The Significance of Mapping Data Sets when Considering Commodity Time Series and their Use in Algorithmically-Traded Portfolios

A thesis submitted for the degree of Doctor of Philosophy

by

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Abstract

Many econometric analyses of commodity futures over the years have been performed using spot or front month contract prices. Using such daily prices without the consideration of the associated contract traded volumes is slightly erroneous because, in reality, traders will typically trade the 'most liquid' contract, that is, the contract with the largest average daily volume (ADV). The reason for this is in order to gain the best price when buying or selling. If this 'true' time series is to be considered, a mapping procedure is required to account for the price jumps at the time when a trader trades out of the expiring contract and enters the new front month contract. A key finding was that this effect was significant, irrespective of the size of the price jump, sometimes referred to as basis or roll and also due to the accumulated roll over a number of years corresponding to multiple contracts. It was also found that the mapping procedure has a significant effect on the time series and should hence always be employed if the realistic traded time series is to be considered. Given this phenomenon, algorithmically-traded commodities futures must necessarily employ such time series when creating metrics or considering an econometric analysis.

The key findings include the importance of diversification in algorithmically-traded portfolios, utilising the AOM and PSI metrics. The mapping of data sets to create realistic 'live-traded' time series was found to be significant, while the optimal day of roll over prior to contract expiry was found to be related to the trading volumes for certain commodities. Other key findings include the causalities and spillovers within the metals sector where various relationships are evident once the results were processed and analysed, both pre and post mapping. Interestingly, the key relationships including bidirectional volatility and shock spillovers between the four key metals existed when the unmapped data was used however, many of the feedbacks within these relationships was lost when the mapped data sets were considered. A significant finding was therefore the consistent differences in findings between mapped and unmapped data sets attributed to the optimisation or favourability of the models (whether econometric or algorithmic). This is due to the unmapped data including roll or basis (which the models are fitted to) taking into account the roll or basis and utilising them in finding relationships between data sets. In the mapped data set (the time series seen by traders) the roll or basis is accounted for and hence the relationships found stand in real-time trading situations. The differences in the results show how the effect of mapping can be significant with unmapped data sets displaying results which will not exist in a real time traded time series.

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The contributions to each individual chapter are stated below:

Chapter 1 is joint work with R.B. Nath, G.S. Metallinos & M.G. Karanasos titled 'An Advanced Approach to Algorithmic-Portfolio Management'. R.B. Nath, G.S. Metallinos & M.G. Karanasos contributed in some of the data collection, mapping and alignment with a combined contribution of 10% to the chapter (approx. 3% each).

Chapter 2 is joint work with R.B. Nath, G.S. Metallinos & M.G. Karanasos titled 'The significance of day of Rollover and Contract Volumes of Commodity Futures in Algorithmic-Trading'. R.B. Nath, G.S. Metallinos & M.G. Karanasos contributed in some of the data collection and mapping with a combined contribution of 10% to the chapter (approx. 3% each).

Chapter 3 is joint work with M.G.Karanasos, P.D. Koutroumpis & R.B. Nath 'The significance of rollover in commodity returns using PARCH models'. M.G.Karanasos, P.D. Koutroumpis & R.B. Nath contributed with mapping of data and interpretation of some of the results with a combined contribution of 10% to the chapter (approx. 3% each).

Chapter 4 is joint work with M.G. Karanasos, F.M. Ali & P.D. Koutroumpis 'Modelling Time Varying Volatility Spillovers and Conditional Correlations Across Commodity Metal Futures'. M.G. Karanasos, F.M. Ali & P.D. Koutroumpis helped in the model specification and contributed to some of the interpretation of the results with a combined contribution of 20% to the chapter (approx. 7% each).

Chapter 5 is joint work with M.G. Karanasos, F.M. Ali & P.D. Koutroumpis 'Time-Varying analysis including Volatility Spillovers for Commodity Futures Metals'. M.G. Karanasos, F.M. Ali & P.D. Koutroumpis helped in the model specification and contributed to the interpretation of the results with a combined contribution of 20% to the chapter (approx. 7% each).

The remaining contributions are by Z.N.P. Margaronis for significant contribution (80% +) in data-collection, data processing, data analysis, results & discussion and write-up throughout all chapters.

List of Abbreviations used:

AOM- Algorithm Optimisation Metric

PSI- Parameter Sensitivity Index

RAP- Risk Adjusted Profits

VWAP- Volume Weighted Average Price

ADV- Average Daily Volume

FND- First Notice Day

WTI- West Texas Intermediate (Crude Oil benchmark)

VIX- CBOE Volatility Index

CME- Chicago Mercantile Exchange

UEDCC- GARCH- Unrestricted Extended Diagonal Conditional Correlation GARCH

NGE- Natural Gas

HOE- Heating Oil

GCE- Gold

CPE- Copper

ZSE- Soybean

ZOE- Oats

OJE (FCOJ) - Frozen Concentrate Orange Juice

LBS- Lumber

PnL- Profit and Loss

RR- Rate of Return

RBOB- Reformulated gasoline blend-stock for oxygen blending

Introduction

RGZ Ltd. (a research company specialising in algorithmic trading) allowed us the use of their algorithm output to develop metrics with which to measure algorithm performance. The algorithms themselves are intellectual property of the company and cannot be revealed but all are based on the same model with 5 parameters (2 of which are significant), optimised on commodities futures and utilising a long/short strategy for each commodity over their 5 year back-tested period. Using this, the importance of diversification in such portfolios is analysed. The metrics are detailed in Chapter 1 and the diversification importance coupled with the metrics is proven to work with the use of correlation matrices. Algorithm output profit profiles from the Nixon algorithm (RGZ Ltd.) were used to analyse the benefits of diversification within many commodity and asset class sectors in order to generate a superior portfolio profile. Metrics developed were the algorithm optimisation metric (AOM) and the parameter sensitivity index (PSI); the former accounts for noise and stability in profit profiles and optimises algorithms and portfolios yielding superior return-risk characteristics, the latter measures the stability of a given algorithm's parameters and proportional changes in profits with respect to each parameter. Comparing these portfolio profits with those of more standard portfolios, demonstrated the superiority of the developed metrics. Alignment of data was found to be a significant factor. Optimising a portfolio with unaligned data outputs leads to incorrect portfolio weightings and an erroneous profit profile on back-tested data. Correlations of prices and algorithmic returns were analysed showing the resultant dilution of correlation due to the effect of the strategy and the trading of security spreads.

In Chapter 2 the importance of the timing of rollover is analysed with respect to the metrics developed and is supported by contract futures volumes data which links in well with Chapter 1. Considering daily commodity futures data for use in practical trading systems, a mapping procedure is employed to show how rolling contracts on varying days prior to expiry can impact the performance characteristics of an algorithmic trading system. This is presented in conjunction with volume data for the contracts as commodities with lower average daily volumes experience significant drops in volume as their contract expiry nears. These changes in volume could be justified by the changes in roll value on different days and vice versa, along with other factors such as first notice day and price slippage.

Chapter 3 employs PARCH models to show the differences between mapped and unmapped time series, delving into the significance of the effects with respect to each individual security. The differences prove that using mapped data as opposed to unmapped data can significantly impact the best fit model. In considering daily commodity data for use in practical trading systems, mapping accounting for rollover at contract expiry is required to modify the data. This is because the individual contract data that constitute a conventional time series do not account for contract expiry and the roll that is inherent. Both mapped and unmapped data series for certain key commodities were investigated using various power ARCH models. This was done across a range of commodities in different sectors in order to observe the significance of roll. This was achieved by analysing the estimated coefficients and differences in model specification. Significant rolls in a given commodity resulted in larger differences in model. The significance of such an approach is that the creation of time series that account for roll will allow more accurate back testing of any algorithmic trading system. Finally we applied (P)ARCH models allowing for breaks, provided by Bai-Perron (2003) both in the conditional mean and variance, as well as conducted a spectral forecasting technique in five commodity futures prices.

