	19.23%	80.46%	43.20%	0.03%	18.48%	81.49%
KW	44.22%	0.78%	17.16%	82.07%	46.98%	0.68%	23.86%	75.45%
MW	46.73%	1.20%	17.47%	81.33%	47.10%	1.29%	18.86%	79.85%
C	43.27%	0.02%	19.07%	80.91%	43.15%	0.00%	18.57%	81.42%
S	44.70%	0.01%	21.38%	78.62%	45.14%	0.02%	23.07%	76.91%

BO	35.87%	0.40%	17.76%	81.84%	36.36%	0.64%	19.63%	79.73%
SM	43.34%	0.17%	21.74%	78.09%	42.46%	0.05%	17.82%	82.13%
PB	67.08%	0.00%	41.24%	58.76%	67.70%	0.28%	41.51%	58.21%
LH	56.96%	0.69%	35.55%	63.76%	58.10%	0.02%	38.21%	61.77%
LC	56.56%	0.01%	31.34%	68.65%	56.42%	0.30%	29.29%	70.41%
FC	49.06%	0.30%	26.90%	72.80%	47.34%	0.00%	21.22%	78.78%
SB	44.95%	0.01%	28.14%	71.84%	44.93%	0.00%	27.67%	72.32%
CC	43.58%	0.02%	21.36%	78.62%	42.91%	0.03%	18.67%	81.29%
KC	47.94%	0.43%	36.36%	63.21%	45.17%	0.08%	29.79%	70.13%
CT	44.90%	0.84%	20.83%	78.33%	44.23%	0.00%	19.57%	80.43%
LB	50.12%	0.05%	26.96%	72.99%	52.07%	1.43%	32.26%	66.31%

Panel D **Speculators**

t distribution

	GARCH				***PARCH***			
	Theil Ineq.	***Bias prop.***	***Variance prop.***	***Covariance prop.***	***Theil Ineq.***	***Bias prop.***	***Variance prop.***	***Covariance prop.***
Minerals								
GC	52.07%	0.23%	36.78%	62.99%	49.33%	2.21%	27.00%	70.79%
SI	41.55%	0.06%	12.20%	87.74%	42.72%	2.07%	15.52%	82.42%
HG	78.16%	0.00%	60.92%	39.08%	68.54%	33.28%	6.54%	60.18%
PL	42.97%	0.49%	21.07%	78.44%	42.66%	0.62%	19.88%	79.50%
CL	67.29%	0.65%	46.98%	52.37%	71.27%	38.59%	20.62%	40.79%
HO	55.93%	0.27%	34.23%	65.50%	50.68%	9.80%	12.79%	77.41%
Financials								
SP	51.66%	0.84%	34.17%	64.98%	47.05%	1.72%	24.08%	74.19%
ED	64.39%	0.01%	49.95%	50.04%	64.18%	0.01%	49.44%	50.55%
US	72.94%	0.77%	53.41%	45.82%	73.70%	0.20%	53.61%	46.19%

Currencies								
BP	80.91%	0.10%	72.64%	27.26%	67.06%	0.46%	45.31%	54.23%
SF	72.98%	0.05%	53.50%	46.45%	73.02%	0.01%	51.35%	48.64%
CD	76.41%	0.00%	63.21%	36.79%	75.80%	0.03%	58.78%	41.19%
JY	52.45%	0.54%	37.29%	62.17%	48.87%	0.69%	25.78%	73.54%
Agriculturals								
W	43.96%	0.01%	21.78%	78.21%	48.98%	18.82%	1.20%	79.98%
KW	45.94%	0.01%	25.32%	74.67%	44.33%	0.14%	13.19%	86.67%
MW	50.51%	0.28%	32.51%	67.20%	54.57%	32.00%	19.29%	48.71%
C	43.49%	0.22%	19.75%	80.03%	47.33%	12.79%	19.05%	68.17%
S	44.71%	0.01%	21.38%	78.61%	44.30%	0.19%	19.44%	80.37%
BO	35.90%	0.43%	17.87%	81.70%	34.69%	0.31%	12.07%	87.61%
SM	44.16%	0.10%	25.23%	74.67%	42.42%	0.16%	16.76%	83.08%
PB	72.85%	2.18%	54.25%	43.57%	80.22%	78.85%	2.06%	19.09%
LH	58.60%	0.32%	39.43%	60.25% t w	74.71%	80.79%	7.02%	12.19%
LC	56.87%	0.01%	32.39%	67.60%	57.61%	0.65%	33.08%	66.27%
FC	49.78%	0.19%	30.54%	69.28%	47.73%	0.04%	22.72%	77.24%
SB	45.21%	0.27%	28.72%	71.01%	55.25%	62.64%	2.29%	35.07%
CC	44.44%	0.18%	25.37%	74.45%	46.77%	26.95%	9.45%	63.60%
KC	45.27%	0.17%	25.64%	74.18%	61.29%	52.67%	20.63%	26.70%
CT	46.92%	0.02%	30.20%	69.78%	46.79%	1.32%	26.17%	72.51%
LB	50.81%	0.04%	30.26%	69.70%	67.20%	60.77%	24.43%	14.80%

/pto

Panel E	Hedgers				Speculators			
	Normal dist.		***t dist.***		***Normal dist.***		***t dist.***	
	GARCH	*PARCH*	*GARCH*	*PARCH*	*GARCH*	*PARCH*	*GARCH*	*PARCH*
Minerals								
GC	2.535	2.694	2.587	2.553	2.771	2.660	2.680	2.681
SI	4.056	4.050	4.059	4.036	4.041	4.069	4.039	4.091
HG	5.849	5.850	5.849	8.373	5.821	5.822	5.821	8.308
PL	3.283	3.285	3.313	3.290	3.348	3.319	3.342	3.354
CL	8.659	8.681	8.178	10.420	8.727	8.216	8.222	11.626
HO	7.407	7.420	7.363	10.911	7.837	7.884	7.766	8.282
Financials								
SP	3.117	3.125	3.131	2.321	3.230	3.234	3.245	3.241
ED	0.275	0.275	0.277	0.277	0.271	0.271	0.272	0.272
US	2.705	2.740	2.720	2.709	2.717	2.827	2.709	2.706
Currencies								
BP	2.646	2.632	2.654	2.561	2.711	2.696	2.726	2.642
SF	3.385	3.398	3.392	3.426	3.405	3.427	3.403	3.423
CD	1.209	1.210	1.208	1.210	1.222	1.223	1.222	1.223
JY	2.355	2.362	2.414	2.492	2.704	2.737	2.738	2.698
Agriculturals								
W	4.587	4.586	4.581	5.123	4.846	4.816	4.821	6.424
KW	4.759	4.806	4.746	4.890	4.853	4.951	4.833	4.948
MW	4.500	4.520	4.512	5.518	4.706	4.708	4.704	5.835
C	4.150	4.179	4.151	4.242	4.440	4.439	4.448	4.939
S	3.282	3.284	3.281	3.283	3.843	3.849	3.843	3.846
BO	3.218	3.218	3.220	3.214	3.108	3.123	3.109	3.088

/pto

SM	3.791	3.873	3.822	3.800	4.221	4.210	4.230	4.226
PB	12.761	12.769	12.909	35.497	12.760	12.801	12.942	38.301
LH	8.184	8.234	8.118	20.279	8.088	8.087	8.344	21.578
LC	3.279	3.286	3.280	3.346	3.285	3.312	3.286	3.311
FC	2.405	2.409	2.415	2.405	2.561	2.546	2.562	2.549
SB	6.067	5.902	6.067	6.138	6.181	6.188	6.202	10.790
CC	5.002	4.975	5.050	5.494	5.264	5.254	5.274	6.284
KC	8.537	8.472	8.489	10.150	9.030	8.799	8.942	14.442
CT	4.616	4.611	4.614	6.029	4.859	4.821	4.862	4.928
LB	7.282	7.241	7.196	12.586	7.208	7.275	7.187	12.671

Table 4.18 (Panel A-D) shows the performance evaluation for hedgers and speculators under (GARCH, normal), (GARCH, *t*), (PARCH, normal) and (PARCH, *t*) volatility models. It can be observed that under normal distribution models, the Theil inequality coefficient is very low for most markets, except for copper, crude oil, Eurodollars, Treasury bonds, British pounds, Swiss francs, Canadian dollars, and pork bellies. Similar markets are found to exhibit high Theil inequality under *t* distribution, in addition to live hogs. These relatively high inequality values suggest that the four models used above perform poorly in these eight and nine markets. This is reflected in the relatively low covariance proportion that measures the remaining unsystematic forecasting errors between actual and forecasted returns. In the remaining 22 or 21 markets, the four models reflect higher covariance proportion figures, suggesting the models fit the actual returns better. It appears that the (PARCH, *t*) model tends to produce smaller covariance proportions, suggesting less unsystematic risk than the three other models[113]. If any of the models is correctly specified, the covariance proportions should be high, and

[113] In fact, the (PARCH, *t*) model had 12 markets with low covariance proportions compared to (PARCH, normal), (GARCH, normal) and (GARCH, *t*) which all had seven markets with low covariance proportions.

relatively higher than the bias and variance proportions. The PARCH model, under t distribution, ranks last in that perspective.

The bias proportions for hedgers and speculators, under all models, appear to be very low except under (PARCH, *t*), where agricultural futures in particular tend to exhibit bigger differences between the forecast returns and the actual returns. For hedgers, such markets are copper, heating oil, Eurodollars, Treasury bonds, British pounds, Swiss francs, Canadian dollars, wheat (Minnesota), pork bellies, live hogs, cotton and lumber. For speculators, markets with high bias proportions are copper, crude oil, British pounds, Swiss francs, Canadian dollars, wheat (Minnesota), pork bellies, live hogs, sugar, coffee, and lumber[114].

Further, under normal distribution, the variance proportions of currencies (except Japanese yen), Eurodollars, Treasury bonds, and copper are relatively high, suggesting that much of the high Theil inequality can be explained due to the high variability between the forecast and actual returns, and not due to differences between actual and forecasted returns. For hedgers, under normal distribution, variance proportions tend to be lower for PARCH models except in nine markets. Also, under *t* distribution, variance proportions tend to be lower for PARCH models except in four markets. However, for speculators, under normal distribution, variance proportions is lower for PARCH only in 13 markets. This compares with 26 markets, where variance proportions are lower for speculators, under *t* distribution.

From Panel E, which reports the root mean squared error (RMSE), it can be seen that under normal distribution, the GARCH (1, 1) model gives the lowest RMSE for hedgers' returns in 13 markets. This is similar to Bracker and Smith (1999) who found that the symmetric GARCH model ranks first with the lowest RMSE compared to other models. This is followed by the GARCH (1, 1) model under *t* distribution with nine markets having the lowest RMSE for hedgers' returns. PARCH models rank 3rd and 4th

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[114] This is also reflected in the relatively higher RMSE in these markets in Panel E.

with only five and four markets having the lowest RMSE. On the other hand, it is the PARCH model, under normal distribution, that ranks 1st, with 11 markets having the lowest RMSE in speculators' returns. This is closely followed by the (GARCH, normal) model with 10 markets having the lowest RMSE, and (GARCH, *t*) ranking 3rd with nine markets. Similar with hedgers, the (PARCH, *t*) ranks last with three markets having the lowest RMSE. In comparing which model has the lowest RMSE between hedgers and speculators, it appears that the (GARCH, normal) model ranks first with 10 markets having the lowest RMSE in explaining hedgers' returns. This is followed by the (GARCH, *t*), where six markets have the lowest RMSE in explaining hedgers' returns. The lowest RMSE results in Panel E are supported by the lowest Theil inequality in 10 markets for hedgers' returns and two markets for speculators' returns. Overall, this suggests that the GARCH model fits the actual returns of hedgers better than that of speculators. The PARCH model fits the actual returns of speculators better under normal distribution. The PARCH model, under *t* distribution, fits the actual returns for both players in the least accurate way among the four models.

4.5 Forecasting Return and Volatility

Backed by Tomek and Peterson (2001) who argued that forecasting models have statistical but not economic significance, a graphical representation is used for forecasting purposes. The sample for forecasting is set from January 2000 to Dec 2000 and a static forecasting technique is used[115]. Supported by Jackson, Maude and Perraudin (1997) who argued that the forecastability of volatilities and the sensitivity of the forecasts to different techniques depend very much on the return series in question, graphs 4.8–4.11 in Appendix 6.14 show the forecasted returns of hedgers and speculators under both GARCH and PARCH models, and under both normal and *t* probability distributions. Actual futures returns complement each graph to compare actual with forecasted returns.

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[115] See Appendix 6.5.13 for more on static forecasting.

Findings in graphs 4.8–4.11 show that both returns for hedgers and speculators, under GARCH and PARCH models, follow nearly the same close trend in all 29 markets. This is further supported by the fact that 95% confidence intervals of the forecasted returns under GARCH and PARCH models are calculated for all 29 markets, and all of them are wide enough to include the actual returns within the intervals range[116]. Moreover, for hedgers' forecasted returns, the (GARCH, normal) underestimates (overestimates) in 13(8) markets, while under (PARCH, normal), hedgers' forecast returns are underestimated (overestimated) in 11(8) markets. For speculators' returns, the (GARCH, normal) model underestimates (overestimates) the forecast in 14(9) markets while under PARCH model in 13(9). Under (GARCH, *t*), hedgers' forecast returns are underestimated (overestimated) in 12(9) markets, and under (PARCH, *t*) in 15(8). For speculators, the (GARCH, *t*) underestimates (overestimates) the forecast returns in 17(8) markets. While the highest number of underestimated forecasts is 17 under (PARCH, *t*) for speculators' forecast returns, the number of overestimated forecasts are generally the same across all four models. This suggests that the GARCH and PARCH models are generally more affected by increasing actual returns compared to decreasing actual returns. This is analogous to the decreasing trend in net positions observed in December 1999 just before the forecast of January 2000. In line with Ding and Granger (1996), the GARCH model under normal distribution puts too much weight on recent observations relative to those in the past. Further, under *t* distribution, the PARCH model with its high number of underestimated returns forecasts can be attributed to high sensitivity of standard deviation over returns. This is in line with Poon and Granger (2003) who found that standard deviation is more proportional to derivatives prices than variance models.

In deciding which of the four models of graphs 4.8–4.11 better predict the actual returns, the first month forecast returns is compared with the actual futures returns, and only those markets' returns which have been correctly forecasted are reported. For hedgers, the (PARCH, normal) model ranks first with ten good forecasts of one-month

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[116] Available on request of author.

return[117]. The (GARCH, normal) and (GARCH, *t*) rank equally 2nd with eight good forecasts[118]. (PARCH, *t*) ranks last in predicting the one-month actual returns. As for speculators, the best models are (PARCH, normal) and (GARCH, *t*) which rank equally 1st with seven good forecasts[119]. (GARCH, normal) ranks 3rd with six good forecasts[120], while (PARCH, *t*) ranks again last with only four good forecasts. The reason for (PARCH, *t*) ranking last is due to the high number of underestimated forecast returns. The (PARCH, normal) ranks first by producing also the least number of underestimated forecast returns. In comparing the number of good forecasts achieved under hedgers' and speculators' returns, it can be observed that hedgers' returns are better forecasted than speculators' returns. Further, the (PARCH, normal) model appears to work better in forecasting hedgers' one-month return than speculators' one-month return[121].

Having looked at the forecasted returns under GARCH and PARCH models, it is also worthwhile to consider the conditional standard deviation under PARCH model and the conditional variance under the GARCH model. Due to the volatile characteristics of standard deviation and variance, it is better to have an outlook of the whole sample data rather than just for the forecast sample. The idiosyncratic volatility used before in this study is also included as a proxy of actual volatility, for comparison with the conditional variance and conditional standard deviation. Based upon the good one-month forecast returns obtained above, it is interesting to know whether the idiosyncratic volatility

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[117] These markets were live hogs, lumber, coffee, cotton, corn, soybean oil, soybean meal, S&P500, sugar and soybean.

[118] Under (GARCH, normal), these markets were lumber, coffee, corn, soybean oil, soybean meal, S&P500, sugar and soybean. Under (GARCH, *t*), in addition to live hogs, the markets were same as (GARCH, normal) except for coffee.

[119] Under (PARCH, normal), these markets were wheat (Minnesota), lumber, copper, crude oil, soybean oil, S&P500, and sugar. Under (GARCH, *t*), in addition to Eurodollars, these markets were the same as under (PARCH, normal) except for wheat (Minnesota).

[120] These markets are the same as under (PARCH, normal) except for S&P500.

[121] It is important to know that only one-month forecast return (January 2000) has been analysed here. Tables 4.3-4.6 show the forecasted returns under December 2000. To check the robustness of that one-month forecast, the same exercise as above can be undertaken over more months. A comparison of actual RMSE with forecast RMSE can be valuable in comparing the models further. Only one-month forecast is studied to analyse the effect of the January 2000 bust where net positions dropped significantly.

measures the corresponding volatility quite accurately or not. Full sample results are reported in the Appendix 6.15.1 and 6.15.2[122].

Graphs 4.7.1 and 4.7.2 in Appendices 6.15.1 and 6.15.2 support that idiosyncratic volatility tends to be more volatile among the three volatility measures. Also as expected, variance (σ_t^2) is larger than standard deviation (σ_t) since theoretically $\sigma_t^2>0$. Under *t* distribution, the PARCH model, as seen before, is much more sensitive than the GARCH model. Markets where variance (σ_t^2) or standard deviation (σ_t) of hedgers are smaller than those of speculators support Smith's (1922) price insurance theory where hedging enables hedgers to insure against the risk of price fluctuations and also Hoffman's (1932) view that hedging is shifting risk. On the other hand, markets where variance (σ_t^2) or standard deviation (σ_t) of hedgers are bigger than those of speculators support Telser (1981) that the motivation to use futures contracts is not primarily driven by the firm's desire to reduce risk, but by the institutional characteristics of the futures exchange itself like regulation ensuring liquidity. Hedgers who wish to avoid price risks of holding inventories can do so without an organized futures market, namely by entering into forward transactions in the cash market. Panel A in both appendices also support that the variance tends to be much more volatile in currency and financial markets. This is analogous to currency and financial markets known to be the most volatile markets in the US.

In comparing the idiosyncratic volatility with the standard deviation and variance in one-month forecast, only in S&P500 futures market does idiosyncratic volatility provide a good measure of volatility for the one-month forecast returns[123]. Panel B, which magnifies the results of Panel A, shows that idiosyncratic volatility is a good measure of volatility to forecast one-month futures return in S&P500, under either

[122] Only markets in footnotes 116-119 are included to compare idiosyncratic volatility with GARCH and PARCH volatility.

[123] This is obviously based on the assumption that the GARCH and PARCH models have provided a good forecast return. Only then can the idiosyncratic volatility be compared with that specific standard deviation and variance.

normal and *t* distribution. For the remaining 28 markets, idiosyncratic volatility fails to provide a good measure of volatility for one-month forecast returns, where volatility is measured as standard deviation and variance, which provides good one-month forecast returns. Consistent with the existing volatility forecasting literature and specifically Manfredo et al. (1999), the poor measure of idiosyncratic volatility confirms the difficulty in finding a "best" volatility forecasting method across alternative data sets and horizons. Importantly too, graphs from Appendices 4.7.1 and 4.7.2 show that the hypothesis that the variance rate on the market remains constant over any appreciable period of time can be rejected. This is consistent with Merton (1980) and Rosenberg (1972).

4.6 Stability and Events Analysis

Although US exchange markets had witnessed huge success in the 1990s due to factors like good macroeconomic policy, luck, and stability in oil shocks[124], Graph 2.1 showed that many events did occur during that decade. As proposed by Frommel and Menkhoff (2003), structural breaks in futures markets may indicate that in addition to permanent micro structural impacts, macro economically-caused shifts are possibly also important for any volatility increase. While it is hard to examine all events of the 1990s in the US, an attempt is made to consider the effect of these major macroeconomic events on the 29 futures markets[125]. In line with the Bank of International Settlements (BIS 1990–2001) reports, the following table depicts more specific details about the event analysis[126].

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[124] See Chapter 2, section 2.17 for more details on events analysis.
[125] More specific details about each event are provided in Appendix 6.9
[126] The 'sample before event' column provides the data sample up to including the nearest COT reporting date just before the event, and the 'sample after event' column provides the data sample up to including the nearest COT reporting date just after the event.

Table 4.19
Major macroeconomic events of the 1990s in the US

Date Range From	To	Event	Duration (Months)	Sample before event	Sample after event
4-Feb-94	6-Jul-95	US Fed tightening of interest rates	20	49	69
23-Mar-94	20-Dec-94	Mexico Crisis	11	51	62
13-Jan-95	12-Jan-96	EM slump & rebound	14	62	76
28-May-94	1-Apr-96	Temporary revival of Japanese Recession	25	53	78
2-Jul-97	1-Mar-98	Asian Crisis	9	94	103
1-Aug-98	23-Sep-98	LTCM near financial collapse	3	108	111
17-Aug-98	31-Dec-99	Russian Crisis and recovery	19	108	127
1-Jan-99	ongoing	Introduction of the Euro Currency	26*	113	139

*26 months has been entered as the duration since the introduction of the Euro Currency
, since our data sample ends in 5th Dec 2000.

Source: BIS (1990-2001) quarterly and annual reports.

To know whether any of these eight events has affected the US futures markets, a stability test is performed upon the behaviour[127] and performance models[128] used before in this study. While the literature is backed by many tests like Perron's (1997) structural break test and Ramsey's (1969) stability test, recursive coefficient estimation is performed to test for the stability of specific coefficients in the models. The recursive coefficient estimation enables us to trace the evolution of estimates for any coefficient as more and more of the sample data are used in the estimation. If the coefficient displays significant variation as more data is added to the estimating equation, it significantly suggests instability. Any dramatic break in coefficient plots suggests that the postulated equation tried to digest a structural break. Any structural break is matched with any of the eight events above, and regressed accordingly using pre-event sample and post-event sample. If there is no structural break for some commodity markets, this suggests that the above named events did not significantly affect the specific futures markets during the last decade, in relation to the models.

4.6.1 Behaviour - Trading Determinant Model

Due to some events (like events one & two) having some small sample sizes, and in order to keep consistency in the models, only variables deemed important are regressed

[127] See Equation 4.1
[128] See Equations 4.10.1, 4.13, 4.14.2

in the models. This means the removal of some unimportant variables like the three information variables and sentiment data[129]. The behaviour model of Equation 4.1 is thus changed to:

$$\Delta NP_{t+1} = \varphi_0 + \varphi_1 R_t + \xi_t \qquad (4.20)$$

Only significant recursive coefficients for the futures returns (with significant *t* ratios[130] after adjusting for structural breaks) in Equation 4.20 are graphically displayed in Appendix 6.16, together with two standard error bands around the estimated coefficients. The highest coefficient estimates of R_t can be found in Canadian dollars, Eurodollars, British pounds, Treasury bonds, Japanese yen and gold[131]. The occurrence of relatively higher coefficient estimates suggests that large players tend to rely more on actual returns R_t to change their net positions next month than large players in agricultural futures markets. Moreover, the coefficient estimates of R_t between hedgers and speculators tend to bear a negative relationship[132]. This is supportive that the futures market is a zero-sum game, and that for every long position there should a short position to net it off. The S&P500 R_t coefficient for hedgers appears to be negative on average. The fact that hedgers were net short during the 2000 burst compared to large speculators who were net long, suggests that following hedgers during that period would have led to less losses and possibly profits than trend-chasing with speculators.

In checking the stability of the behaviour model, most of the markets appear to be stable with rare occasions of structural breaks. It is important to neglect the instability of the coefficient estimates in early stages of the graph, since ΔNP_{t+1} would be highly

[129] Information variables are removed due to their insignificance as shown in earlier parts of the study. Sentiment data is removed since they were exhibiting a bullish behaviour, which was quite predictable.
[130] Significant t ratios are those independent variables being siginificant at 10% significance level.
[131] Markets like British pounds, Canadian dollars, Eurodollars, Swiss francs, Treasury bonds, S&P500, copper, live cattle and live hogs all had negative coefficients for hedgers' return coefficient estimates.
[132] Except for crude oil, Japanese yen and heating oil where both hedgers and speculators tend to add to their next month's net position when actual returns are positive.

sensitive to R_t [133]. Those markets with significant breaks in their returns coefficient estimates are crude oil, cotton, Eurodollars, soybean, wheat (Chicago) and cocoa (for speculators); and corn, Japanese yen, soybean and cocoa (for hedgers)[134]. This is consistent with Cheung and Wong (2001) that macroeconomic announcements have a smaller impact on the gold market than on the Eurodollars and Japanese yen. As further asserted by Fung and Patterson (2001), the Eurodollar, although influenced substantially by domestic US news, is an international asset that is traded globally and thus more readily reflects changes in risk premiums among different Eurocurrency rates in the international financial market. Table 4.21 in Appendix 6.16 shows that while all breaks for hedgers' returns coefficients estimates are trending upwards, speculators' returns breaks are heading in both directions. Results show that hedgers' actual returns coefficient estimates go up for corn, Japanese yen, soybean and cocoa after the major economic event brought more stability to previous economic conditions. For instance, soybeans and corn returns have more effect on net positions of hedgers after the end of the US long period of tightening interest rates. The same analogy can be concluded with cocoa and Japanese yen returns bearing more effect on net positions of hedgers at the start of the temporary revival from Japanese recession.

On the other hand, the effect of speculators' returns on next-month net positions, as expected, is backed by positive feedback behaviour, where speculators take more long positions when major economic events are an indication of easing economic conditions, and take more short positions where events tend to show tightening economic conditions. For instance, speculators took less long positions in Eurodollars after the LCTM near financial collapse, but then took more *long* positions after the buyouts occurred to save LTCM from affecting financial markets. The same analogy can be applied to the upwards jumps in returns coefficients occurring due to more favourable economic conditions like the end of US tightening interest rates, introduction of the Euro currency,

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[133] To ensure consistency throughout this event analysis, any instability before sample 49 is rejected for analysis. This allows us to analyse any structural break starting with US Fed tightening of interest rates, which occurred in sample 50.

[134] While there were more structural breaks in the 29 markets, only those structural breaks that match any of the eight events of Table 4.19 are analysed.

and downward breaks due to less favourable economic conditions like LTCM near collapse, Russian crisis, EM slump, US tightening interest rates, and Japanese recession. The only exceptions would be Eurodollars returns coefficient estimates which jumped at the start of US tightening of interest rates. This can be explained by speculators going more net long in Eurodollars, as an alternative to less attractive US dollars. More importantly, t statistics show that only soybeans, cotton, wheat (Chicago) and cocoa have significant return coefficient estimates (all from speculators). This supports BIS (1995–2001) reports on these major economic events that the eight named events do not affect significantly futures markets in the US, except in four markets above at a specific point in time.

4.6.2 Mean Equation Model

Using the same understanding about small size sampling as above, the mean equation model of 4.10.1 is simplified to Equation 4.21 below, and regressed to obtain the estimated recursive coefficients of net positions[135].

$$R_t = \varphi_0 + \varphi_1 NP_t + \xi_t \qquad (4.21)$$

As can be seen in the graphs of Appendix 6.16 (Table 4.22), all the recursive coefficients of returns tend to be stable over the ten-year period. The small amount of structural breaks in that mean equation model was expected due to the low coefficient estimates of net positions obtained in Table 4.10.1 and Table 4.10.2 earlier in the study. This supports that positive feedback trading persists in the long run where the recursive coefficient estimates are greater than zero. Only crude oil return estimate tended to rise in a more upward fashion than the rest, but nonetheless keeping its stability feature over the ten-year period. Overall, this is in line with Frankel and Froot (1988) who found that market

[135] Note that net positions are adjusted for stationarity before regressing Equation 4.21. Results are reported at 10% significance level.

participants expect recent price changes (short run) to trigger others in the same direction, while also expecting prices to return to their fundamental values in the long run. This is also consistent with De Bondt and Thaler (1987) who found that extreme movements in prices eventually revert, as long as part of these movements is accounted for by positive feedback trading. Only corn, cocoa, cotton, coffee and lumber have had structural breaks in the net positions of speculators, and only coffee and live hogs have had structural breaks. Further, results from Table 4.22 seem to indicate that only the temporary revival from Japanese recession event and US tightening of interest rates event have had some effect on these six markets. More importantly, only coffee[136] and live hogs have significant negative coefficient estimates when the effect of the event is taken into account. The jump in the change of net positions coefficient estimates for coffee, due to the start of the temporary revival from Japanese recession, can be attributed to more confidence of hedgers about selling their futures contracts later at a better price. The jump in live hogs net positions coefficient estimates, due to the start of US Fed tightening interest rates, can be attributed to hedgers shorting fewer contracts in the expectation of interest rates easing in the future. Overall findings suggest that all the eight major events have had hardly any significant effect on futures markets, where the impact of monthly net positions on returns is assessed.

4.6.3 Risk and Return Relationship

As observed in Graph 1.1 in Chapter 1, investors tend to change their attitude towards risk during specific events like LTCM near financial collapse and Asian crisis turmoil. Using this same analogy that risk can be proxied as standard deviation and variance, the actual return R_t is regressed against standard deviation and then against variance as follows:

$$R_t = \varphi_0 + \varphi_1 \sigma_t + \varepsilon_t \qquad (4.22)$$

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[136] The net positions of hedgers for coffee had to be differenced for stationarity. Therefore, the estimated coefficient is that of a change in net positions of coffee.

$$R_t = \varphi_0 + \varphi_1 \sigma_t^{\,2} + \varepsilon_t \tag{4.23}$$

where σ_t is the standard deviation from PARCH model (Equation 4.14.2) and $\sigma_t^{\,2}$ is the variance from GARCH model (Equation 4.13). The pattern of the recursive coefficients (σ_t and $\sigma_t^{\,2}$) show whether there is any relationship between the measure of risk and return. The recursive estimated coefficients of σ_t and $\sigma_t^{\,2}$ also help in finding whether any significant break can be attributed due to the occurrence of a major macroeconomic event, which changes the attitude of large hedgers and large speculators towards risk. Any structural break in the relationship between return and risk which is matched with any of the eight events is reported in Appendix 6.16 (Table 4.23).

Results from Panel A show a positive significant relationship between hedgers' risk (standard deviation) and return for soybean oil, gold, coffee and soybean, and a significant negative relationship for live cattle; and a positive significant relationship between speculators' risk (standard deviation) and return for gold, coffee, live hogs, sugar and S&P500, and a significant negative relationship for live cattle and silver at 10% significance level. From Panel B, there is a different mixture of findings again due to the different sensitivity of the proxy of risk over return. Panel B shows a positive significant relationship between hedgers' risk (variance) and return for soybean oil, coffee, wheat (Minnesota) and platinum; a negative significant relationship for gold and wheat (Chicago, Kansas); a significant positive relationship between speculators' risk (variance) and return for feeder cattle, coffee, platinum and sugar; and a significant negative relationship for gold, copper and Treasury bonds. While the findings of a positive relationship between risk and return supports portfolio theory that a higher risk is compensated with a higher return and vice versa, the findings of a significant relationship between risk and return can be explained by Glosten, Jagannathan and Runkle (1993) who discussed special circumstances that would make it possible to observe a negative correlation between current returns and current measures of risk. For instance, investors may not demand high risk premium if they are better able to bear risk at times of particular volatility. Moreover, if the future seems risky, the investors may want to save more in the present, thus lowering the need for larger premium. And, if transferring income to future is risky and the opportunity of investment in a risk-free asset is absent, then the price of a risky asset may increase considerably, hence reducing the risk premium. In addition to Glosten et al. (1993) who argued that both positive and negative relationships between current returns and current variances (risk) are possible, the study adds contribution by also finding more negative relationships between current returns and current standard deviation (risk). The higher number of negative significant relationships is due to derivatives prices being more proportional to standard deviation than variance, hence the higher sensitivity as supported by Poon and Granger (2003).

Panel A shows that speculators' returns are affected with seven structural breaks in risk that occurred during the listed macroeconomic events at 10% significance level. These structural breaks in the return and risk relationship of Equation 4.22 occur in cotton, feeder cattle, Japanese yen, coffee, live hogs, soybean and Treasury bonds for speculators; and soybean, crude oil, cotton and copper for hedgers' attitude towards risk. Since speculators' attitude towards risk are more affected than hedgers', this suggests that speculators not only bear more risk than hedgers, but also that speculators' returns are more affected during major macroeconomic events. However, generalization about this suggestion is questionable since only soybean and Treasury bonds have significant risk coefficient estimates before and after the event. This is consistent with Flood and Rose (1999) who demonstrated that exchange rate volatility cannot be linked to changes in underlying fundamentals. The jump of the effect of hedgers' risk on return for the soybean futures market has been occurring after the end of the long period of US tightening interest rates. This can be explained by hedgers in the soybean futures market taking more risk towards obtaining their return, due to the instability of US interest rates that eased after a long period of tightening. On the other hand, the fall of the effect of speculators' risk on return for the Treasury bonds market has been occurring at the start of the temporary revival from the Japanese recession. This can be explained by speculators using less risk to obtain a desired return, due to the stability regained in the global economy after the temporary recovery of the Japanese recession. Overall, Panel A supports that the major global economic events named in Table 4.19 did not have much effect on the risk and return relationship, except for soybean for hedgers' return and Treasury bonds for speculators' return.

In contrast to Panel A, Panel B shows that there is a smaller occurrence of structural breaks that occurred during the major economic events used in the study. Speculators' attitude towards risk changed in copper, Japanese yen, wheat (Kansas, Chicago) and Treasury bonds, while hedgers' attitude towards risk changed only in wheat (Kansas). The lower number of breaks in Panel B can be explained since many of the recursive coefficient estimates of standard deviation from Panel A were larger in magnitude than their recursive coefficient estimates of variance. This is supported by Poon and Granger (2003) who found that derivative prices are roughly proportional to standard deviation. The only structural break, due to the same economic event, where risk is measured as variance and standard deviation, occurs in Japanese yen, where speculators' return was more negatively affected by the end of the long period of US tightening interest rates in 1995. However, more importantly, none of the structural breaks in Panel B significantly affected the risk and return relationship in the futures markets. Either measurement of risk (standard deviation and variance) tends to return to their stable long-run estimate very shortly after the macroeconomic event has disturbed the risk/return relationship in all the 29 futures markets. This is inconsistent with Christie and Chaudhry (1999) who showed that volatility persists following macroeconomic events, particularly for liquid financial markets. The study adds contribution to BIS (1999) reports that events like the Russian crisis, LTCM near financial collapse, Asian crisis, and Mexico crisis did not have significant effect upon the attitude towards risk of large speculators and even lesser significance for large hedgers.

4.6.4 Trading Activity and Volatility

In the same spirit as Roth et al. (2003), who found a positive relation between volatility and open interest for both hedgers and speculators, Equations 4.24 and 4.25 are regressed to see whether there is such a relation between volatility and net positions[137]. Volatility is proxied as standard deviation in Equation 4.24, and variance in Equation 4.25.

$$NP_t = \varphi_0 + \varphi_1 \sigma_t + \varepsilon_t \tag{4.24}$$

$$NP_t = \varphi_0 + \varphi_1 \sigma_t^{\,2} + \varepsilon_t \tag{4.25}$$

Findings upon regressing Equation 4.24 show that volatility, when measured as standard deviation, has a mixed effect on the trading activity of hedgers and speculators, where trading activity is measured as current net positions. Recursive estimates of volatility had a significant negative effect on net positions of hedgers for soybean oil, British pounds, copper, live hogs and Swiss francs; and only a significant positive effect for Japanese yen. On the other hand, recursive estimates of volatility had a significant positive effect on net positions of speculators for copper, Japanese yen, wheat[138] (Chicago); and a significant negative effect for corn, soybean, cocoa[139], cotton, pork bellies, sugar, S&P500, and Treasury bonds. The boundaries within which recursive estimates of volatility lie are much broader in currency markets like Japanese yen, British pounds and Swiss francs; and financial markets like S&P500. This is consistent with Christie-David and Chaudhry (1999) who reported that more liquid financial instruments show longer volatility persistence following macroeconomic announcements.

Recursive estimates of variance from Equation 4.25 have a significant and negative effect on hedgers' trading activity in soybean oil, cotton, wheat (Chicago, Minnesota), soybeans, silver and S&P500; and a significant positive effect in crude oil, heating oil, Swiss francs and platinum at 10% significance level. Recursive estimates of volatility have a significant positive effect on net positions of speculators for Japanese

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[137] Due to the high correlation between net positions and volatility, there were too many breaks occurring within the model, making it impractical to test for any significant structural break.

[138] Stationary after first level differencing.

[139] Cocoa and soybeans are stationary at first level differencing.

yen[140], coffee and cotton; and a significant negative effect in crude oil, wheat (Minnesota), pork bellies, and sugar. The boundaries between which the coefficient estimates of variance lie are smaller than those of standard deviation. This can be attributed to variance which is expected to be the squared of standard deviation. The significant negative relationship observed between standard deviation and net positions, and between variance and net positions, is consistent with Peck (1981), Bessembiner and Seguin (1992), but inconsistent with Roth et al. (2003) who found a positive relation between net position and open interest for both hedgers and speculators. However, it is also important to note that Roth et al. (2003) pointed out that the positive significance of open interest and volatility is highly sensitive to the volatility measure used, particularly for hedgers' trading activity.

Conclusion

The trading determinant model suggests hedgers are positive feedback traders in most markets. Speculators' behaviour is inconclusive due to higher trading frequency level suspected. Hedgers also have superior market timing abilities than speculators, on a monthly basis. Hedging pressure effects are mostly insignificant, suggesting no transfer of risk from hedgers to speculators. The negative market timing of hedgers in heating oil and Japanese yen, and positive feedback trading behaviour, suggest large hedgers destabilized futures prices in these markets, suggesting a need to look again at CFTC's stringent position limits imposed on speculators. Overall, information variables are insignificant in determining monthly trading decisions.

The decomposed mean equation in the performance section, with a higher number of expected net positions, suggests hedgers are more prone in setting an expected net positions at the start of the month in determining actual returns rather than readjusting their net positions althroughout the rest of the month. The lower number of significant

[140] Stationary after first level differencing.

expected net position variables in determining volatility further added support that hedgers are better informed, where their trading at the start of the month has less effect on the volatility than compared with speculators. Higher expected volatility of hedgers in crude oil and heating oil added support to their destabilizing features. The GARCH model suggested the importance of both lagged volatility and news of volatility from previous month in determining actual volatility. Both players' volatility had a tendency to decay over time in response to shocks, supporting the informative traits of these large players. The PARCH model, by capturing more significant negative impact of variables, is a better model than the GARCH model for both hedgers and speculators. Expected idiosyncratic volatility and unexpected volatility had a mixed effect on returns, supporting the poor measure of idiosyncratic volatility as a measure of risk. Both variance- and standard deviation- based models, under normal and t distribution, reported the returns tend to be leptokurtic. The (PARCH, t) model represented actual returns less accurately, while the (GARCH, normal) and (PARCH, normal) models ranked first in explaining hedgers' and speculators' actual returns. The (PARCH, normal) model ranked first in forecasting one-month return. Idiosyncratic volatility poorly forecasted volatility in forecasting one-month returns.

The trading determinant model, mean equation model, and risk/return relationship model were all stable over the 10 years. Major economic events had little or no significant effect on hedgers' and speculators' trading decisions, and risk attitude. Lastly, the trading activity and volatility relationship model showed stronger effect of volatility on speculators' trading activity, particularly in financial and currency markets. All models tend to capture more structural breaks, where risk was proxied as standard deviation, due to the higher sensitiveness of standard deviation to futures prices than variance.

CHAPTER 5

SUMMARY AND CONCLUSION

5.1 Introduction

Two important issues in the international derivatives markets are studied, namely the behaviour and performance of large speculators and large hedgers in the US futures markets over the 1990s period. The academic contributions are first laid out. Then, the summary and findings are presented below, starting with the behaviour and performance section. The behaviour section summarizes findings about the trading determinant, market timing abilities and hedging pressures models. The performance section summarizes findings about the different return and volatility models used, followed by the forecasting abilities of one-month futures return. Then, the events analysis section summarizes the results about stability in the behaviour and performance models and if they were affected by major economic events in the 1990s. The remaining sections of this chapter lay out the main limitations, policy implications, practical significance of study, and a generalization of findings. The chapter ends with some final concluding remarks.

5.2 Academic Contributions

This is the first study to analyse the behaviour and performance of 29 US futures markets. Regarding behaviour, areas like trading determinants of large hedgers and large speculators, market timing abilities, and hedging pressure effects, were analysed using variables like sentiment index, net positions, returns, and priced risk information variables. The trading determinant model helped in understanding how large hedgers and large speculators change their net positions following the previous month's return, and as such, whether they exhibited positive feedback trading or contrarian trading. An increase (decrease) in net positions in one-month's time, due to an increase (decrease) in actual return, would suggest positive feedback trading (contrarian trading). The non-significance of information variables also helped in understanding that these large players did not consider that information like the three-month Treasury bill yield, S&P500 dividend yield and corporate spread played a very important role in their monthly trading decisions. The market timing ability test also helped in understanding whether hedgers or speculators predicted the one-month futures return accurately, based on actual change in their net positions. A significant positive value for the change in net positions would support that hedgers or speculators had good market timing abilities in judging the future prices and hence a higher return in one month. More importantly, it helped in supporting Keynes (1930) theory of normal backwardation where it is assumed speculators would have no forecasting or market timing ability, to support the existence of risk premium. The hedging pressure effect tests helped in ascertaining the existence of the transfer of risk from hedgers to speculators due to the existence of significant risk premium in futures markets. The existence of significant positive feedback trading and significant negative market timing ability for hedgers in specific markets encouraged the need to reconsider regulation, in that these players would destabilize prices away from fundamentals.

In the performance section, this study is the first to decompose net positions, sentiment, and information variables against return and volatility. The decomposition of these variables into expected and unexpected components helped in further understanding how significant expected and unexpected variables affected the actual returns and idiosyncratic volatility at the start or during the rest of the month. The use of a lagged hedging pressure variable against actual return and volatility also is a first, and helped in determining how significant risk premium affects futures return and actual idiosyncratic volatility. Further, the idiosyncratic volatility was also decomposed into expected and unexpected volatility. This is also the first to be done and helps in finding markets where significant expected volatility is positive. More importantly, the use of GARCH and PARCH volatility models, assuming symmetry, is the first to be done when it comes to using standard deviation and variance in explaining actual returns. The performance evaluation of GARCH and PARCH models set the pace in knowing whether standard deviation or variance accurately explained the futures returns in the 29 futures markets. In that same line of thought, the risk and return relationship model was used to help in understanding the attitude towards risk of speculators and hedgers over a specific period of time. The use of GARCH and PARCH models was further extended by using both normal and t distributions. This is the first study to show not only how these two models explained actual returns of both hedgers and speculators, but also how they differed under normal and *t* distribution. The forecasting of one-month futures return using these four models, i.e. (GARCH, normal), (GARCH, *t*), (PARCH, normal) and (PARCH, *t*), helped to determine whether standard deviation- or variance-based models provide better forecasting for one-month futures return. This study is the first one to compare idiosyncratic volatility against standard deviation and variance, and how accurately idiosyncratic volatility matched the volatility (standard deviation or variance) that accurately forecasted one-month futures return.

In the events analysis section, the study is the first one to analyse the effect of structural breaks over the trading determinant behaviour model, mean equation model, and risk and return model. The use of coefficient estimates in the recursive stability test helped to match structural breaks with eight major economic events like the long period of tightening of US interest rates in early 1990s, the temporary revival from Japanese recession, the Russian crisis, the LTCM near financial collapse, and the introduction of the Euro currency in 1999. The recursive coefficient estimates of returns in the trading determinant model showed if there were any significant jump in futures returns which affected net position of hedgers and speculators in a one-month period. The recursive coefficient estimates of net positions (or change in net positions if not stationary at levels) showed if there was any break that would significantly affect the actual returns in the mean equation model. More interestingly, the recursive coefficient estimate in the risk/return model showed whether speculators' and hedgers' attitude towards risk changed significantly during the eight major economic events, where risk was both proxied as variance and standard deviation. Finally, but not least, the recursive coefficient estimate in the trading activity model showed how the relationship between volatility and net positions of hedgers and speculators is affected during the major economic events.

5.3 Summary of Findings

5.3.1 Behaviour Section

The trading determinant model showed that large hedgers exhibited significant positive feedback trading behaviour in 15 markets, and significant contrarian behaviour in five markets. This was consistent with Grinblatt and Keloharju (2000) who found sophisticated investors pursued positive feedback strategies. Speculators, on the other hand, exhibited significant positive feedback trading behaviour only in seven markets, and contrarian behaviour in Eurodollars only. With 23 markets having speculators exhibiting positive feedback trading, and only significant in seven of them, the monthly data interval was found to be not synchronous enough to determine speculators' trading decisions. Hedgers (speculators) were also found to respond negatively (positively) to market sentiment after controlling for market risk, which was consistent with De Bondt (1993) and Wang (2003). Information variables were insignificant in most markets, suggesting that the large players did not use these monthly yields significantly in their trading decisions.

Hedgers had significant market timing ability in getting a positive return in one-month's time for silver, corn, cocoa and coffee, while exhibiting similar poor abilities in Treasury bonds, Japanese yen, soybean oil, crude oil and heating oil. This can be contrasted with speculators having significant market timing ability in wheat (Minnesota) and cocoa only. This was consistent with Khoury and Perrakis (1998) that hedgers in silver, corn and coffee properly change their net positions to increase their futures return in one month's time, and hence are better informed than speculators in these markets, but inconsistent with Chatrath et al. (1997) that speculators were the most profitable in the 1990s. The poor or negative market timing ability for hedgers was supported by Working (1953) that short hedgers tend to lose money to speculators on their hedge transactions. However, due to the poor market timing ability of speculators, a higher frequency data interval was recommended to fully test their market timing ability. Using the monthly data, the poor market timing ability of speculators do support Keynes (1930) assumption that speculators do not have any forecasting ability, thereby, giving further support to the existence of risk premium. To test the existence of risk premium, own- and cross-hedging pressure effect tests were used and revealed significant risk premium only in few markets, which was consistent with Besseminder (1993) that hedging pressures do not affect the futures returns. Further, price pressure tests were performed to test the robustness of hedging pressure tests. After controlling for price pressures, silver, crude oil and live cattle continued to exhibit significant risk premium, suggesting the transfer of risk from hedgers to speculators in those markets. Significant positive feedback trading behaviour and negative market timing ability in Japanese yen, crude oil and heating oil, suggested hedgers tend to destabilise the futures markets by pushing away prices from their fundamental values. In particular, hedgers in Japanese yen and heating oil suggested a tendency to be destabilisers, since there was no significant risk premium after controlling for price pressures. A review of the regulation regarding stringent position limits imposed upon speculators in these markets was suggested. This was further supported with the decline in speculation in these markets, and also where net positions of speculators were less than net positions of hedgers, both for the mean and standard deviation figures.

5.3.2 Performance Section

The mean equation showed that hedgers' net positions were negatively related to returns in 18 markets, which was consistent with the negative correlation between the two variables. Speculators' returns were significantly related with their net positions only in four markets, which was consistent with the low correlation between the two variables. Sentiment index was highly associated with returns for both players, which can be explained by the bullish trend in the US. The lagged hedging pressure variables were mostly significant for agricultural markets, which was consistent with Keynes (1930). As expected from earlier findings, information variables tend to be insignificant in determining returns. An ARMA decomposition of net positions showed that expected net positions of hedgers are negatively related to returns in 17 markets, where 15 were from the agricultural group. The fewer positive expected net positions of speculators and relatively more unexpected net positions of speculators suggested that these players were less informed than hedgers in setting their net positions at the start of the month, but rather speculators changed their net positions more often than hedgers during the rest of the month with the expectation of higher returns. The expected net position coefficients for both hedgers and speculators in 15 and six markets were consistent with Canoles et al. (1998) that, in these markets, they were both financially sophisticated, well educated, and hedgers were better informed in setting a better expected net position at the start of the trading month to determine actual returns. The low significance of expected net positions for speculators also suggested other non-return motivational factors like recreation, which were further supported by the poor correlation between returns and net positions. Decomposed sentiment variables and lagged hedging pressure variables were still significantly positive and negative as found in the non-decomposed mean equation. As for decomposed information variables, unexpected T-bill yield appeared to be more negatively significant to return for speculators, and unexpected corporate spread and dividend yield to be more positively significant to returns of speculators, particularly for financials, minerals and currencies.

The decomposition of variables against idiosyncratic volatility helped in confirming that hedgers were better informed in setting a current net position level at the start of the month that would have a smaller impact of their risk levels and that speculators would rather set net positions that change more frequently to satisfy their risk appetites. Net positions of hedgers (expected and unexpected) tend to have less effect on volatility compared to speculators' net positions (expected and unexpected) that tended to add to volatility. This was consistent with the Shalen (1993) and Chen et al. (1995) models, where speculators' volatility was positively related with trading demand. More significant expected and particularly unexpected variables affecting volatility were found within the currency group for both players, supported by the fact that the foreign exchange markets were among the most actively traded contracts. Information variables appear not to have significant effect upon volatility of large players. A decomposition of idiosyncratic volatility showed that speculators had 22 markets with significant expected volatility, with 17 being positive. Expected volatility of hedgers was significant and positive in 14 markets, and negative in seven markets. While both speculators and hedgers had significant positive expected volatility in heating oil and crude oil, the magnitude of the coefficients was larger for hedgers, suggesting more active trading in these markets by hedgers at the start of the month rather than for the rest of the month.

Using a GARCH (1, 1) model, news about volatility from the previous month was positive and significant in 10 (15) markets for hedgers (speculators), suggesting that the ARCH term was important in determining current volatility levels for hedgers (speculators), especially in agricultural futures markets. The GARCH term (lagged volatility) was significant in 24 (19) markets, which was consistent with Yang and Brorsen (1993). The greater significance of the news about volatility from the previous month for speculators suggested their greater reliance on noise trading and herding behaviour, where news from previous periods affected current volatility. Further, hedgers' volatility in Treasury bonds and coffee, and speculators' volatility in gold and S&P500 futures, had experienced increasing volatility persistence to shocks over the 1990s. In all remaining markets, hedgers' and speculators' volatility had shown a tendency to decay over time in response to shocks, supporting that both players were informed and reacted well to news volatility. The PARCH model, in contrast, exhibited more significant negative variables for both lagged volatility and news about volatility from previous month for speculators. By capturing more significant negative impact of lagged volatility and news of volatility from previous month, the PARCH was suggested to be more informative than the GARCH model for speculators' current volatility. The PARCH model, by capturing both more negative and positive impacts of lagged volatility and news of volatility from previous month for hedgers' current volatility, was also preferred over the GARCH model. As a robust check, model performance evaluation was carried out and the GARCH model, under normal distribution, gave the lowest RMSE for hedgers' returns in 13 markets, which was consistent with Bracker and Smith

(1999). On the other hand, the PARCH model under normal distribution ranked first in explaining speculators' actual returns, with 11 markets having the lowest RMSE. The PARCH model, under *t* distribution, fitted the actual returns for both players in the least accurate way among all ARCH-based models.

An analysis of the return and risk relationship showed that expected volatility had a positive and significant effect on hedgers' return only in crude oil, heating oil and wheat (Chicago), thereby further enhancing the need to re-check position limits of hedgers in those markets. In markets like silver, Eurodollars, Japanese yen, wheat (Kansas, Minnesota) and pork bellies, expected volatility significantly decreased hedgers' return which was consistent with portfolio theory that hedgers' risk should be insignificant or low due to the purpose of minimizing risk as stated by Hoffman (1932). Due to the informed traits of hedgers, unexpected volatility was also theoretically expected to be low and insignificant, suggesting that their return are less affected by changing risk attitudes that occur during the month rather than at the start of the month. However, unexpected volatility in gold, silver, Swiss francs, coffee and cotton was positively related to returns, suggesting that in these markets changing risk level that occur during the rest of the month have a positive effect on returns. On the other hand, speculators' expected volatility, as theoretically expected, was positive and significant in crude oil, heating oil, and wheat (Kansas, Chicago), but negative in Eurodollars, Canadian dollars and pork bellies. Unexpected volatility, theoretically expected to be higher or more significant for speculators due to overreaction towards noise information, was so in gold, silver, Swiss francs and cotton, but negative and significant in Japanese yen, pork bellies and wheat (Chicago). Overall, in line with Marshall (1919), the hedger did not speculate but insured, thereby reinforcing the higher expected risk borne by speculators.

In testing the normality assumptions of the error distributions of the GARCH and PARCH volatility models, skewness values of hedgers' and speculators' returns under (PARCH, normal) and (PARCH, *t*) were more negative than under GARCH models due to the higher sensitivity of the PARCH model to negative returns. Theoretically, hedgers' kurtosis should be smaller due to their risk-minimizing profiles. The (GARCH, normal), (GARCH, *t*), (PARCH, normal) models supported that claim in copper, crude oil, heating oil, soybean oil, and sugar, where hedgers managed to have a lower risk relative to speculators. Overall findings were supported by Mann and Heifner (1976), Blattberg and Gonedes (1984) and Houthakker (1961) that the distribution of large hedgers' and speculators' returns were leptokurtic.

Forecasting of one-month return showed that both returns for hedgers and speculators, under GARCH and PARCH models, followed nearly the same close trend in all 29 markets, with actual returns being within 95% confidence intervals bands of the forecasted returns. While the highest number of underestimated forecast was 17 under (PARCH, *t*) for speculators' forecast returns, the number of overestimated forecast were generally the same across all four models. This suggested that the GARCH and PARCH models were generally more affected by increasing actual returns compared to decreasing actual returns. This was analogous to the decreasing trend in net positions observed in December 1999 just before the forecast of January 2000. Also, in line with Poon and Granger (2003) and Ding and Granger (1996), GARCH models under normal distribution put too much weight on recent observations relative to those in the past. The (PARCH, *t*) model's high number of underestimated returns forecasts could be attributed to high sensitivity of standard deviation over returns. This was in line with Poon and Granger (2003) who found that standard deviation is more proportional to derivatives prices than variance models. For hedgers, the (PARCH, normal) model ranked first with 10 good forecasts of one-month return. As for speculators, the best models were (PARCH, normal) and (GARCH, *t*) who ranked equally first with seven good forecasts. In comparing the number of good forecasts achieved under hedgers' and speculators' returns, it could be observed that models using hedgers' net positions provided better forecasts than using speculators' net positions-based models.

The standard deviation and variance for both players were mixed in magnitude. Markets whose variance or standard deviation of hedgers were smaller than those of speculators supported Smith's (1922) price insurance theory where hedging enabled hedgers to insure against the risk of price fluctuations and also Hoffman's (1932) view that hedging was about shifting risk. On the other hand, markets where variance or standard deviation of hedgers were bigger than those of speculators supported Telser (1981) that the motivation to use futures contracts was not primarily driven by the firm's desire to reduce risk, but by the institutional characteristics of the futures exchange itself like regulation ensuring liquidity. Variance appeared to be more volatile in currency and financial markets due to their highly traded activity. In comparing the idiosyncratic volatility with the standard deviation and variance in one-month forecast, only in the S&P500 futures market did idiosyncratic volatility provide a good measure of volatility for the one-month forecast returns. Consistent with the existing volatility forecasting literature and specifically Manfredo et al. (1999), the poor measure of idiosyncratic volatility confirmed the difficulty in finding a "best" volatility forecasting method across alternative data sets and horizons.

5.3.3 Stability and Events Analysis Section

The trading determinant model showed that the highest return coefficient estimates could be found in Canadian dollars, Eurodollars, British pounds, Treasury bonds, Japanese yen and gold. The occurrence of relatively higher coefficient estimates suggested that large players in currency and financial markets tended to rely more on actual returns to change their net positions the following month than large players in agricultural futures markets. Moreover, the return coefficient estimates between hedgers and speculators had a tendency to bear a negative relationship. This was supportive of the idea that the futures market is a zero-sum game, and that for every long position there should a short position to net it off. With the exception of most markets being stable, only speculators in soybeans, cotton, wheat (Chicago) and cocoa had structural breaks with significant return coefficient estimates. The effect of speculators' returns on next month's net positions, as expected, is backed by positive feedback behaviour, where speculators took more long positions (in soybean and cocoa) when major economic events was an indication of easing economic conditions, and took more short positions (wheat (Kansas) and cotton) under events upholding tight economic conditions. This supported BIS (1995–2001) that major economic events did not affect significantly futures markets in the US, except in the four markets mentoned above at a specific point in time.

Similarly, few structural breaks were found in the mean equation, supporting that positive feedback trading persisted in the long run where the recursive coefficient estimates were greater than zero. This was consistent with De Bondt and Thaler (1987) and Frankel and Froot (1988), who found that extreme movements in prices eventually revert, as long as part of these movements was accounted for by positive feedback trading. More importantly, only coffee and live hogs had structural breaks with significant negative coefficient estimates when the effect of the event was taken into account. The jump in the change of net positions coefficient estimates for coffee, due to the start of the temporary revival from Japanese recession, could be attributed to more confidence of hedgers selling their futures contracts later at a better price. The jump in live hogs net positions coefficient estimates, due to the start of the US Fed tightening interest rates, could be attributed to hedgers shorting fewer contracts in the expectation of interest rates easing in the future.

In the risk and return relationship model, recursive estimates of risk were mixed, where risk was both proxied as standard deviation and variance. There were more significant recursive estimates where standard deviation was used as a measure of risk. This was due to standard deviation being more proportional to futures prices. While the findings of a positive relationship between risk and return supported portfolio theory that a higher risk was compensated with a higher return and vice versa, the findings of a significant negative relationship between risk and return could be explained by Glosten, Jagannathan and Runkle (1993) where investors may not demand high risk premium if they were better able to bear risk at times of particular volatility. Moreover, if the future seems risky, the investors may want to save more in the present, thus lowering the need for larger premiums. When using standard deviation as a risk proxy, there were more structural breaks occurring for speculators, suggesting that speculators' returns were more affected during major macroeconomic events. However, the structural breaks were significant only in soybean for hedgers and Treasury bonds for speculators. No structural breaks were significant where variance was proxied as risk.

Finally, but not least, the relationship between trading activity and volatility was looked at. Recursive estimates had more positive and negative effects on trading activity of speculators than hedgers, where standard deviation was used as a proxy of volatility. The boundaries within which recursive estimates of volatility lie were much broader in currency markets like Japanese yen, British pounds and Swiss francs; and financial markets like S&P500, which is consistent with Christie-David and Chaudhry (1999) that financial instruments showed longer volatility persistence. The boundaries between which the coefficient estimates of variance lay were smaller than those of standard deviation. The significant negative relationship observed between standard deviation and net positions, and between variance and net positions, was consistent with Peck (1981), Bessembiner and Seguin (1992), but inconsistent with Roth et al. (2003) who find a positive relation between net position and open interest for both hedgers and speculators. More importantly, volatility estimates (standard deviation) had a significant positive effect on net position of hedgers for Japanese yen. Similarly, volatility estimates (variance) had a significant positive effect on hedgers' trading activity in crude oil, heating oil, Swiss francs and platinum. The suggestion that volatility in hedgers' returns tended to add to their net positions, added further support for the need to re-check the speculators' stringent position limits status quo in Japanese yen, crude oil and heating oil. The case for crude oil was further enhanced by the significant negative effect of volatility (variance) on speculators' net positions.

5.4 Policy Implications and Practical Significance

In the Commodity Futures Modernization Act (CFMA) and Commodity Exchange Act (CEA) in the US, it is well observed that large speculators have imposed penalties like position limits in the futures markets. This study encouraged such stringent regulation to be revaluated from CFTC policy makers. Findings in the behaviour section showed that hedgers exhibited both significant positive feedback trading and significant negative market timing in the crude oil, heating oil, and Japanese yen futures markets. This suggests that hedgers destabilise futures prices by pushing away the prices from their fundamental value, and thereby encourages the need to re-assess the relaxed regulation imposed on hedgers in these markets. Particular emphasis is recommended for the heating oil and Japanese yen, since there was no significant risk premium that was borne by speculators, after controlling for price pressure effects. Further support is brought from findings in the performance section, where volatility (standard deviation) had a significant positive effect on hedgers' net positions in Japanese yen; volatility (variance) had a similar effect in crude oil and heating oil; and volatility (variance) had a significant negative effect on speculators' net positions in crude oil.

A better understanding of whether risk is better proxied as standard deviation or variance in specific futures markets can be a very useful risk-management tool for investment companies and traders alike. For instance, using a conditional standard deviation-based model and the return model (mean equation), under normal distribution, would have produced an accurate forecast of one-month return for live hogs, lumber, coffee, cotton, corn, soybean oil, soybean meal, sugar and soybean for both large hedgers and large speculators. Similarly, the recursive coefficient estimates of risk (standard deviation and variance) against return have shown not only the actual attitude of hedgers and speculators towards risk, but also that these key market players' returns are not significantly affected by jumps or breaks in the return/risk relationship during major global economic events.

The trading determinant behaviour model used can also help investors, quantitative analysts and such likes to understand that large hedgers exhibit significant positive feedback trading in 15 of the futures markets studied, and large speculators do not appear to follow a clear-cut positive feedback or contrarian behaviour strategy. This suggests that hedgers do not significantly change their net positions in intervals less than one month, but also that a higher frequency data interval is required to test trading determinants of speculators. The trading determinant model also shows that information variables like S&P500 dividend yield, three-month Treasury bill and corporate yield spread do not significantly affect these market players' trading decisions. Further, the recursive coefficient estimates of return in the events analysis and stability model appear to be higher in financial and currency markets rather than agricultural markets. This suggests that key market players tend to rely more on actual returns in determining next month's change in net position in financial and currency markets than agricultural markets.

Moreover, the use of the market timing ability model gives information if large hedgers and large speculators can obtain positive returns in one month's time, based on the actual change in net positions. For instance, the change in actual net positions in silver, corn, cocoa and coffee increased one-month futures return for hedgers, but decreased one-month futures return in copper, heating oil, Japanese yen and crude oil. The market timing ability model fails to deliver significant results in explaining speculators' returns due to the higher trading frequency they trade in. This result not only helps in suggesting that hedgers are more informed by operating on a longer time interval, but also that speculators' returns are due to market timing abilities on higher trading frequency intervals. The result, using monthly data, also support the assumption from the theory of normal backwardation, that speculators do not have any forecasting ability. Similarly, the hedging pressure effects models help to understand the existence of a transfer of risk through significant risk premium. Results of significant negative hedging pressure variable coefficients not only support that hedgers are net short on average in most markets, but also that cross-hedging pressures exist in most markets, particularly agricultural markets. This suggests that many markets make use of cross-spreading futures in achieving a risk/return target and those investors seeking the out-performance of large players in specific markets should consider cross-markets information rather than just the underlying market on which the futures contract is based on.

The decomposed mean equation shows how much expected and unexpected components of net positions, sentiment, and information variables affect the actual returns for hedgers and speculators. For instance, hedgers' actual returns are more significantly negatively related to expected net positions than unexpected positions compared to speculators' returns that are more significantly related to unexpected net positions. This suggests that hedgers, on average, are more inclined than speculators in setting a better net position or change in net position at the start of the trading month in determining the futures returns. The mean equation model adds further support to the non-significance of information variables in determining returns by large hedgers and speculators. Finally, the recursive coefficient estimates in the mean equation suggest that major global economic events did not significantly affect net positions in determining actual returns.

5.5 Areas for Future Research

This study has been conducted using monthly data, due to factors like good performance of market players on long-term investment horizons, consistency in models with release of monthly macroeconomic variables, and consistency of previous empirical results over different time horizons. The data sample also is set from May 1990 to December 2000 to set the study in the context of a US decade that was very successful in all areas of macroeconomic policies, globalisation and financial deregulation. The former assumption of monthly data can be relaxed for future research by using exclusive proprietary daily data like that employed in Haigh et al. (2005). This would be particularly important for assessing the behaviour and performance of large speculators, which appeared to be more prone to structural breaks than large hedgers. The latter assumption of using data up to December 2000 can also be extended to more up-to-date data to test for robustness in stability in the models and also to see the effect of important events like 9/11 and more volatile oil price shocks.

The GARCH and PARCH volatility analyses have been conducted, assuming symmetry in the models. Due to high skewness values, and non-normality in most futures markets in explaining hedgers and particularly speculators' returns, asymmetrical models such as Exponential GARCH (EGARCH) and Component GARCH (CGARCH) can be implemented to ensure non negativity in the forecast of conditional variance to account for mean reversion and non-linearity in volatility. The usage of asymmetrical models would also not only add value to the performance evaluation of the models in explaining returns, but also further ascertain whether standard deviation and/or variance can accurately forecast one-month futures return and whether idiosyncratic volatility can be a good measure of risk. For instance, McKenzie et al. (2001) provides a nomenclature of nested ARCH model specifications where the estimation of the power term δ in the PARCH model is of critical importance. In that same line of thought, forecasting can be tested for more than one-month (or weekly) return. For example, the usage of daily data can help to reveal whether the GARCH/PARCH model can predict speculators' returns in one day's time.

A third and yet very important area to be considered for future research would be the relationship between speculators' and hedgers' returns and net positions. While we have found significant negative correlation between net positions (or change in net positions) between hedgers and speculators, the same actual futures return for both large players was assumed. This important assumption can be relaxed in the future, if proprietary data about speculators' and hedgers' returns can be provided. Further, the effect of S&P500 futures or similar indices can be integrated into the models to estimate the effect of S&P500 returns or net positions in each futures market's future net position or returns. More interestingly, testing who leads, lags, or follows some non-random positioning in the futures markets can help to know where the futures markets might be heading in the future. For instance, Caginalp and Laurent (1998) found traders are reacting to expectations involving strategies and resources of other participants. In a similar fashion, uninformed traders overreact to another's trades, thereby exaggerating price movements (Daigler and Wiley, 1999). By integrating theories like herding, lead/lag relationships and causality; by using data about the concentration of positions held by the largest four and eight traders; and by also implementing small traders as defined by CFTC into the models, future research can further help in understanding the behaviour and performance of key market players in the US futures markets.

Finally, but not least, it would be interesting to consider the Commodity Futures Trading Commission (CFTC) actions in response to the "Comprehensive Review of the Commitments of Traders Reporting Program" (June 21, 2006). As from 5 January 2007, CFTC will publish an additional COT report called the "COT – Supplemental". The new report will show aggregate futures and option positions of Non-commercial, Commercial, and Index Traders in 12 selected agricultural commodities. These so-called "Index Traders" will be drawn from both the current Non-commercial and the Commercial categories. Coming from the Non-commercial category will be managed funds, pension funds and other institutional investors that generally seek exposure to commodity prices as an asset class in an unleveraged and passively-managed manner using a standardized commodity index. Coming from the Commercial category will be entities whose positions predominantly reflect hedging of OTC transactions involving commodity indices—for example, swap dealers holding long futures positions to hedge short OTC commodity index exposure opposite institutional traders such as pension funds. These latter position holders are those traders called "non-traditional commercials." That would be an exciting path for future research to further differentiate hedgers and speculators into traditionals and non-traditionals, and use this finer distinction to look at the behaviour and performance of these key market players in the US Futures markets.

5.6 Generalisation of Results

Besides the limitations of this study which can form prominent areas of future research, as laid out in section 5.5, it is important to be careful before generalising about the findings of this study. First and foremost, while 29 markets have been studied within developed, highly liquid financial derivatives markets (US), the sample is one that can be at most generalized for the US futures markets only, and not extended to emerging ones. The uniqueness of the COT data is available only in the US futures exchanges, making the study comparable only to other studies using that same US data.

This study being the first—particularly in analyzing 29 markets in the trading determinant model; market timing model; GARCH and PARCH volatility models under both normal and *t* distribution; risk/return relationship model; trading activity and volatility relationship model; and recursive estimates in events analysis—makes the results justifiable only for the last decade period, using monthly decision intervals by large hedgers and large speculators only. The 21st century is a different episode with factors like more volatility in Fed rates, unstable price shocks, and September 11-like events. Although the results can serve for guidance for small traders as to the behaviour and performance of key market players like large hedgers, the results in no sense represent small traders. Further, although herding and mean reversion in the net positions of hedgers and speculators is expected, this study didn't test for these explicitly. Moreover, it was assumed hedging pressure effects (cross hedging) flow only within a similar commodity group and not within groups. Importantly too, we assumed large hedgers and large speculators behave separately and do not depend on either party before buying or selling futures contracts.

The results among the 29 futures markets are mixed due to different econometric models, methodologies, and underlying assumptions. This study was geared towards getting a big picture of the behaviour and performance of large hedgers and large speculators in those markets only in the 1990s. Similarities and non-similarities of significant results in the models and with other scholars' results used have helped towards that end. Superior market timing abilities were tested for robustness with hedging pressure effect tests, which were in turn tested for robustness with the price pressure test. The destabilising feature of hedgers in crude oil, heating oil and Japanese yen markets is based on the assumption that hedgers traded on a monthly interval. However, results for speculators appear insignificant due to their higher trading frequency interval. Other models such as trading determinant models, risk/return relationship model, trading activity and volatility relationship model, and mean equation model were also tested for robustness with the recursive stability test. All these models were found stable with few or no significant structural breaks found that matched any of the eight macroeconomic events used in this study. Other models such as decomposed mean equation were also tested by diagnostic tests. Overall, care should still be taken before generalizing the results of this study due to the uniqueness of the data, the timeframe chosen, events underlying the decade, and the sound economic system of the US in the 1990s.

5.7 The Behaviour and Performance of Key Market Players in US Futures Markets: Final Concluding Remarks

The uniqueness of this study can be attributed not only to the COT unique data, but also to the disaggregation of the market into large hedgers and large speculators. Beaver (1972) argued, "…it is important to distinguish between securities markets and individual investors, because the role of information can vastly be different in each context. To a certain extent, the distinction is artificial, in that aggregate actions of individuals determine market behaviour.." However, more importantly, the process of aggregation is often deceptive, and if we fail to make the distinction, we may be subject to any one of a number of fallacies of composition (Winsen, 1976). In that spirit, this study helps to shed further light on behaviour and performance of large hedgers and large speculators in 29 US futures markets.

The policy implications are critical in terms of position limits for specific players, as well as the practical significance which can help towards a better understanding of risk and return of the largest traders in the US futures markets. This study is only a step forward in the wilderness of behavioural finance in helping to get a view of how hedgers and speculators change their monthly trading decisions; how they can do so and achieve positive return in one month's time; why the transfer of risk from one party to another is an important concept in futures markets; that information variables are not significant variables in these large players' decisions; how different error distributions can result in different model performance; how well standard deviation- or variance-based models help to predict one-month return better than idiosyncratic volatility; and how stable are trading decisions and attitudes towards risk during major economic events. Everything comes back to the two most important things: the risk and return of hedgers and speculators, where the latter is conceptualized after accepting certain level of risk. As Greenspan put it so well, "Management of risk is definitely a must to avoid contagion and near collapse like LCTM ... that's why understanding the risk and return of key market players become ultimately the key issue for all entities dealing with derivatives like futures markets…" I rest my case by quoting an interview with a pioneer of behavioural finance, Hersh Shefrin, who said:

"It is really behavioral finance that ultimately will tell you why a particular trading rule is likely to work, because technical trading does, for the most part, exploit market inefficiencies. Otherwise, you might as well just buy and hold, but if you are looking for abnormal returns, then you have to be using the right technical trading strategies.."[141]

[141] Excerpted from an article originally published in the March 2000 issue of *Technical Analysis of Stocks and Commodities* magazine

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Appendix 6.1

Table 4.0
Terms used in Methodology and Analysis stages

	Normal dist.		***t dist.***		***Normal dist.***		***t dist.***		
	GARCH	***PARCH***	***GARCH***	***PARCH***	***GARCH***	***PARCH***	***GARCH***	***PARCH***	***idiosyncratic volatility***
Actual Returns (h) ***(s)***	R_t	R_t	R_t	R_t	σ_t^2	σ_t	σ_t^2	σ_t	
RSOYBEAN_OIL	P13BOHF	P14BOHF	P15BOHF	P16BOHF	EBOH	BBOH	GBOH	OBOH	SOYBEAN_OILR
	P13BOSF	P14BOSF	P15BOSF	P16BOSF	EBOS	BBOS	GBOS	OBOS	SOYBEAN_OILRS
RPOUND	P13BPHF	P14BPHF	P15BPHF	P16BPHF	EBPH	BBPH	GBPH	OBPH	POUNDR
	P13BPSF	P14BPSF	P15BPSF	P16BPSF	EBPS	BBPS	GBPS	OBPS	POUNDRS
RCOCOA	P13CCHF	P14CCHF	P15CCHF	P16CCHF	ECCH	BCCH	GCCH	OCCH	COCOAR
	P13CCSF	P14CCSF	P15CCSF	P16CCSF	ECCS	BCCS	GCCS	OCCS	COCOARS
RCANADIAN_DOLLAR	P13CDHF	P14CDHF	P15CDHF	P16CDHF	ECDH	BCDH	GCDH	OCDH	CANADIAN_DOLLARR
	P13CDSF	P14CDSF	P15CDSF	P16CDSF	ECDS	BCDS	GCDS	OCDS	CANADIAN_DOLLARRS
RCORN	P13CHF	P14CHF	P15CHF	P16CHF	ECH	BCH	GCHH	OCH	CORNR
	P13CSF	P14CSF	P15CSF	P16CSF	ECS	BCS	GCSS	OCS	CORNRS
RCRUDE_OIL	P13CLHF	P14CLHF	P15CLHF	P16CLHF	ECLH	BCLH	GCLS	OCLH	CRUDE_OILR
	P13CLSF	P14CLSF	P15CLSF	P16CLSF	ECLS	BCLS	GCLH	OCLS	CRUDE_OILRS
RCOTTON	P13CTHF	P14CTHF	P15CTHF	P16CTHF	ECTH	BCTH	GCTH	OCTH	COTTONR
	P13CTSF	P14CTSF	P15CTSF	P16CTSF	ECTS	BCTS	GCTS	OCTS	COTTONRS
REURODOLLAR	P13EDHF	P14EDHF	P15EDHF	P16EDHF	EEDH	BEDH	GEDH	OEDH	EURODOLLARR
	P13EDSF	P14EDSF	P15EDSF	P16EDSF	EEDS	BEDS	GEDS	OEDS	EURODOLLARRS
RFEEDER_CATTLE	P13FCHF	P14FCHF	P15FCHF	P16FCHF	EFCH	BFCH	GFCH	OFCH	FEEDER_CATTLER
	P13FCSF	P14FCSF	P15FCSF	P16FCSF	EFCS	BFCS	GFCS	OFCS	FEEDER_CATTLERS
RGOLD	P13GCHF	P14GCHF	P15GCHF	P16GCHF	EGCH	BGCH	GGCH	OGCH	GOLDR
	P13GCSF	P14GCSF	P15GCSF	P16GCSF	EGCS	BGCS	GGCS	OGCS	GOLDRS
RCOPPER	P13HGHF	P14HGHF	P15HGHF	P16HGHF	EHGH	BHGH	GHGH	OHGH	COPPERR
	P13HGSF	P14HGSF	P15HGSF	P16HGSF	EHGS	BHGS	GHGS	OHGS	COPPERRS
RHEATING_OIL	P13HOHF	P14HOHF	P15HOHF	P16HOHF	EHOH	BHOH	GHOH	OHOH	HEATING_OILR
	P13HOSF	P14HOSF	P15HOSF	P16HOSF	EHOS	BHOS	GHOS	OHOS	HEATING_OILRS
RJAPANESE_YEN	P13JYHF	P14JYHF	P15JYHF	P16JYHF	EJYH	BJYH	GJYH	OJYH	JAPANESE_YENR
	P13JYSF	P14JYSF	P15JYSF	P16JYSF	EJYS	BJYS	GJYS	OJYS	JAPANESE_YENRS
RCOFFEE	P13KCHF	P14KCHF	P15KCHF	P16KCHF	EKCH	BKCH	GKCH	OKCH	COFFEER
	P13KCSF	P14KCSF	P15KCSF	P16KCSF	EKCS	BKCS	GKCS	OKCS	COFFEERS
RWHEAT__KW_	P13KWHF	P14KWHF	P15KWHF	P16KWHF	EKWH	BKWH	GKWH	OKWH	WHEAT__KW_R
	P13KWSF	P14KWSF	P15KWSF	P16KWSF	EKWS	BKWS	GKWS	OKWS	WHEAT__KW_RS
RLUMBER	P13LBHF	P14LBHF	P15LBHF	P16LBHF	ELBH	BLBH	GLBH	OLBH	LUMBERR
	P13LBSF	P14LBSF	P15LBSF	P16LBSF	ELBS	BLBS	GLBS	OLBS	LUMBERRS
RCATTLE_LIVE	P13LCHF	P14LCHF	P15LCHF	P16LCHF	ELCH	BLCH	GLCH	OLCH	CATTLE_LIVER
	P13LCSF	P14LCSF	P15LCSF	P16LCSF	ELCS	BLCS	GLCS	OLCS	CATTLE_LIVERS
RHOGS	P13LHHF	P14LHHF	P15LHHF	P16LHHF	ELHH	BLHH	GLHH	OLHH	HOGSR
	P13LHSF	P14LHSF	P15LHSF	P16LHSF	ELHS	BLHS	GLHS	OLHS	HOGSRS
RWHEAT__MW_	P13MWHF	P14MWHF	P15MWHF	P16MWHF	EMWH	BMWH	GMWH	OMWH	WHEAT__MW_R
	P13MWSF	P14MWSF	P15MWSF	P16MWSF	EMWS	BMWS	GMWS	OMWS	WHEAT__MW_RS
RPORC_BELLIES	P13PBHF	P14PBHF	P15PBHF	P16PBHF	EPBH	BPBH	GPBH	OPBH	PORCBELLIESR
	P13PBSF	P14PBSF	P15PBSF	P16PBSF	EPBS	BPBS	GPBS	OPBS	PORCBELLIESRS
RPLATINUM	P13PLHF	P14PLHF	P15PLHF	P16PLHF	EPLH	BPLH	GPLH	OPLH	PLATINUMR
	P13PLSF	P14PLSF	P15PLSF	P16PLSF	EPLS	BPLS	GPLS	OPLS	PLATINUMRS
RSUGAR	P13SBHF	P14SBHF	P15SBHF	P16SBHF	ESBH	BSBH	GSBH	OSBH	SUGARR
	P13SBSF	P14SBSF	P15SBSF	P16SBSF	ESBS	BSBS	GSBS	OSBS	SUGARRS
RSWISS_FRANC	P13SFHF	P14SFHF	P15SFHF	P16SFHF	ESFH	BSFH	GSFH	OSFH	SWISSFRANCR
	P13SFSF	P14SFSF	P15SFSF	P16SFSF	ESFS	BSFS	GSFS	OSFS	SWISSFRANCRS
RSOYBEAN	P13SHF	P14SHF	P15SHF	P16SHF	ESH	BSH	GSH	OSH	SOYBEANR
	P13SSF	P14SSF	P15SSF	P16SSF	ESS	BSS	GSS	OSS	SOYBEANRS
RSILVER	P13SIHF	P14SIHF	P15SIHF	P16SIHF	ESIH	BSIH	GSIH	OSIH	SILVERR
	P13SISF	P14SISF	P15SISF	P16SISF	ESIS	BSIS	GSIS	OSIS	SILVERRS
RSOYBEAN_MEAL	P13SMHF	P14SMHF	P15SMHF	P16SMHF	ESMH	BSMH	GSMH	OSMH	SOYBEAN_MEALR
	P13SMSF	P14SMSF	P15SMSF	P16SMSF	ESMS	BSMS	GSMS	OSMS	SOYBEAN_MEALRS
RS_P500	P13SPHF	P14SPHF	P15SPHF	P16SPHF	ESPH	BSPH	GSPH	OSPH	S_P500R
	P13SPSF	P14SPSF	P15SPSF	P16SPSF	ESPS	BSPS	GSPS	OSPS	S_P500RS
RTBONDS	P13USHF	P14USHF	P15USHF	P16USHF	EUSS	BUSH	GUSH	OUSH	TBONDSR
	P13USSF	P14USSF	P15USSF	P16USSF	EUSH	BUSS	GUSS	OUSS	TBONDSRS
RWHEAT__W_	P13WHF	P14WHF	P15WHF	P16WHF	EWS	BWH	GWH	OWH	WHEAT_W_R
	P13WSF	P14WSF	P15WSF	P16WSF	EWH	BWS	GWS	OWS	WHEAT_W_RS

Appendix 6.2: US futures markets growth in activity

Table 1.4
Trading Volume of the 25 Largest US Exchange-Traded Futures and Option Contracts in 1998

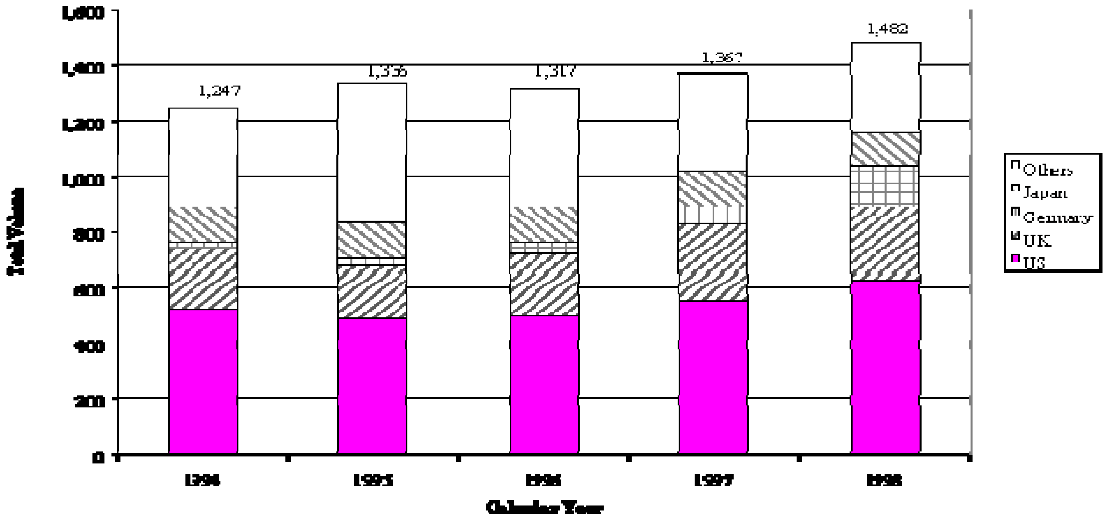
Trading Volume of the 25 Largest U.S. Exchange-Traded Futures and Option Contracts in 1998, with Comparisons to 1993 (in millions of contracts)

Contract	*Exchange*	*Category*	*1993*	*1998*	*% Change*
Bond	CBT	Interest Rate	102.9	152.2	48%
Dollars	CME	Interest Rate	81.4	142.6	75
Note (10Year)	CBT	Interest Rate	21.4	41.8	95
Sweet	NYMEX	Energy	32	38	18
S&P 500 Index	CME	Stock Index	16.1	36.4	126
Note (5Year)	CBT	Interest Rate	10.1	21.2	110
Corn	CBT	Domestic Agriculture	13.5	20	49
(Henry Hub)	NYMEX	Energy	5	19.1	281
Soybeans	CBT	Domestic Agriculture	14.6	16.3	12
Gold - COMEX	NYMEX	Metal	10.6	10.9	3
N.Y. No. 2	NYMEX	Energy	9.4	9.5	1
Japanese Yen	CME	Currency	8.3	9	9
Regular Gasoline	NYMEX	Energy	7.4	8.7	18
Deutschemark	CME	Currency	18.8	7.6	-60
Sugar #11	CSCE	Foreign Agriculture	5.2	7.6	47
Soybean Meal	CBT	Domestic Agriculture	5	7.4	48
Soybean Oil	CBT	Domestic Agriculture	4.8	7.3	51
Wheat	CBT	Domestic Agriculture	3.7	7	88
Silver - COMEX	NYMEX	Metal	6	4.9	-17
Live Cattle	CME	Domestic Agriculture	3.8	4.9	29
S&P 500 E-mini	CME	Stock Index		4.5	
Cotton #2	NYCE	Domestic Agriculture	2	4.3	119
Swiss Franc	CME	Currency	6.2	4.3	-32
Industrial Index	CBT	Stock Index		3.8	
Coffee “C”	CSCE	Foreign Agriculture	2.5	3.1	25
Sub-total			390.8	592.4	
U.S. total			421	631	
Sub-total / U.S. total			93.0%	93.9%	

Source: BIS

Appendix 6.3: Global exchange traded commodity volume and US futures markets market positions

Graph 1.2
Global exchange traded commodity volume-total and top 4 countries. (1994-1998) (millions of contracts)



Source: BIS

Table 1.5
US futures markets market positions (1990-2000)

	Dec-90	Dec-91	Dec-92	Dec-93	Dec-94	Apr-95	Jun-98	Dec-98	Jun-99	Dec-99	Jun-00
Derivatives market turnover[1]											
Exchange traded derivatives[2]						1222	1373				
OTC derivatives						880	1265				
Derivatives market positions[3]											
Exchange traded derivatives	2290	3519	4634	7771	8862	10310	14792	13932	14440	13522	13904
Interest rate futures				4960	5807	5876	5978	7580	8019	7913	
Currency futures				34	40	34	37	42	32	37	
Stock market index futures				110	127	172	195	211	290	334	

Source: Bank of International Settlements (BIS) : Central Bank survey of foreign exchange and derivatives market activity 95 & 98, BIS Quarterly Reviews 1990-2001

[1] Daily average in billions of US dollars.
[2] Sourced from Futures Industry Associations, various futures and options exchanges
[3] Notional amounts outstanding in billions of US dollars
[4] US ranked second after UK as the second largest derivatives market activity location.