In Chapter 4 we take a closer look at the metals sector by looking at shock and volatility spillovers from one metal to the other with respect to returns and similarly. Chapter 5 looks at unidirectional and bidirectional effects, including spillovers. Chapters 4 and 5 are joint chapters as a result of collaborations with Professor M. Karanasos, Dr. P.D. Koutroumpis and Dr. F. M. Ali (combined 20% contribution). Chapter 4 examines how the most prevalent stochastic properties of key metal futures returns have been affected by the recent financial crisis. Our results suggest that copper and gold futures returns exhibit time varying persistence in their corresponding conditional volatilities over the crisis period; in particular, such persistence increases during periods of high volatility compared with low volatility. The estimation of a bivariate GARCH model shows the existence of time varying shock and volatility spillovers between these returns during the different stages of such a crisis. Our results, which are broadly robust irrespective of the use of mapped or unmapped data, suggest that the volatilities of copper and gold are inherently linked, despite these metals have very different applications.

Chapter 5 looks at the mapped and unmapped time series of the metals commodities which is especially interesting due to the physical interactions metals share. The precious and industrial nature of these commodities, coupled with their occasional use as reserve currencies makes for an interesting analysis when cross effects are considered. In addition, the relatively small roll/basis associated with the metals shows that changes in cross effects between mapped and unmapped time series is evident.

Chapter 1: An Advanced Approach to Algorithmic Portfolio Management

Chapter 1 is joint work with R.B. Nath, G.S. Metallinos & M.G. Karanasos titled 'An Advanced Approach to Algorithmic-Portfolio Management'. R.B. Nath, G.S. Metallinos & M.G. Karanasos contributed in some of the data collection, mapping and alignment with a combined contribution of 10% to the chapter (approx. 3% each).

The remaining contributions are by Z.N.P. Margaronis for significant contribution (90%) in data-collection, data processing, data analysis, results & discussion and write-up throughout the Chapter.

Keywords: Algorithmic trading, commodity spreads, crude oil benchmarks, AOM, RAP, PSI, portfolio management

1.1 Introduction

This study investigates the superior performance of including security spreads, primarily inter-commodity spreads, using a commercially-developed trading algorithm (RGZ Ltd.). The chief characteristic of security spreads, for example that of the crude oil benchmarks WTI and Brent, is that they are more stable and more predictable than the individual commodities themselves. This leads to a superior risk-return characteristic upon which the algorithm can capitalise. This is detailed later when a spread is compared to a single commodity. The algorithms themselves are multi parameter models which are coupled with a trading rule. The algorithms use back-tested daily futures data of settlement prices (over a number of years) to build a time series on which the model parameters are optimised. Typically, trades are very low frequency, lasting a number of days and in some cases weeks. The optimisation of the algorithms is subject to the metrics presented in this study and the diversification benefits of optimising long/short trading systems or portfolios using these metrics are explored.

Given recent turmoil in financial markets, commodities must now play a key role in standard investment portfolios consisting of stocks, bonds and cash deposits (Financial Times 2010). This is because of the fact that there are very low yields on fixed term deposits, stock market returns are currently very risky, and there is significant default risks associated with bonds, particularly those of the PIGS economies. The issues regarding the PIGS has become an increasing issue lately as elections in these countries are bringing in new political parties, as seen lately in Greece. These events had knock on effects to many economies due to various degrees of exposure with respect to currency, trade and other factors. The commercial importance of trading security spreads together with single commodities cannot be understated given the trading yields of the algorithm.

Crude oil, precious metals and other soft commodities such as cocoa and coffee, although fundamentally volatile if considered on their own, can be used in cointegrated pairs and as single securities hedging each other, where they are significantly more stable and predictable. Any price changes in the security due to structural, market or supply and demand factors do not significantly impact the spread of security pairs. An exception to this is the front-second month basis spread where the price structure of the market is considered, depending on whether it is in flat, backwardation or contango. They exhibit trends that can be exploited by virtue of trading algorithms based on such commodity prices and their spreads. The developed strategy can also be extended to other securities including foreign exchange, bonds and equity indices. In practice there are periods of upward and downward trends where the 'noise' component or volatility is low. The strategy is also applied to single securities which can be shown to hedge each other as will be seen later.

A successful algorithm should be able to generate consistent profits in the key regimes of trends and stationary oscillations. The current RGZ algorithm is able to do this with Sharpe Ratios in excess of 4.2 (annualised) and annualised returns in excess 140%. The algorithm is a seven non-linear parameter model back-tested on daily closing price data (Bloomberg/Thomson Reuters 2012) over 5 years throughout the financial crisis. This is contrary to Chatrath et al. (2001) who show commodity prices to be chaotic to a certain degree. Of course this study only considers the prices of four agricultural commodities that tend to 'spike' more often, usually due to demand and supply shocks. Chatrath et al. (2001) use ARCH models to explain the non-linearity in data (see also Karanasos et al., 2015) however given the stability of trading algorithms in terms of their returns, the extra volatility obtained in certain seasons exists but is not significant for a trading system which trades at a low frequency. This is because the optimisation of the algorithm takes into account any extra volatility obtained even if it is seasonal.

Vivian et al. (2012) mention that the volatility obtained by commodities in the recent financial crisis is not significant and that there are no real volatility breaks that result. This is however not true for other financial crises where the volatility breaks are more obvious. For this chapter the recent financial crisis is more of interest as the optimisations are carried out over 5 years of data (see also Karanasos et al., 2015 for a comprehensive analysis of breaks in the volatility of commodities futures). The fact that Vivian et al.'s (2012) findings show no real evidence of volatility breaks despite the financial crisis is important. This is because the profits obtained from the trading algorithms also show no structural break in volatility even during the financial crisis. This may be supported by viewing the homoskedasticity of the profit profiles.

Current algorithmic trading systems utilise simple ‘channel trade’ systems available where user is required to view current prices continually ensuring the trade occurs at the correct instant. These types of model take advantage of volatility during certain times of the day where fluctuations may occur perpetually. It allows for consistent trades to be made and give multiple trades of similar value while also sometimes incorporating degrees of sentimental trading. Of course more advanced systems exist where models are used for trading of various securities that incorporate Bollinger bounds and other such established methods. Most models are top secret and therefore remain the intellectual property of the investment bank, hedge fund or other financial institution which developed or purchased it. More advanced models try to capture volatility and trends and usually have a detailed econometric study supporting them. The key is to develop a model that captures trends, spikes and can deal with the volatility between trends and spikes.

Cheung et al. (2010) agree that diversification benefits can be gained by investing in commodities and also that the diversification benefit of commodities is far more complex than is generally understood in finance. The view that commodities regimes change is also interesting as we see a huge amount of heteroskedasticity throughout our analysis. However diversifying into portfolios with commodities yielding a positive risk- return relationship compared to international equities is in line with what we believe. The RGZ (2010) algorithms have showed however that being diversified correctly can lead to a superior portfolio performance even in times of bearish commodity environments. The reason being the existence of spreads and the fact that algorithms, despite correlations in prices, do not display these correlations in their profits since different algorithms are in different buy/sell positions, constantly hedging themselves with respect to historical back-testing.