Appendix 6.5 Econometric Methodology

6.5.1 Stationary of individual time series

ADF test

The Augmented Dickey-Fuller (1979) ADF test assumes that the *y* series follows an AR (*p*) process and adds lagged difference terms of the dependent variable to the right hand side of the test regression as follows:

$$\Delta y_t = \alpha y_{t-1} + x_t{}'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + v_t \quad (1)$$

This is then used to test (using conventional t ratios[142])

$$H_0\colon \alpha = 0$$
$$H_1\colon \alpha < 0 \quad (2)$$

An important result obtained by the test is that the asymptotic distribution of the *t*-ratio for α is independent of the number of lagged first differences included in the ADF regression.

6.5.2 Panel Unit Root Tests

Panel unit root tests are similar, but not identical to unit root tests carried out on a single series. Firstly, classification of unit root tests is done on the basis of whether there are restrictions on the autoregressive process across cross-sections or series. Consider a following AR (1) process for panel data:

$$y_{it} = \rho_i y_{it-1} + X_{it}\delta_i + \epsilon_{it} \quad (3)$$

---

142 $t_\alpha = \hat{\alpha}/(se(\hat{\alpha}))$

, where i= 1,2,…N cross-section units or series, that are observed over periods t = 1,2,…T_i. X_{it} represent the exogenous variables in the model, including any fixed effects or individual trends, ρ_i are the autoregressive coefficients, and the errors ϵ_{it} are assumed to be mutually independent idiosyncratic disturbance. If $|\rho_i| < 1$, y_i, is said to be weakly trend-stationary. On the other hand, if $|\rho_i| = 1$, then, y_i contains a unit root. For purposes of testing, there are two natural assumptions that is made about the ρ_i. First, the persistence parameters are common across cross-sections so that $\rho_i = \rho$ for all i. The Levin, Lin, and Chu (LLC), Breitung, and Hadri tests all employ this assumption. Alternatively, one can allow ρ_i varying freely across cross-sections. The Im, Pesaran, and Shin (IPS), and Fisher-ADF and Fisher-PP tests are of this form.

- **Im, Pesaran, and Shin**

Im, Pesaran, and Shin (2003) began by specifying a separate ADF regression for each cross section:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X'_{it}\delta + \epsilon_{it} \tag{4}$$

The null hypothesis may be written as,

$$H_0: \alpha_i = 0, \text{ for all } i \tag{5}$$

, while the alternative hypothesis is given by:

$$H_1: \begin{cases} \alpha_i = 0 & \text{for } i = 1, 2, \ldots, N_1 \\ \alpha_i < 0 & \text{for } i = N+1, N+2, \ldots, N \end{cases} \tag{6}$$

(where the i may be reordered as necessary) which may be interpreted as a non-zero fraction of the individual processes is stationary. After estimating the separate ADF regressions, the average of the t-statistics for α_i from the individual ADF regressions, $t_{iT_i}(p_i)$:

$$\bar{t}_{NT} = \left(\sum_{i=1}^{N} t_{iT_i}(p_i) \right) / N \tag{7}$$

is then adjusted to arrive at the desired test statistics. In the case where the lag order is always zero $(p_i = 0 \text{ for all } i)$, simulated critical values for $\bar{t}_{NT}$ are provided in the IPS paper for different numbers of cross sections N, series lengths T, and for test equations containing either intercepts, or intercepts and linear trends (IPS, 2003). EViews uses these values, or linearly interpolated values, in evaluating the significance of the test statistics. In the general case where the lag order in equation 5 may be non-zero for some cross-sections, IPS shows that a properly standardized has an asymptotic standard normal distribution:

$$W_{\bar{t}_{NT}} = \frac{\sqrt{N}\left(\bar{t}_{NT} - N^{-1} \sum_{i=1}^{N} E(\bar{t}_{iT}(p_i)) \right)}{\sqrt{N^{-1} \sum_{i=1}^{N} Var(\bar{t}_{iT}(p_i))}} \rightarrow N(0, 1) \tag{8}$$

The expressions for the expected mean and variance of the ADF regression t-statistics, $E(\bar{t}_{iT}(p_i))$ and $Var(\bar{t}_{iT}(p_i))$, are provided by IPS for various values of *T* and *p* and differing test equation assumptions, and are not provided here.

- **Fisher-ADF**

An alternative approach to panel unit root tests, proposed by Maddala and Wu (1999), uses Fisher's (1932) results to derive tests that combine the *p*-values from individual unit root tests. If π_i is defined as the p-value from any individual unit root test for cross-section *i*, then under the null of unit root for all *N* cross-sections, the asymptotic result is:

$$-2 \sum_{i=1}^{N} \log(\pi_i) \rightarrow \chi^2_{2N} \tag{9}$$

In addition, Choi (2001) demonstrates that:

$$Z = \frac{1}{\sqrt{N}_i} \sum_{i=1}^{N} \Phi^{-1}(\pi_i) \rightarrow N(0, 1) \tag{10}$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function.

EViews reports both the asymptotic χ^2 and standard normal statistics using ADF individual unit root tests. The null and alternative hypotheses are the same as for the as IPS. For the ADF Fisher test, the exogenous variables must be specified for the test equations.

6.5.3 Lag optimization -Akaike Information Criteria (AIC)

The Akaike Information Criterion determines the model order *p* by minimizing an information theoretic function of *p*, AIC (*p*) and is defined as follows:

$$-2l/T + 2k/T \tag{11}$$

where l is the log likelihood, $l = -\frac{T}{2}(1 + \log(2\pi) + \log(\hat{\epsilon}'\hat{\epsilon}/T))$. The AIC is often used in model selection for non-nested alternatives—smaller values of the AIC are preferred. Other information criteria such as BIC form a useful class of indexes, as they penalize for the number of parameters, and thus consider the thriftiness of models. Although the information statistics have rather different origins, they all have a similar structure in that they involve the same information. Lower information index values indicate better fit (Wicherts and Dolan, 2004).

6.5.4 The GARCH (1,1) Model

A simple GARCH (1, 1) specification is as follows:

$$Y_t = X_t'\theta + \epsilon_t \tag{12}$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{13}$$

where: the mean equation given in Equation (12) is written as a function of exogenous variables with an error term. Since σ_t^2 is the one- period ahead forecast variance based on past information, it is called the *conditional variance*. The conditional variance equation specified in (13) is a function of three terms:

- A constant term: ω
- News about volatility form the previous period measured as the lag of the squared residual from the mean equation: ε_{t-1}^2 (the ARCH term)
- Last period forecast variance: $\sigma_{t-1}{}^2$ (the GARCH term)

The (1, 1) in GARCH (1, 1) refers to the presence of a first order auto regressive GARCH term (the first term in parentheses) and a first- order moving average ARCH term (the second term in parentheses). An ordinary ARCH model is a special case of a GARCH specification in which there are no lagged forecast variances in the conditional variance equation – i.e., a GARCH (0, 1). This is often interpreted in a financial context where an agent or trader predicts this period's variance by forming a weighted average of a long term average (the constant), the forecasted variance from the last period (the GARCH term) and information about volatility observed in the previous period (the ARCH term). If the asset return is unexpectedly larger, then the trader will increase the approximate value of the variance for the next period. This model is also consistent with the volatility clustering often seen in financial returns data, where large changes in returns are likely to be followed by further large changes.

There are two equivalent representations of the variance equation that may aid in interpreting the model:

- If the lagged variance on the right hand side of Equation (13) is recursively substituted, the conditional variance can be expressed as a weighted average of all the lagged squared residuals:

$$\sigma_t^2 = \frac{\omega}{(1-\beta)} + \alpha \sum_{j=1}^{\infty} \beta^{j-1} \epsilon_{t-j}^2 . \tag{14}$$

It can be observed that the GARCH (1, 1) variance specification is analogous to the sample variance but that it down weights more distant lagged squared errors.

- The error in the squared returns is given by $\upsilon_t = \varepsilon^2_{t-1} - \sigma_t^2$. Substituting for the variances in the equation the model can be written in terms of the error term as follows:

$$\epsilon_t^2 = \omega + (\alpha + \beta)\epsilon_{t-1}^2 + \upsilon_t - \beta\nu_{t-1}. \quad (15)$$

Thus, the squared errors follow a heteroskedastic ARMA (1, 1) process. The autoregressive root which administers the persistence of volatility shocks is the sum of α and β. In many applied settings, this root is very close to unity so that shocks die out rather slowly. If no ARCH effects exist, then, no GARCH effects can exist (Hamilton, 1989).

Moreover, higher order GARCH models, denoted GARCH (*q, p*), can be estimated by choosing either *q* or *p* greater than 1 where *q* is the order of the autoregressive GARCH terms and *p* is the order of the moving average ARCH terms, as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 \quad (16)$$

6.5.5 The Power ARCH (PARCH) Model

Taylor (1986) and Schwert (1989) introduced the standard deviation GARCH model, where the standard deviation is modelled rather than the variance. This model, along with several other models, is generalized in Ding et al. (1993) with the Power ARCH specification. In the Power ARCH model, the power parameter δ of the standard deviation can be estimated rather than imposed, and the optional γ parameters are added to capture asymmetry of up to order *r* as follows:

$$\sigma_t^\delta = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta + \sum_{i=1}^{p} \alpha_i (|\epsilon_{t-i}| - \gamma_i \epsilon_{t-i})^\delta$$

where $\delta > 0$, $|\gamma_i| \le 1$ for $i = 1, \ldots, r$, $\gamma_i = 0$ for all $i > r$, and $r \le p$. (17)

The symmetric model sets γ_i=0 for all *i*. Note that if $\delta = 2$ and γ_i=0 fo all *i*, the PARCH model is simply a standard GARCH specification. As in the previous models, the asymmetric effects are present if $\gamma \neq 0$. To estimate the Taylor-Schwert's model, for example, the order of the asymmetric terms is set to zero and δ to 1.

6.5.6 ARIMA theory

ARIMA (autoregressive integrated moving average) models are generalizations of the simple AR model that use three tools for modeling the serial correlation in the disturbance:

- The first tool is the autoregressive, or AR, term. The AR (1) model uses only the first-order term, but in general, higher-order AR terms can be used. Each AR term corresponds to the use of a lagged value of the residual in the forecasting equation for the unconditional residual. An autoregressive model of order *p*, AR (*p*) has the form:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \ldots + \rho_p u_{t-p} + \epsilon_t . \quad (18)$$

- The second tool is the integration order term. Each integration order corresponds to differencing the series being forecast. For instance, a first-order integrated component means that the forecasting model is designed for the first difference of the original series.

- The third tool is the MA, or moving average term. A moving average forecasting model uses lagged values of the forecast error to improve the current forecast.

For instance, a first-order moving average term uses the most recent forecast error. An MA (q) has the form:

$$u_t = \epsilon_t + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \dots + \theta_q\epsilon_{t-q}. \tag{19}$$

The autoregressive and moving average specifications can be combined to form an ARMA (p, q) specification:

$$\begin{aligned} u_t = {} & \rho_1 u_{t-1} + \rho_2 u_{t-2} + \dots + \rho_p u_{t-p} + \epsilon_t \\ & + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \dots + \theta_q\epsilon_{t-q} \end{aligned} \tag{20}$$

Although econometricians typically use ARIMA models applied to the residuals from a regression model, the specification can also be applied directly to a series. This latter approach provides a univariate model, specifying the conditional mean of the series as a constant, and measuring the residuals as differences of the series from its mean.

6.5.7 Principles of ARIMA Modeling (Box-Jenkins 1976)

In ARIMA forecasting, a complete forecasting model is set up by using combinations of the three building blocks described above. The first step in forming an ARIMA model for a series of residuals is to look at its autocorrelation properties. The next step is to decide what kind of ARIMA model to use. If the autocorrelation function dies off smoothly at a geometric rate, and the partial autocorrelations were zero after one lag, then a first-order autoregressive model is suitable. Otherwise, if the autocorrelations were zero after one lag and the partial autocorrelations fell geometrically, a first-order moving average process would seem appropriate. If the autocorrelations appear to have a seasonal pattern, this would suggest the presence of a seasonal ARMA structure.

The goal of ARIMA analysis is a simple representation of the process governing the residual. Only enough AR and MA terms should be used to fit the properties of the residuals. The Akaike information criterion and Schwarz criterion provided with each set of estimates may also be used as a guide for the appropriate lag order selection. After fitting a candidate ARIMA specification, verification is done to ensure that there are no remaining autocorrelations that the model has not accounted for. This is done by examining the autocorrelations and the partial autocorrelations of the innovations (the residuals from the ARIMA model) to see if any important forecasting power has been overlooked. EViews provides views for diagnostic checks after estimation.

6.5.8 Estimating ARIMA Models

EViews estimates general ARIMA specifications that allow for right-hand side explanatory variables. To specify ARIMA model:

• Dependent variable is differenced, if necessary, to account for the order of integration.

• Structural regression model is defined (dependent variables and regressors) and any AR or MA terms added.

Seasonal ARMA Terms

Box and Jenkins (1976) recommend the use of seasonal autoregressive (SAR) and seasonal moving average (SMA) terms for monthly or quarterly data with systematic seasonal movements. The lag polynomial used in estimation is the product of the one specified by the AR terms and the one specified by the SAR terms. The purpose of the SAR is to allow the formation of product of lag polynomials. Similarly, SMA (*q*) can be included in your specification to specify a seasonal moving average term with lag. The lag polynomial used in estimation is the product of the one defined by the MA terms and the one specified by the SMA terms. As with the SAR, the SMA term allows the building of up a polynomial that is the product of underlying lag polynomials.

For example, a second-order AR process without seasonality is given by,

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \epsilon_t , \tag{21}$$

which can be represented using the lag operator L, $L^n x_t = x_{t-n}$ as:

$$(1 - \rho_1 L - \rho_2 L^2) u_t = \epsilon_t . \tag{22}$$

A second-order MA process without seasonality may be written,

$$u_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} , \tag{23}$$

or using lag operators: $u_t = (1 + \theta_1 L + \theta_2 L^2) \epsilon_t .$ (24)

Adding a seasonal AR part, say, SAR (4) to equation (25) gives:

$$(1 - \rho_1 L - \rho_2 L^2)(1 - \phi L^4) u_t = \epsilon_t . \tag{25}$$

which is equivalent to :

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \phi u_{t-4} - \phi \rho_1 u_{t-5} - \phi \rho_2 u_{t-6} + \epsilon_t . \tag{26}$$

The parameter ϕ is associated with the seasonal part of the process. Note that this is an AR (6) process with nonlinear restrictions on the coefficients. Adding a seasonal MA part, say, SMA (4) to equation (25) gives:

$$u_t = (1 + \theta_1 L + \theta_2 L^2)(1 + \omega L^4) \epsilon_t \tag{27}$$

, which is equivalent to:

$$u_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \omega \epsilon_{t-4} + \omega \theta_1 \epsilon_{t-5} + \omega \theta_2 \epsilon_{t-6} . \tag{28}$$

ARMA Equation Diagnostics

-ARMA Structure

This set of views provides several diagnostic tests to assess the structure of the ARMA portion of the estimated equation. The view is currently available only for models specified by list that includes at least one AR or MA term and estimated by least squares. Only specifications for correlograms are displayed below.

1. **Correlograms**

The correlogram view compares the autocorrelation pattern of the structural residuals and that of the estimated model for a specified number of periods (recall that the structural residuals are the residuals after removing the effect of the fitted exogenous regressors but *not* the ARMA terms). For a properly specified model, the residual and theoretical (estimated) autocorrelations and partial autocorrelations should be "close".

Autocorrelations (AC)

The autocorrelation of a series Y at lag k is estimated by:

$$\tau_k = \frac{\sum_{t=k+1}^{T} (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{T} (Y_t - \bar{Y})^2} \tag{29}$$

, where $\bar{Y}$ is the sample mean of Y. This is the correlation coefficient for values of the series k periods apart. If τ_1 is nonzero, the series is first order serially correlated. If it declines more or less geometrically with increasing lag k, it is a sign that the series follows a low-order autoregressive (AR) process. If it drops to zero after a small number of lags, it is a sign that the series follows a low-order moving-average (MA) process.

Partial Autocorrelations (PAC)

The partial autocorrelation at lag k is the regression coefficient on Y_{t-k}, when Y_t is regressed on a constant, $Y_{t-1}, \ldots, Y_{t-k}$. This is a *partial* correlation since it measures the correlation of Y values that are periods apart after removing the correlation from the intervening lags. If the pattern of autocorrelation is one that can be captured by an autoregression of order less than k, then the partial autocorrelation at lag k will be close to zero. The PAC of a pure autoregressive process of order, AR (*p*) cuts off at lag *p*, while the PAC of a pure moving average (MA) process gradually asymptotes to zero. EViews estimates the partial autocorrelation at lag k recursively by:

$$\phi_k = \begin{cases} \tau_1 & \text{for } k = 1 \\ \dfrac{\tau_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\tau_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\tau_{k-j}} & \text{for } k > 1 \end{cases} \tag{30}$$

where τ_k is the estimated autocorrelation at lag k and where,

$$\phi_{k,j} = \phi_{k-1,j} - \phi_k \phi_{k-1,k-j}. \tag{31}$$

This is a consistent approximation of the partial autocorrelation. The algorithm is described in Box and Jenkins (1976). To obtain a more precise estimate of ϕ, simply run the regression:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \dots + \beta_{k-1} Y_{t-(k-1)} + \phi_k Y_{t-k} + e_t \tag{32}$$

, where ϵ_t is a residual. The dotted lines in the plots of the partial autocorrelations are the approximate two standard error bounds computed as $\pm 2/(\sqrt{T})$. If the partial autocorrelation is within these bounds, it is not significantly different from zero at (approximately) the 5% significance level.

6.5.9 Q-Statistics

The Ljung-Box Q test is based on the autocorrelation plot. However, instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags. That is why, it is often referred to as a "portmanteau" test (Giot, 2003). In fact, the Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k and is computed as:

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{\tau_j^2}{T-J} \tag{33}$$

, where τ_j is the j-th autocorrelation and is the number of observations. If the series is not based upon the results of ARIMA estimation, then under the null hypothesis, Q is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of autocorrelations. If the series represents the residuals from ARIMA estimation, the appropriate degrees of freedom should be adjusted to represent the number of autocorrelations less the number of AR and MA terms previously estimated.

The Q-statistic is often used as a test of whether the series is white noise. There remains the practical problem of choosing the order of lag to use for the test. If a too small lag is chosen, the test may not detect serial correlation at high-order lags. However, if a too large lag is chosen, the test may have low power since the significant correlation at one lag may be diluted by insignificant correlations at other lags. For further discussion, see Ljung and Box (1979).

6.5.10 Serial Correlation LM Test

As an alternative to the Q-statistics for testing serial correlation, the LM can be used. Unlike the Durbin-Watson statistic for AR (1) errors, the LM test may be used to test for higher order ARMA errors and is applicable whether or not there are lagged dependent variables. It is recommended over the Durbin Watson test statistic whenever there is the possibility that the errors exhibit autocorrelation. Besides, Bera and Jarque (1987) suggest two aspects of the LM test as being useful. First, this test has asymptotic power characteristics (asymptotically efficient) including maximum local asymptotic power on the basis of small sample properties. Second, computation of this test is easy: to calculate the LM statistic, only estimation under the null hypothesis is required.

The null hypothesis of the LM test is that there is no serial correlation up to lag order *p*, where is a *p* pre-specified integer. The alternative is ARMA(r, *q*) errors, where the number of lag terms *p*=max(*r*,*q*). Note that this alternative includes both AR (*p*) and MA (*p*) error processes, so that the test may have power against a variety of alternative autocorrelation structures (Godfrey, 1988). If the LM test is greater than the critical test value, the null hypothesis is rejected (Sadorsky, 2003).

The test statistic is calculated as follows. First, suppose the following regression is carried out:

$$y_t = X_t\beta + \epsilon_t \tag{34}$$

, where *b* are the estimated coefficients and ϵ are the errors. The test statistic for lag order *p* is based on the auxiliary regression for the residuals $e = y - X\hat{\beta}$:

$$e_t = X_t\gamma + \left(\sum_{s=1}^{p} \alpha_s e_{t-s}\right) + v_t . \tag{35}$$

Following the suggestion by Davidson and MacKinnon (1993), EViews sets any presample values of the residuals to 0. This approach does not affect the asymptotic distribution of the statistic, and Davidson and MacKinnon argue that doing so provides a test statistic that has better finite sample properties than an approach that drops the initial observations. This is a regression of the residuals on the original regressors and lagged residuals up to order *p*. EViews reports the Obs*R-squared statistic which is the Breusch-Godfrey LM test statistic. This LM statistic is computed as the number of observations, times the (uncentered) R^2 from the test regression. Under quite general conditions, the LM test statistic is asymptotically distributed as $\chi^2(p)$. Finally, the original regression may include AR and MA terms, in which case the test regression will be modified to take account of the ARMA terms.

6.5.11 Jacques Bera normality test statistic

Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution is computed as:

$$\frac{N-k}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{36}$$

, where S is the skewness, K is the kurtosis and k represents the number of estimated coefficients used to create the series.

Under the null hypohesis of a normal distribution, the Jarque – Bera statistic is distributed as X^2 with two degrees of freedom. The reported probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed under the null hypothesis- a small probability value leads to the rejection of the null hypothesis of a normal distribution at the 5% level but not at the 1% significance level.

6.5.12 ARCH LM Test

This is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). This particular specification of heteroskedasticity was motivated by the observation that in many financial time series, the magnitude of residuals appeared to be related to the magnitude of recent residuals. ARCH itself does not invalidate standard LS inference. However ignoring ARCH effects may result in loss of efficiency. The ARCH LM test statistic is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH up to order q in the residuals, the following regression is run:

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2\right) + v_t\,, \tag{37}$$

, where ε is the residual. This is a regression of the squared residuals on a constant and lagged squared residuals up to order *q*. Eviews reports two test statistics from this test regression. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. The Obs*R-squared statistic is Engle's LM test statistic, computed as the number of observations times the R^2 from the test regression. R^2 is the proportion of variability in the specific data series that is accounted for by the ARMA model. The exact finite sample distribution of the F-statistic unde H_0 is not known but the LM test statistic is asymptotically distributed $X^2(q)$ under quite general conditions. The ARCH LM test is available for equations estimated by least squared, two-stage squares and non-linear least squares.

6.5.13 Static forecasting

- **Static Forecasting**

Static forecasting performs a series of one-step ahead forecasts of the dependent variable and is computed always using the actual value of the lagged endogenous variable as follows:

$$\hat{y}_{S+k} = \hat{c}(1) + \hat{c}(2)x_{S+k} + \hat{c}(3)z_{S+k} + \hat{c}(4)y_{S+k-1} \tag{38}$$

Static forecasting requires that data for both the exogenous and any lagged endogenous variables be observed for every observation in the forecast sample. As above, EViews will, if necessary, adjust the forecast sample to account for pre-sample lagged variables. If the data are not available for any period, the forecasted value for that observation will be an NA. The presence of a forecasted value of NA does not have any impact on forecasts for subsequent observations.

6.5.14 Bias, variance, and covariance proportions of the forecast errors for the discrete-time models are discussed.[16]

[16]The mean squared forecast error can be decomposed as

$$\sum (\sigma_{f,t} - \sigma_t)^2/n = (\bar{\sigma}_f - \bar{\sigma})^2 + (S_f - S)^2 + 2(1 - \rho)S_f S$$

where $\bar{\sigma}_f$, $\bar{\sigma}$, S_f, and S are the means and standard deviations of σ_f and σ, respectively, and ρ is the correlation coefficient between and σ_f and σ. The proportions then are defined as

$$\text{Bias prop.: } \frac{(\bar{\sigma}_f^2 - \bar{\sigma}^2)^2}{\sum(\sigma_{t,f}^2 - \sigma_t^2)^2/n} \tag{39}$$

$$\text{, Variance prop.: } \frac{(S_f - S)^2}{\sum(\sigma_{t,f}^2 - \sigma_t^2)^2/n}, \tag{40}$$

$$\text{Covariance prop.: } \frac{2(1 - \rho)S_f S}{\sum(\sigma_{t,f}^2 - \sigma_t^2)^2/n} \tag{41}$$

where $\sigma^{-2}, \sigma_f^{-2}, S$ and S_t are the means and standard deviations of and , respectively, and ρ is the correlation coefficient σ_t^2 and $\sigma_{t,f}^2$ between σ_t^2 and $\sigma_{t,f}^2$. The bias proportion tells us how far the mean of the forecast is from the mean of the actual series. The variance proportion tells us how far the variation of the forecast is from the variation of the actual series. The covariance proportion measures the remaining unsystematic forecasting errors. The bias, variance, and covariance proportions must add up to one. If the forecast is good, the bias and variance proportions should be small so that most of the bias should be concentrated on the covariance proportion. One primary measure of forecasting ability is the root-mean-squared-forecast-error (RMSFE) measured in terms of the difference between actual and forecast annualized standard deviation of returns using GARCH/PARCH (Bracker and Smith, 1999). The root mean squared forecast error is then measured as:

$$\text{RMSFE} = \left[(1/M) \sum_{m=1}^{M} (AS(s)_m - FSTD(s)_m)^2 \right]^{1/2} \tag{42}$$

, where *FSTD*(*s*)*m* is the forecast standard deviation (also annualized) for an *s* day horizon beginning on day *m* using one of the four forecasting procedures outlined in the last section. *M* represents the number of forecast periods.

6.5.15 Theil inequality (model performance)

As an alternative to R^2 measures, the Theil inequality coefficient (TIC) is computed for the conditional variance of the different futures. The Theil inequality coefficient always lies between 0 and 1, where 0 indicates a perfect fit:

$$TIC = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\sigma_i^2 - \sigma_{i,f}^2)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\sigma_i^2)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\sigma_{i,f}^2)^2}} \quad (43)$$

, where σ_t^2 and $\sigma_{t,f}^2$ are the actual and forecasted values of squared return deviation. The *TIC* values describe the fit of the discrete-time models for the actual variance of the return change.

6.5.16 Skewness and Kurtosis

• **Skewness** is a measure of asymmetry of the distribution of the series around its mean. Skewness is computed as:

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{\hat{\sigma}}\right)^3 \quad (44)$$

, where $\hat{\sigma}$ is an estimator for the standard deviation that is based on the biased estimator for the variance $(\hat{\sigma} = s\sqrt{(N-1)/N})$. The skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail.

• **Kurtosis** measures the peakedness or flatness of the distribution of the series. Kurtosis is computed as:

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{\hat{\sigma}}\right)^4 \qquad (45)$$

, where $\hat{\sigma}$ is again based on the biased estimator for the variance. The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

Appendix 6.6: Other factors behind success of 1990s

- **1. Food and Energy Price Shocks**

One of the most important supply shocks in recent US history was the food and energy shocks of the 1970s which led to a rise in global inflation. In contrast, the low standard deviation of inflation in Mankiw (2001) supports that large supply shocks were uncommon in the 1990s. Moreover, the negative value for the average shock indicates that good shocks were more common than bad shocks. By contrast, the worst shock of the 1990s was less than one-fourth as large as those in the 1970’s. This shock occurred in 1990 as a result of the Gulf War. For the rest of the decade, there was no adverse food and energy shock as large as a full percentage point. Given these information, it is hard not to conclude that the macroeconomic success of the 1990s was in part due to luck. Food and energy prices behaved well, and the economy benefited from this stability.

- **2. The stock market**

Mankiw (2001) showed the performance of US financial markets were outstanding with low volatility and high returns. While low volatility in the stock market reflects low volatility in the overall economy, the high return reflects the surprising speeding up in productivity growth, which helped increase growth in company profits. See Mankiw (2001) for a detailed review of how stock markets also had a role to play in monetary policy in the 1990's.

- **3. Good medium term macroeconomic policy**

Good fiscal and monetary policies contributed significantly to the strong economic performance of the 1990s. Three key fiscal policy turning points included the 1990 budget agreement, the 1993 budget agreement, and the 1998-2000 preservation of the emerging unified budget surpluses for debt reduction. See Mankiw (2001) for more details on these three major fiscal policy implementations. For instance, the Federal state's movement from deficit to surplus resulted in a progress in net national saving between 1993 and 2000. This additional saving reduced long-term interest rates, thereby boosting private-sector domestic investment. In the same line of thought, the public had learned from the experience of the 1980s to be aware of politicians selling snake-oil tax cuts (Frankel and Orszag, 2002).

Monetary policy- The Clinton Administration made two contributions to monetary policy. Firstly, the elimination of the budget deficit allowed the Fed to lower interest rates. Secondly, the Clinton Administration's monetary policy was wholly led by the Fed. Complying to this policy is more complicated than it sounds. The political appeal is always strong to push the central bank toward an easier monetary policy. However, with amazingly few exceptions, the Administration held on to its self-imposed rule of silence[143]. With a skilful Fed, the lack of Administration interference worked.

[143] In particular, long before he was US Secretary Treasury, Lawrence Summers (1991) wrote, "the optimal inflation rate is surely positive, perhaps as high or 2 or 3 percent." Although Summers has never had direct control over monetary policy, Fed policymakers were well aware of the views of prominent Treasury

The truly noteworthy aspect of the 1990s was not just its low inflation, but, its low and steady inflation[144]. Like Paul Volcker before him, Greenspan followed a tight monetary yet moderated policy. His patience during 1995-1998, even as growth and employment exceeded levels previously considered inflationary, was a gamble; but it turned out to be a wise gamble and an important component of the expansion's durability (Frankel and Orszag, 2002).

4. Long-term factors

Many of the most fundamental factors in explaining US economic performance during the 1990s stretch back over at least two decades as follows:

- **Deregulation.** This started under Carter's Administration, with the deregulation in trucking, airline, natural gas and banking, followed by telecommunication under Reagan's term. More recently, further deregulation took place in the electricity market, and market-friendly environmental regulation, such as in the sulfur dioxide permit program (Frankel and Orszag, 2002). The overall effect of deregulation made the US economy more efficient in the long run. This was all possible with different Administration carrying on the work previous management has properly started.

- **Globalization**. With a policy of free trade since World War II, the ratio of trade to GDP has more than tripled since the middle of the twentieth century. Economic theory tells us that trade improves economic performance. This holds for both old trade theory (classical "comparative advantage") and of new trade theory (which allows for changing technology, increasing returns to scale, and imperfect

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officials. Moreover, nations that have adopted a policy of inflation targeting (which were common during the 1990s) have typically chosen a positive number, rather than zero, for their target.

[144] The 1990s look more exceptional once the standard deviation of inflation is looked at. Inflation was far more stable during the 1990s than during any other recent decade (Mankiw, 2001). The differences are substantial in magnitude. Inflation was only one-third as volatile during the 1990s as it was during the 1980s. It was 24 percent less volatile during the 1990s than it was during the 1960s, the second-best decade as ranked by inflation volatility. There is no doubt that by historical standards the 1990s were a decade of remarkably stable inflation. After January 1992, inflation remained in a remarkably narrow range from 1.34 percent to 3.32 percent (Mankiw, 2001).

competition). The empirical evidence showed that openness contributed to growth. Exports grew rapidly, a major selling point for international free trade policy (Frankel and Orszag, 2002). Moreover, increases in imports and in the trade deficit during the 1990s were a useful safety net during the strongest phase of the US expansion. They freed pressure from rapidly growing domestic demand, pressure that would otherwise have shown up as higher inflation and interest rates.

- **The Role of Luck-** Standard economic analysis divide shocks into two types. While demand shocks are those that alter the overall demand for goods and services, supply shocks are those that change the prices at which firms are willing and able to supply goods and services. Demand shocks were the easier type for the Fed to handle because they pushed output, employment, and inflation in the same direction. For instance, a stock market crash reduces aggregate demand, putting downward pressure on output, employment, and inflation (Frankel and Orszag, 2002). The standard reaction was for the Fed to lower interest rates by increasing the money supply. Supply shocks pose a more difficult problem. An increase in the world price of oil, for instance, raises firms' costs and the prices they charge, which tends to raise inflation and push the economy toward recession. The Fed then had to choose between contracting policy to fight inflation and expanding policy to battle recession. In the face of supply shocks, the Fed can not stabilize inflation and the real economy at the same time, forcing a tradeoff between inflation stability and employment stability (Frankel and Orszag, 2002). Yet during the 1990s the US economy enjoyed stability of both kinds. One possible reason is dumb luck. Perhaps the economy just did not experience the supply shocks that caused so much turmoil in earlier decades.

Appendix 6.8.1: Reportable positions

Reportable Positions - Futures commission merchants, clearing members and foreign brokers (collectively called "reporting firms") file daily reports with the Commission, showing futures and option positions of traders that hold positions above specific reporting levels set by CFTC regulations. (Current Commission reporting levels can also be found at the Commission's website http://www.cftc.gov/cftc/cftclawreg.htm). In any market, the total of all traders' positions reported to the Commission usually represents 70 to 90 percent of the total open interest. Regularly, the Commission will change the reporting levels in specific markets to hit a balance between collecting sufficient information to oversee the markets and minimizing the reporting burden on the futures industry.

Appendix 6.8.2: Classification among entities

A trader can be classified as a commercial in some commodities and as a non-commercial in other commodities. A single trading body can not be classified as both a commercial and non-commercial in the same commodity. Nevertheless, a multi-functional organization that has more than one trading body may have each trading entity classified separately in a commodity.

Appendix 6.9

<u>Event 1 (US Tightening of Interest rates)</u>

- **MONETARY POLICY AND INTEREST RATES IN THE SHORT RUN**

Fed Reserve Policy Changes in 1990s (after first tightening in 1994)

Table 5.1
Fed reserve policy changes in the 1990s

			Date of Change		Days Since Previous Change	Change In Fed Funds	New Rate Levels Fed Funds	New Rate Levels Discount
	Duration (in months)	12	1994	4-Feb	518	25	3 1/4	n/c
	Number of moves:	7		22-Mar	46	25	3 1/2	n/c
	Cumul. change in Fed Funds:	300		18-Apr	27	25	3 3/4	n/c
				17-May	29	50	4 1/4	3 1/2
				16-Aug	91	50	4 3/4	4
				15-Nov	91	74	5 1/2	4 3/4
			1995	1-Feb	78	50	6	5 1/4
Easing:	Duration (in months)	7		6-Jul	155	-25	5 3/4	n/c
	Number of moves:	3		19-Dec	166	-25	5 1/2	n/c
	Cumul. change in Fed Funds:	-75	1996	31-Jan	43	-25	5 1/4	5
Tightening:	Duration (in months)	13	1997	25-Mar	419	25	5 1/2	n/c
	Number of moves:	1						
	Cumul. change in Fed Funds:	25						
Easing:	Duration (in months)	2	1998	29-Sep	553	-25	5 1/4	5
	Number of moves:	3		15-Oct	16	-25	5	4 3/4
	Cumul. change in Fed Funds:	-75		17-Nov	33	-25	4 3/4	4 1/2
Tightening:	Duration (in months)	9	1999	30-Jun	225	25	5	n/c
	Number of moves:	6		24-Aug	55	25	5 1/4	4 3/4
	Cumul. change in Fed Funds:	175		16-Nov	84	25	5 1/2	5
			2000	2-Feb	78	25	5 3/4	5 1/4
				21-Mar	48	25	6	5 1/2
				16-May	56	50	6 1/2	6

Source: Board of the governors of the Federal Reseve System and Commodity Research Bureau

- **Monetary policy**

The importance of the Federal Funds rate[145] is indicated by the fact that since 1983 the Federal Reserve has targeted the Federal Funds rate (Patelis, 1997). Events related to monetary policy changes were the most significant economic factor leading to changes in exchange rates in the 1990s (Lobo, 2002). Lagged values of the Federal Funds rate volatility are important determinants of stock return volatility where stock return volatility is calculated from monthly stock return data. Some of these results can be attributed to the fact that conditional stock market volatility estimated from monthly data (rather than daily data) tends to be more highly correlated with the conditional volatilities of the macroeconomic factors (Sadorsky, 2003).

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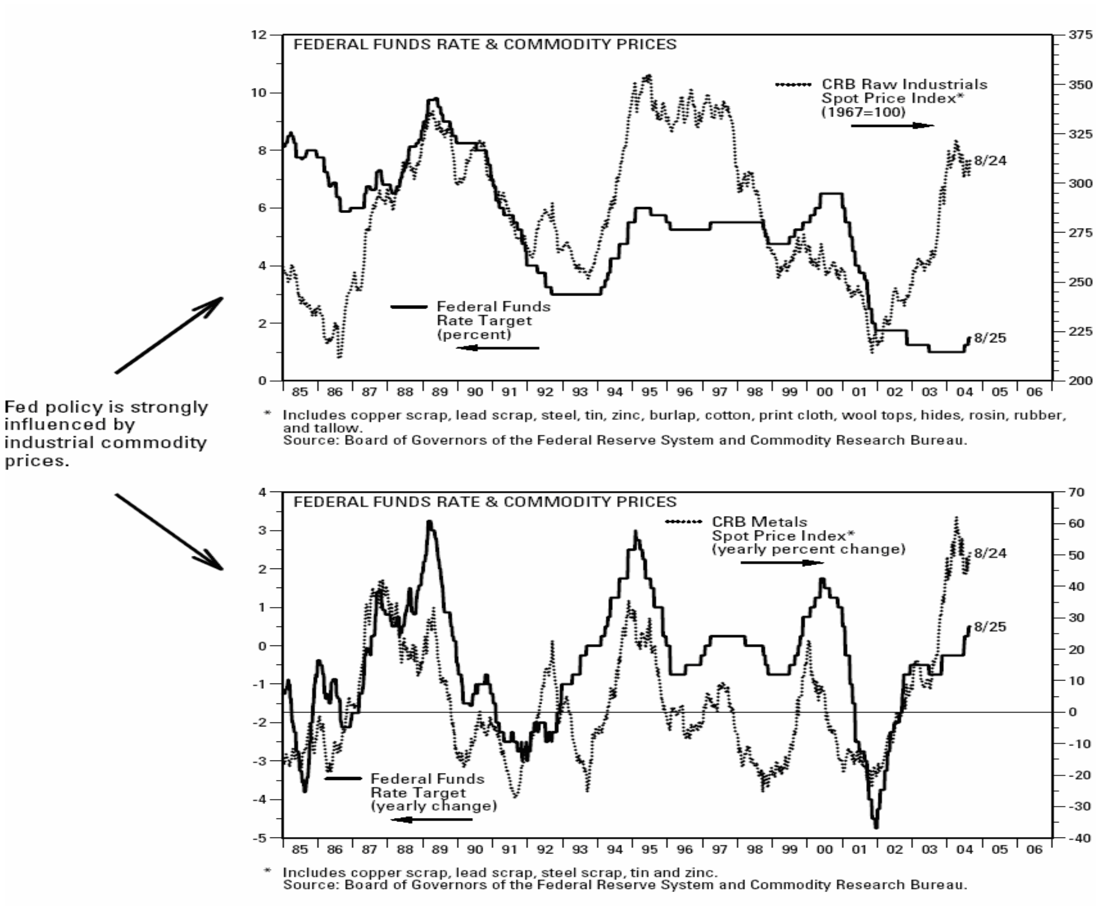
[145] See graph 5.2 and 5.3.

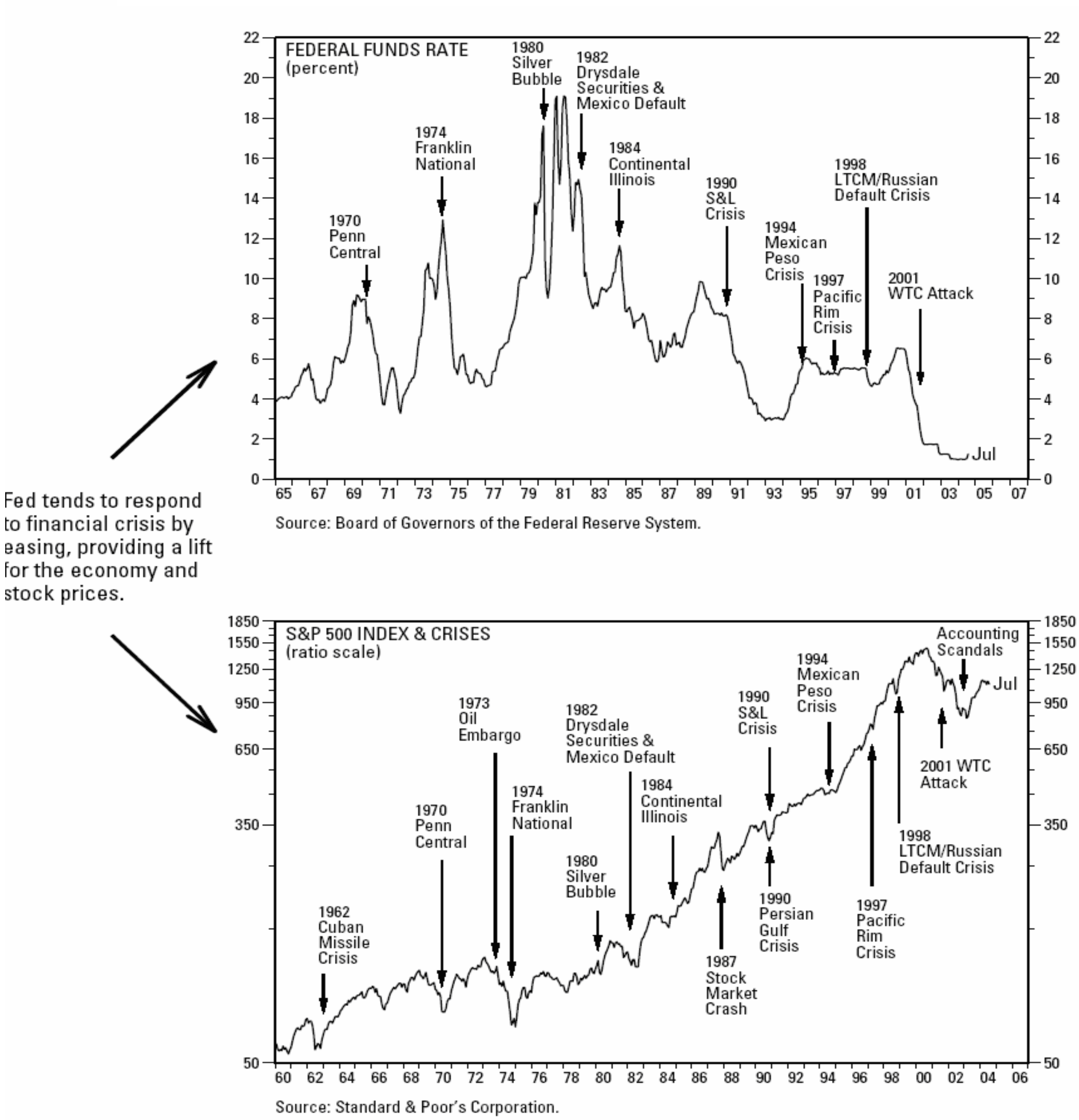
- **Fed funds rate and Commodity prices**

Graph 5.2
Fed funds rate and commodity prices



- **Fed funds rate and financial crisis**

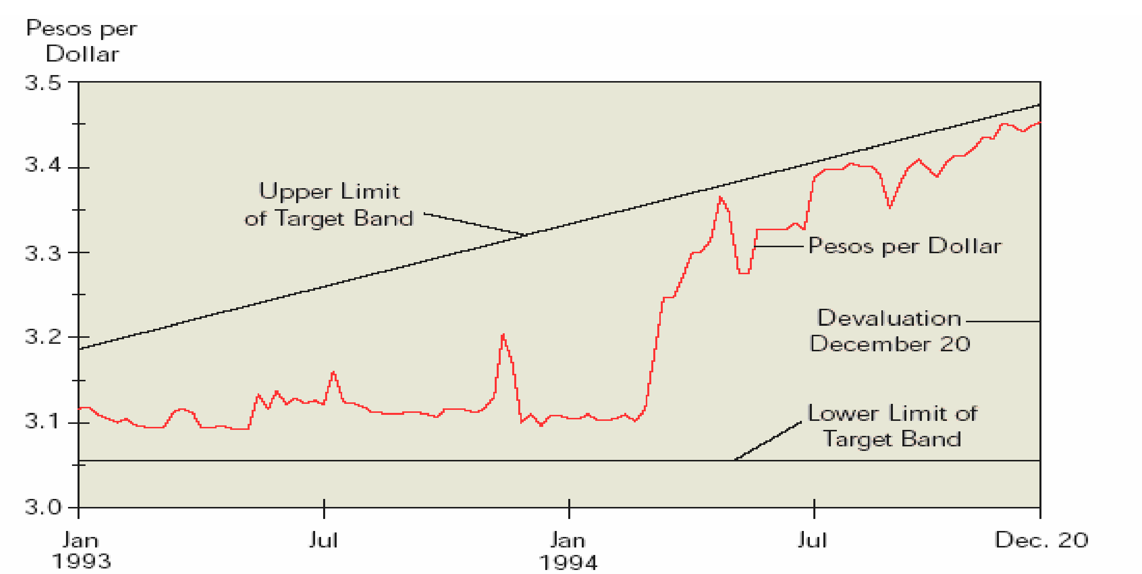
Graph 5.3
Federal Funds rate and Financial Crisis



Event 2: Mexico Crisis

In the early 1990s, the Mexican economy appeared vigorous. It was growing again after the "lost decade" of the 1980s, when the 1982 debt crisis and the 1986 collapse of oil prices sent the economy booming (Whitt, 1996). Inflation fell considerably, foreign investors were putting money into the country, and the central bank had accumulated billions of dollars in reserves (Whitt, 1996). Moreover, North American Free Trade Agreement (NAFTA) reduced trade barriers between US and Mexico's. Less than twelve months after NAFTA took effect in 1994, Mexico faced economic disaster where the Mexican government devalued the local currency. This sent inflation soaring and set off a severe recession in Mexico. The main factor was Mexico's current account deficit, which jumped from $6 billion in 1989 to $15 billion in 1991 and to more than $20 billion in 1992 and 1993 (Whitt, 1996). To some extent, the current account deficit was a favourable development, reflecting the capital inflow stimulated by Mexican policy reforms. However, the large size of the deficit led some observers to worry that the peso was becoming overvalued, a circumstance that could discourage exports, stimulate imports, and lead eventually to a crisis. Backed by a crawling peg system, the state intervention kept the exchange rate against the dollar within a narrow target band, but the upper limit (see Graph 5.4) of the band was raised slightly every day by a pre-announced amount, allowing for a gradual nominal depreciation (a "crawling peg") of the peso (Whitt, 1996).

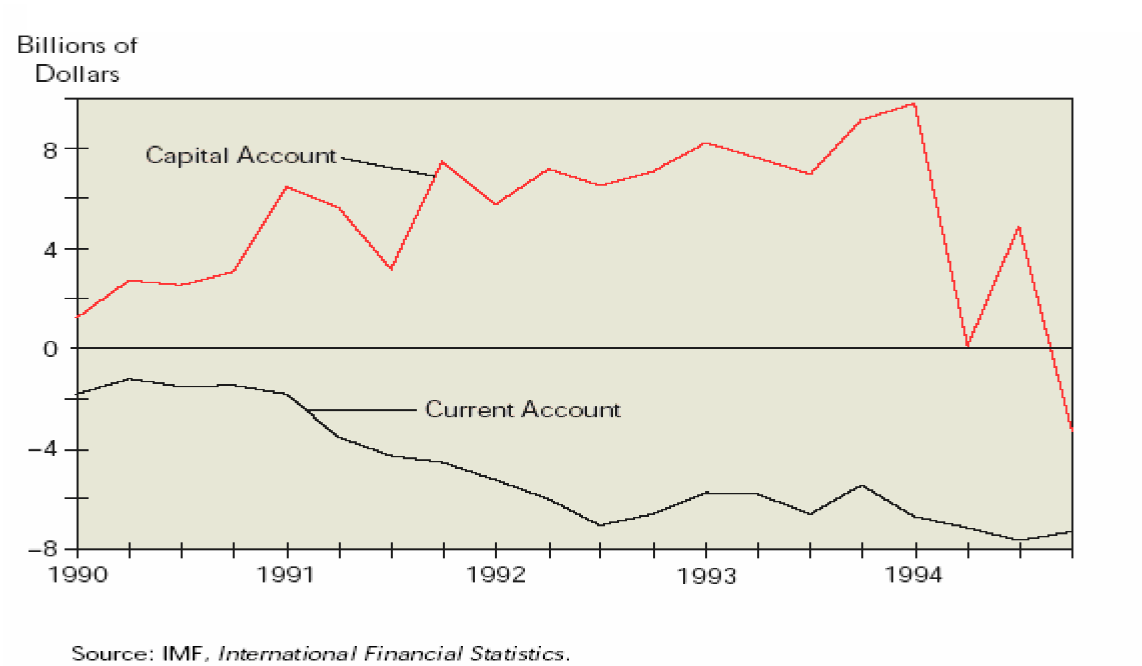
Graph 5.4
Mexican exchange rate and target band prior to devaluation (Jan 93-Dec 94)



Source: IMF, *International Financial Statistics.*

However, in real (price-adjusted) terms, the peso was gaining value, contributing to the increasing current account deficit as seen in Graph 5.5.

Graph 5.5
Mexico current and capital account (Quarterly data)



Mexico Political instability and foreign reserves

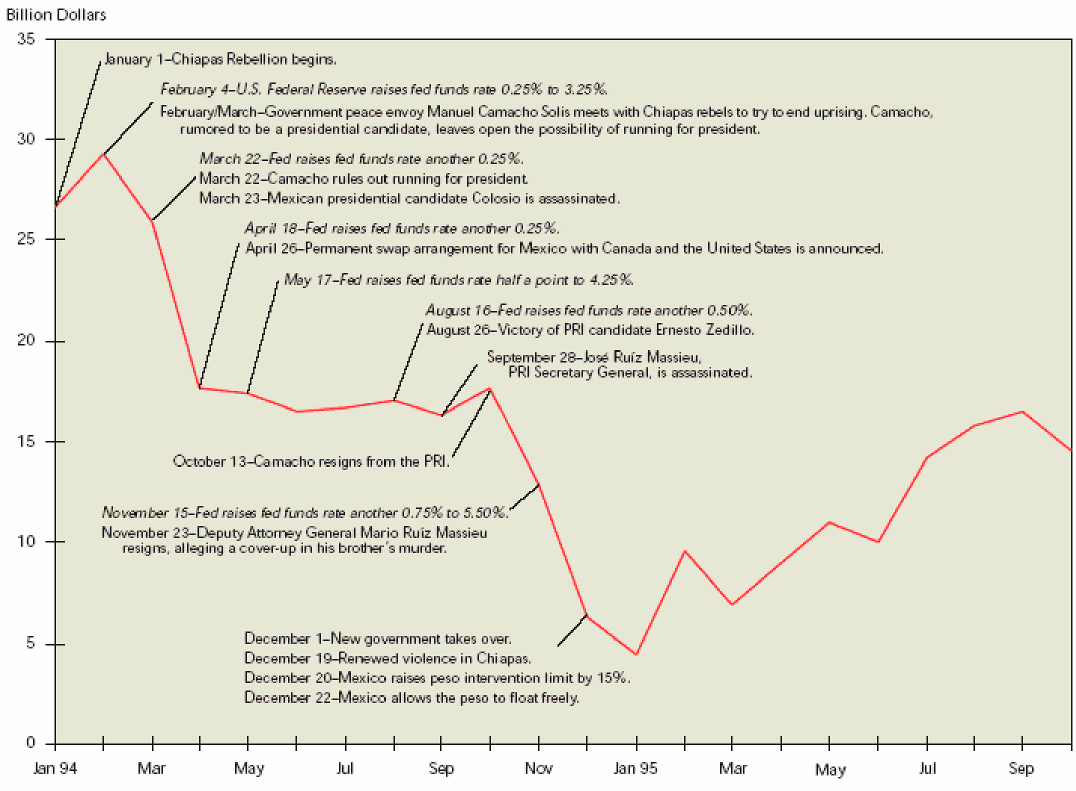
In early January 1994, Mexico experienced major political instability (See Graph 5.6 for a chronology of political events and monetary policy actions during 1994). This set off a minor financial crisis that preceded the major crisis by roughly nine months. With disturbed confidence among investors, this created immediate difficulties for Mexican banks and put downward pressure on the dollar price of the peso. The government reacted by selling huge quantities of foreign exchange reserves and allowing domestic interest rates to increase sharply (Whitt, 1996). These moves seemed to be successful, in the sense that the government was able to defend its peso peg without draining its foreign exchange reserves (which were, however, greatly reduced; see Graph 5.6 below).

Panic and Crisis

Starting to lose confidence in the economy, investors reacted by committing less or no funds to Mexico. The supply of foreign funds started to shift back in November, and the government was again forced to sell large amounts of reserves. By December 20 the reserves were nearly exhausted, and the government responded by devaluing the peso by 15 percent (Whitt, 1996). Paradoxically, in the weeks and months following the crisis it became clear that the various threats to Mexican political stability were considerably less serious than they had appeared in November and December of 1994. The basic cause of the crisis was the political turmoil[146] in Mexico that led foreign lenders to become concerned about the fate of their investments. It is the nature of political crisis however that often seemed far more serious at the time they break out than they do a few weeks or months later (Mathur et al., 2002).

[146] Furthermore, investors considered the replacement of a significant amount of short-term debt with "tesebonos"- securities convertible to US dollars at maturity- as a troubling sign regarding confidence in the Peso (Mathur et al., 2002).

Graph 5.6
Mexican foreign reserves (Jan 1994-1995)



Source: Reuters News Service, Haver Analytics, and International Monetary Fund.

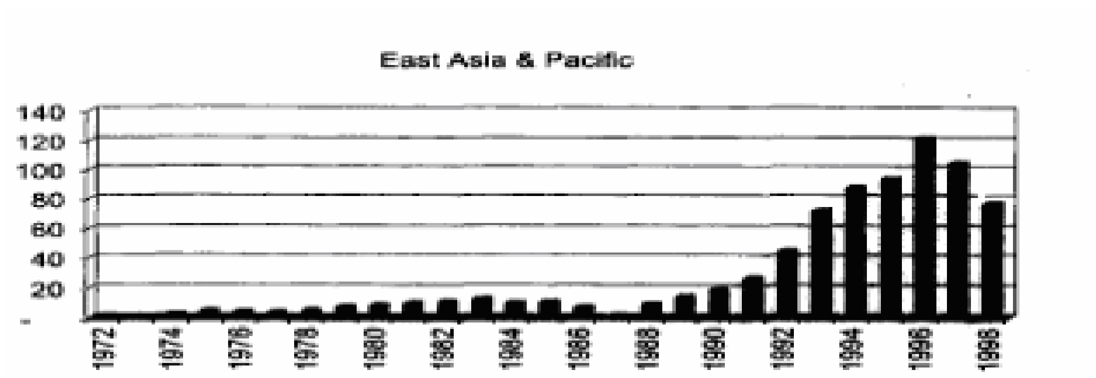
Event 3: Asian Crisis

Growth began to slow in a number of Asian economies in the 1990s—a reaction to shocks such as the devaluation of the Chinese currency in 1994, the depreciation of the Japanese yen against the dollar in 1995, and falling semiconductor prices. However, the belief was that East Asia was basically healthy, and that a "soft landing" could be fruitfully implemented (Radelet and Sachs, 1998). The collapse of the Thai baht in July 1997 brusquely interrupted this picture, starting a wave of depreciation and stock market declines. During the second part of 1997, the value of the most affected East Asian currencies had fallen 33%-75% against the US dollar. Stock indices also declined sharply after June 1997, falling 36 percent in Indonesia, 43 percent in Korea and 22 percent in Thailand through April 1998. Measured from their peaks earlier in the 1990s, the stock price declines have been far sharper in Korea and Thailand. Disturbance in bank balance sheets resulted in the closure of financial institutions and the bankruptcies of numerous firms, as well as a break in credit flows in most affected economies (Radelet and Sachs, 1998). Thus, while collapsing pegs are expected to improve output in the medium term, short-term economic activity has slowed radically in the most affected economies, and interest rates have risen due to uncertainty of investors. All these resulted in a revised reduced forecast of East Asian growth in 1998, compared to the forecasts made when the crisis began in July 1997. For instance, the mean forecast of Indonesian 1998 GDP fell from *growth* of 7.6 percent for the forecasts made in July 1997, to a *contraction* of 7.8 percent for the forecasts made in May 1998[147] (Moreno et al., 1998).

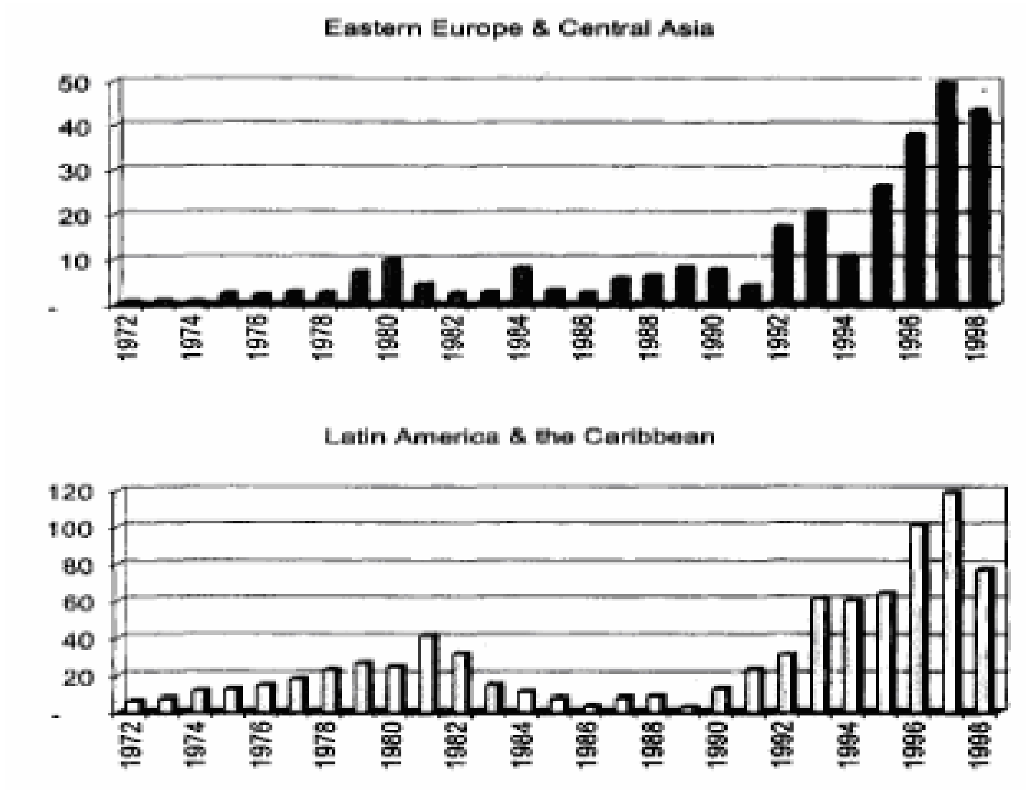
Event 4: Emerging Markets Recovery

Perhaps the best way to look at EM recovery is to picture the rising trend in capital flows for emerging economies (Kaminsky et al., 2001), as shown in Graph 5.7:

Graph 5.7
Total net private capital flows to developing countries
(Billions of US dollars)



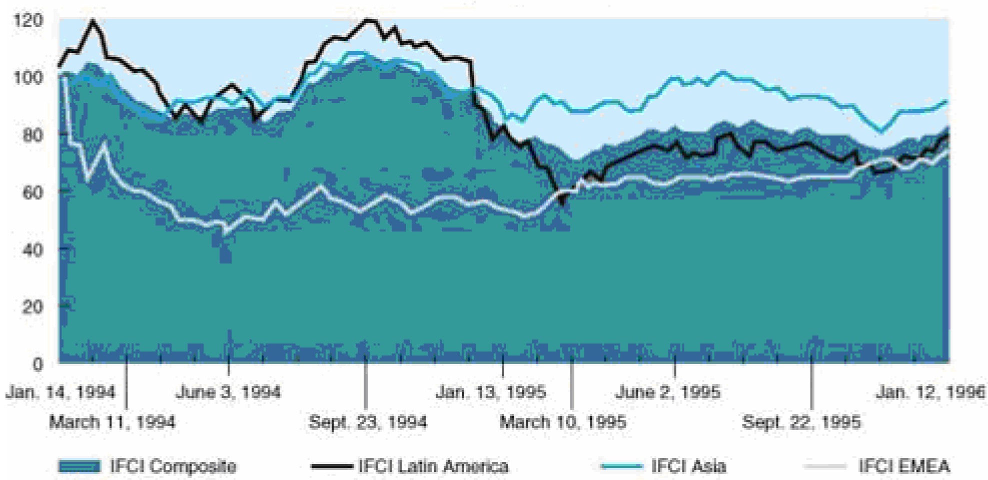
[147] Cheng, Fung, and Chan (2000) argue the crisis took place from January 1996 to June 1997.



Source: World Bank

Graphs 5.7 shows net capital flows towards developing countries, including bank and trade-related lending, bond and portfolio equity flows, and foreign direct investment. Through its Emerging Markets Database, IFC monitors the performance of more than 1,600 stocks in 27 developing countries. Using a random number of stocks in each market, IFC calculates daily, weekly, and monthly indexes of stock market performance that are consistent across national boundaries (Littler and Maalouf, 1996). This is shown in Graph 5.8.

Graph 5.8
Emerging stock market rebounding after decline in 1995
Changes in IFC Index (Jan 94-96, US dollars)
(Jan 14, 1994 =100)



Source: World Bank

As shown in the graph above, emerging markets recovered after declines in 1995. The most outstanding feature of emerging market performance in 1995 was the fall of Latin America's stock markets. Generally, the IFCI Latin America Index lost 19 percent in 1995, despite a rebound in December (Littler and Maalouf, 1996). As the year started, share prices in Latin America fell; the IFCI Mexico Index lost 32 percent in January and another 18 percent in February, among concerns about the stability of Mexico's banking system, an uncertain outlook for the peso, the impact of interest rate increases on economic growth and company solvency, and a nervous political situation. Latin America's market recovered shortly in April, caused in part by views that Mexico's economic situation was stabilizing and by the Chilean government's easing of limits on equity investments by pension funds. By August, however, share prices started to fall again, the result of fresh concern about Mexico, talk about higher taxes in Brazil, and a political crisis in Colombia. The IFCI Latin America Index stayed down in the dumps until December, when it gained 1.8 percent, attributed largely due to increases in the IFCI Indexes for Argentina, Colombia, and Venezuela (Littler and Maalouf, 1996).

The IFCI Asia Index was heading downhill with only 7 percent for the year, as a gain of 4.4 percent in December compensated losses in some markets during the earlier part of the year. A number of markets had recorded gains in the spring--elections in the Philippines boosted the IFCI Index for that country, and China's stock market surged in response to a government ban on trading in bond futures--but prices began to drop again in August (Littler and Maalouf, 1996). The IFCI Indexes for the Philippines and China were down 12.9 percent and 22.7 percent, respectively, at the end of the year. Although the IFCI Index for the Republic of Korea resisted the downward trend in the fall—personal income and company tax cuts and rising foreign investor interest led to a 9 percent gain in September--it still fell 7.9 percent for the year. Despite a gain of 8.2 percent in the last month of the year, the IFCI Index for Taiwan Province of China was down 31.5 percent as the year closed (Littler and Maalouf, 1996). Pakistan, where share prices climbed 11.2 percent in December, could not avoid losses due to political confusion earlier in the year; its market registered a net loss of 33.7 percent. Nevertheless, the year ended on a positive note. Losses in many markets were reduced by the rebound in December, which was fueled by attractive stock valuations, improved political and economic conditions in many countries, and optimistic equity markets and declining bond yields in industrial countries (Littler and Malouf, 1996).

Event 5: Japanese Recession

Subsequent to the asset bubble burst in early 1990, Japanese growth gradually deteriorated through the first half of the 1990s, rebounded briefly at mid-decade, but has been generally weak since then. The economy led CPI downward, falling below zero in 1995. As such, Japanese short-term interest rates were lowered nearly to zero by late 1995 and have stayed close to zero ever since. However, with prices declining, real interest rates remained positive, thereby restraining growth. The balance-sheet problems of corporate borrowers led to a weakening in loan performance and in the financial strength of the banking system.[148] Owing both to weaknesses in the Japanese supervisory system and to embed practices among Japanese bankers, Japanese banks failed to resolve their non-performing loans problems and sufficiently recapitalize themselves. The sustained fragility of the banking system, then, has limited its capacity to extend new

[148] See, *inter alia*, Hoshi and Kashyap (2000), Friedman (2000).

loans and sustain economic recovery.[149] All of these factors weighed heavily on growth, which declined from nearly 5 percent in 1990 to nearly zero in both 1992 and 1993. In addition, the yen reinforced considerably starting in early 1990, contributing to the falloff in economic activity and posing further downward pressure on prices. Twelve-month CPI inflation fell to almost 1 percent by the close of 1993, while the growth of the GDP deflator fell off even more rapidly. Few observers expected the slowdown to be as deep and protracted as it turned out to be. With a temporary revival of growth, starting in mid-1994 and extending through 1996, that undercut the need for further stimulus in the eyes of many policymakers (Ahearne et al., 2002).

With the Asian financial crisis in 1997-98, the economy once more fell into a protracted slump[150], interrupted only briefly by the high-tech boom in 2000. Moreover, inflation after briefly becoming negative in 1995 (partly due to a sharp temporary surge in the yen) and then moving up slightly in 1996 and 1997, has been consistently negative since September 1999 (Ahearne et al., 2002). In fact, hampered with a huge volume of bad debt aggravated by still-falling land prices, financial organizations squeezed their lending policies, thereby forcing companies to reduce plant and equipment investments. This, together with falling exports caused by the Asian economic crisis, resulted in lower profits in almost all industries. Finally, but not least, studies using average growth rate or deviation from trend output showed that, though the initial decline in Japan was much milder than US Great Depression, slow down in output growth has persisted longer (Iwaisako,2000).

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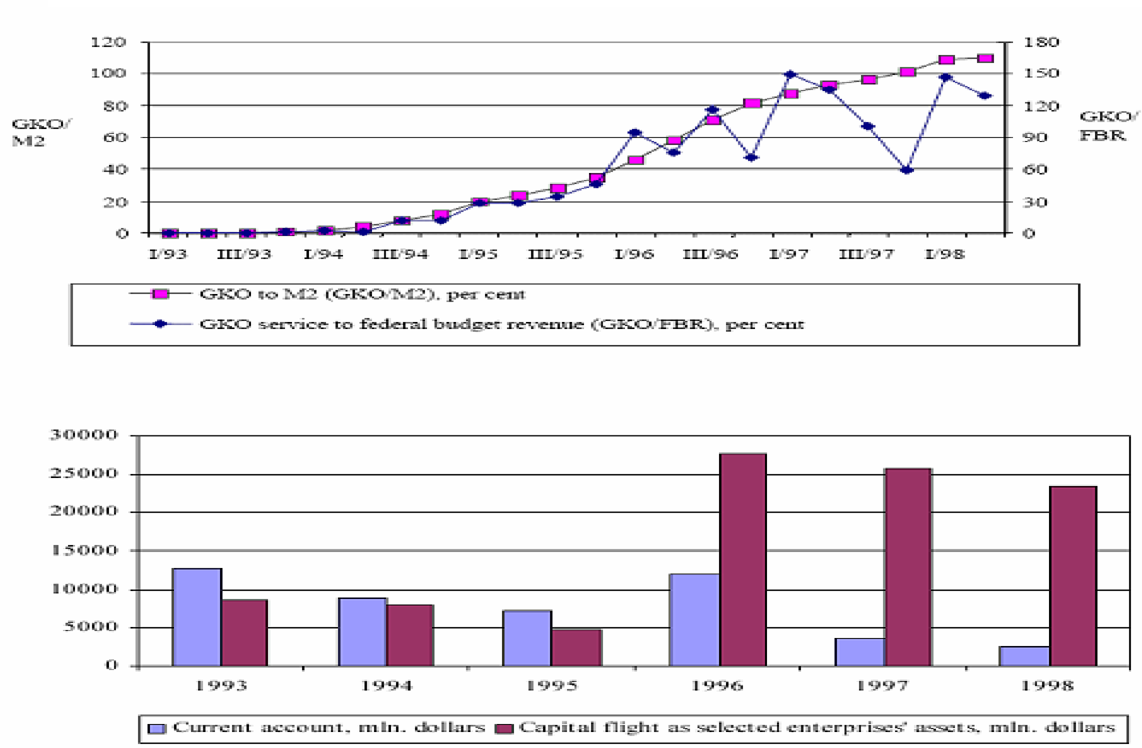
[149] Bayoumi (2000) presents evidence that real economic activity in Japan was affected, via bank lending, by movements in assets prices.

[150] In fact, under the supposition that by the year 1996 the Japanese economy had already got over the recession caused by the bubble burst in the asset markets, the Japanese government changed from an expansionary to a contractionary policy, so that the cumulative debts of the government might be reduced. However, the introduction of the policy such as increasing the consumption tax rate from 3 % to 5 %, abolition of temporary income tax cuts, and increase in the medical insurance burden, caused the GDP growth back to zero or negative in 1997 and 1998 (Shinjo, 2002).

Event 6: Russian crisis

The ratio of local debt servicing costs to federal budget revenues exceeded 100% in the third quarter of 1996, in 1997 (excluding the fourth quarter) and in the first half of 1998 (Stroutchenevski, 1999). Therefore, due to short-maturity of domestic debt, Russian government found itself in a very uncomfortable position already in the end of 1996 as shown below. The Russian government was in a debt trap and could not cover the debt itself (Stroutchenevski, 1999). Moreover, high interest rates made the Russian bond market attractive to foreign investors and financial liberalization made the bond market accessible. Non-residents were allowed to invest in government treasuries (GKOs) at the end 1996. Despite of the huge capital inflows; the price for this was the dependence of the local market upon the mood swings of foreign investors as shown in Graph 5.9. When the investors were skeptic about the government to repay its debts, capital inflows ended and the financial system collapsed eventually (Stroutchenevsk, 1999).

Graph 5.9
Growth of GKO Debt, current account surplus and capital flight



Source: CBR

Event 7: LTCM

What sunk Long-Term Capital Management (LTCM) is that it has expected worst-case situations where it would lose $2 billion out of its $5 billion in capital .[151] In fact, LTCM's problem was that, once it lost this money, it could not settle other positions due to their enormous size (LTCM had more than $1250 billion in derivatives notional, or 2.5% of the global swap market and 6% of the global futures market). Furthermore, once it had announced its loss, it was unable to raise more capital. This can be equally attributed to LTCM's lack of transparency. Investors may well be keen to trust blindly a winning strategy, but certainly not a losing strategy (Jorion, 2000).

Event 8: The introduction of the Euro Currency

1. Financial markets

The introduction of the euro as the only currency of twelve member countries has eliminated exchange risk for cross-border investments throughout most of the Union. It also has the effect of creating large, deep and liquid euro-denominated financial markets, which should help to deliver higher rates of sustainable output growth and employment creation in the EMU economy (BIS, 1999). Upon deciding to carry out euro-area monetary policy in euro, ECB brought about instant amalgamation of the unsecured segments of the market, mainly the inter-bank market and the short-term derivatives market. The perseverance of different issuing instruments and techniques among the 12 independent government debt issuers remains a source of fragmentation. Nevertheless, the market is share more similar features than before 1999 (BIS, 1999). The non-government segments of the euro-area bond market have also prospered in EMU. Probably a major development has been the rapid growth in the euro-denominated corporate bond market, which has increased several-fold in size and is now characterised by issues of above EUR 1 billion. EMU has also encouraged integration in EU equity markets, where structural developments have been dominated by a series of high-profile

[151] See Jorion (2000) for risk management lessons from the LTCM disaster.

mergers and attempted mergers. Finally, but not least, in the derivatives industry, the launch of the euro had somewhat distinct implications for organised exchanges and over-the-counter (OTC) markets in the first quarter of 1999. Anticipation of the single currency had given rise in 1998 to a contest of new contracts among exchanges. The Euribor contract and the bund contract at Eurex at LIFFE were the clear winners, as liquidity played in their favour (BIS, 1999).

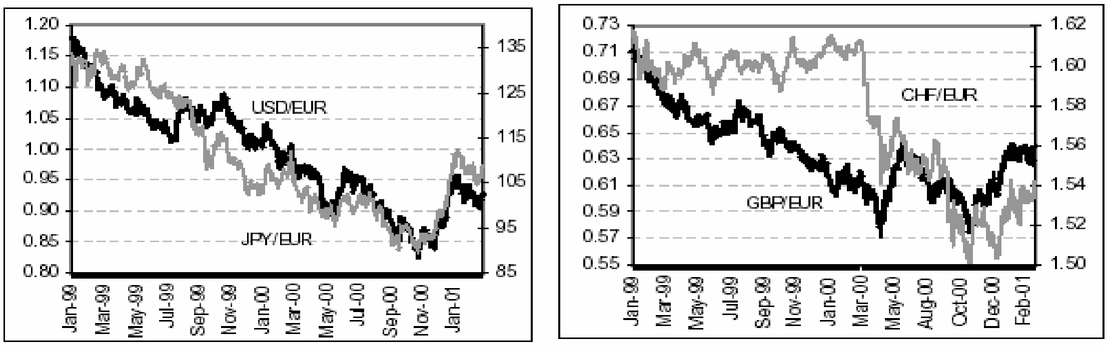
2. The euro exchange rate and external aspects of EMU

Developments in the exchange rate of the euro, particularly against the US dollar, have attracted massive public opinion, policy makers and the media. The first two years of the existence of the euro, as seen in Graph 5.10, have been characterised by a strong depreciation against all major world currencies. The depreciation continued until autumn 2000, when, following several rounds of official intervention and changes in the international economic outlook, the euro started a recovery (BIS, 1999). By the end of 2000, the nominal effective exchange rate of the euro was 13% lower than at launch[152]. The real depreciation was larger (17%), as a result of lower cost inflation in the euro area than (on average) in its trading partners. Most of the fall in the euro's exchange rate in 1999 can be explained by its relatively high initial value, subsequent the appreciation of the participant currencies in the second half of 1998, and by the surprising buoyancy of the US economy which contrasted with uncertain prospects for the euro-area economy. At that time, the current and anticipated growth differential warranted a depreciation in the euro against the dollar both via its impact on market expectations for interest rates in the US and in the euro area, and via the accessibility of better investment opportunities in the US than in the euro area (BIS, 1999).

---

[152] The nominal and real effective exchange rates of the euro are measured against the currencies of 13 industrialised countries (Australia, Canada, Denmark, Greece, Japan, Mexico, Sweden, Switzerland, New Zealand, Norway, Turkey, UK and US). The real effective exchange rate is based on unit labour costs in the whole economy.