Karali et al. (2009) support the view of diversification through the inclusion of different instruments in different sectors, especially within commodities so as to balance a portfolio given the increased volatility in recent years in commodities markets. Macroeconomic variables impact commodity prices but affect separate sectors in different ways. This suggests and supports the idea that diversification is crucial even if it is within a single market with sectors within it.

The study is comprised of four main sections which in turn have their own sub-sections:

Section 1.1 details the Introduction

Section 1.2 details the AOM & RAP Metrics Development with the following sub-sections.

3.5.2 Spreads
3.5.3 Diversification and AOM (Algorithm Optimisation Metric)
3.5.4 RAP (Risk Adjusted Profits)
3.5.5 Data

Section 1.3 details the PSI (Parameter Sensitivity Index)

Section 1.4 details Significance for Portfolio Management AOM & RAP Metrics Development-Spreads with the following sub-sections.

2.4.6 Portfolios
2.4.7 Alignment
2.4.8 Correlations
2.4.9 Acknowledgements
2.4.10 Conclusions

The conclusions are then followed by the References and Appendix.

1.2. AOM and RAP Metrics Development

1.2.1 Spreads

Trading of spreads allows for a more stable and less risky strategy because one does not expose oneself to intraday or daily volatility of a single particular security. For example when trading equity indices it may be wise to try and capture trends in spreads between similar economies such as the French and German rather than play a single equity index. This is because if there is a financial shock, such as in 2008, the spread of two indices will not be affected nearly as much as a single equity index. Figure 1.1 shows how the spread is far more stable than the absolute price. This can be seen clearly by comparing the two vertical axes and their scales and is a phenomenon that exists across many cointegrated pairs.

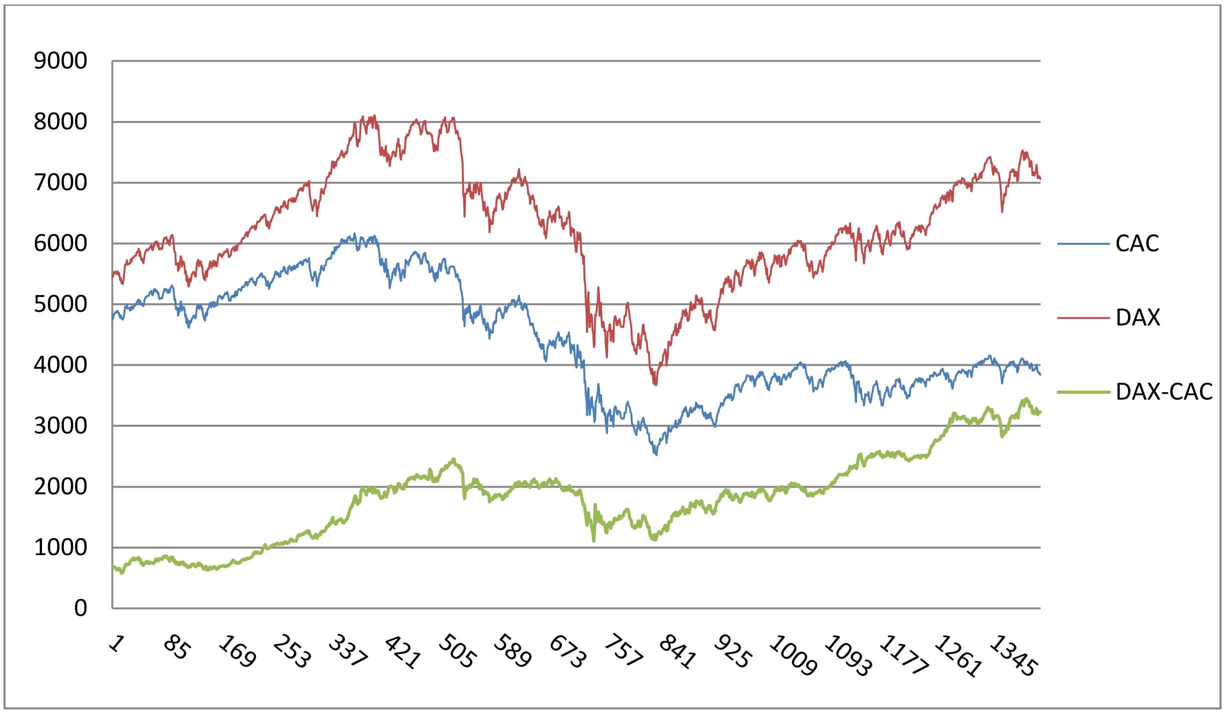


Figure 1.1 DAX and CAC Daily Closing PX-Last (Bloomberg)

Trading two securities as a spread is particularly interesting (see Margaronis et al. 2011 and Karanasos et al. 2015 for a comprehensive cointegration analysis of commodity futures). For example, the prices of WTI and Brent crude oils seem to be highly cointegrated with WTI leading the price of Brent as shown in the cointegration analysis of the two major crude oil benchmarks.

The current chapter will analyse the results of a newly engineered trading algorithm created and owned by RGZ. The algorithm itself remains property of the company RGZ, however the results of the profit profiles and other outputs will be analysed here in order to obtain a new portfolio optimising metric and investigate algorithmic portfolio behaviour. The algorithm itself was designed to trade commodity spreads but after applying it to various securities it was clear it could be utilised and adapted in other markets and single (outright) securities.

1.2.2 Diversification and Algorithm Optimisation Metric (AOM)

It is important to apply this to various securities as it allows for diversification within a portfolio which is imperative for day-to-day stability. The types of diversification are important; for example, not all trading systems should be identical across the constituent instruments. Further, different types of securities should be included such as grains, energy, equity indices, metals, foreign exchange, softs and bonds. This is important because the various sectors behave differently as may be observed by their pairwise correlations. The way in which the margin is apportioned is important because over-margining in energy, for instance will make the portfolio unbalanced and lead to unnecessary exposure to this sector. Finally, it is imperative that both spreads and single securities are used since both behave differently in different stages of the business cycle.

As a result, such diversification with a suitable trading system is able to make consistent profits, even in times of financial turmoil, a phenomenon which is frequent more recently.

Qiang et al. (2011) found that the impacts of the oil market spill over into other commodity markets. This may indeed be true in terms of price however it is clear that after applying a trading strategy to a range of instruments, the way in which the algorithm trades differs due to different optimised parameters. It is important to remember the significance of diversification along with the idea of trading spreads which reduces the exposure to any single commodity. This is linked to the correlation analysis where the prices may be correlated but the returns of the algorithms are not, even if prices are correlated the algorithms are not necessarily in the same buy/sell position.

Looking at a profit profile of various trading histories it is clear that a metric can be developed to minimise aspects that would make a portfolio undesirable. It was found that such a metric was more powerful in this respect than the Sharpe ratio. The Algorithm Optimisation Metric (AOM) looks at three aspects of portfolio performance, and optimises performance by minimising noise in a back-tested PnL (profit and loss) profile, rewarding linearity and penalising drops of PnL known as maximum drawdown. The maximum drawdown of a profile is measured as the greatest drop in PnL including successive negative trades as well as small increases resulting from positive trades. Evidence that the AOM is a better way to measure stability will be investigated with a series of graphs depicting several extreme scenarios of profit profile and explaining why these might be undesirable. The three undesirable regimes are shown and these include profiles that draw down, have poor positive to negative or 'noise' ratios and are not linear. The AOM's three components minimise the undesirable aspects wealth managers and other stakeholders often see in their profit profiles and would like to eradicate.