Graph 5.10
USD/EUR, JPY/EUR, GBP/EUR, CHF/EUR after the introduction of the Euro currency



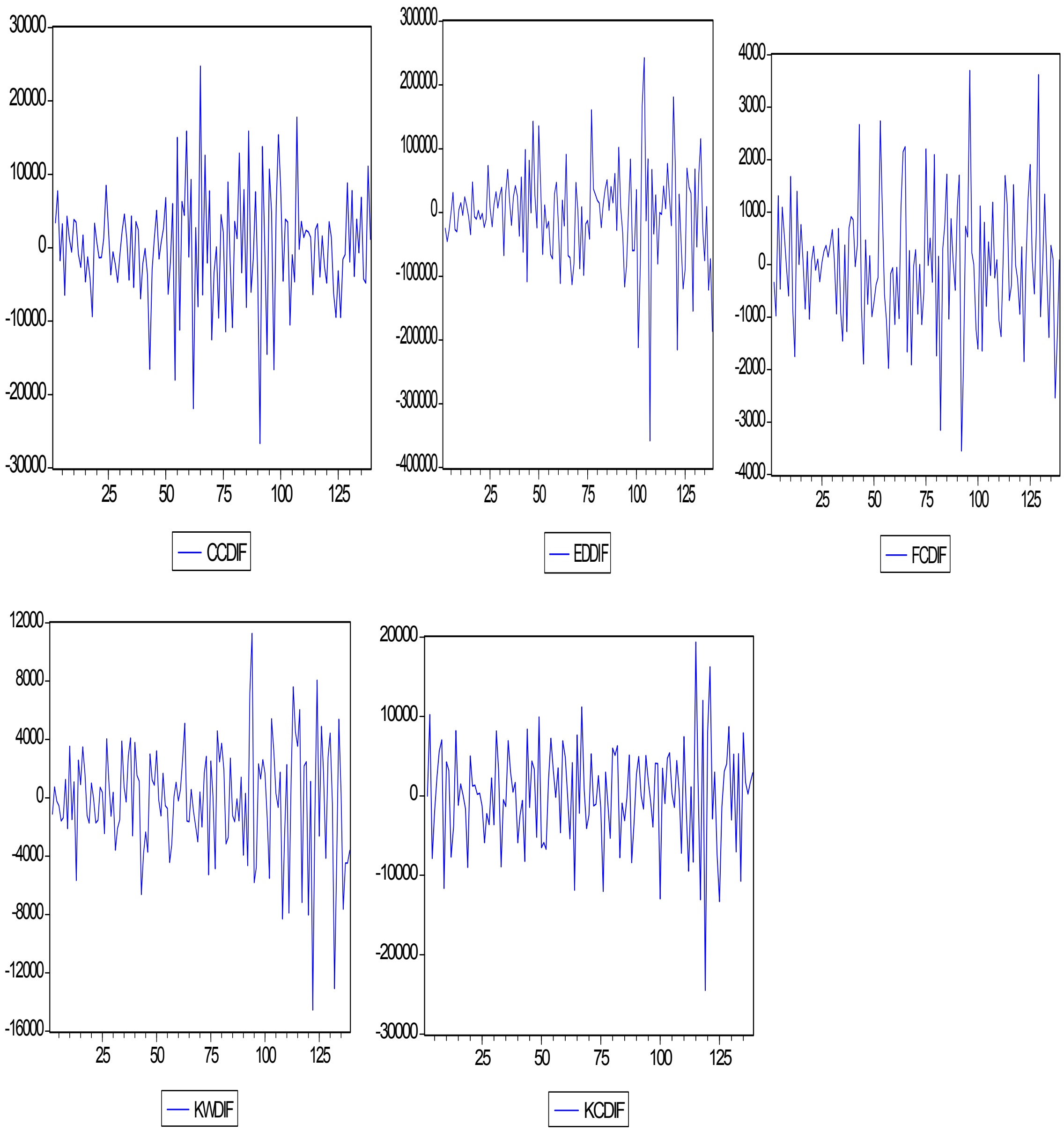
Source: BIS (1999)

By the second half of 2000 a consensus had emerged in international institutions, central banks and in most of the private sector that the depreciation in the euro represented a clear case of undervaluation compared to its medium term equilibrium level. Most model estimates suggest that the real exchange rate of the euro was 20% or more below its medium-term equilibrium level (BIS, 1999). Although exchange rates are not expected to be always at their equilibrium level, such a large undervaluation was hard to rationalise on the basis of economic progress. Troubled by the repercussion of developments in the euro exchange rate, on 22 September 2000, the ECB jointly with the US Federal Reserve and the central banks of the UK, Japan and Canada interceded in foreign exchange markets in support of the euro (BIS, 1999).

From a domestic EU perspective, by getting rid of the risk of intra-euro-area exchange-rate variations the euro has created an area of stability in which the full benefits of the single market can be reaped. This is in addition to the positive impact which the introduction of the euro is expected to have on the single market through increased price transparency and product market competition (European Commission, 2001). During the 1980s and 1990s, occasional high volatility and episodes of misalignment between EU currencies sometimes threatened the sound functioning of the single market. The euro, however, has removed the risk of a sub-optimal resource allocation due to economically-unjustified and protracted movements in nominal exchange rates (European Commission, 2001).

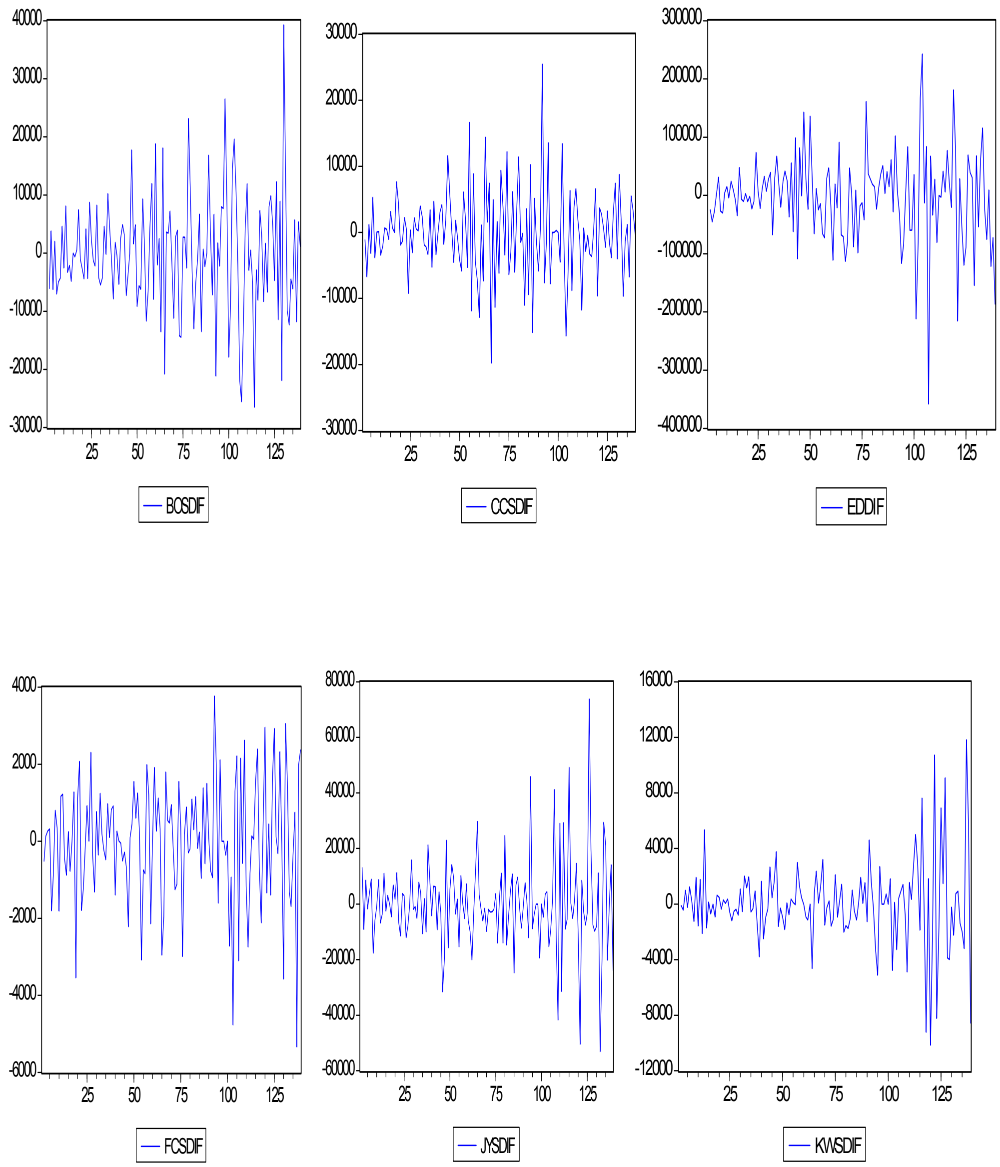
Graph 4.1
Stationarity of net positions of hedgers (after differencing)

The following graphs show the stationarity of net position of large hedgers, after differencing the level series. Differenced series are cocoa (ccdif), Eurodollars (eddif), feeder cattle (fcdif), wheat from Kansas (kwdif), and coffee (kcdif).

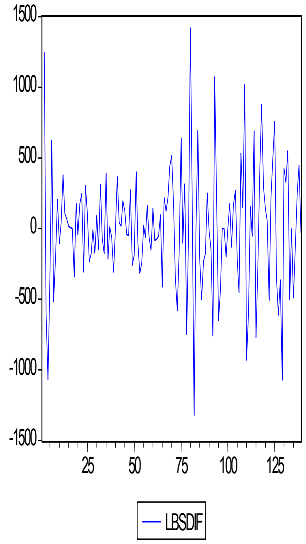


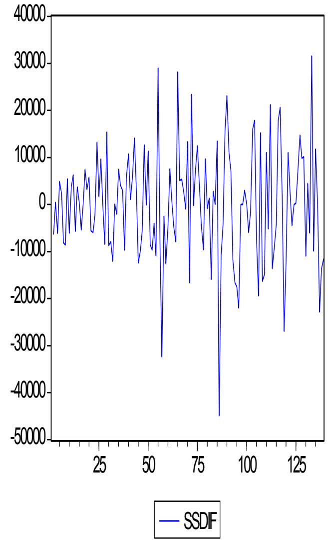
Graph 4.2
Stationarity of Net Positions of Speculators (after differencing)

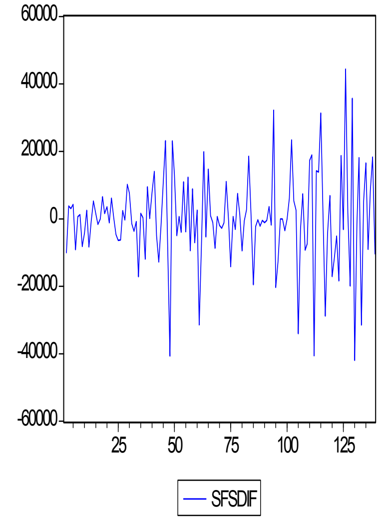
The following graphs show the stationarity of net position of large speculators, after differencing the leve series. Differenced series are soybean oil (bosdif), cocoa (ccdif), Eurodollars (eddif), feeder cattle (fcdif) Japanese yen (jysdif), wheat from Kansas (kwdif), lumber (lbsdif), soybean (ssdif) and s&p500 (spsdif).



Stationarity of Net Positions of Speculators (differenced) *\/pto*







Stationarity of Net Positions of Speculators (differenced)

Table 4.4
Unit Root test for differenced series of net positions of hedgers and speculators

This table shows the test for unit root for the differenced series of net positions for large hedgers and large speculators, using Augmented Dickey-Fuller (ADF) test. Net positions (NP) are defined as the long positions less the short positions of a trader type on the basis of the CFTC's COT reports, in units of 1,000 contracts. *(**) (***) denotes significance of ADF test at 1%(5%)(10%) level. Both Akaike and Schwar: information selection criteria are used. Only results of series which were non stationary at levels are reported here. Specification of ADF test, Akaike and Schwarz information criteria can be found in appendices.

Stationary of time series (net positions)- differenced

	Hedgers NP		*Speculators NP*	
	Information criteria		**Information criteria**	
	Akaike	Schwarz	Akaike	Schwarz
ED	-11.749	-11.749		
US	-10.074			
SF			-6.868	
JY			-8.232	
S	-7.869	-10.608	-8.061	-11.158
BO			-7.542	
SP	-13.793	-13.793		
FC	-7.835		-11.372	
W			-6.751	
KW	-6.419	-11.452	-7.895	
CC	-6.799	-15.830	-7.542	
KC	-8.631			
LB			-10.199	

Table 4.5.1.1
Panel unit root test using ADF Fisher test
(Akaike information criteria)

This table shows the test for panel unit root for futures returns, using the ADF Fisher test. Akaike (AIC) information selection criteria is used. Specification of test ADF Fisher test, Akaike information criteria can be found in appendices.

Date: 10/16/06 Time: 15:51
Sample: 1 139
Series : All 29
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic selection of lags based on AIC: 0 to 12
Total number of observations: 4071
Cross-sections included: 30

Method	Statistic	Prob.**
ADF - Fisher Chi-square	1638.81	0
ADF - Choi Z-stat	-36.4339	0

** Probabilities for Fisher tests are computed using an asympotic Chi -square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results RETURNS

Series	Prob.	Lag	Max Lag	Obs
CD	0	0	13	138
CL	0	9	13	129
CC	0	4	13	134
KC	0	4	13	134
HG	0	0	13	138
C	0	0	13	138
CT	0	0	13	138
CL	0	2	13	136
ED	0.0001	2	13	136
FC	0	3	13	135
GC	0	0	13	138
HO	0	1	13	137
LH	0.1632	12	13	126
JY	0.0122	8	13	130
LB	0	4	13	134
PL	0	1	13	137
PB	0	0	13	138
BP	0.0001	9	13	129
SP	0	1	13	137
SI	0	0	13	138
S	0	1	13	137
SM	0	1	13	137
BO	0	0	13	138
SB	0	4	13	134
SF	0	0	13	138
US	0	2	13	136
KW	0	0	13	138
MW	0	0	13	138
W	0	0	13	138

Table 4.5.1.2
Panel unit root test using ADF Fisher test (Schwarz information criteria)

This table shows the test for panel unit root for futures returns, using the ADF Fisher test. Schwarz (SIC) information selection criteria is used. Specification of test ADF Fisher test, Schwarz information criteria can be found in appendices

Date: 10/16/06 Time: 15:53
Sample: 1 139
Series: All 29
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic selection of lags based on SIC: 0 to 2
Total number of observations: 4136
Cross-sections included: 30

Method	Statistic	Prob.**
ADF - Fisher Chi-square	2327.05	0
ADF - Choi Z-stat	-46.2045	0

** Probabilities for Fisher tests are computed using an asympotic Chi -square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results RETURNS

Series	Prob.	Lag	Max Lag	Obs
CD	0	0	13	138
CL	0	2	13	136
CC	0	0	13	138
KC	0	0	13	138
HG	0	0	13	138
C	0	0	13	138
CT	0	0	13	138
CL	0	0	13	138
ED	0	0	13	138
FC	0	0	13	138
GC	0	0	13	138
HO	0	1	13	137
LH	0	0	13	138
JY	0	0	13	138
LB	0	0	13	138
PL	0	0	13	138
PB	0	0	13	138
BP	0	0	13	138
SP	0	0	13	138
SI	0	0	13	138
S	0	0	13	138
SM	0	0	13	138
BO	0	0	13	138
SB	0	0	13	138
SF	0	0	13	138
US	0	0	13	138
KW	0	0	13	138
MW	0	0	13	138
W	0	0	13	138

Table 4.5.2.1
Panel unit root test using Im, Perasan & Chin test (Akaike information criteria)

This table shows the test for panel unit root for futures returns, using the Im, Pesaran and Shin test. Akaike (AIC) information selection criteria is used. Specification of Im, Pesaran and Shin test, Akaike information criteria can be found in appendices.

Null Hypothesis: Unit root (individual unit root process)
Date: 10/16/06 Time: 15:45
Sample: 1 139
Series: All 29
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic selection of lags based on AIC: 0 to 12
Total number of observations: 4071
Cross-sections included: 30

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-46.934	0

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Series	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
CD	-12.556	0	-1.532	0.735	0	13	138
CL	-6.1694	0	-1.456	0.818	9	13	129
CC	-6.3363	0	-1.495	0.771	4	13	134
KC	-5.982	0	-1.495	0.771	4	13	134
HG	-12.428	0	-1.532	0.735	0	13	138
C	-10.834	0	-1.532	0.735	0	13	138
CT	-13.117	0	-1.532	0.735	0	13	138
CL	-6.1712	0	-1.514	0.754	2	13	136
ED	-4.9479	0.0001	-1.514	0.754	2	13	136
FC	-5.0304	0	-1.512	0.761	3	13	135
GC	-13.826	0	-1.532	0.735	0	13	138
HO	-9.2039	0	-1.53	0.745	1	13	137
LH	-2.3335	0.1632	-1.456	0.818	12	13	126
JY	-3.4145	0.0122	-1.456	0.818	8	13	130
LB	-6.5503	0	-1.495	0.771	4	13	134
PL	-9.4176	0	-1.53	0.745	1	13	137
PB	-13.85	0	-1.532	0.735	0	13	138
BP	-4.8018	0.0001	-1.456	0.818	9	13	129
SP	-9.7276	0	-1.53	0.745	1	13	137
SI	-12.655	0	-1.532	0.735	0	13	138
S	-8.7867	0	-1.53	0.745	1	13	137
SM	-8.5939	0	-1.53	0.745	1	13	137
BO	-12.098	0	-1.532	0.735	0	13	138
SB	-6.4044	0	-1.495	0.771	4	13	134
SF	-11.346	0	-1.532	0.735	0	13	138
US	-7.3948	0	-1.514	0.754	2	13	136
KW	-11.224	0	-1.532	0.735	0	13	138
MW	-10.755	0	-1.532	0.735	0	13	138
W	-11.589	0	-1.532	0.735	0	13	138
Average	-8.9612		-1.514	0.755			

Table 4.5.2.2
Panel unit root Test using Im, Perasan & Chin test (Schwarz information criteria)

This table shows the test for panel unit root for futures returns, using the Im, Pesaran and Shin test. Schwarz (SIC) information selection criteria is used. Specification of Im, Pesaran and Shin test, Schwarz information criteria can be found in appendices

Null Hypothesis: Unit root (individual unit root process)
Date: 10/16/06 Time: 15:27
Sample: 1 139
Series: All 29
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic selection of lags based on SIC: 0 to 2
Total number of observations: 4136
Cross-sections included: 30

Im, Pesaran and Shin W-stat	-64.771	0

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Series	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
CD	-12.556	0	-1.532	0.735	0	13	138
CL	-9.053	0	-1.514	0.754	2	13	136
CC	-14.324	0	-1.532	0.735	0	13	138
KC	-12.65	0	-1.532	0.735	0	13	138
HG	-12.428	0	-1.532	0.735	0	13	138
C	-10.834	0	-1.532	0.735	0	13	138
CT	-13.117	0	-1.532	0.735	0	13	138
CL	-9.9564	0	-1.532	0.735	0	13	138
ED	-10.162	0	-1.532	0.735	0	13	138
FC	-12.253	0	-1.532	0.735	0	13	138
GC	-13.826	0	-1.532	0.735	0	13	138
HO	-9.2039	0	-1.53	0.745	1	13	137
LH	-10.639	0	-1.532	0.735	0	13	138
JY	-10.161	0	-1.532	0.735	0	13	138
LB	-12.112	0	-1.532	0.735	0	13	138
PL	-12.412	0	-1.532	0.735	0	13	138
PB	-13.85	0	-1.532	0.735	0	13	138
BP	-11.084	0	-1.532	0.735	0	13	138
SP	-13.327	0	-1.532	0.735	0	13	138
SI	-12.655	0	-1.532	0.735	0	13	138
S	-11.892	0	-1.532	0.735	0	13	138
SM	-12.068	0	-1.532	0.735	0	13	138
BO	-12.098	0	-1.532	0.735	0	13	138
SB	-10.709	0	-1.532	0.735	0	13	138
SF	-11.346	0	-1.532	0.735	0	13	138
US	-10.712	0	-1.532	0.735	0	13	138
KW	-11.224	0	-1.532	0.735	0	13	138
MW	-10.755	0	-1.532	0.735	0	13	138
W	-11.589	0	-1.532	0.735	0	13	138
Average	-11.676		-1.531	0.736			

Table 4.9.2
Cross hedging pressure effects

This table shows the results for the cross-hedging pressure effects of the 29 Futures markets. θ_1 is the own hedging pressure variable. θ_2, $\theta_3, \ldots \theta_{16}$ are the cross hedging pressure variables and $t(\delta_2)$ are the t ratios of own and cross hedging pressure variables. R_{t+1} is the futures return in one month time, in percent. Values of t ratios are shown in bold at 10% significance level. Estimated equation used is

$$R_{i,t+1}^{(j)} = \varphi_0^{(j)} + \sum_{n=1}^{N} \varphi_{i,n}^{(j)} \lambda_{n,t}^{(j)} + \xi_{t+1}^{(j)}$$

where i (i = 1, 2, 3... , n) refers to the futures market and j (j=1,..,4) refers to the specific group the futures market belong to. $\sum_{n=1}^{N} \varphi$ represent the coefficients of own- and cross-hedging pressure variables for each futures market within each of the four groups.

Cross Hedging Pressure Effects

(1) Financials

	θ_1	θ_2	θ_3
R_{t+1}: sp			
	sp	**ed**	**us**
	-6.252	7.037	-6.443
$t(\delta_2)$	-0.989	0.886	-0.913
R_{t+1}: ed			
	ed	**sp**	**us**
	0.959	-0.253	0.768
$t(\delta_2)$	**1.829**	-0.557	1.282
R_{t+1}: us			
	us	**sp**	**ed**
	1.434	-1.525	-0.235
$t(\delta_2)$	0.241	-0.441	-0.049

(2)Minerals

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6
R_{t+1}: gc						
	gc	**si**	**hg**	**pl**	**cl**	**ho**
	-1.699	0.974	-1.921	1.800	3.687	0.183
$t(\delta_2)$	-0.881	0.366	-1.366	1.045	0.636	0.045
R_{t+1}: si						
	si	**gc**	**hg**	**pl**	**cl**	**ho**
	-7.672	-2.220	-6.850	1.608	14.240	-9.514
$t(\delta_2)$	**-2.339**	-0.883	**-2.642**	0.640	1.094	-1.249
R_{t+1}: hg						
	hg	**si**	**gc**	**pl**	**cl**	**ho**
	1.993	5.995	-0.107	0.982	7.224	-2.045
$t(\delta_2)$	0.676	1.518	-0.040	0.401	0.651	-0.285
R_{t+1}: pl						
	pl	**hg**	**si**	**gc**	**cl**	**ho**
	1.498	-0.365	-0.691	-4.682	11.753	-7.143
$t(\delta_2)$	0.671	-0.183	-0.248	**-2.290**	1.493	-1.254
R_{t+1}: cl						
	cl	**pl**	**hg**	**si**	**gc**	**ho**
	20.089	2.742	2.743	8.074	-5.846	22.708
$t(\delta_2)$	1.113	0.788	0.838	**1.733**	**-1.665**	**1.664**
R_{t+1}: ho						
	ho	**cl**	**pl**	**hg**	**si**	**gc**
	13.074	-7.282	4.886	-0.254	5.050	-6.581
$t(\delta_2)$	0.987	-0.402	1.147	-0.055	0.839	-1.517

(3) Currencies

	θ_1	θ_2	θ_3	θ_4
R_{t+1}: bp				
	bp	**sf**	**cd**	**jy**
	0.199	-0.539	0.845	0.393
$t(\delta_2)$	0.286	-0.830	1.127	0.510
R_{t+1}: sf				
	sf	**bp**	**cd**	**jy**
	-0.498	0.197	-0.272	0.178
$t(\delta_2)$	-0.799	0.272	-0.226	0.170
R_{t+1}: cd				
	cd	**sf**	**bp**	**jy**
	0.350	-0.080	0.092	0.180
$t(\delta_2)$	1.125	-0.300	0.366	0.535
R_{t+1}: jy				
	jy	**cd**	**sf**	**bp**
	0.809	-0.119	1.285	-1.104
$t(\delta_2)$	1.023	-0.151	**1.715**	-1.343

/pto

Cross-hedging pressure effects (continued)

(4) Agriculturals

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}	θ_{11}	θ_{12}	θ_{13}	θ_{14}	θ_{15}	θ_{16}
R_{t+1}: w																
	w	**kw**	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**
	-0.254	8.578	-0.574	0.116	0.238	-0.623	-2.703	-0.704	-2.613	2.339	-5.055	-0.972	7.695	-11.328	-6.062	1.130
$t(\delta_2)$	-0.062	1.074	-0.084	0.026	0.058	-0.216	-0.641	-0.418	-1.038	0.575	**-2.402**	-0.385	1.157	**-2.386**	**-1.845**	0.644
R_{t+1}: kw																
	kw	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	7.410	1.300	0.339	1.235	-1.363	-2.742	-0.778	-3.541	-0.788	-5.267	-1.734	7.548	-9.100	-4.144	0.663	1.404
$t(\delta_2)$	1.014	0.201	0.073	0.308	-0.486	-0.677	-0.501	-1.411	-0.204	**-2.492**	-0.723	1.240	**-2.093**	-1.279	0.417	0.324
R_{t+1}: mw																
	mw	**kw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	1.050	7.495	2.773	0.430	-1.628	-2.224	-0.240	-4.766	-1.317	-3.745	-3.009	4.903	-4.413	-3.484	0.628	-1.367
$t(\delta_2)$	0.164	1.135	0.604	0.115	-0.650	-0.590	-0.163	**-1.978**	-0.361	**-1.767**	-1.270	0.832	-1.231	-1.186	0.430	-0.286
R_{t+1}: c																
	c	**mw**	**kw**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	4.203	11.039	1.392	-2.515	-2.973	-4.614	-0.232	-2.260	9.680	-2.087	-2.579	3.684	-2.605	0.184	2.988	-5.688
$t(\delta_2)$	1.022	1.409	0.218	-0.665	-1.013	-1.039	-0.148	-0.838	**1.809**	-1.034	-0.982	0.655	-0.653	0.061	**2.068**	-1.269
R_{t+1}: s																
	s	**mw**	**c**	**kw**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	1.083	0.580	2.338	5.195	1.385	-6.110	-0.611	-0.549	9.287	-1.568	-3.338	0.632	-2.961	-2.752	2.250	-6.842
$t(\delta_2)$	0.291	0.102	0.593	0.904	0.553	-1.445	-0.391	-0.291	**2.041**	-0.872	-1.376	0.115	-0.923	-1.011	**1.996**	-1.576
R_{t+1}: bo																
	bo	**mw**	**c**	**s**	**kw**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	0.783	0.309	5.347	-1.831	6.254	-7.256	-2.027	-0.669	3.978	-2.830	-1.424	4.238	-0.212	-1.333	1.578	-6.768
$t(\delta_2)$	0.300	0.057	1.467	-0.575	1.149	**-1.825**	-1.597	-0.364	0.941	**-1.759**	-0.615	0.908	-0.066	-0.494	1.490	-1.189
R_{t+1}: sm																
	sm	**mw**	**c**	**s**	**bo**	**kw**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	-4.378	-2.169	-2.928	3.340	-0.431	3.129	-0.550	-0.103	9.836	-0.870	-3.581	3.912	-7.402	-1.192	2.272	-6.431
$t(\delta_2)$	-1.016	-0.345	-0.665	0.943	-0.140	0.518	-0.352	-0.041	**2.009**	-0.425	-1.215	0.587	**-1.839**	-0.389	1.697	-1.436
R_{t+1}: pb																
	pb	**mw**	**c**	**s**	**bo**	**sm**	**kw**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	3.691	-5.813	-11.261	8.557	4.187	5.442	6.448	-5.656	-4.580	2.561	-4.455	-16.083	4.397	-3.446	3.634	-1.422
$t(\delta_2)$	1.236	-0.417	-1.115	0.929	0.574	0.500	0.456	-1.110	-0.384	0.480	-0.644	-1.216	0.392	-0.531	1.065	-0.119
R_{t+1}: lh																
	lh	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**kw**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	0.190	7.156	2.746	7.823	-1.169	-8.307	0.414	2.822	2.024	4.382	-4.714	-12.006	6.915	-1.696	1.340	-10.606
$t(\delta_2)$	0.051	0.812	0.434	1.247	-0.221	-1.239	0.204	0.280	0.240	1.207	-0.922	-1.019	0.921	-0.360	0.577	**-1.705**
R_{t+1}: lc																
	lc	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**kw**	**fc**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	-4.684	-2.175	-4.454	0.004	-0.330	2.561	-0.035	-1.841	2.253	-0.255	0.284	2.094	-4.069	0.635	0.372	3.409
$t(\delta_2)$	**-1.708**	-0.589	-1.526	0.002	-0.191	1.025	-0.038	-1.098	0.747	-0.194	0.159	0.524	-1.389	0.364	0.434	0.875
R_{t+1}: fc																
	fc	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**kw**	**sb**	**cc**	**kc**	**ct**	**lb**	**w**
	-2.460	-3.508	-5.845	1.172	1.864	3.544	0.241	0.353	-2.701	1.292	1.731	-6.229	-0.237	0.759	-0.305	-2.019
$t(\delta_2)$	**-2.032**	-1.065	**-2.549**	0.641	1.303	1.753	0.313	0.312	-1.053	0.372	1.225	**-1.767**	-0.087	0.416	-0.485	-0.744
R_{t+1}: sb																
	sb	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**kw**	**cc**	**kc**	**ct**	**lb**	**w**
	-0.238	-6.267	-0.221	6.448	2.946	-1.029	-2.716	3.914	-9.261	1.291	7.075	5.355	-10.318	-0.836	-2.227	3.102
$t(\delta_2)$	-0.060	-0.821	-0.035	0.941	0.609	-0.147	-1.312	1.294	-1.282	0.396	0.797	0.521	-1.404	-0.201	-0.959	0.467
R_{t+1}: cc																
	cc	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**kw**	**kc**	**ct**	**lb**	**w**
	-10.687	-18.288	2.789	-1.747	2.701	5.712	0.675	-1.637	-4.256	-1.421	4.760	4.420	9.529	0.054	0.789	0.574
$t(\delta_2)$	-1.140	**-2.553**	0.496	-0.299	0.731	0.993	0.355	-0.597	-0.717	-0.597	1.290	0.602	1.575	0.014	0.403	0.119
R_{t+1}: kc																
	kc	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kw**	**ct**	**lb**	**w**
	-21.177	3.705	-17.141	18.781	8.147	-10.522	-1.335	-0.981	11.984	-6.682	2.693	8.731	2.281	-5.663	3.580	-4.481
$t(\delta_2)$	**-2.810**	0.256	**-2.013**	**3.032**	**1.669**	-1.312	-0.400	-0.220	1.135	-1.552	0.482	0.654	0.171	-1.031	1.373	-0.562
R_{t+1}: ct																
	ct	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**kw**	**lb**	**w**
	-2.046	-3.329	2.946	-1.611	3.207	-3.374	-0.857	1.025	3.262	1.315	-3.176	7.682	-2.825	4.297	-0.208	-6.571
$t(\delta_2)$	-0.668	-0.486	0.705	-0.382	0.826	-0.814	-0.606	0.363	0.671	0.520	-0.983	0.997	-0.556	0.722	-0.129	-1.242
R_{t+1}: lb																
	lb	**mw**	**c**	**s**	**bo**	**sm**	**pb**	**lh**	**lc**	**fc**	**sb**	**cc**	**kc**	**ct**	**kw**	**w**
	3.699	-3.724	-0.186	0.819	4.761	-4.725	-1.296	-1.260	5.409	-3.490	-7.664	-6.036	5.260	-3.576	11.828	9.530
$t(\delta_2)$	1.641	-0.438	-0.029	0.144	1.087	-0.679	-0.500	-0.334	0.796	-1.013	**-1.748**	-0.642	0.846	-0.799	1.186	1.616

Appendix 6.11

Table 4.10.6
Residual diagnostic tests for mean equation 4.10.3 and 4.10.4.

This table shows the residual test for the mean equations 4.10.3 and 4.10.4. Panel A shows the autocorrelation (AC), partial autocorrelation (PAC), Ljung-Box Q statistics and its probability, and the probability of Q statistics of squared residuals are displayed. If the mean equations have been properly specified, the AC and PAC should be close and near zero. The probabilities for Q statistics of residuals and squared residuals test that the residuals are not correlated up to a specified number of lags. A high probability value suggests less occurrence of autocorrelation. Panel B reports the Breusch Godfrey serial correlation LM test and its probability; and the probability of the ARCH observed r-squared test. Both tests in panel B add support towards efficiency of the mean models.

Panel A	Hedger					Speculator				
	AC	PAC	Q statistics	Prob. (Q statistics)	Prob. (Q statistics of squared residuals)	AC	PAC	Q statistics	Prob. (Q statistics)	Prob. (Q statistics of squared residuals)
Minerals										
GC	-0.002	-0.002	13.628	0.995	0.999	-0.008	-0.008	14.716	0.991	0.999
SI	0.044	0.034	27.751	0.584	0.862	0.057	0.016	22.327	0.842	0.987
HG	0.019	-0.003	47.107	0.024	0.981	0.021	0.004	46.608	0.027	0.939
PL	0.006	-0.033	14.064	0.994	0.999	0.002	-0.025	12.364	0.998	0.999
CL	-0.037	-0.036	8.841	0.999	0.999	-0.011	-0.001	5.867	0.999	0.999
HO	-0.038	-0.047	18.359	0.952	0.419	-0.020	-0.010	16.322	0.980	0.715
Financials										
SP	0.071	0.041	25.097	0.720	0.999	0.042	0.024	23.266	0.804	0.999
ED	0.010	-0.010	42.960	0.059	0.697	0.007	-0.011	42.796	0.061	0.693
US	0.047	0.056	21.764	0.862	0.999	0.033	0.027	21.536	0.870	0.999
Currencies										
BP	0.049	0.076	27.528	0.533	0.270	0.031	0.072	27.357	0.572	0.475
SF	0.040	0.046	17.744	0.692	0.944	0.016	0.026	15.897	0.833	0.943
CD	0.108	0.071	36.022	0.204	0.992	0.085	0.050	35.499	0.214	0.989
JY	0.022	-0.029	22.947	0.817	0.945	0.045	-0.057	33.673	0.294	0.908

/pto

Agriculturals

W	0.040	0.036	12.268	0.998	0.873	0.017	0.018	13.874	0.995	0.979
KW	-0.035	-0.055	17.758	0.962	0.296	-0.024	-0.037	18.348	0.953	0.287
MW	0.010	-0.010	27.173	0.614	0.283	0.011	-0.016	23.169	0.808	0.094
C	-0.001	0.003	26.729	0.637	0.830	-0.027	-0.034	25.514	0.700	0.924
S	0.062	0.055	25.757	0.636	0.998	0.029	0.022	14.004	0.994	0.677
BO	0.032	0.000	24.037	0.770	0.946	0.005	-0.019	17.975	0.959	0.968
SM	0.022	0.040	17.826	0.955	0.626	-0.041	-0.014	25.357	0.707	0.307
PB	0.030	0.071	29.195	0.471	0.593	0.026	0.062	31.332	0.378	0.782
LH	0.006	-0.424	53.931	0.005	0.470	-0.004	-0.465	51.976	0.008	0.380
LC	0.087	0.115	51.660	0.008	0.421	0.101	0.127	48.263	0.019	0.563
FC	0.049	0.045	33.011	0.322	0.018	0.031	0.022	35.045	0.241	0.030
SB	0.042	0.046	16.276	0.980	0.981	0.001	0.012	16.039	0.982	0.558
CC	0.006	-0.018	34.110	0.276	0.999	-0.014	-0.063	43.747	0.050	0.999
KC	-0.023	-0.067	18.085	0.957	0.024	-0.055	-0.042	27.387	0.603	0.112
CT	-0.057	-0.079	27.880	0.577	0.995	-0.057	-0.045	28.445	0.547	0.996
LB	-0.089	-0.026	60.412	0.001	0.000	-0.089	-0.030	59.960	0.001	0.000

Panel B	*Hedger*			*Speculator*		
	Breusch-Godfrey serial correlation LM test	**Prob. (Breusch-Godfrey serial LM test)**	**Prob. (ARCH observed r-squared test)**	**Breusch-Godfrey serial correlation LM test**	**Prob. (Breusch-Godfrey serial LM test)**	**Prob. (ARCH observed r-squared test)**
Minerals						
GC	28.609	0.538	0.156	29.892	0.471	0.482
SI	28.622	0.538	0.871	23.870	0.778	0.991
HG	50.635	0.011	0.778	51.826	0.008	0.813
PL	29.737	0.479	0.333	27.697	0.586	0.265
CL	16.624	0.977	0.890	12.367	0.998	0.681
HO	17.689	0.963	1.000	17.749	0.962	0.998
Financials						
SP	40.062	0.104	0.031	40.741	0.091	0.029
ED	44.768	0.041	0.839	47.011	0.025	0.786
US	30.186	0.456	0.998	33.841	0.287	0.999
Currencies						
BP	38.780	0.131	0.168	41.814	0.074	0.320
SF	32.016	0.367	0.984	27.620	0.591	0.980
CD	49.283	0.015	0.985	50.168	0.012	0.994
JY	34.875	0.247	0.944	41.895	0.073	0.760

/pto

Agriculturals

W	16.841	0.974	0.836	17.789	0.962	0.955
KW	17.562	0.965	0.485	18.948	0.941	0.575
MW	20.615	0.900	0.415	22.132	0.849	0.097
C	31.351	0.398	0.980	33.374	0.307	0.920
S	40.427	0.097	0.063	20.859	0.892	0.049
BO	19.718	0.924	0.947	19.741	0.923	0.933
SM	20.984	0.888	0.591	22.590	0.832	0.546
PB	48.910	0.016	0.473	47.267	0.023	0.594
LH	67.873	0.000	0.019	66.739	0.000	0.034
LC	40.794	0.090	0.717	39.602	0.113	0.761
FC	27.368	0.604	0.194	29.857	0.473	0.371
SB	36.997	0.177	0.737	32.380	0.350	0.766
CC	39.707	0.111	0.797	48.406	0.018	0.632
KC	23.394	0.799	0.205	30.734	0.429	0.200
CT	33.947	0.283	1.000	30.940	0.418	1.000
LB	46.593	0.027	0.283	46.601	0.027	0.227

Appendix 6.12

Table 4.12.2
ARMA model specification for decomposed idiosyncratic volatility for hedgers and speculators

This table shows the results for ARMA model specification (seasonality adjusted) for decomposed idiosyncratic volatility equation 4.12.1. The Ljung-Box Q statistics and the Breusch-Godfrey LM test are carried out to check for autocorrelation in the residuals. Autoregressive processes (AR) and Moving Average processes (MA) are applied in ARMA model specification up to including 10 lags and Akaike Information Criteria (AIC) is used to determine optimum number of lags. The uncorrelated ARMA model specification is displayed on the right hand sheet of each sheet.

	Hedger			Speculator		
	Q statistic	*Breusch-Godfrey LM test*	*ARMA model specification*	*Q statistic*	*Breusch-Godfrey LM test*	*ARMA model specification*
Minerals						
GC	0.000	0.873	arma(1)	0.000	0.855	arma(1)
SI	0.003	0.740	arma(1)	0.002	0.783	arma(1)
HG	0.000	0.770	ma(2) ar(1)	0.013	0.809	arma(1) sma(1)
PL	0.000	0.960	ar(1) sar(1)	0.000	0.745	ar(1) sar(1)
CL	0.000	0.824	ar(1)	0.000	0.847	ar(1)
HO	0.043	0.730	ar(1) ma(2) sma(1)	0.000	0.879	ar(1) ma(2)
Financials						
SP	0.007	0.737	ar(1) sar(1)	0.002	0.630	arma(1) sar(1)
ED	0.000	0.629	ar(2) sar(1)	0.000	0.628	ar(2) sar(1)
US	0.001	0.963	ar(1) ma(1)	0.011	0.869	ar(1) ma(1)
Currencies						
BP	0.000	0.957	ar(1) ma(1)	0.001	0.820	ar(1)
SF	0.000	0.983	ar(1)	0.001	0.771	ar(1)
CD	0.000	0.882	ar(1) ma(1)	0.000	0.954	ar(1)
JY	0.000	0.659	ar(1) sar(1)	0.002	0.807	ar(1)

/pto

Agriculturals						
W	0.001	0.871	ar(1)	0.007	0.746	ar(1)
KW	0.000	0.987	ar(1)	0.000	0.813	ar(1)
MW	0.000	0.910	ar(1)	0.000	0.973	ar(1)
C	0.001	0.677	ar(1)	0.000	0.968	ar(1)
S	0.630	0.630	ar(2) sar(1)	0.001	0.924	) ma(2) sar(1) sma(1)
BO	0.000	0.870	ar(2) sar(1)	0.006	0.876	arma(1)
SM	0.001	0.828	ar(1) sar(1)	0.003	0.795	ar(1) sar(1)
PB	0.009	0.659	ar(1) ma(1)	0.000	0.850	ar(1)
LH	0.000	0.995	ar(1)	0.000	0.746	ar(1)
LC	0.000	0.868	arma(1)	0.000	0.961	arma(1)
FC	0.012	0.879	arma(1)	0.000	0.970	arma(1) sma(1)
SB	0.000	0.908	ar(1) ma(2)	0.000	0.733	arma(1) sma(1)
CC	0.000	0.906	ar(1)	0.001	0.837	ar(1)
KC	0.001	0.708	arma(1)	0.002	0.726	arma(1)
CT	0.005	0.756	arma(1)	0.000	0.916	arma(1)
LB	0.002	0.666	arma(1) sma(1)	0.000	0.770	arma(1) sar(1)

Appendix 6.13

Table 4.16
Model specification test (ARCH tests) for GARCH and PARCH volatility models for hedgers and speculators, under normal and *t* distribution.