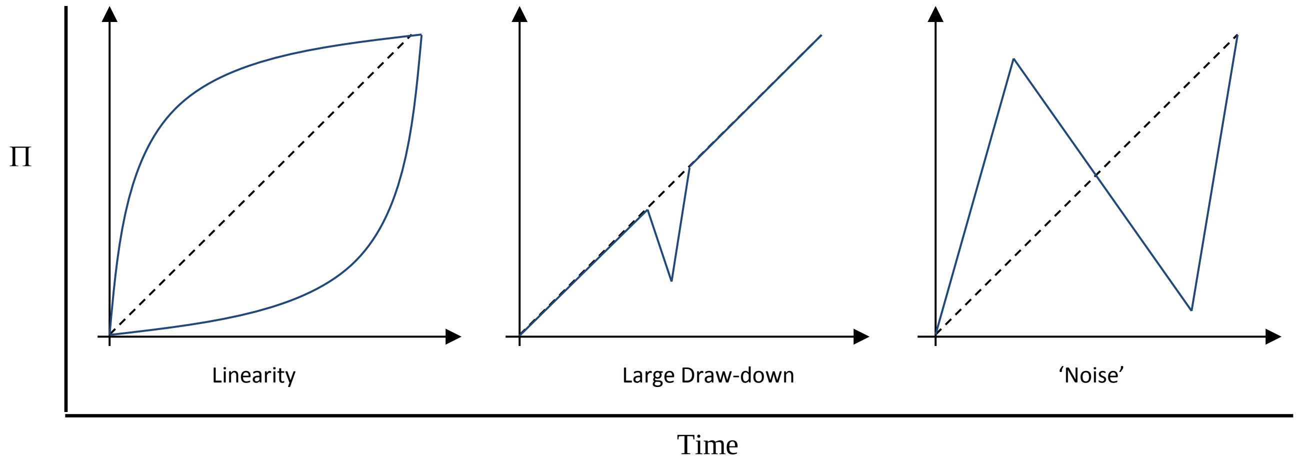


Figure 1.2 Representation of limiting cases for undesirable portfolio performance with regimes of poor linearity, large draw down and large noise

The profit plotted against time profiles in Figure 1.2 represent extreme departures from a desirable linear PnL profile (dashed) that stakeholders and wealth managers would find undesirable in a portfolio's performance. These represent limiting cases for which the AOM should be penalised. The idea is for the metric developed to minimise the three scenarios where essentially linearity is key assuming no reinvestment. It is imperative for the noise, as seen in the last graph, to be minimised, and finally for sudden drops such as in the second graph to be penalised.

The AOM is defined thus:

$$AOM = NR \cdot DC \cdot R^2$$

Where:

$$R^2 \ is\ the\ coefficient\ of\ determination$$

$$NR\ is\ the\ noise\ ratio\ defined\ as:$$

$$NR = \frac{\sum \Delta^+ \pi}{\sum \Delta^+ \pi + |\sum \Delta^- \pi|}$$

With

$$\pi \ the \ P \ \& \ L \ (profit \ \& \ loss),$$

$$\Delta^{+} \ the \ positive \ daily \ change,$$

$$\Delta^{-} \ the \ negative \ daily \ change,$$

And

$$DC \ is \ the \ drawdown \ coefficient \ defined \ as:$$

$$DC = 1 - \frac{MD}{MD + \frac{252\pi_{max}}{N}}$$

With:

$$MD \ is \ maximum \ drawdown$$

$$N \ is \ the \ number \ of \ trading \ days \ in \ sample$$

$$252 \ is \ the \ number \ of \ trading \ days \ in \ a \ year$$

1.2.3 Risk-Adjusted Profits

Risk-Adjusted Profits (RAP) is a term used for the product of the profit of an algorithm for its entire back-tested history and the AOM associated with it. This is because in reality, a trading system is utilised to generate profits. Maximising stability through the AOM can therefore be combined with the PnL generated to form the RAP of an algorithm. The RAP is a standardised way to distinguish between optimal and non-optimal parameters as is the AOM, while also weighting performance on profit too. It is an efficient measure of allowing balancing between securities or security pairs when considering degrees of diversification.

The optimisation and trading algorithms were developed using Fortran 95 programming language where each individual security or pair has its own designated program. The outputs of the optimisation programs include a list of algorithm parameters and all combinations thereof as well as the AOM and RAP associated with each set of parameter combinations. The combination of parameters that give the highest RAP is chosen as the optimal parameters for that particular algorithm. A brute strength approach is used in optimising the algorithm parameters as all possible combination of parameters is tried and tested against the data.

1.2.4 Data

The data used throughout is daily PX_LAST futures prices obtained from Bloomberg. Specifically, this study considers the front month contract of these various futures and this is typically because the front month tends to have the highest volumes and hence liquidity, making it the prime candidate contract for trading by speculators. PX_LAST is the price at the close of business while the prices themselves were procured over approximately a 5 year period from 2007 onwards during the financial crisis and the beginning of economic recovery. The number of prices (or days as daily prices are considered) varies from instrument to instrument due to different markets following different holiday conventions. The raw data was mapped using a mapping procedure developed by RGZ Ltd. (RGZ Research 2011) while the mapping procedure itself is detailed in Margaronis et al. (2011).

The data considered in this study includes ten raw data sets. From these ten sets, two spreads are considered and the rest are taken as outright positions resulting in a total of eight separately tradable futures.

Three equities indexes are considered which includes the Nasdaq, Dax and Cac, which the Dax and Cac are considered as a spread i.e. Dax-Cac. The metals are represented by Copper as it is the main industrial metal with significant traded volume. The agriculturals considered are Cocoa and Oats while the energies, which are typically the most prominent sector in commodities, are Natural Gas, WTI Crude and Brent Crude. In this study, the crude oils are considered in a spread which is commonly known as the WTI-Brent spread. The construction of spreads within the energies sector allows for hedging and hence lower exposure to the famously highly volatile crude oil markets. Finally, EURUSD is considered representing the foreign exchange futures sector. It is clear that there is a good degree of diversification with respect to the markets and sectors and the analysis which follows will show how portfolio construction in algorithmic trading may benefit by utilising spreads, diversifying markets and of course utilising bespoke metrics.

1.3. PSI Metric Development

A Parameter Sensitivity Index (PSI) is developed which allows for the stability of the constituent parts of the trading system to be measured by applying it to each security or security pair. The way in which the PSI program works is by varying a single parameter (100% plus or minus its optimised value) while keeping all the others constant and carrying this out for all parameters. The PSI is then evaluated as the ratio of actual versus maximal (optimised) profits. This allows for the user to see how changing a single parameter changes the level of RAP, AOM and profit generated. A matrix is then generated whereby the sensitivities are plotted for the two primary parameters and a surface plot can then be used to visualise the stability of each security. This can be utilised to judge whether an algorithm is too parameter-sensitive (unstable) or not. Also it helps to show if there are multiple regions of higher levels of RAP and AOM. More importantly it can allow for a region of lower AOM and RAP to be selected because of its superior stability. Examples of PSI outputs are shown in Figure 1.4.

The actual PSI is evaluated by looping through a series of values of single parameters (100% plus or minus its value) by keeping all other parameters constant and then repeating this process for all parameters. In order to be able to create a surface that may be visualised and because it was found that two of the parameters were the most sensitive (primary parameters), the graphs for AOM or RAP are plotted for the primary parameters. The way in which a value of PSI is then generated is by considering the area under the graph of the parameter in question and comparing it to the maximum possible area. This is once again seen more clearly on the graph in Figure 1.3.

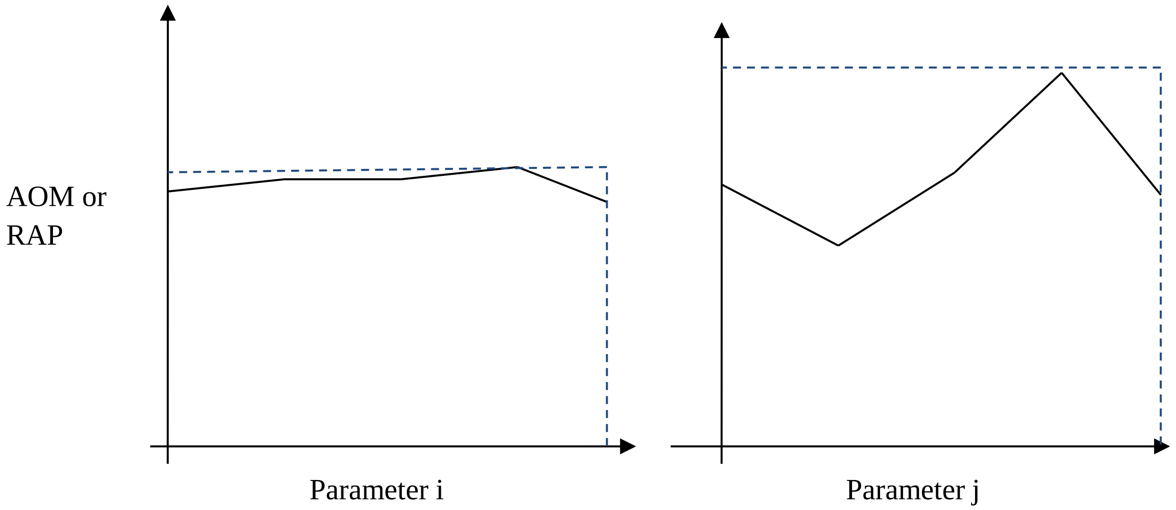
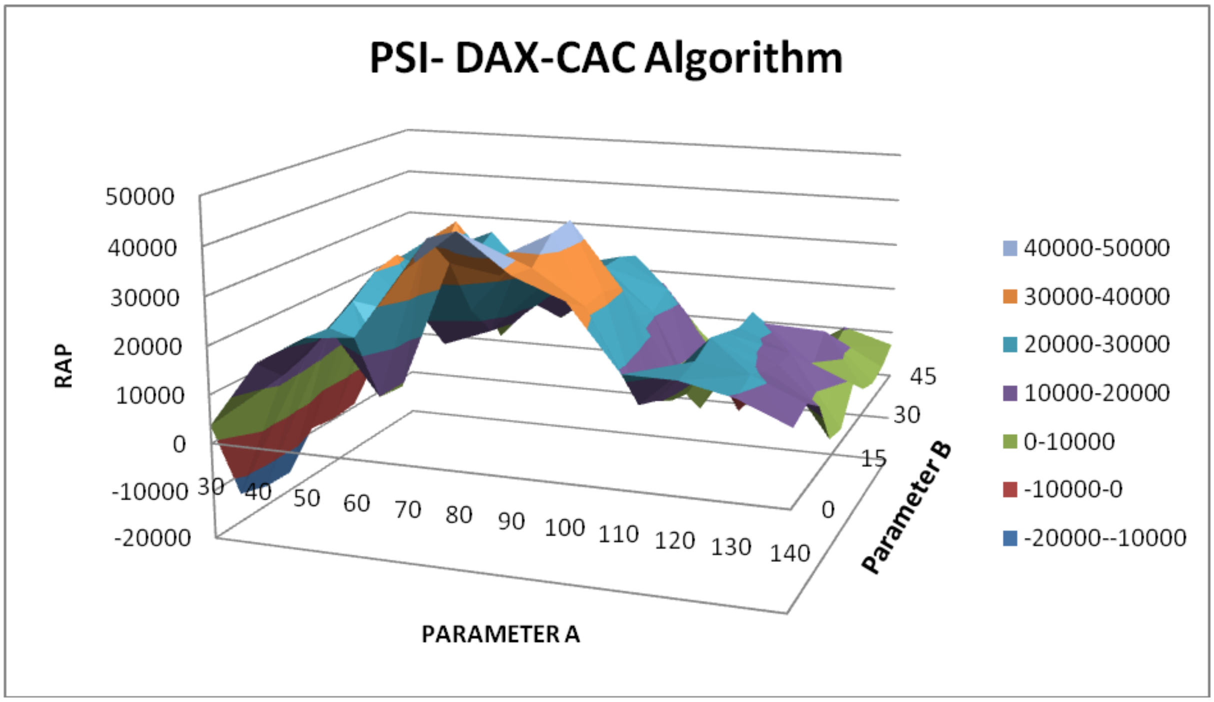
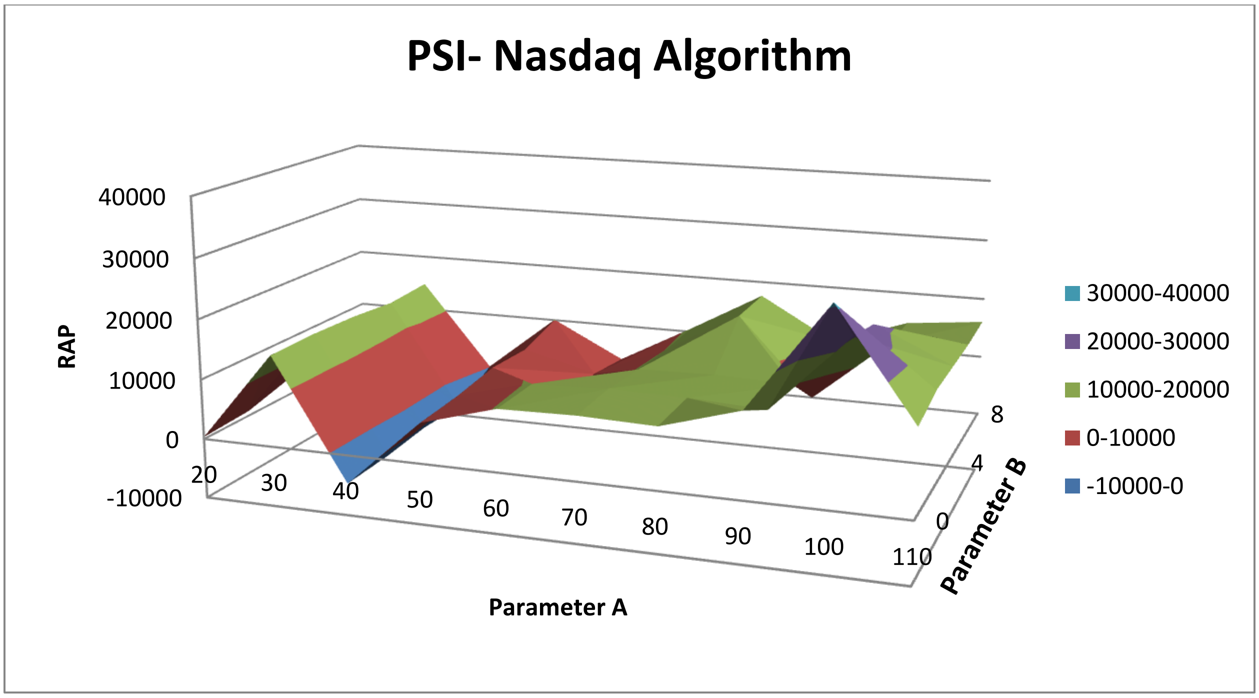


Figure 1.3 RAP/AOM variations with (a) insensitive parameter and (b) sensitive parameter

The two profiles of Figure 3 depict what the output from a PSI file may look like with the (a) depicting an insensitive parameter since the AOM and RAP values do not vary a great deal with parameter value. On the other hand, (b) shows a relatively sensitive parameter where the values of AOM and RAP seem to change dramatically as parameter value is changed. The dashed lines represent the maximum possible values of AOM or RAP obtainable by the parameter value. The ratio of positive areas under the actual and maximal profiles provides a reasonable measure by which to measure parameter sensitivity. Actual outputs of PSI are shown below where surfaces are presented as they are a plot of two parameter sensitivities. A total PSI can then be calculated by calculating the product of all security sensitivities across all parameters.