This table shows the results for the autoregressive conditional heteroskedasticity (ARCH) LM test and Q statistics for the correlograms of squared residuals. A low Q statistics value and a high probability (observed r-squared) suggest no ARCH in the residuals. Panel A reports the results both hedgers' volatility under GARCH (see equation 4.13) and PARCH (see equation 4.14.2) volatility models. Results are also provided both for normal and t distribution. Panel B reports the results for speculators.

Model Specification test

	GARCH				PARCH			
	Normal dist.		*t dist.*		*Normal dist.*		*t dist.*	
Panel A: Hedger	*Q statistics of squared residuals*	*Prob. (obs r-squared)*	*Q statistics of squared residuals*	*Prob. (obs r-squared)*	*Q statistics of squared residuals*	*Prob. (obs r-squared)*	*Q statistics of squared residuals*	*Prob. (obs r-squared)*
Minerals								
GC	0.006	0.940	0.026	0.875	16.865	0.000	1.935	0.170
SI	0.280	0.620	0.192	0.686	0.297	0.610	0.027	0.849
HG	0.075	0.777	0.068	0.786	0.328	0.564	0.016	0.905
PL	0.426	0.517	0.040	0.844	0.353	0.555	0.007	0.936
CL	0.258	0.608	0.945	0.338	0.336	0.566	0.095	0.758
HO	1.489	0.242	0.025	0.872	0.044	0.835	22.302	0.000
Financials								
SP	0.423	0.524	0.255	0.618	0.274	0.608	0.902	0.346
ED	0.654	0.365	0.706	0.360	0.391	0.474	0.616	0.393
US	0.003	0.940	0.078	0.778	2.954	0.088	0.510	0.478
Currencies								
BP	3.138	0.081	0.009	0.923	0.196	0.664	4.595	0.034
SF	0.016	0.908	0.147	0.723	0.112	0.744	0.068	0.780
CD	0.606	0.443	0.475	0.497	0.524	0.472	0.654	0.423
JY	0.110	0.744	0.325	0.572	6.628	0.011	2.979	0.089

/pto

Agriculturals								
W	0.000	0.966	0.005	0.965	0.468	0.484	8.383	0.005
KW	0.599	0.436	0.432	0.511	0.433	0.504	0.450	0.505
MW	1.113	0.296	0.862	0.360	0.316	0.579	1.181	0.285
C	0.958	0.342	0.378	0.555	0.390	0.551	0.549	0.473
S	0.213	0.648	0.460	0.501	0.193	0.664	6.785	0.009
BO	0.719	0.424	0.769	0.407	0.208	0.681	3.795	0.035
SM	1.454	0.234	1.342	0.253	0.966	0.328	4.576	0.033
PB	2.365	0.123	2.365	0.123	0.172	0.699	2.090	0.138
LH	0.578	0.462	0.371	0.553	0.070	0.800	1.605	0.155
LC	0.034	0.857	0.073	0.791	1.284	0.267	1.084	0.301
FC	1.340	0.244	2.220	0.138	0.398	0.522	2.655	0.101
SB	0.008	0.930	0.008	0.930	0.188	0.673	0.254	0.619
CC	0.629	0.431	0.364	0.553	0.440	0.505	0.624	0.336
KC	0.030	0.858	0.212	0.642	0.074	0.785	26.109	0.000
CT	0.275	0.616	0.098	0.764	16.134	0.000	0.272	0.616
LB	0.029	0.868	0.035	0.852	0.013	0.901	1.325	0.245

Panel B: Speculator

	Q statistics of squared residuals	*Prob . (obs r-squared)*	*Q statistics of squared residuals*	*Prob . (obs r-squared)*	*Q statistics of squared residuals*	*Prob . (obs r-squared)*	*Q statistics of squared residuals*	*Prob . (obs r-squared)*
Minerals								
GC	0.021	0.890	0.026	0.875	0.732	0.396	2.328	0.132
SI	0.727	0.417	0.812	0.390	2.109	0.159	0.428	0.428
HG	0.884	0.339	0.824	0.356	1.099	0.288	0.062	0.846
PL	0.459	0.491	0.041	0.841	0.185	0.689	0.021	0.882
CL	0.049	0.820	0.645	0.428	12.696	0.000	2.209	0.144
HO	0.024	0.910	0.142	0.699	0.147	0.735	2.944	0.093

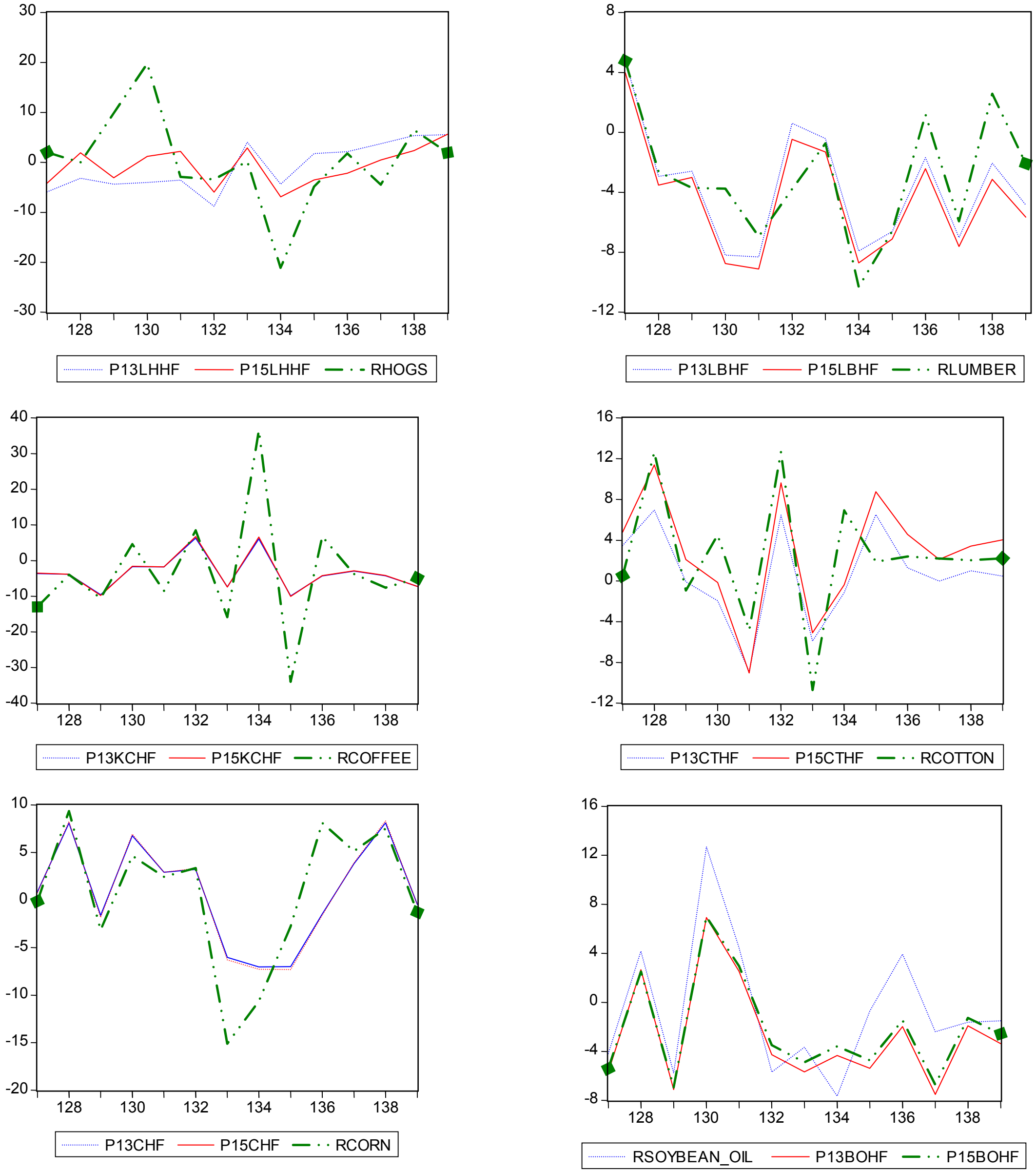
/pto

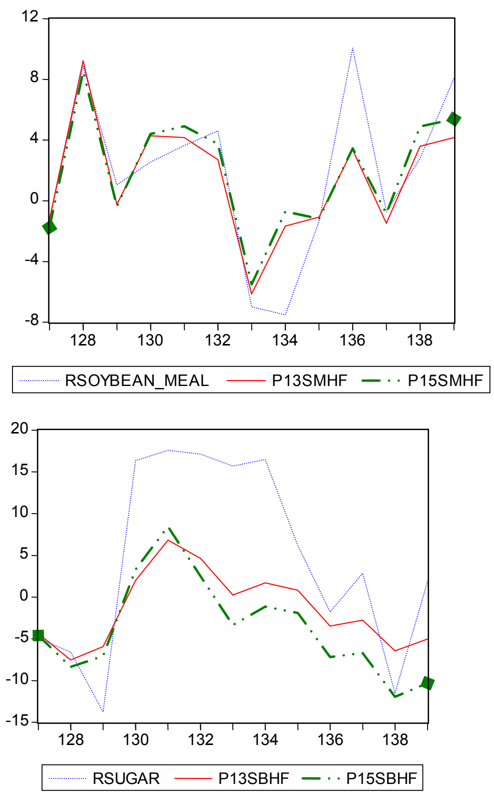
Financials								
SP	0.002	0.954	0.005	0.923	0.691	0.392	0.985	0.365
ED	1.130	0.272	1.054	0.290	0.773	0.362	0.910	0.326
US	0.035	0.863	0.049	0.823	1.653	0.201	0.482	0.491
Currencies								
BP	3.916	0.051	0.043	0.831	0.905	0.349	3.855	0.051
SF	0.175	0.661	0.467	0.486	0.271	0.606	0.000	0.988
CD	0.308	0.579	0.291	0.589	0.207	0.649	0.202	0.653
JY	0.117	0.737	0.410	0.525	0.048	0.831	6.622	0.011
Agriculturals								
W	1.366	0.237	0.002	0.951	0.265	0.598	0.102	0.860
KW	0.452	0.507	0.385	0.540	2.300	0.136	0.036	0.861
MW	0.944	0.341	0.573	0.460	1.179	0.288	1.925	0.176
C	0.149	0.716	0.203	0.668	0.069	0.809	0.380	0.557
S	0.001	0.953	0.001	0.952	0.091	0.739	15.062	0.000
BO	0.029	0.840	0.001	0.955	0.062	0.778	8.816	0.001
SM	1.868	0.178	1.870	0.177	0.001	0.983	1.576	0.211
PB	0.290	0.612	0.117	0.748	4.209	0.041	3.785	0.048
LH	0.612	0.445	0.275	0.608	0.000	0.994	0.495	0.413
LC	0.014	0.911	0.030	0.866	0.149	0.698	0.938	0.338
FC	0.335	0.563	0.778	0.388	3.065	0.082	1.332	0.246
SB	0.003	0.953	0.035	0.845	0.017	0.897	3.884	0.053
CC	0.458	0.497	0.403	0.527	0.113	0.733	0.611	0.404
KC	0.032	0.856	0.016	0.894	22.063	0.000	20.767	0.000
CT	0.447	0.515	0.141	0.716	0.382	0.537	0.722	0.397
LB	0.012	0.913	0.006	0.936	0.577	0.443	1.431	0.226

Appendix 6.14

Graph 4.8
Forecasted returns of hedgers under GARCH and PARCH models under normal distribution

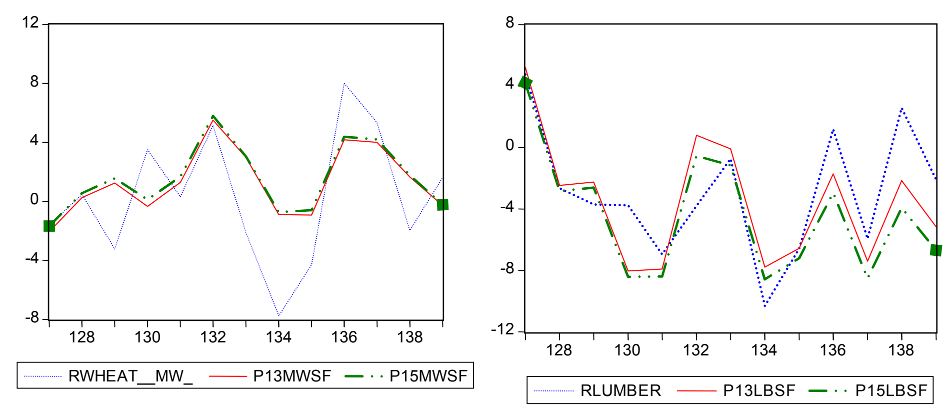
This graph shows the forecasted returns for hedgers under normal distribution, for both the GARCH and PARCH model. The actual futures returns are included to compare the forecasted returns with the actual returns. The forecasting sample is from Jan 2000 to Dec 2000.

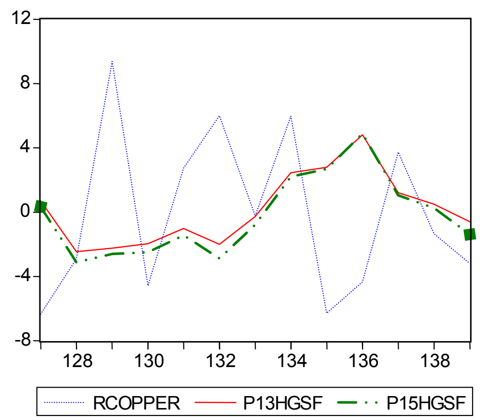


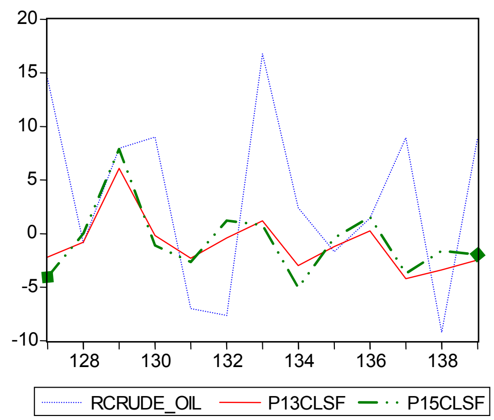


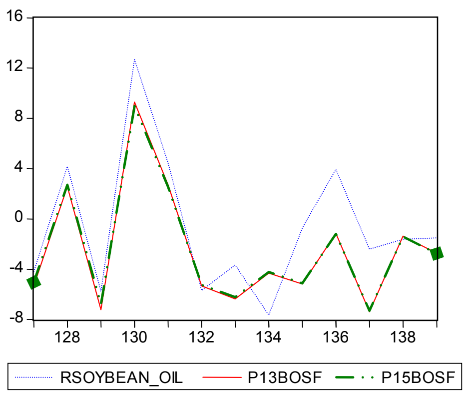
Graph 4.9
Forecasted returns of speculators under GARCH and PARCH models under normal distribution

This graph shows the forecasted returns for speculators under normal distribution, for both the GARCH and PARCH model. The actual futures returns are included to compare the forecasted returns with the actual returns. The forecasting sample is from Jan 2000 to Dec 2000.




12
8
4
0
-4
-8
128 130 132 134 136 138
RCOPPER
P13HGSF
P15HGSF


20
15
10
5
0
-5
-10
128 130 132 134 136 138
RCRUDE_OIL
P13CLSF
P15CLSF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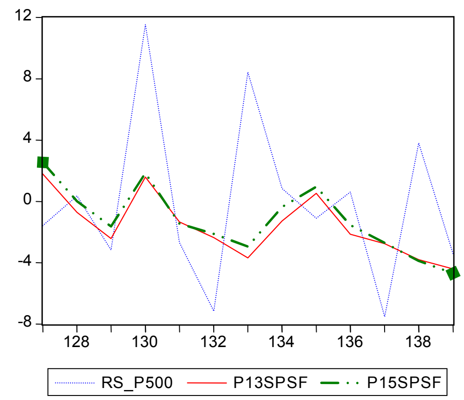
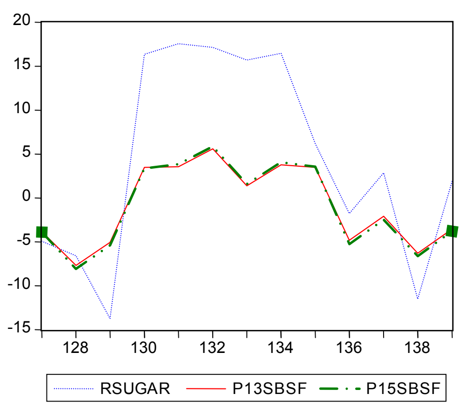
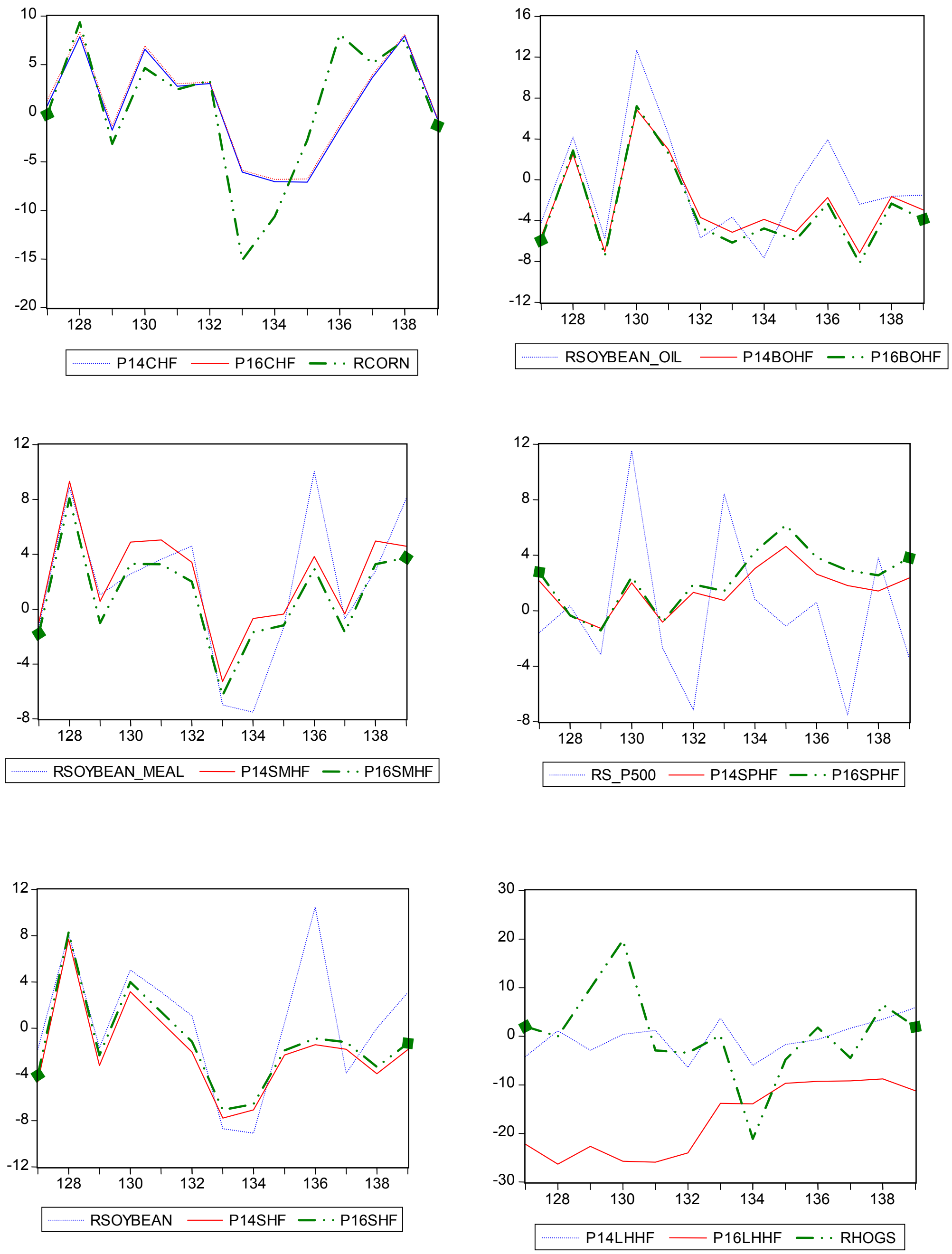
12
8
4
0
-4
-8
128 130 132 134 136 138
RSOYBEAN_OIL
P13BOSF
P15BOSF

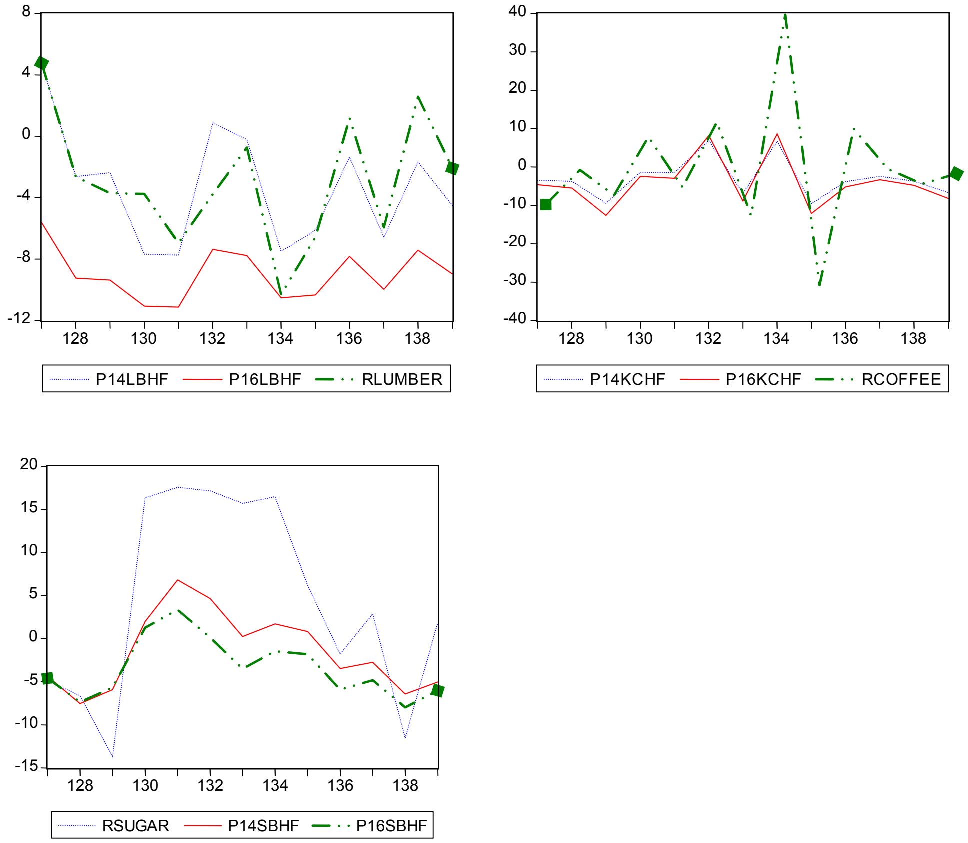

12
8
4
0
-4
-8
128 130 132 134 136 138
RS_P500
P13SPSF
P15SPSF


20
15
10
5
0
-5
-10
-15
128 130 132 134 136 138
RSUGAR
P13SBSF
P15SBSF

Graph 4.10
Forecasted returns of Hedgers under GARCH and PARCH models under *t* distribution

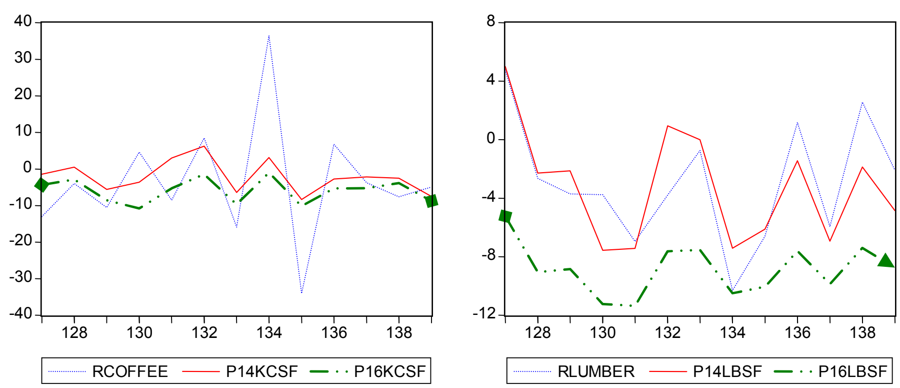
This graph shows the forecasted returns for hedgers under *t* distribution, for both the GARCH and PARCH model. The actual futures returns are included to compare the forecasted returns with the actual returns. The forecasting sample is from Jan 2000 to Dec 2000.

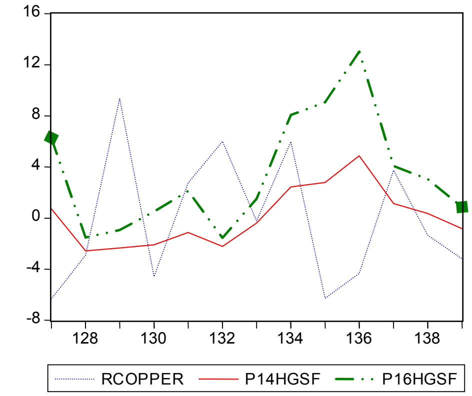


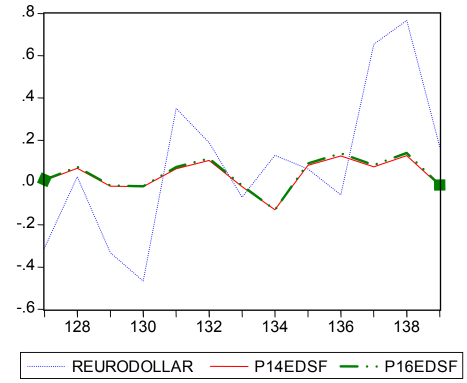


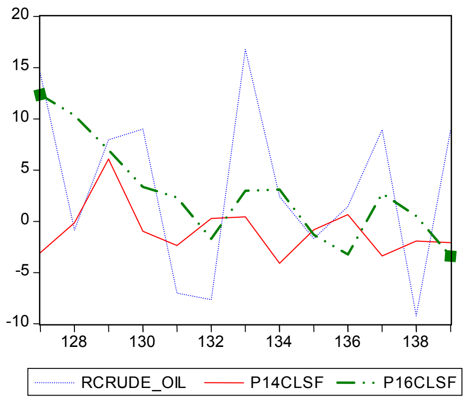
Graph 4.11
Forecasted returns of speculators under GARCH and PARCH models under *t* distribution

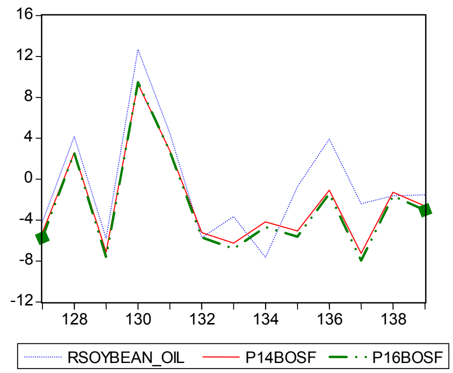
This graph shows the forecasted returns for speculators under *t* distribution, for both the GARCH and PARCH model. The actual futures returns are included to compare the forecasted returns with the actual returns. The forecasting sample is from Jan 2000 to Dec 2000.




16
12
8
4
0
-4
-8
128 130 132 134 136 138
RCOPPER P14HGSF P16HGSF


.8
.6
.4
.2
.0
-.2
-.4
-.6
128 130 132 134 136 138
REURODOLLAR P14EDSF P16EDSF


20
15
10
5
0
-5
-10
128 130 132 134 136 138
RCRUDE_OIL P14CLSF P16CLSF


16
12
8
4
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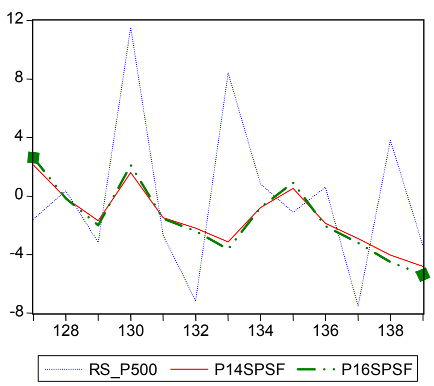
-4
-8
-12
128 130 132 134 136 138
RSOYBEAN_OIL P14BOSF P16BOSF


12
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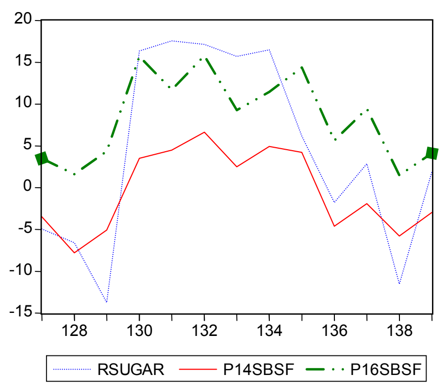
4
0
-4
-8
128 130 132 134 136 138
RS_P500 P14SPSF P16SPSF


20
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10
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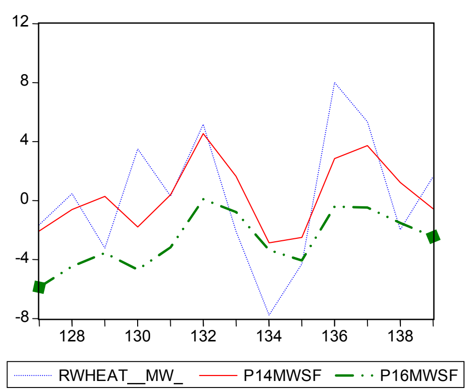
0
-5
-10
-15
128 130 132 134 136 138
RSUGAR P14SBSF P16SBSF

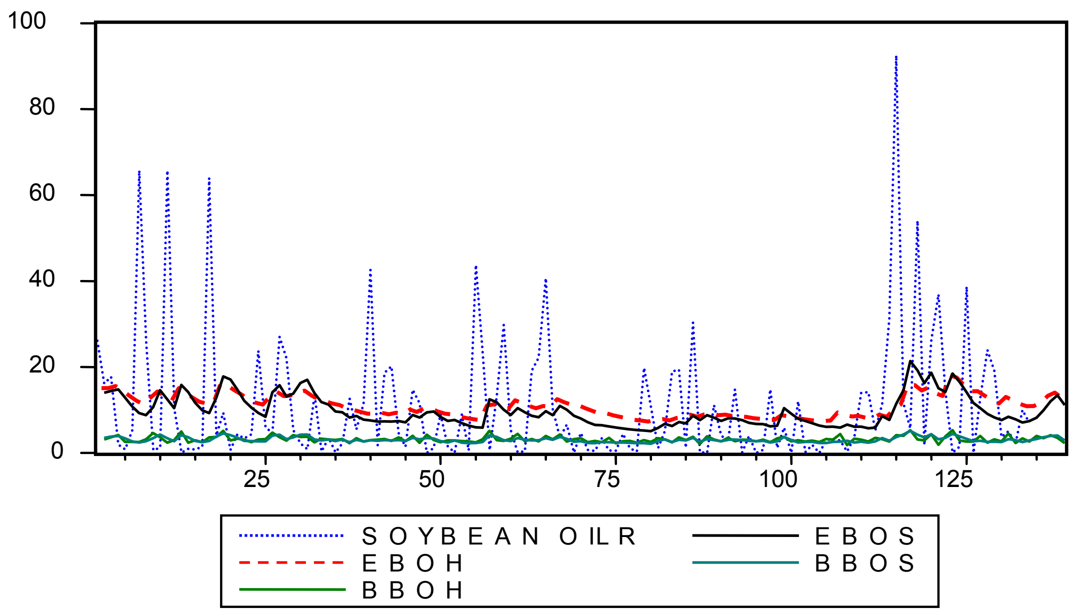

12
8
4
0
-4
-8
128 130 132 134 136 138
RWHEAT__MW_ P14MWSF P16MWSF

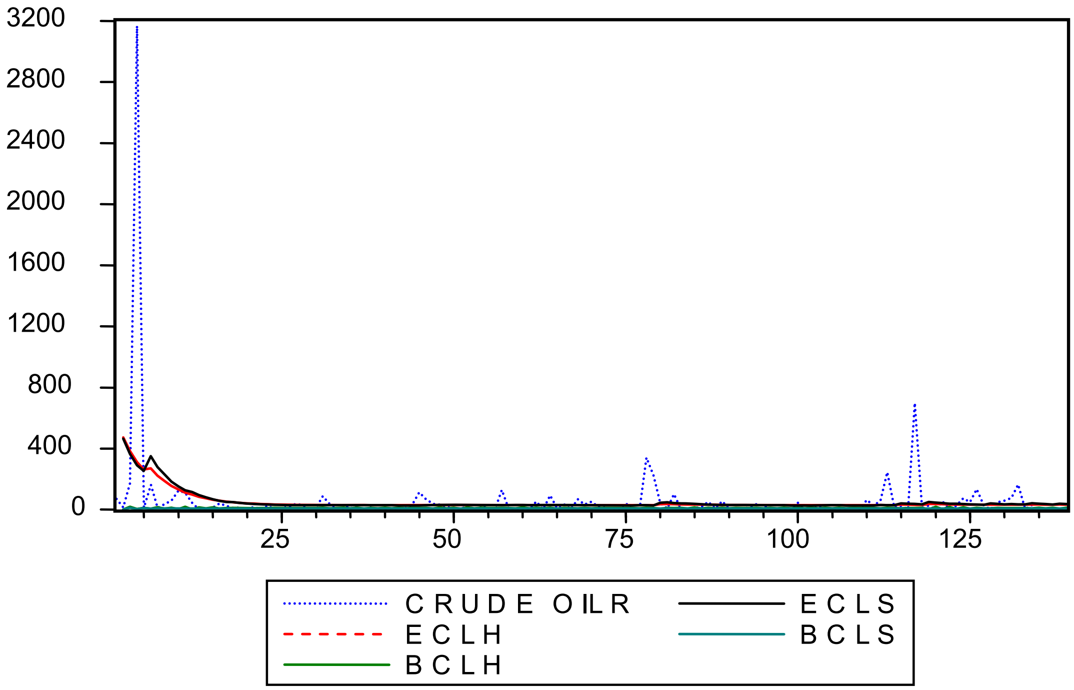
Appendix 6.15.1

Graph 4.7.1
Idiosyncratic volatility, conditional standard deviation and variance for hedgers and speculators' returns under normal distribution

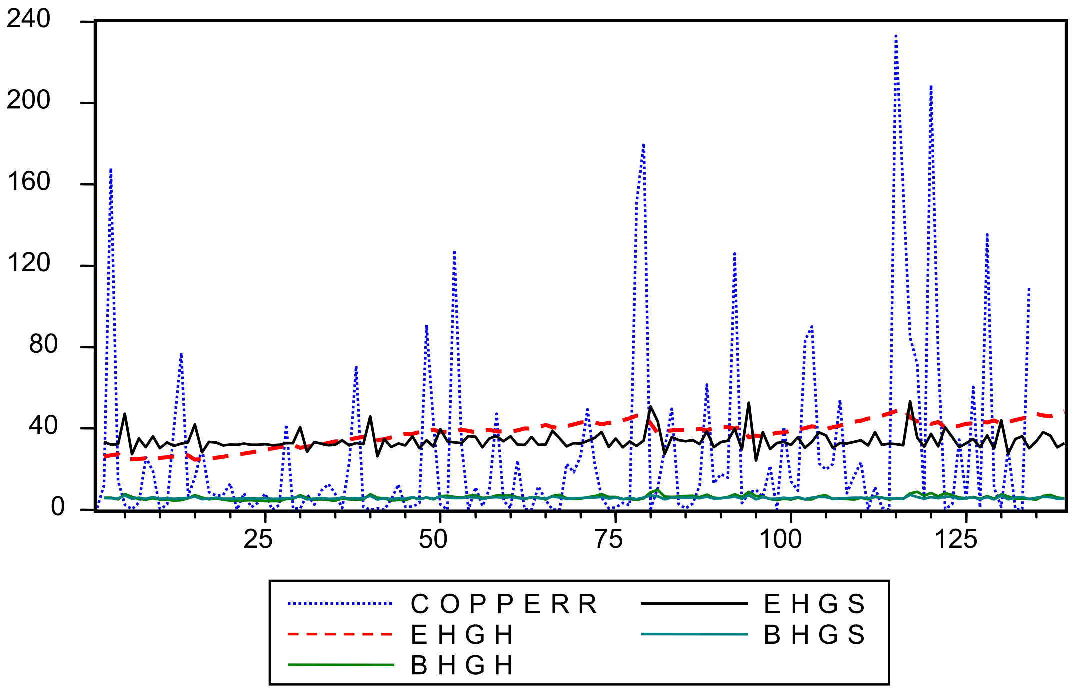
This graph shows the idiosyncratic volatility, conditional variance and standard deviation under GARCH and PARCH model for hedgers and speculators under normal distribution. The full sample size (1 139) is included in Panel A since conditional variance and standard deviation are not expected to change much in the forecasted sample. Actual data are used for out-of-sample observations. Idiosyncratic volatility is used as a proxy of actual volatility. Panel B shows a clearer view of the forecasted sample 127 139.