(a)

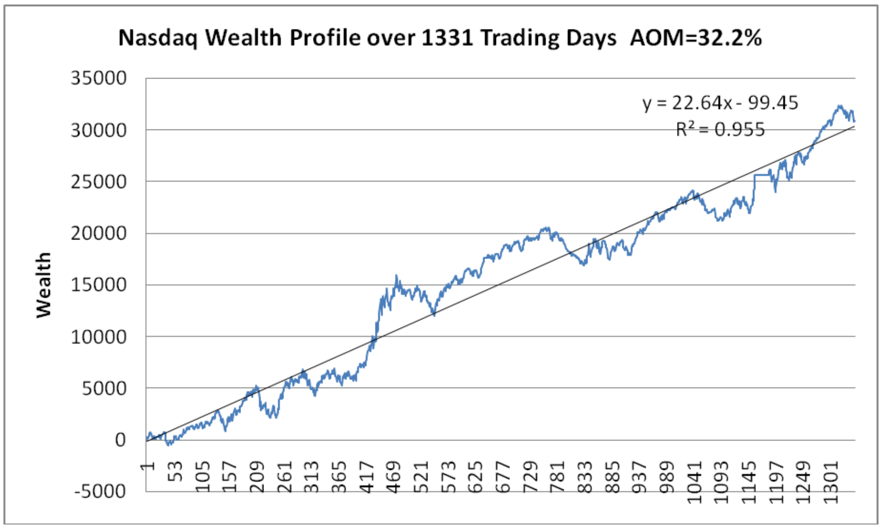


(b)

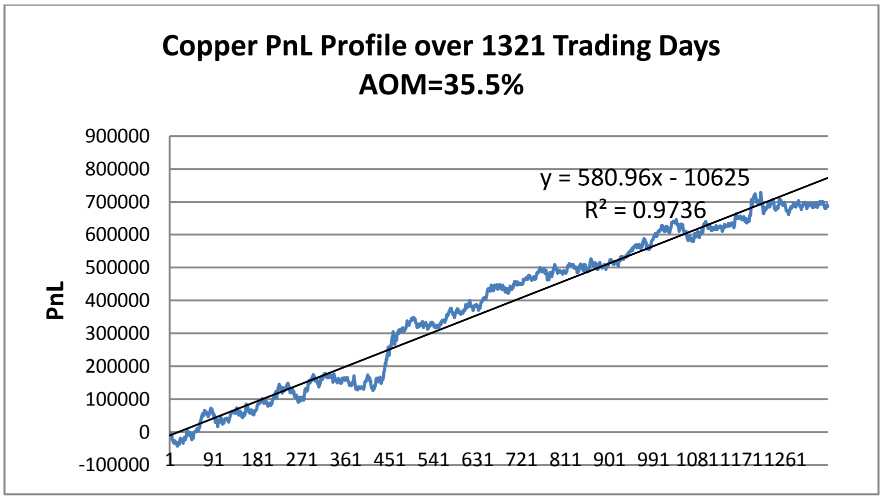
Figure 1.4 PSI plot for sensitive and insensitive instruments

From the two surfaces of Figure 1.4, it is clear that the Nasdaq algorithm is far more sensitive with respect to parameter A than the DaxCac algorithm. The PSI values for Nasdaq and DaxCac are 14.2% and 27.1% respectively. As a result, the DaxCac algorithm is far more stable because changing these parameters does not translate into a significant drop in the RAP meaning the algorithm will still perform near its peak performance. This is not the case for the Nasdaq algorithm where small changes in parameter A result in significant decreases in RAP which suggests the algorithm may not perform well and may actually make losses with small deviations in behaviour.

It is clear that this entire analysis is useful in real-life trading situations and does not aim to simply optimise a theoretical tool by maximising a single outcome. Some profit profiles for various algorithms are presented in Figure 1.5. The profiles shown in Figure 1.5 are outputs from the algorithms developed and owned by RGZ (2010). Those for other instruments are presented in the Appendix. The post analysis is what we are interested in - for managing a portfolio and maximising its performance.



(a)



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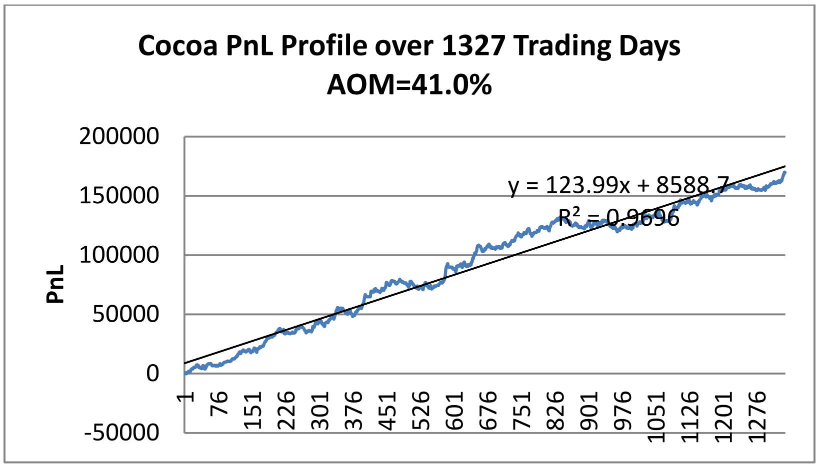

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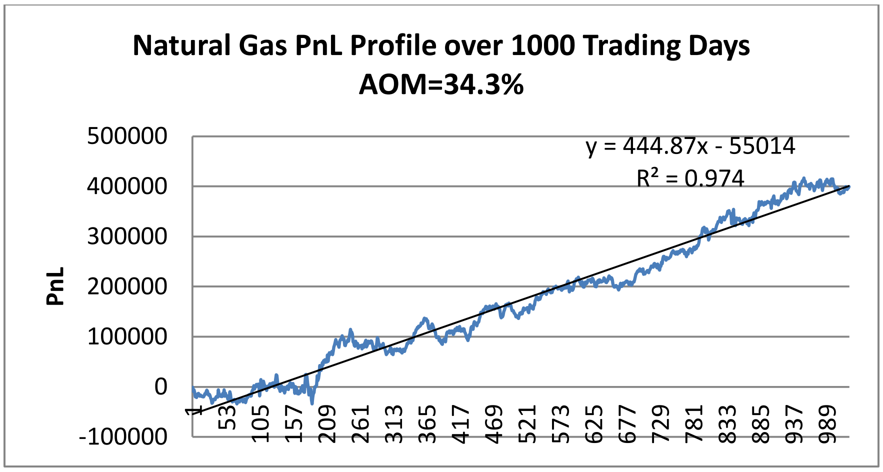