Panel A

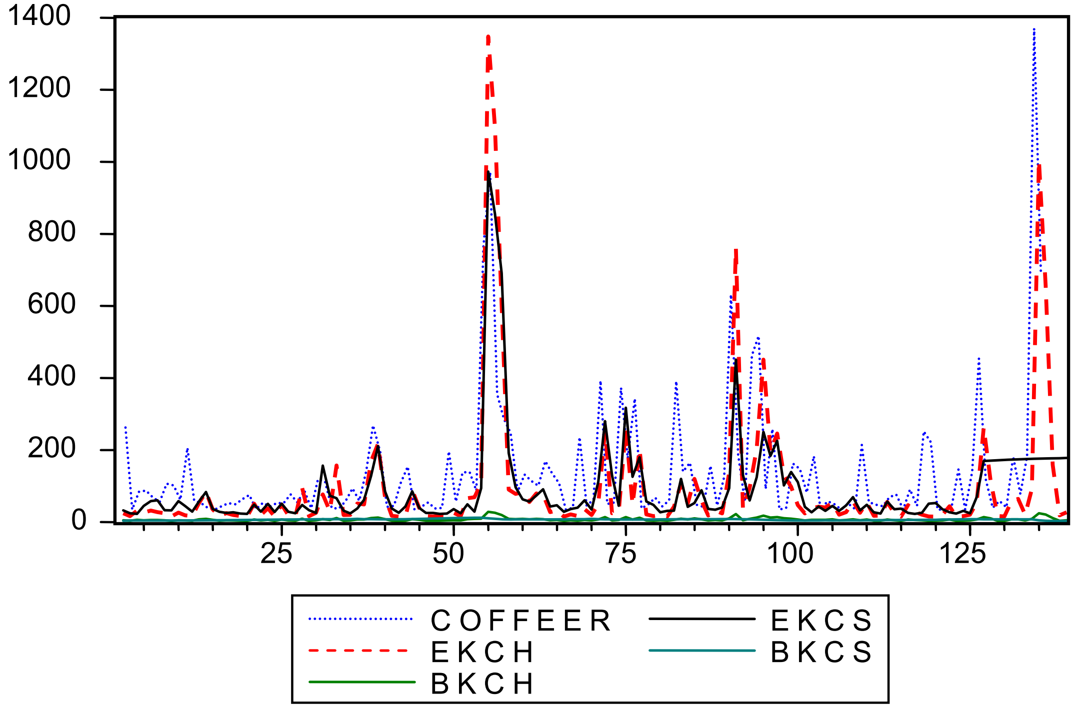




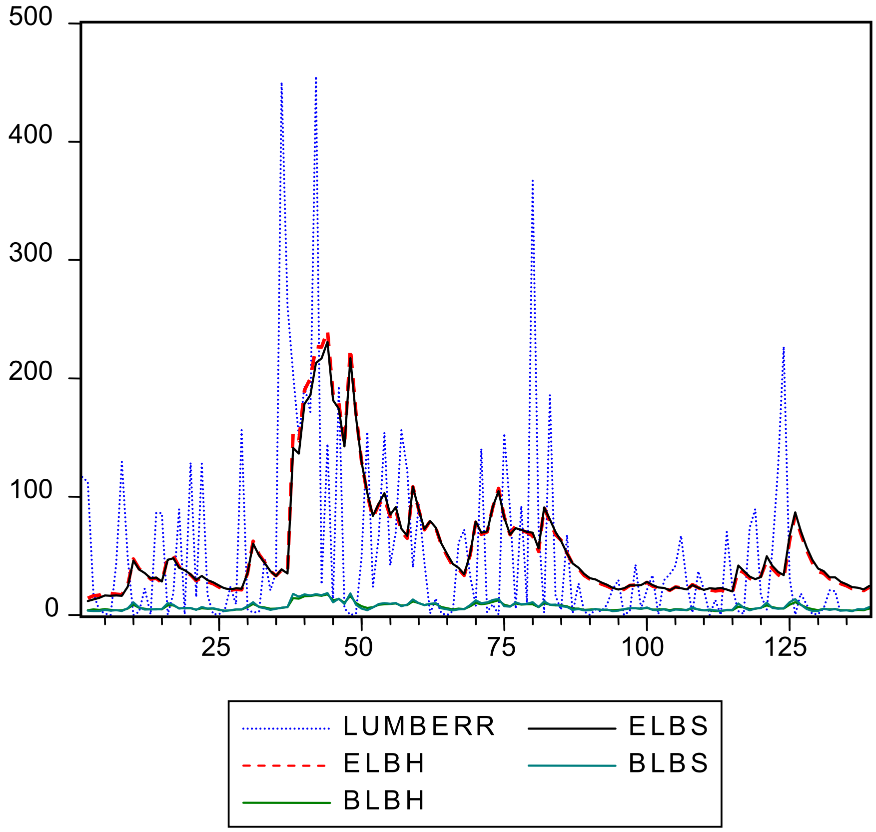
3200
2800
2400
2000
1600
1200
800
400
0
25
50
75
100
125
CRUDE OILR
ECLS
ECLH
BCLS
BCLH



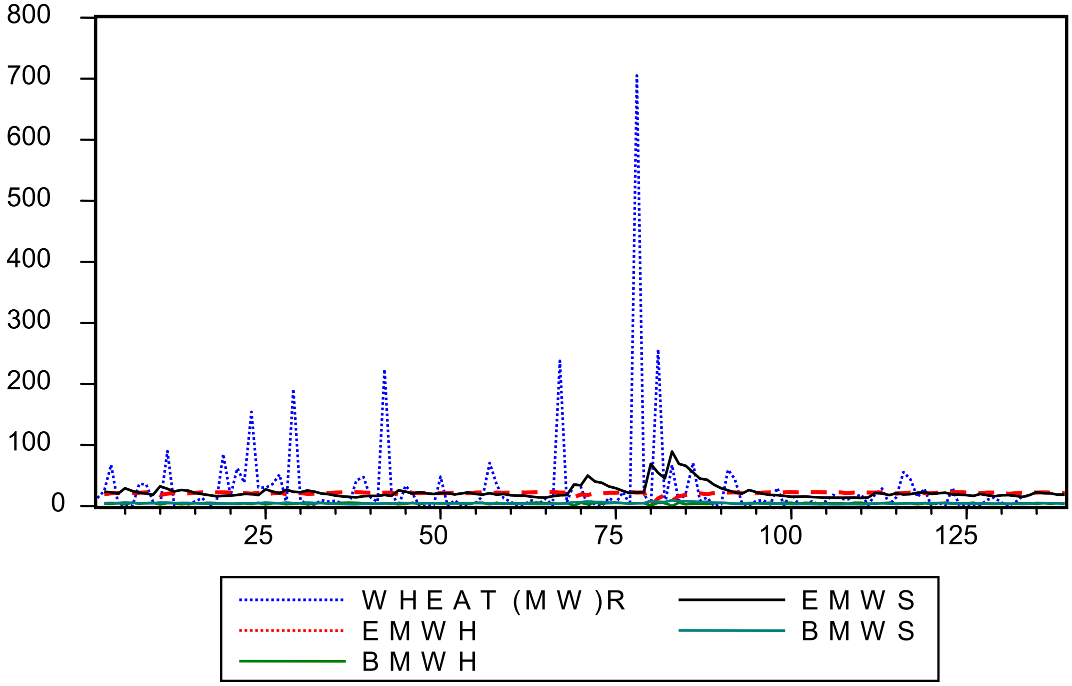
240
200
160
120
80
40
0
25
50
75
100
125
COPPERR
EHGS
EHGH
BHGS
BHGH

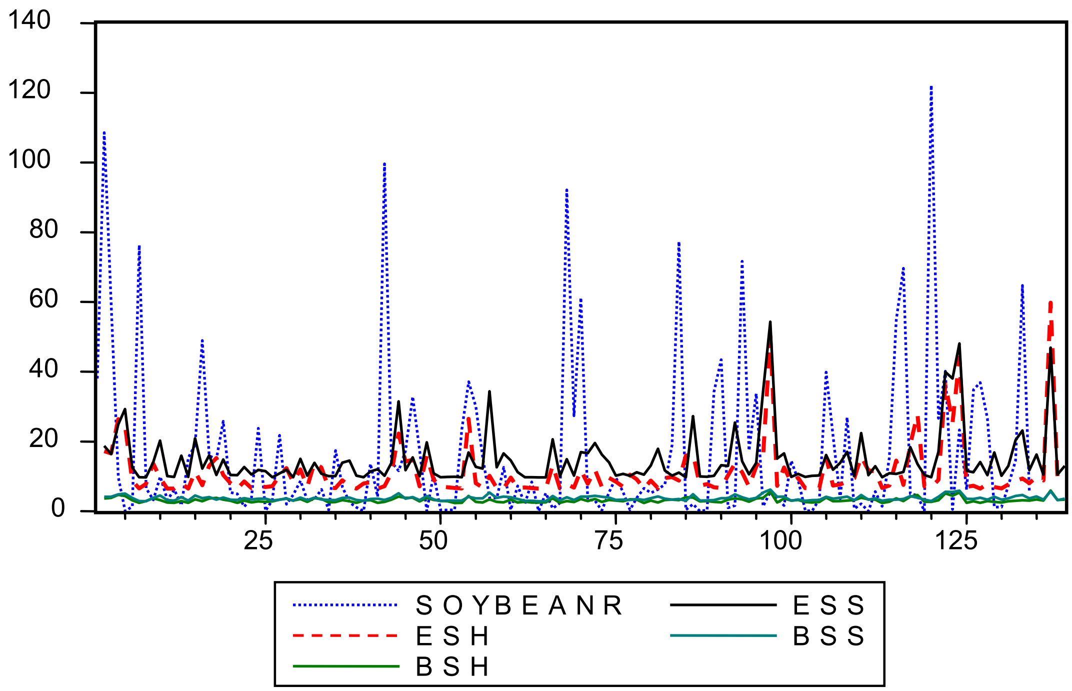


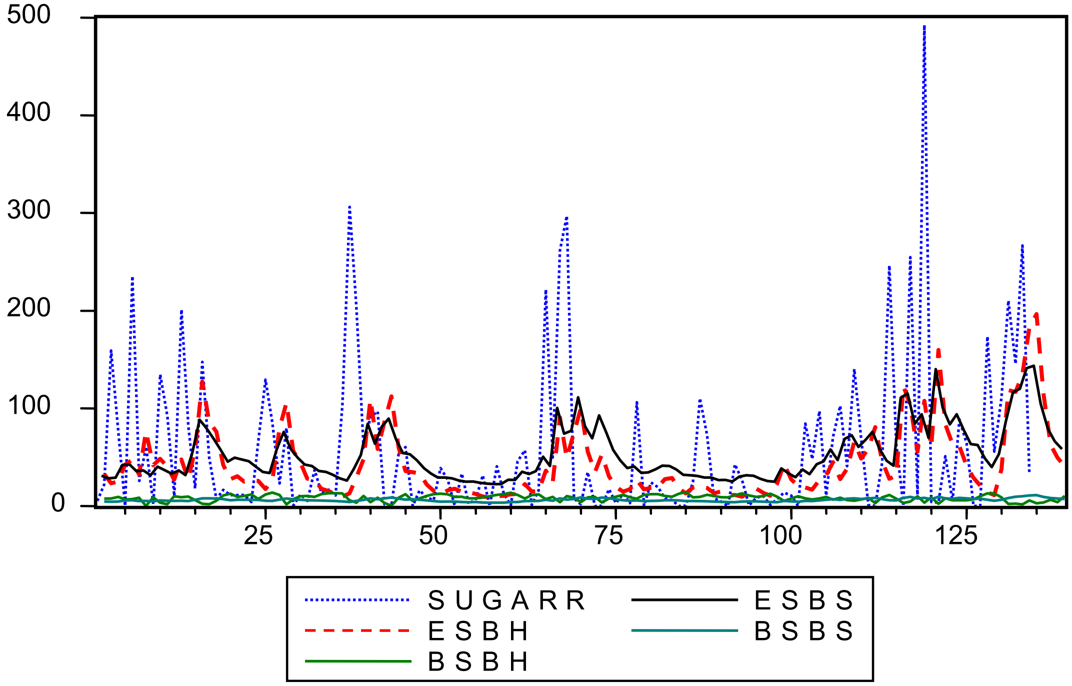
1400
1200
1000
800
600
400
200
0
25
50
75
100
125
COFFEER
EKCH
BKCH
EKCS
BKCS



500
400
300
200
100
0
25
50
75
100
125
LUMBERR
ELBH
BLBH
ELBS
BLBS


800
700
600
500
400
300
200
100
0
25
50
75
100
125
W H E A T (M W)R
E M W H
B M W H
E M W S
B M W S


140
120
100
80
60
40
20
0
25
50
75
100
125
S O Y B E A N R
E S H
B S H
E S S
B S S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400
300
200
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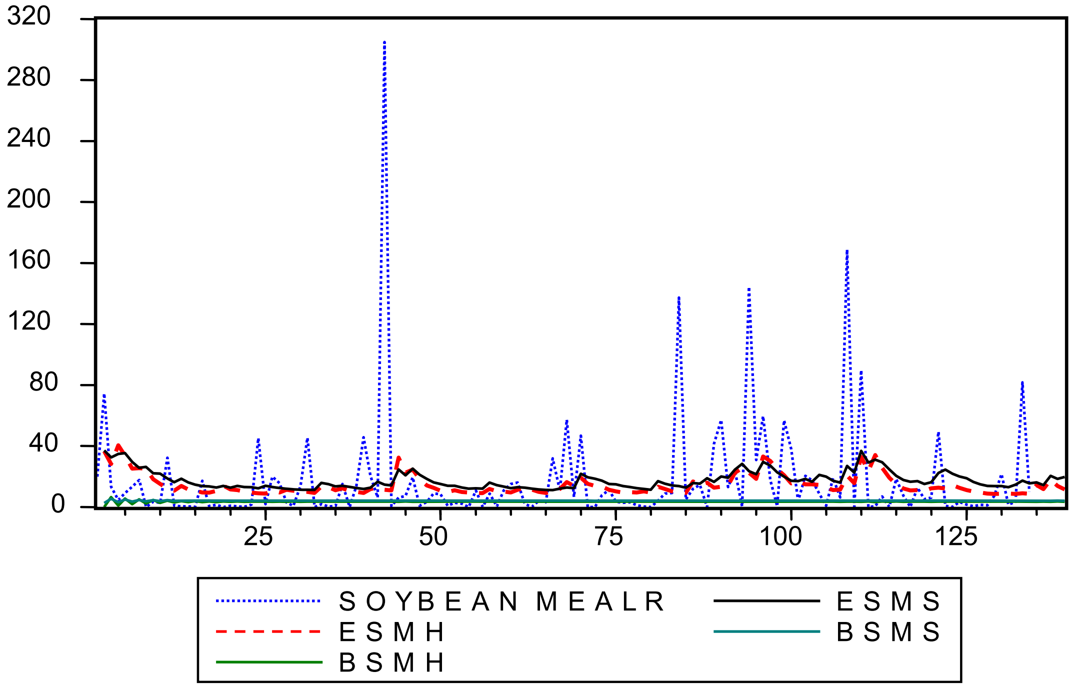
0
25
50
75
100
125
SUGARR
ESBS
ESBH
BSBS
BSBH


320
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240
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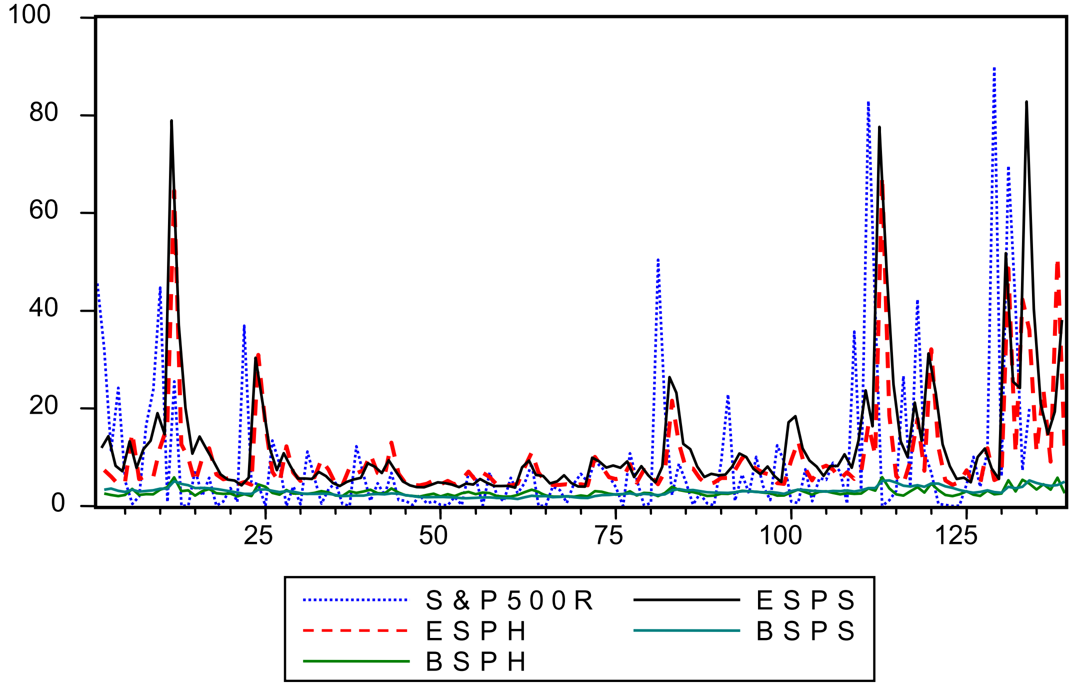
120
80
40
0
25
50
75
100
125
SOYBEAN MEALR
ESMS
ESMH
BSMS
BSMH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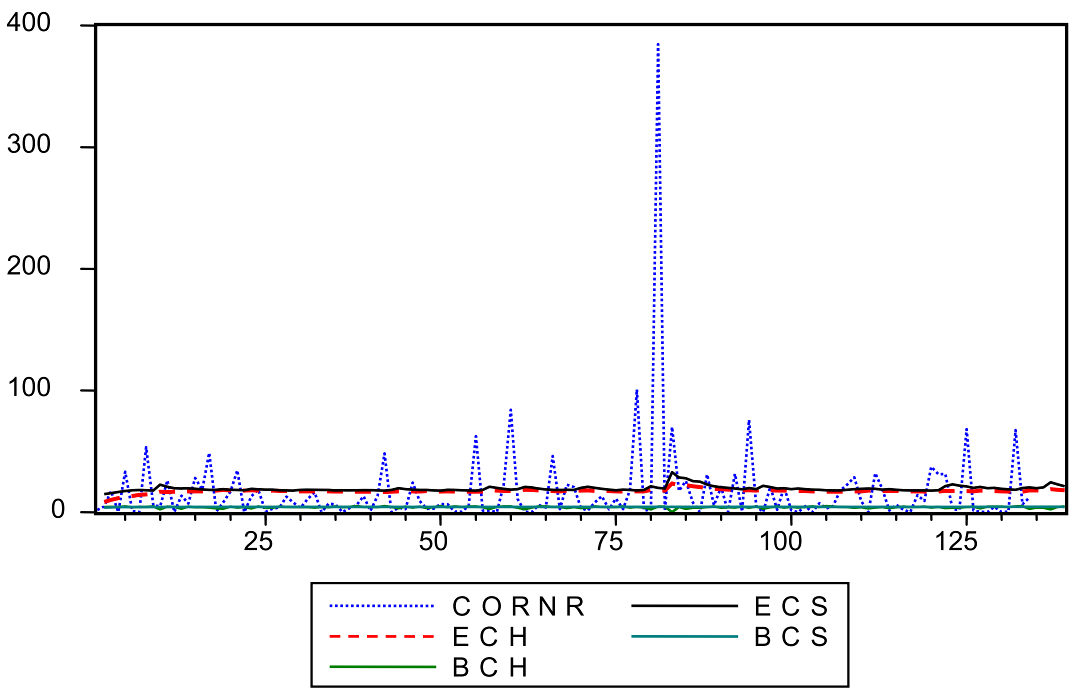
60
40
20
0
25
50
75
100
125
S&P500R
ESPS
ESPH
BSPS
BSPH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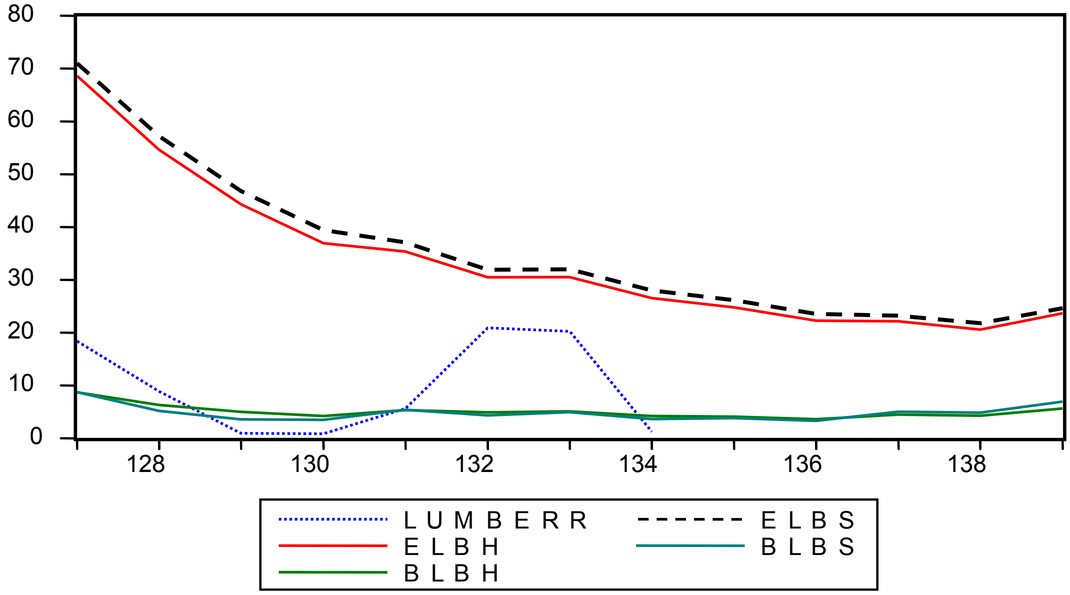
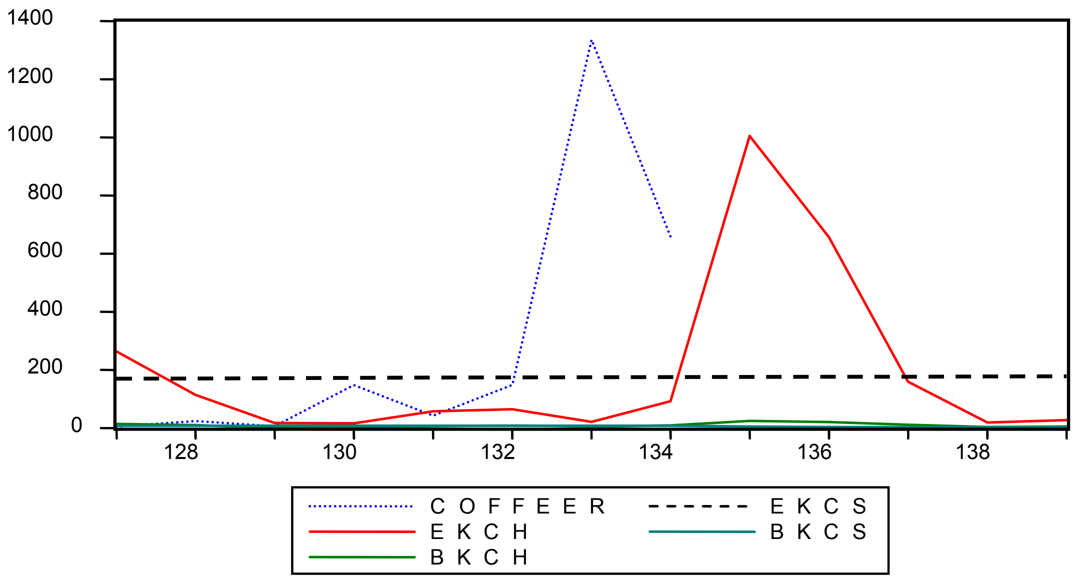
25
50
75
100
125
CORNR
ECS
ECH
BCS
BCH

Panel B



80
70
60
50
40
30
20
10
0
128
130
132
134
136
138
LUMBERR
ELBS
ELBH
BLBS
BLBH


1400
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1000
800
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200
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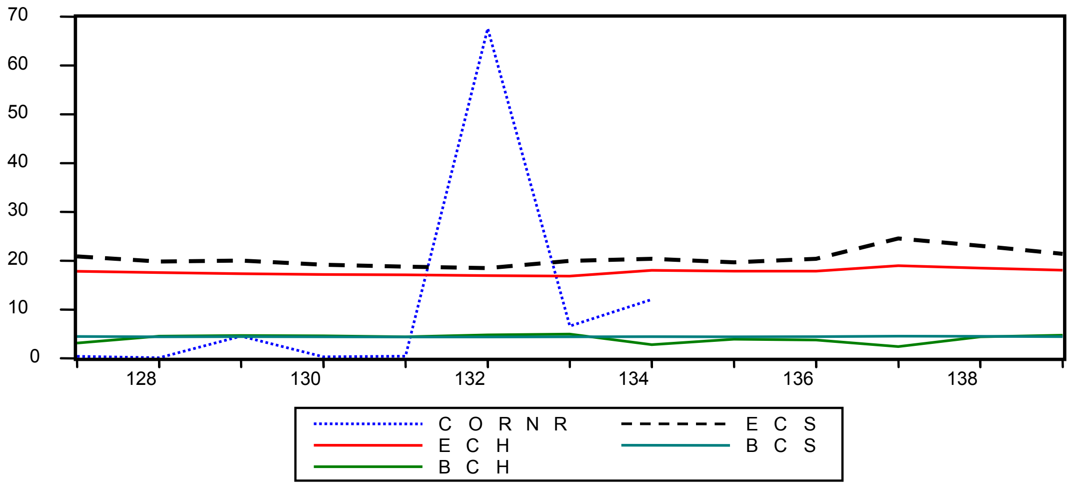
138
C O F F E E R
E K C S
E K C H
B K C S
B K C H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134
136
138
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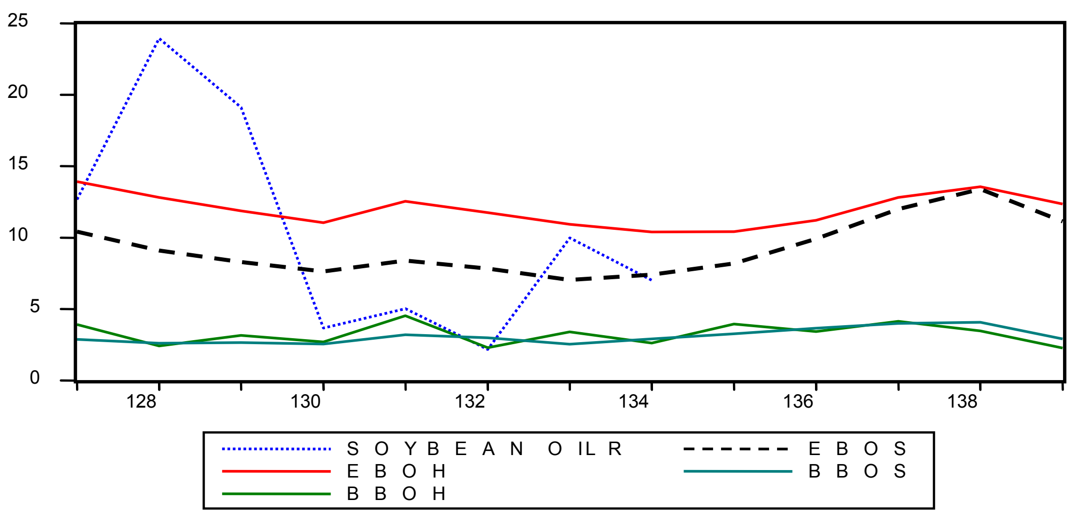
E C S
E C H
B C S
B C H


25
20
15
10
5
0
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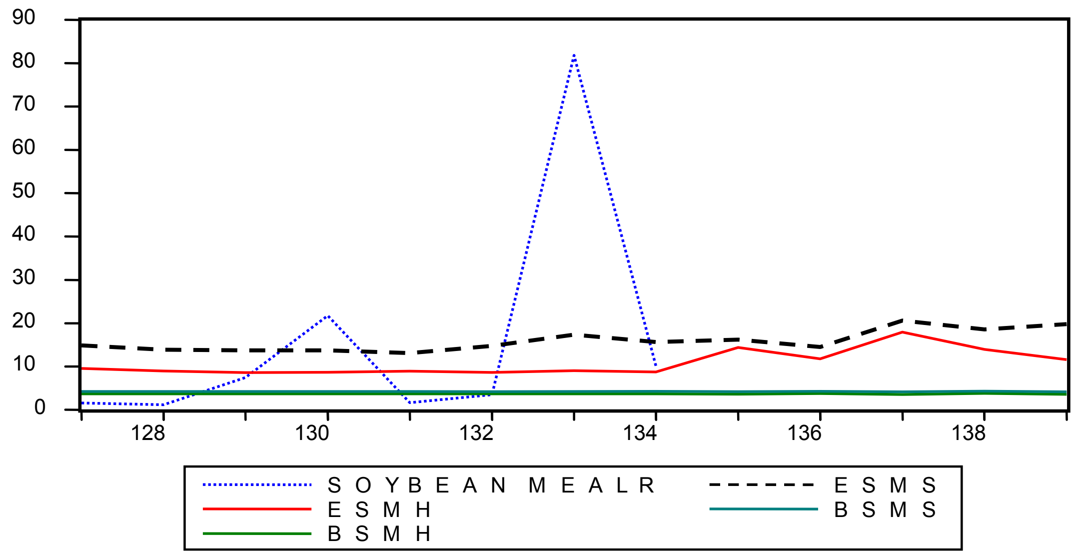
130
132
134
136
138
S O Y B E A N O IL R
E B O S
E B O H
B B O S
B B O H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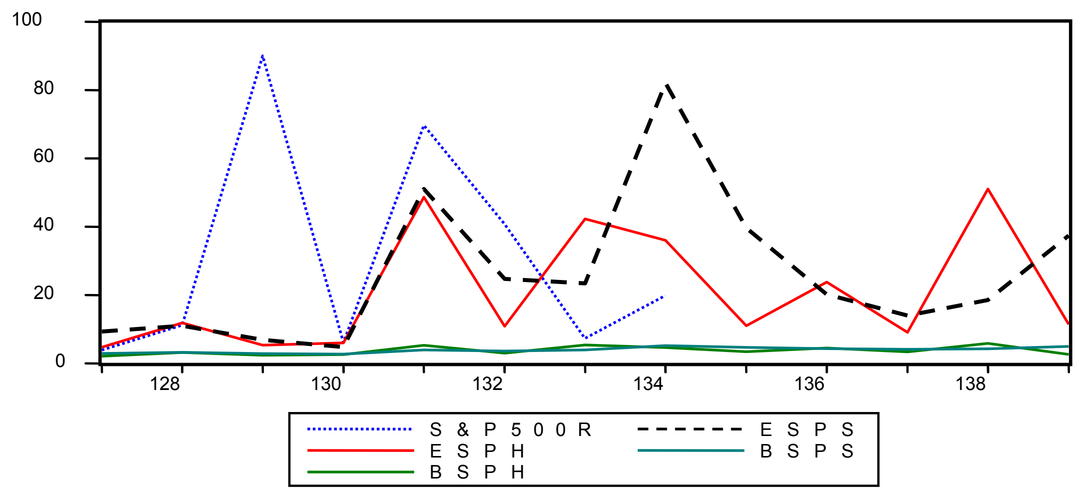
E S M S
E S M H
B S M S
B S M H


100
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136
138
S & P 5 0 0 R
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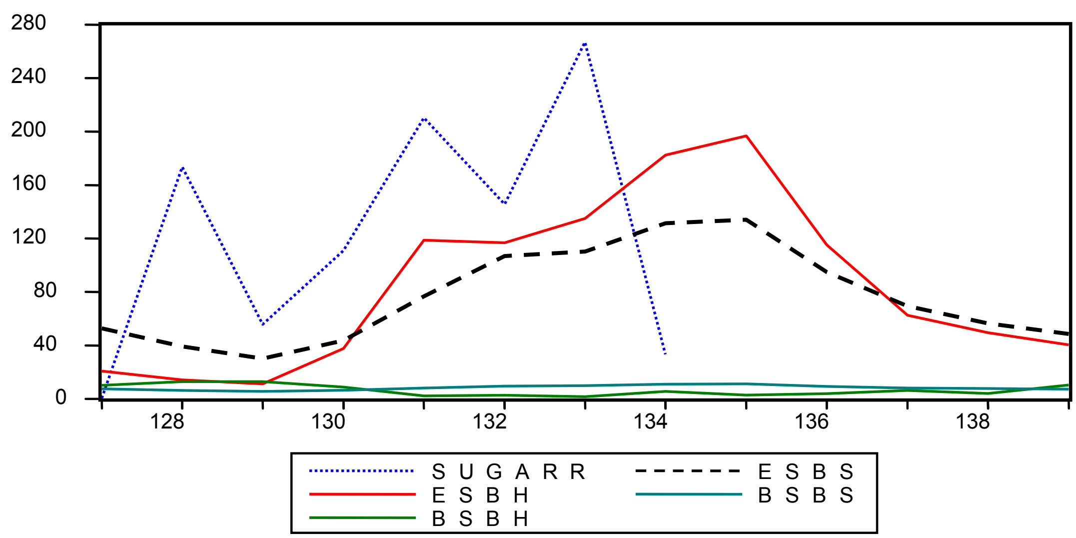
E S P H
B S P S
B S P H


280
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200
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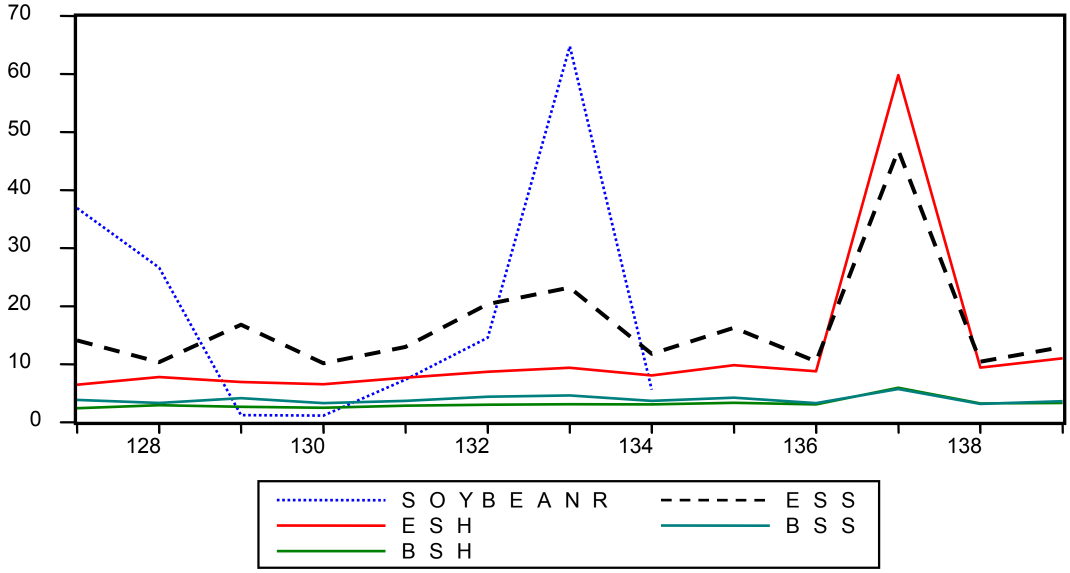
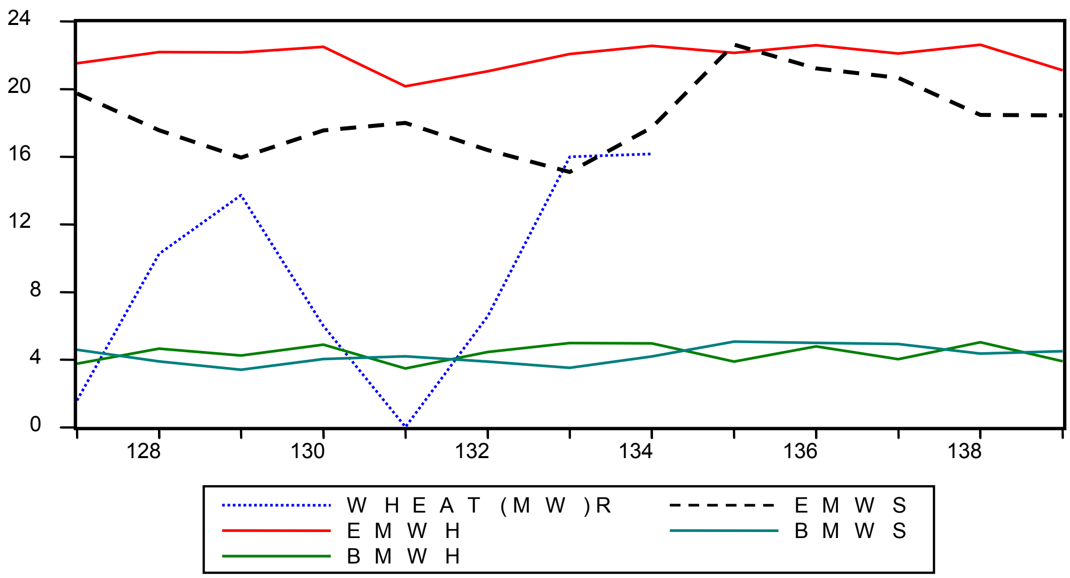
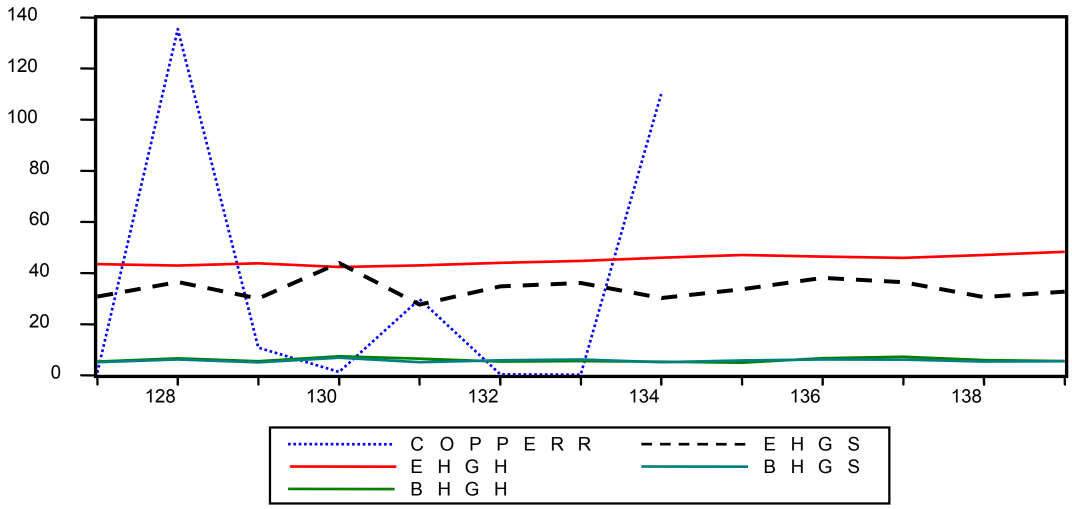
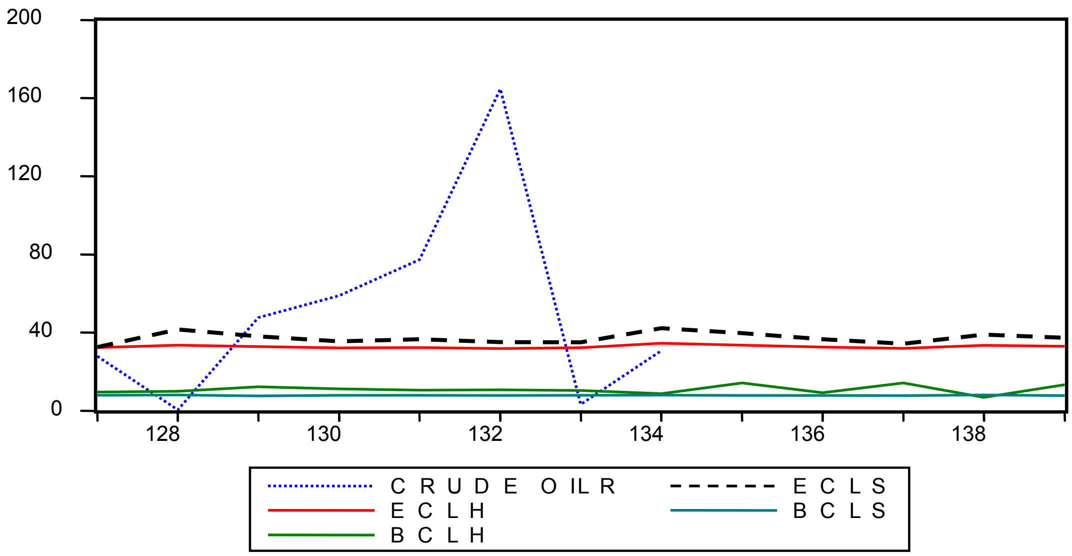
120
80
40
0
128
130
132
134
136
138
S U G A R R
E S B S
E S B H
B S B S
B S B H