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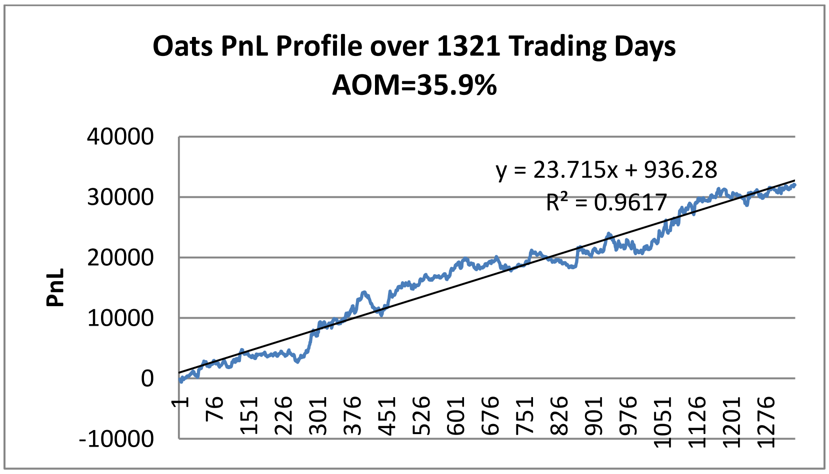


(e)

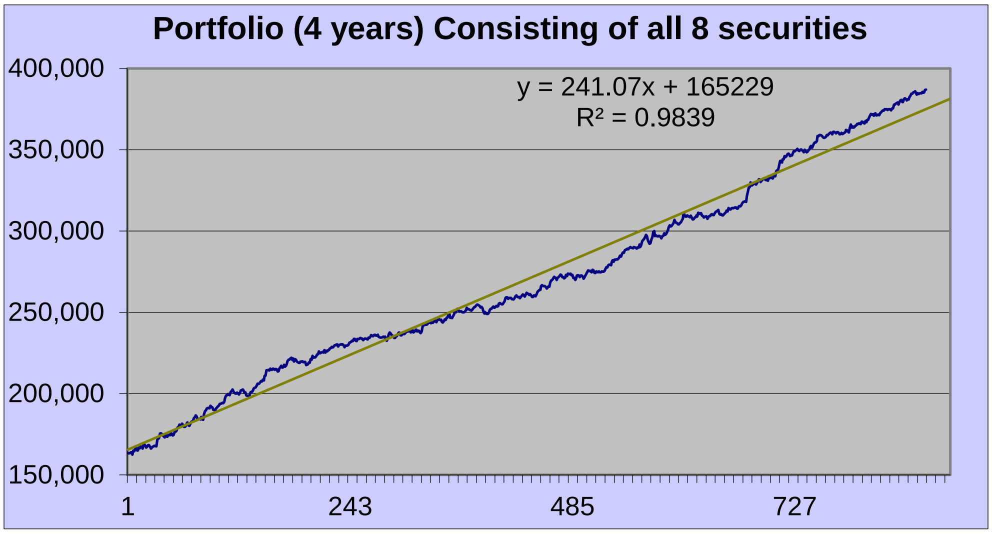
Figure 1.5 Profit profiles from algorithm outputs for various instruments

1.4. Significance in Portfolio Management

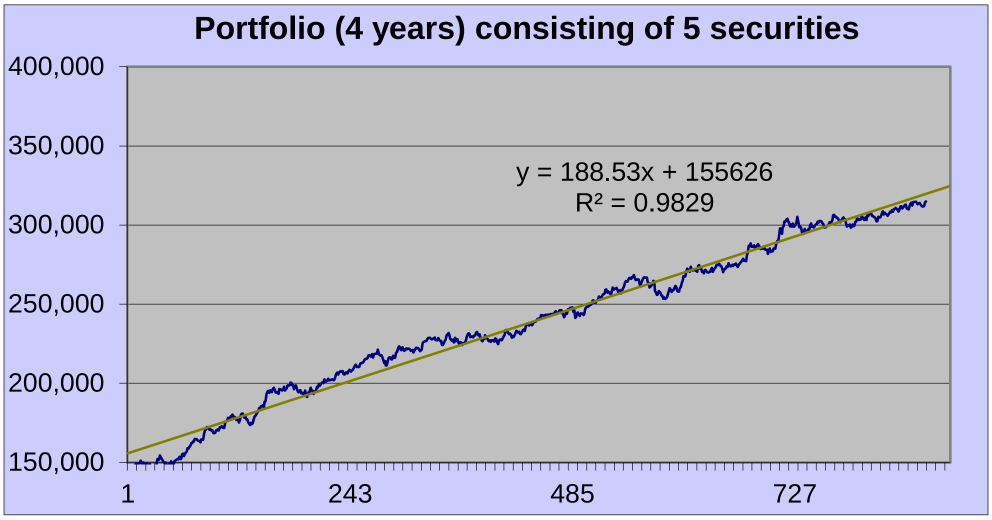
1.4.1 Portfolios

These individual instrument profiles will now be added given certain weightings in order to obtain a diversified portfolio where the noise component and drawdown are minimised and linearity is maximised given a specific margin investable; that is to say that the overall AOM and RAP of the portfolio is maximised.

The final profit profiles shown in Figure 6 are for portfolios. Figure 1.6(a) represents a portfolio containing all the securities considered in this study. Figure 1.6(b) shows the portfolio accumulated when only certain securities, as described in the main section of this chapter, are included. The reason for showing both is to show the effects of diversification and how important it is in minimising volatility in a portfolio. Both profiles have been chosen based on RAP and a margin of $100,000.



(a)



(b)

Figure 1.6 Portfolios (a) consisting of all 8 securities and (b) consisting of 5 securities, representing the impact on performance of successful diversification

From the two profiles shown in Figure 1.6, the latter (b) has a larger component of noise in the PnL profile. The volatility of the second portfolio, whose margin is the same, is far greater. Hence, it is concluded that diversification is imperative, even in algorithmic trading, and thus the requirement for stability and consistency of returns in such a portfolio.

1.4.2 Alignment

In order for an accurate portfolio AOM and RAP to be generated, the output profit data had to be aligned by date. The true performance of a portfolio can only be generated if the dates are known for each particular level of PnL for each security or pair. This is an imperative but tedious process as it involves aligning the daily outputs of a range of securities which have different trading days as they are traded on different exchanges. This was again automated in order to account for non-trading days of certain securities. It allowed correct correlation matrices for the securities to be generated (discussed below) and therefore allowed correct diversification to be obtained. The weightings were obtained by a program which used this aligned data to find the optimal portfolio. The date was used as a reference point. By using a nominal portfolio value and individual security margins based on 10:1 leveraging level, the program generated possible combinations of weightings for each security. This program then selects the optimal combination of weightings based on maximisation of RAP for the entire set representing the real-time daily behaviour of the portfolio. The program is able to apportion initial margin to each security or pair and give a superior outcome of performance regarding RAP. The margins themselves are determined by and procured from (through Bloomberg and Thomson Reuters) the main exchanges used to trade commodities futures (CME and ICE). Computational time was minimised by only creating combinations for portfolio margins within a certain range since the optimisation approach was brute strength. The AOMs generated from this program are substantially superior to any of the individual securities or pairs. In this way, by combining the real-time date, margin and optimised profits of each algorithm, a real historical performance of a portfolio can be seen and then traded with confidence due to its accuracy.