70
60
50
40
30
20
10
0
128
130
132
134
136
138
S O Y B E A N R
E S S
E S H
B S S
B S H


24
20
16
12
8
4
0
128
130
132
134
136
138
W H E A T (M W) R
E M W S
E M W H
B M W S
B M W H


140
120
100
80
60
40
20
0
128
130
132
134
136
138
C O P P E R R
E H G S
E H G H
B H G S
B H G H

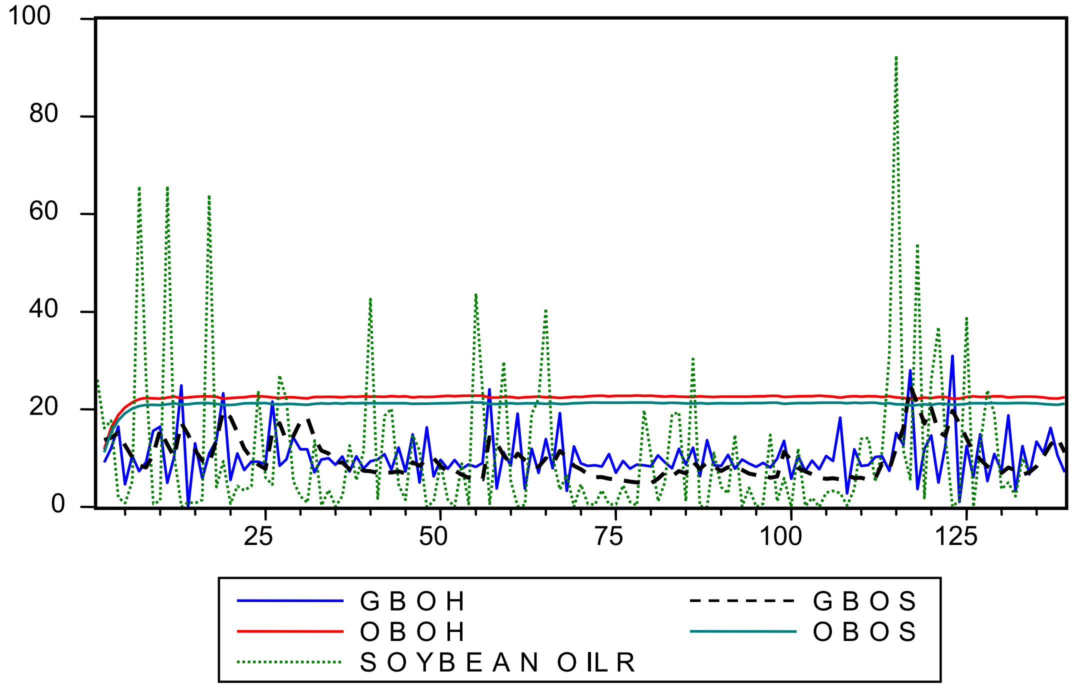

200
160
120
80
40
0
128
130
132
134
136
138
C R U D E O IL R
E C L S
E C L H
B C L S
B C L H

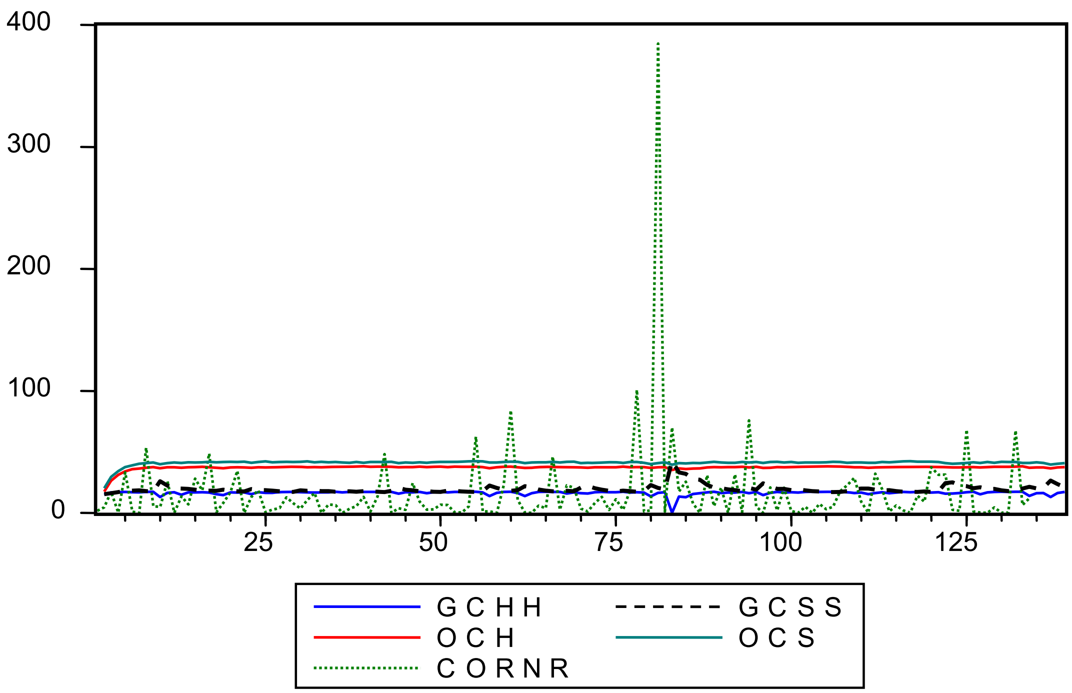
Appendix 6.15.2

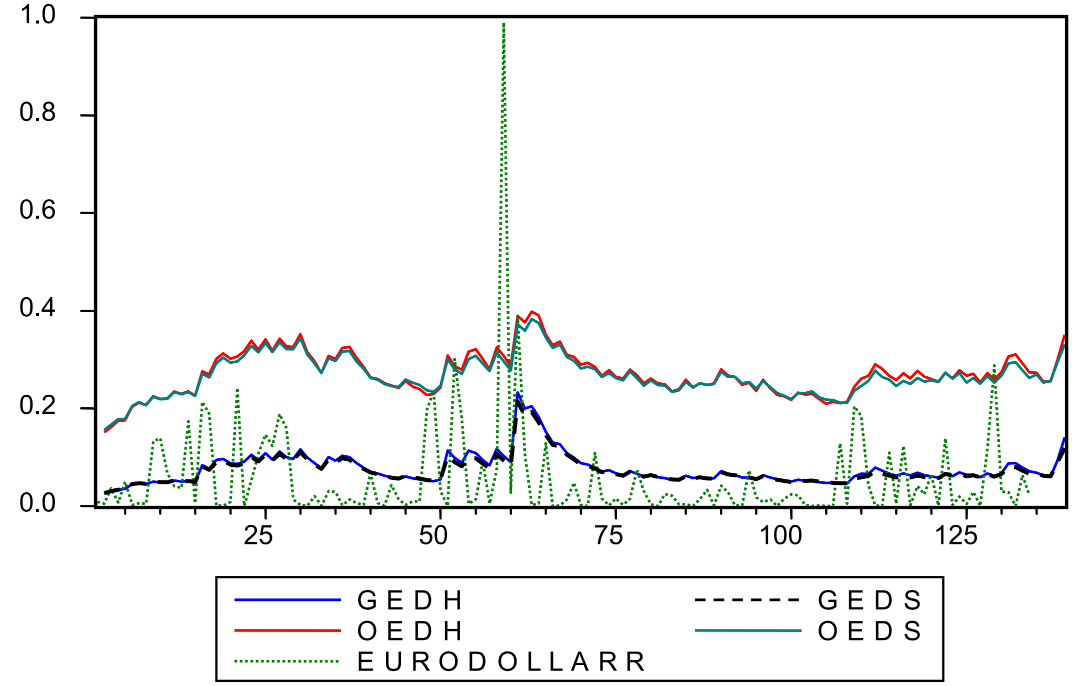
Graph 4.7.2
Idiosyncratic volatility, conditional standard deviation and variance for hedgers and speculators' returns under *t* distribution

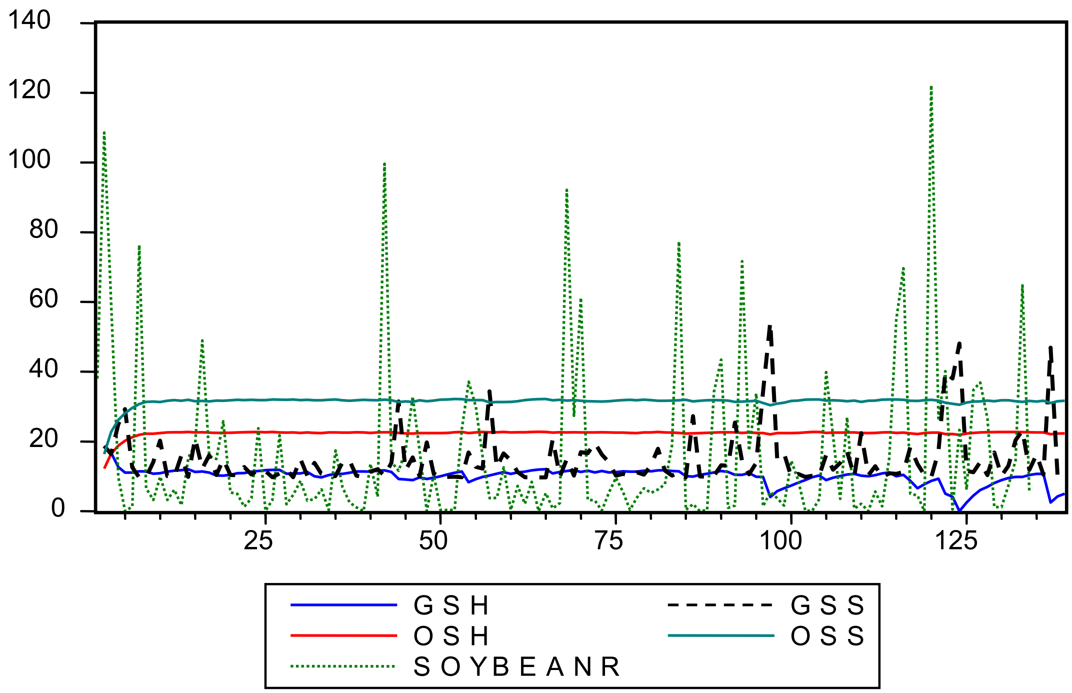
This graph shows the idiosyncratic volatility, conditional variance and standard deviation under GARCH and PARCH model for hedgers and speculators under *t* distribution. The full sample size (1 139) is included in Panel A since conditional variance and standard deviation are not expected to change much in the forecasted sample. Actual data are used for out-of-sample observations. Idiosyncratic volatility is used as a proxy of actual volatility. Panel B shows a clearer view of the forecasted sample 127 139.

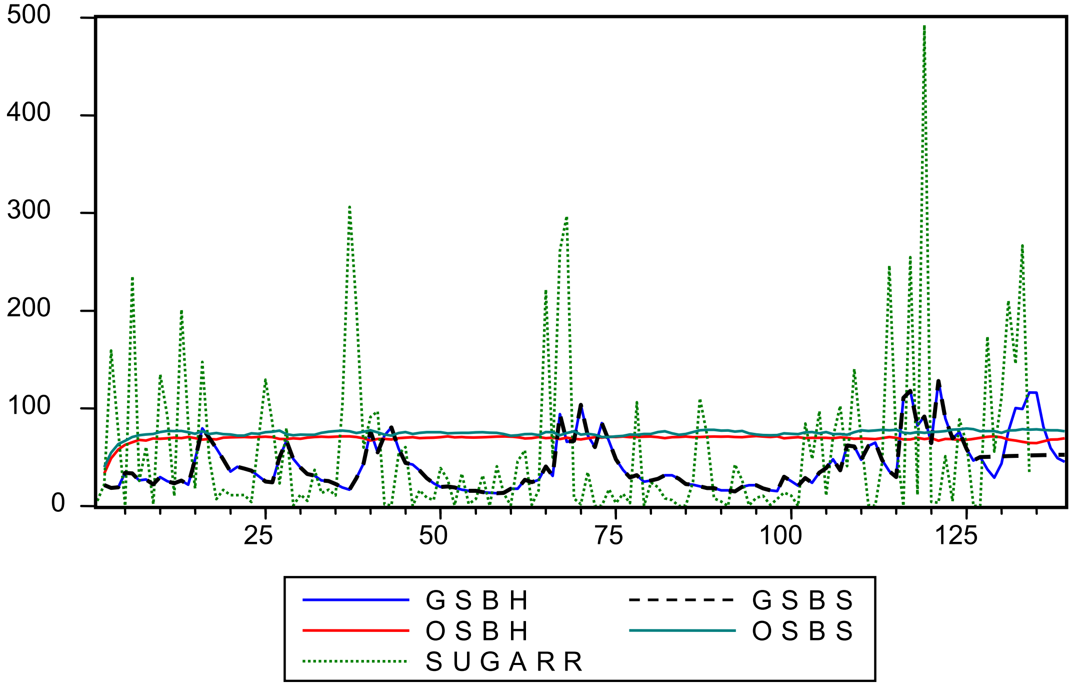
Panel A



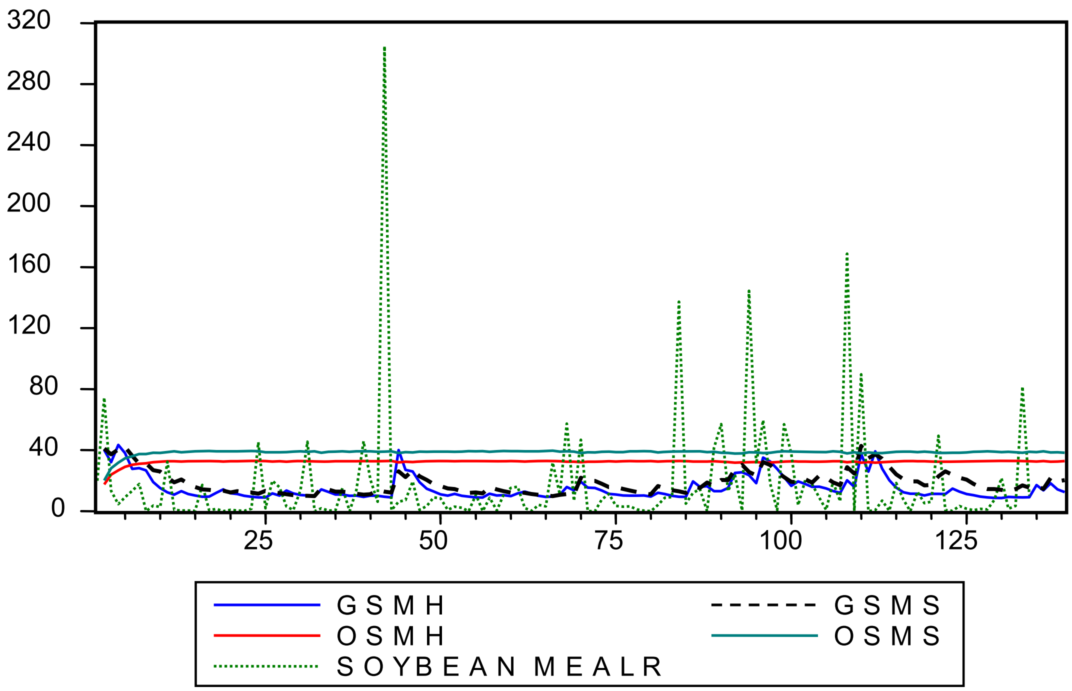



1.0
0.8
0.6
0.4
0.2
0.0
25
50
75
100
125
GEDH
GEDS
OEDH
OEDS
EURODOLLARR

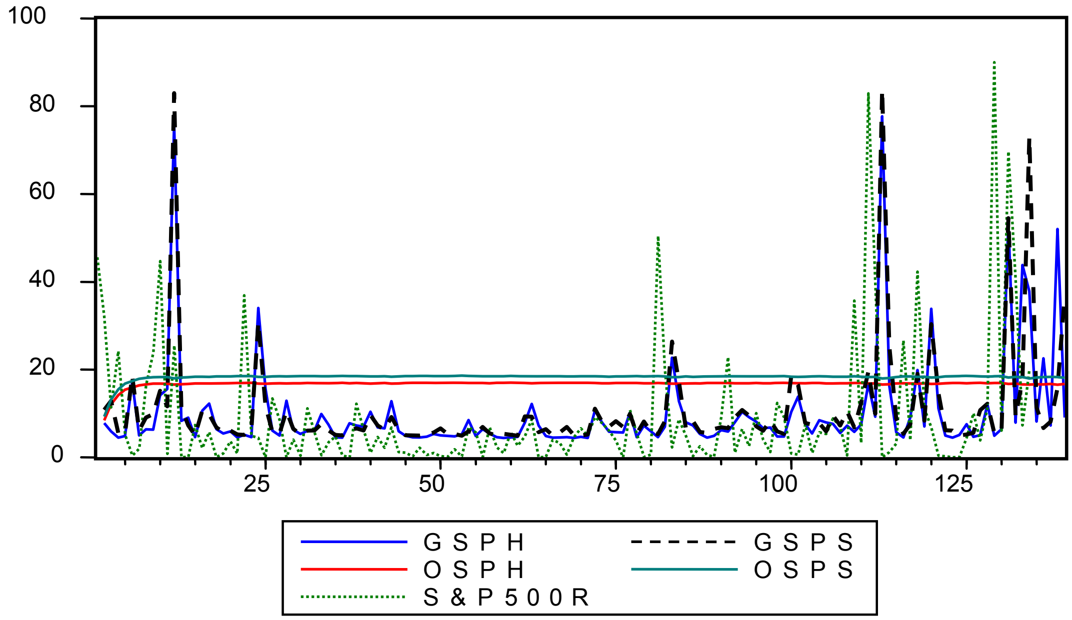

140
120
100
80
60
40
20
0
25
50
75
100
125
GSH
GSS
OSH
OSS
SOYBEANR



500
400
300
200
100
0
25
50
75
100
125
GSBH
GSBS
OSBH
OSBS
SUGARR

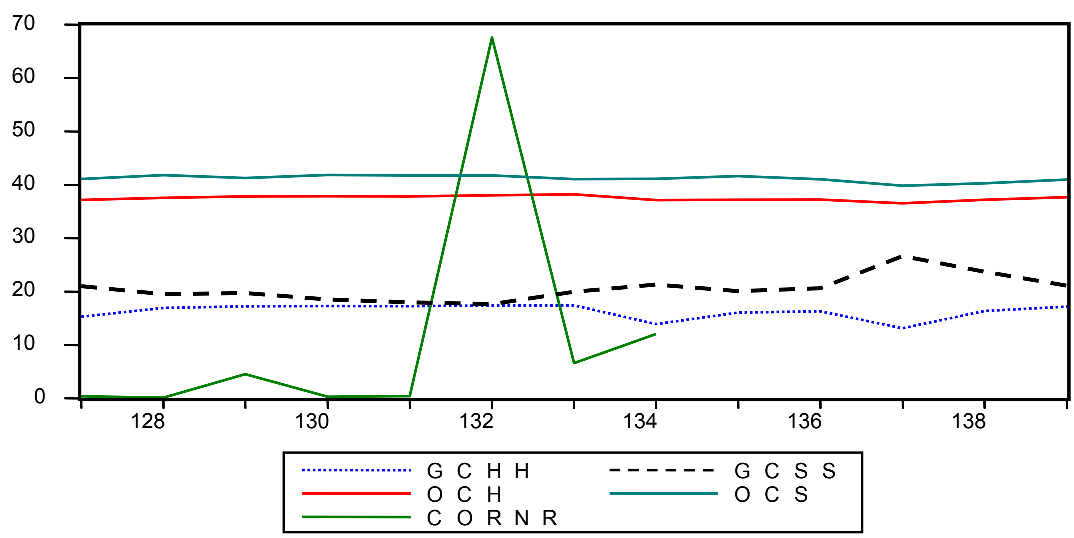


320
280
240
200
160
120
80
40
0
25
50
75
100
125
GSMH
GSMS
OSMH
OSMS
SOYBEAN MEALR

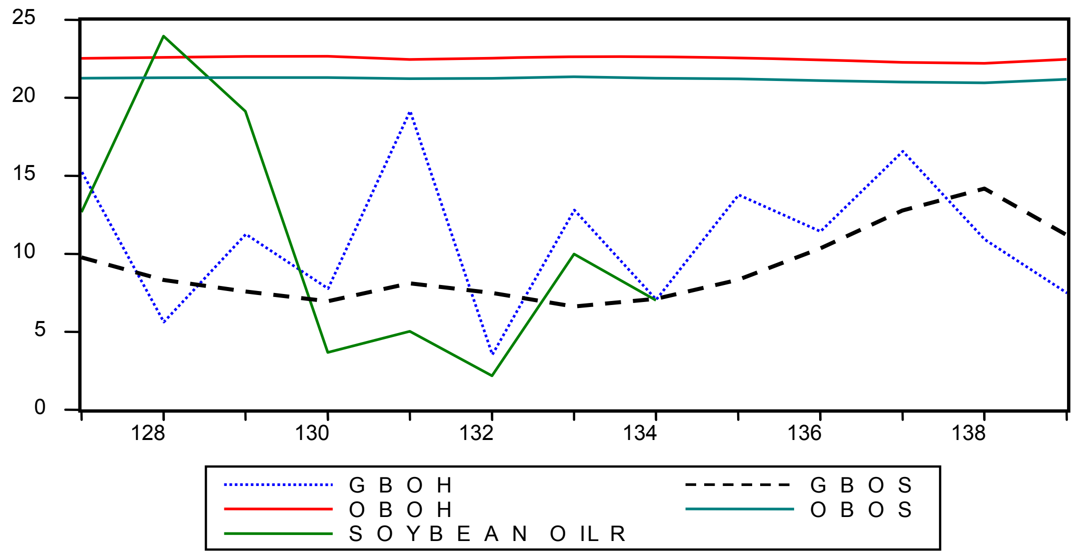


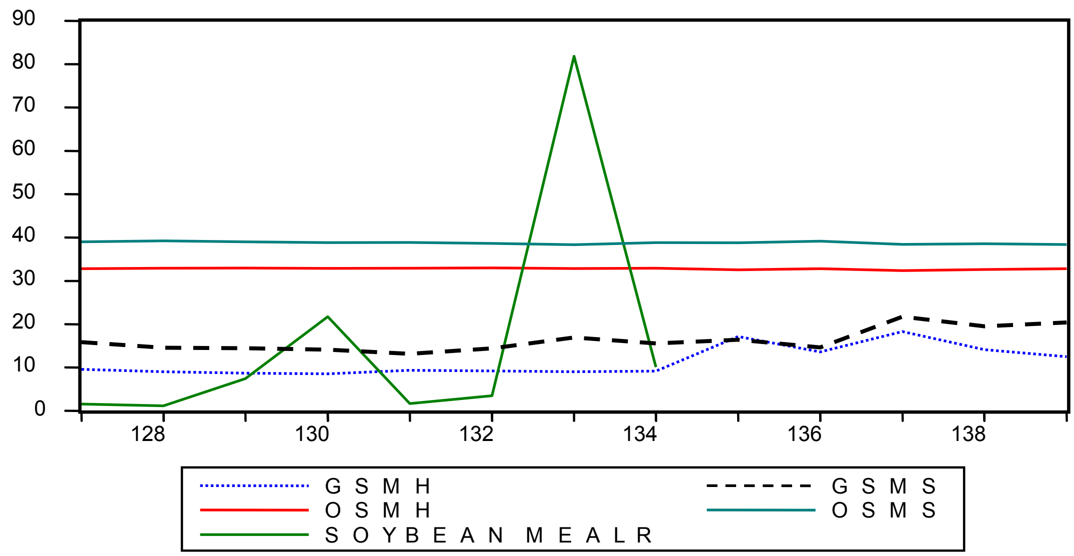
100
80
60
40
20
0
25
50
75
100
125
G S P H
G S P S
O S P H
O S P S
S & P 5 0 0 R

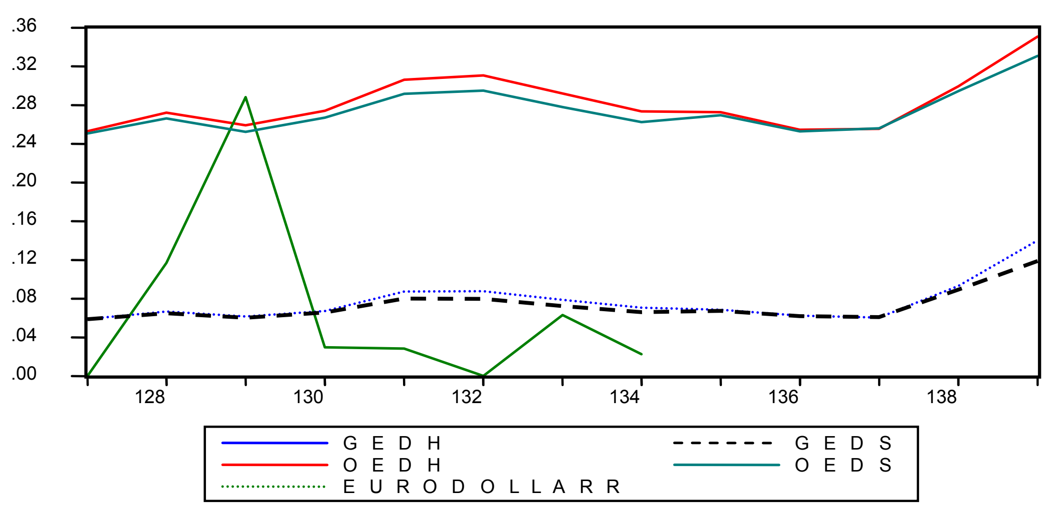
Panel B

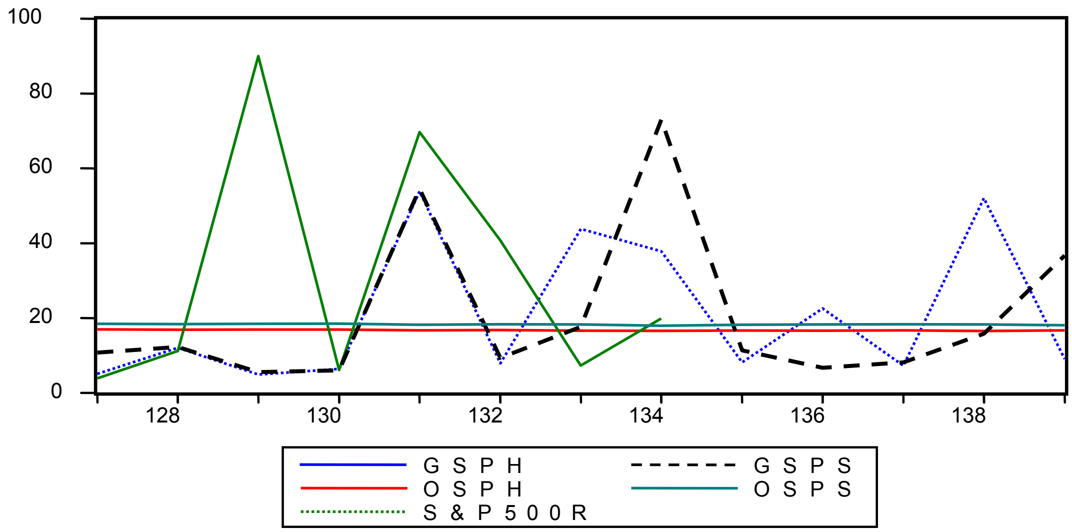


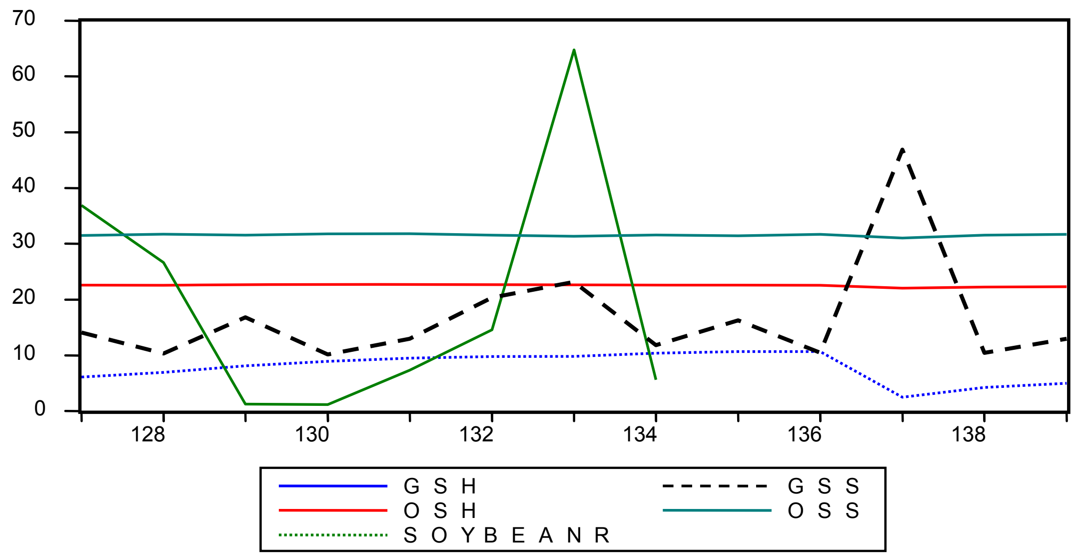
70
60
50
40
30
20
10
0
128
130
132
134
136
138
G C H H
G C S S
O C H
O C S
C O R N R

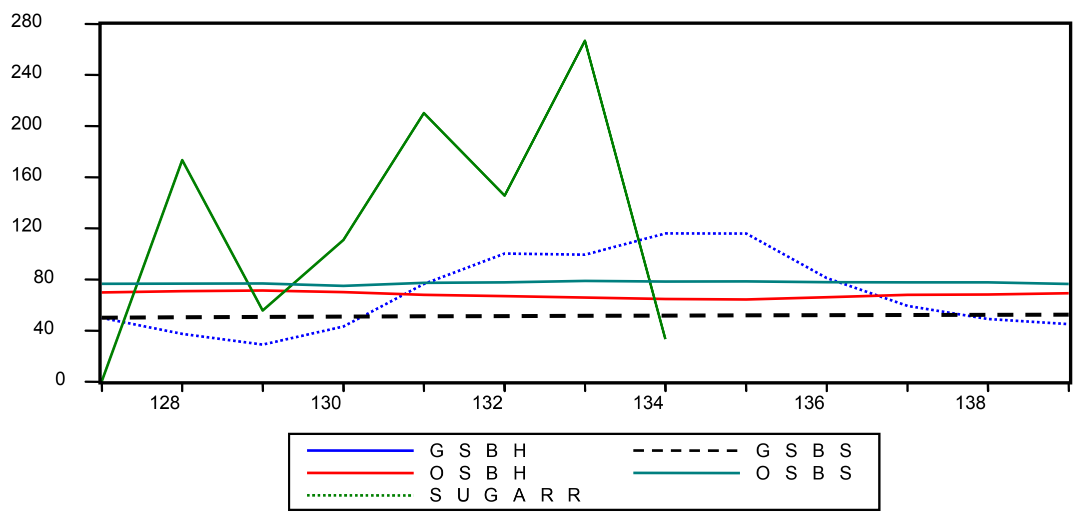

25
20
15
10
5
0
128
130
132
134
136
138
G B O H
G B O S
O B O H
O B O S
S O Y B E A N O IL R


90
80
70
60
50
40
30
20
10
0
128
130
132
134
136
138
G S M H
G S M S
O S M H
O S M S
S O Y B E A N M E A L R


.36
.32
.28
.24
.20
.16
.12
.08
.04
.00
128
130
132
134
136
138
G E D H
G E D S
O E D H
O E D S
E U R O D O L L A R R


100
80
60
40
20
0
128
130
132
134
136
138
G S P H
O S P H
S & P 5 0 0 R
G S P S
O S P S

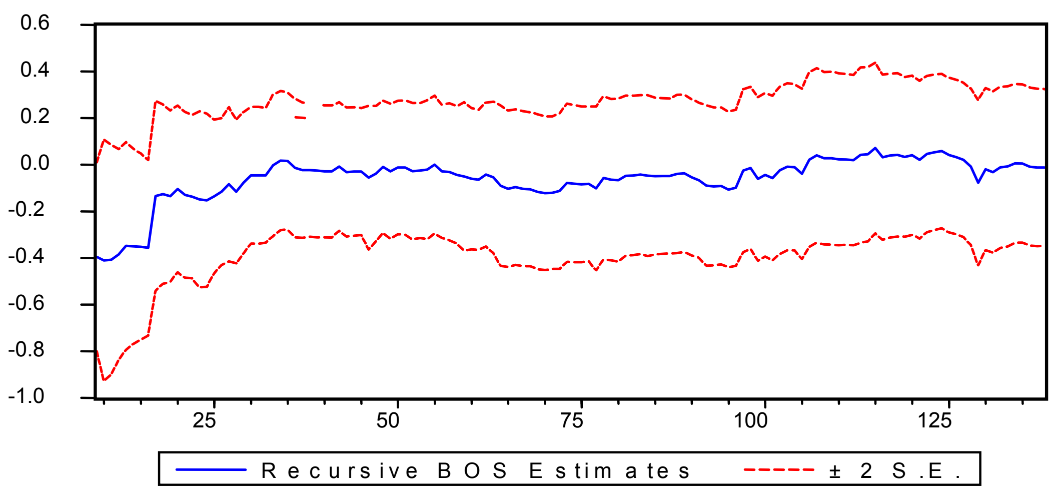

70
60
50
40
30
20
10
0
128
130
132
134
136
138
G S H
O S H
S O Y B E A N R
G S S
O S S

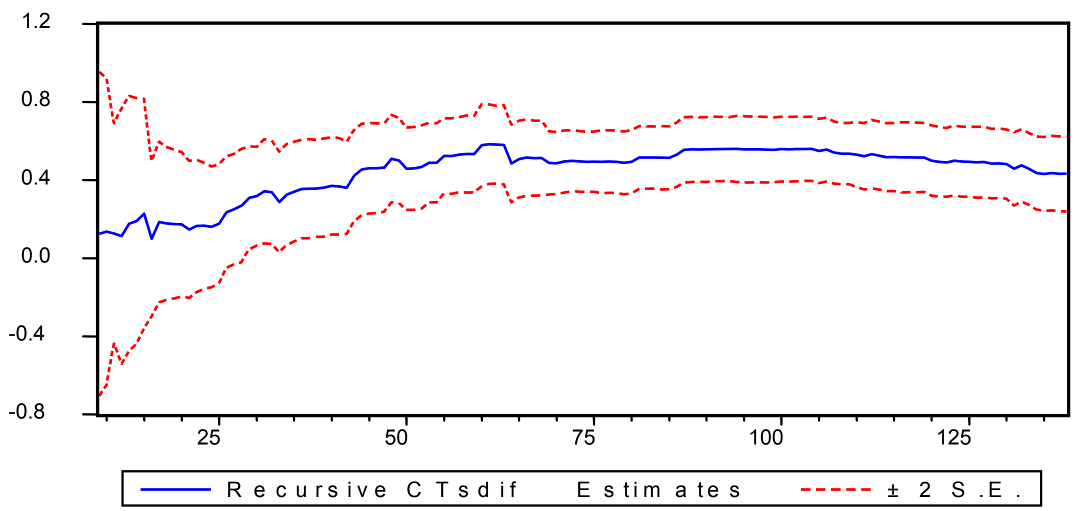

280
240
200
160
120
80
40
0
128
130
132
134
136
138
G S B H
O S B H
S U G A R R
G S B S
O S B S

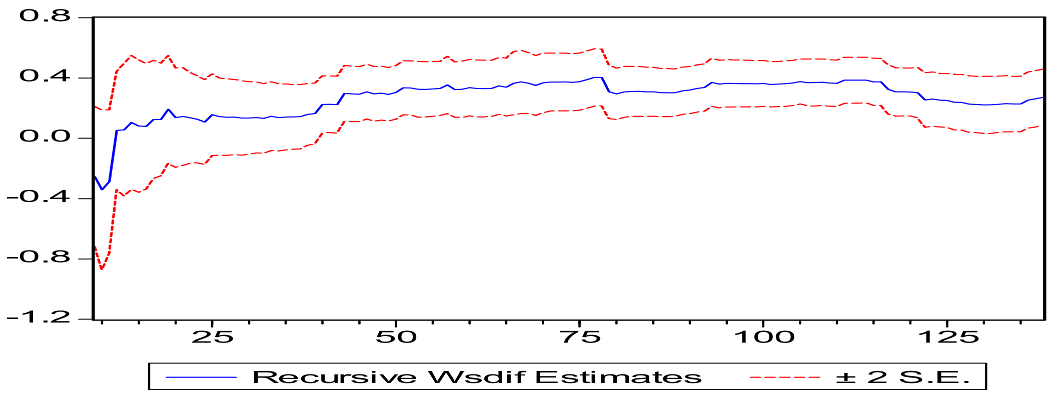
Appendix 6.16

Graph 4.20
Recursive coefficient estimates of futures returns in behaviour model

This set of graph shows the recursive coefficient estimates of futures returns from equation 4.20. The ability to trace the evolution of the returns over the whole sample (1 139) helps in finding whether the behaviour equation 4.20 is stable. If coefficient plots show dramatic jumps, this suggests the postulated equation is trying to digest a structural break. Any significant structural break is matched with a possible specific event listed in table 4.19.







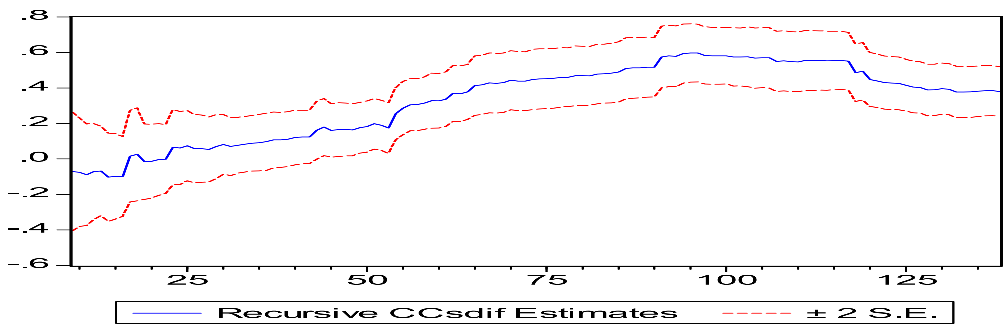


Table 4.21
Structural breaks and macroeconomic events (on behaviour - trading determinant model)

This table shows the structural breaks for those markets that matched any of the 8 major macroeconomic events of the 1990s. The arrow signs show whether there was an upward jump or downward jump in the recursive coefficient estimates of hedgers' and speculators' returns.

Structural breaks

	Hedgers	*Speculators*	*date*	*Event*
Crude oil		↓	4/02/1996	End of temporary revival from Japanese recession
		↓	12/08/1998	Start of the Introduction of Euro currency
Corn	↑		25/07/1995	End tightening of US Interest rates
Cotton		↓	10/01/1995	Start of EM slump
Eurodollars		↑	11/01/1994	Start of US tightening interest rates
		↓	21/07/1998	Start of LTCM near financial collapse/ Russian crisis
		↑	13/10/1998	End of LTCM near collapse
Japanese yen	↑		11/01/1994	Start of temporary revival from Japanese recession
Soybean	↑		07/25/1995	End tightening of US Interest rates
		↑	3/05/1994	Start of temporary revival from Japanese recession
S&P500		↑	1/04/2000	End of Russian crisis
Wheat (Chicago)		↓	4/02/1996	End of temporary revival from Japanese recession
Cocoa	↑	↑	3/05/1994	Start of temporary revival from Japanese recession

Table 4.22
Structural breaks and macroeconomic events (on mean equation model)

This table shows the structural breaks for those markets that matched any of the 8 major macroeconomic events of the 1990s. The arrow signs show whether there was an upward jump or downward jump in the recursive coefficient estimates of hedgers' and speculators' net positions. Net positions are adjusted for stationarity using ADF unit root test.

Structural breaks

	Hedgers	*Speculators*	*date*	*Event*
Cocoa		↓	3/05/1994	Start of temporary revival from Japanese recession
Corn		↓	11/01/1994	Start of US tightening interest rates
Cotton		↑	11/01/1994	Start of US tightening interest rates
Coffee	↑	↑	3/05/1994	Start of temporary revival from Japanese recession
Lumber		↓	4/02/1996	End of temporary revival from Japanese recession
Live hogs	↑		11/01/1994	Start of US tightening interest rates

Table 4.23
Structural breaks in the risk and return relationship for large hedgers and large speculators

This table shows the structural breaks for those markets that matched any of the 8 major macroeconomic events of the 1990s. The arrow signs show whether there was an upward jump or downward jump in the recursive coefficient estimates of hedgers' and speculators' attitude towards risk. Both standard deviation and variance are used as proxies of risk when modelling the relationship between risk and return. Panel A reports the matched structural breaks with standard deviation used as a proxy to risk, and Panel B with variance as a proxy to risk.

Structural breaks in Return and Risk relationship

Panel A (σ_t as a measure of risk)

	Hedgers	*Speculators*	*date*	*Event*
Crude oil	↓		4/02/1996	End of temporary revival from Japanese recession
Cotton	↑		25/07/1995	End tightening of US Interest rates
		↓	11/01/1994	Start of US tightening interest rates
		↑	10/01/1995	Start of EM slump
feeder cattle		↓	3/05/1994	Start of temporary revival from Japanese recession
copper	↑		4/02/1996	End of temporary revival from Japanese recession
japanese yen		↓	25/07/1995	End tightening of US Interest rates
coffee		↑	3/05/1994	Start of temporary revival from Japanese recession
live hogs		↑	8/12/1998	Introduction of Euro currency
soybean	↑		25/07/1995	End tightening of US Interest rates
treasury bonds		↓	3/05/1994	Start of temporary revival from Japanese recession

Panel B (σ_t^2 as a measure of risk)

	Hedgers	*Speculators*	*date*	*Event*
copper		↑	3/05/1994	Start of temporary revival from Japanese recession
		↓	4/02/1996	End of temporary revival from Japanese recession
japanese yen		↓	25/07/1995	End tightening of US Interest rates
wheat (Kansas)	↑	↑	25/07/1995	End tightening of US Interest rates
Treasury bonds		↓	8/03/1994	Start of Mexico crisis
Wheat (Chicago)		↓	4/02/1996	End of temporary revival from Japanese recession