In selecting the correct combination of securities to trade, it is imperative that the program has the traded behaviour of algorithms with respect to time in order to minimise ‘noise’ component of the portfolio. This can therefore result in a true maximised RAP portfolio. A profile of aligned profit profiles and non-aligned profit profiles will be compared to show how significant this error can be. This is also very important because the program needs to have accurate daily behaviours for all traded instruments in order to make a correct selection for a noise-minimising portfolio. An example of how the misalignment can mislead someone when taking positions is shown in Figure 1.7. Presented here is a simple portfolio profit profile containing only copper and three positions of the crude oil spread (WTI-Brent) shown for 400 days. Two profiles are shown where one is the actual aligned profits with respect to dates and the other is not. It is important to remember that the misalignment in the second profile is up to about 10 days, which is realistic given the time span. Real portfolio drops are underestimated and gains can be overestimated. Also the noise component is ‘ironed out’ or smoothed. It is therefore clear that by inputting the incorrect graph into an optimisation program which maximises RAP, that the noise, drawdown and linearity of a misaligned data set will be erroneous and ultimately incorrect, hence resulting in incorrect weightings and exposure to risk due to this.

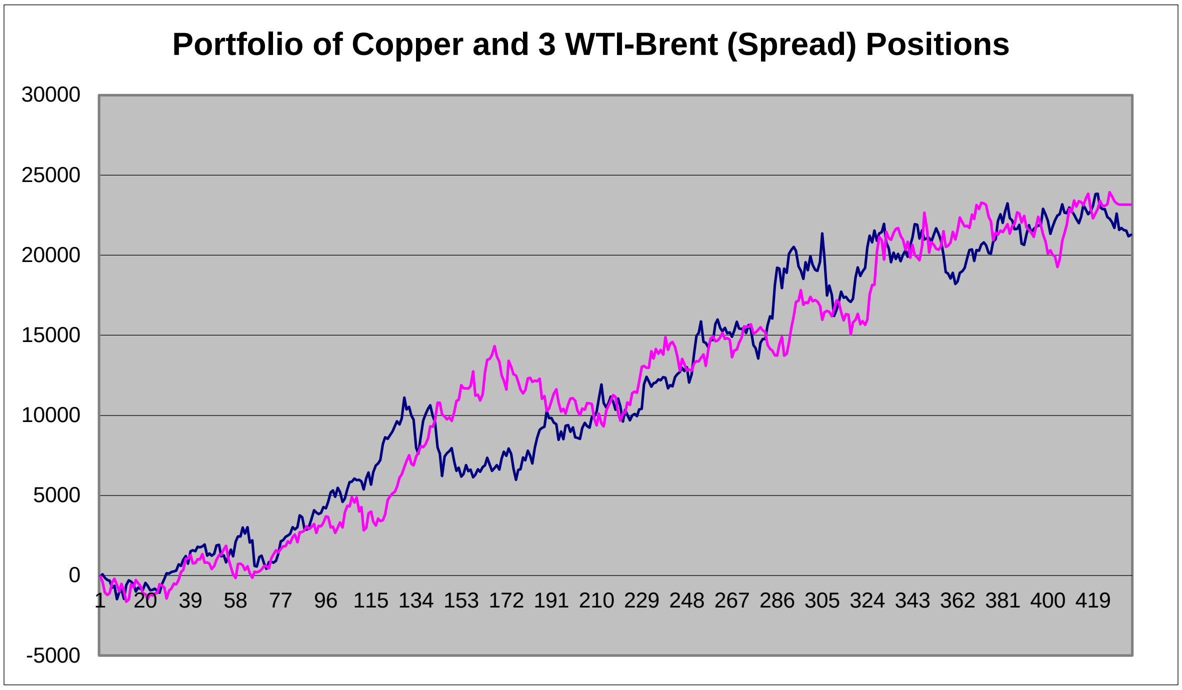


Figure 1.7 Portfolio performance over 400 days showing alignment error between aligned (blue) and unaligned (pink) profits

To show that the maximum RAP is indeed the most effective method for optimising a portfolio, it must be compared to other more conventional methods such as the return-risk ratio (RR), minimum variance and even perhaps comparing the maximum AOM to maximum RAP combinations to see possible differences in portfolio performance with respect to consistent and stable profits.

In order to show this, a number of important characteristics need to be considered. This is because the differences will not be clear from a profit profile. A table was created showing the measures of optimising portfolio performance and the characteristics of those portfolios. The characteristics used will include the negative ratio (NR) which is a measure of downward movements in profit of the profile, the coefficient of determination (R^2), the maximum loss which is simply the value (in USD) of the greatest drop in profit over the trading history and the return on margin (ROM) which is the returns generated in relation to the amount of capital margined out initially in the portfolio. The RR is calculated by the ratio of the mean to standard deviation of the daily returns. The equally-weighted portfolio is simply a combination of weightings whose margin is equal. We assume all these portfolios have a nominal margin of $50,000 and trade for a four year period.

	Max RAP	Max RR	Min Variance	Max AOM	Equally-Weighted
AOM (%)	58.9	59.6	58.2	59.4	52.7
NR (%)	65.3	67.0	66.6	66.4	61.8
R^2 (%)	98.0	97.1	96.8	97.7	98.2
Max Loss ($)	34,662	27,401	28,750	29,474	38,144
ROM (%)	1054	755	700	769	621
RAP	824,533	620,588	535,290	654,915	457,489
Profit ($)	1,399,887	1,041,255	919,742	1,102,551	868,101

Table 1.1 Portfolio characteristics for various optimisation metrics

From the Table 1.1, it may be observed that the portfolios' performance across the metrics is fairly similar, however the maximum RAP combination is superior in the amount of profit generated and its ROM. Across the table, all other characteristics seem similar and therefore it must be concluded that the maximum RAP combination is most desirable especially due to its significantly larger return.

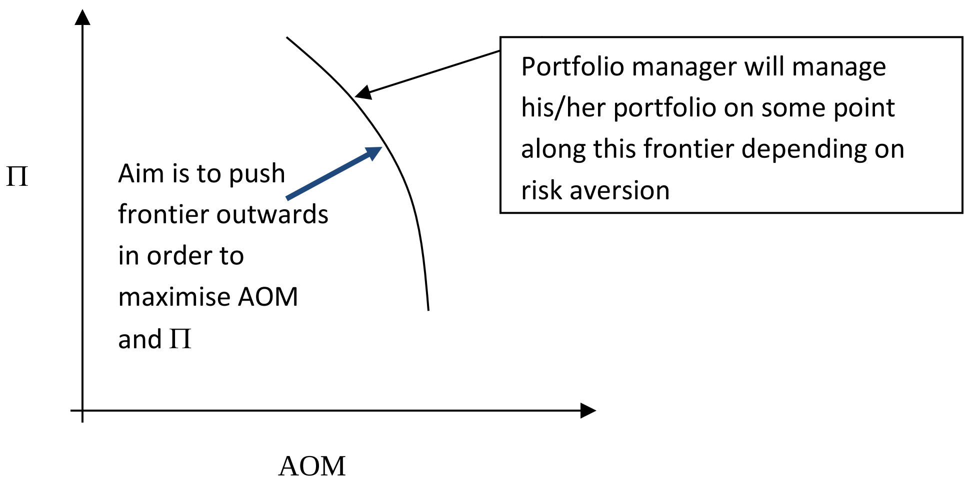


Figure 1.8 Profit against AOM plot showing existence of frontier of trading and where portfolio operates

Another tool to show portfolio diversification is the correlation matrix of daily price changes for all the component securities as well as a correlation of all the daily profit changes. This allows a direct comparison to be made between these two correlation matrices. The reason price returns were not used is due to the CFD (contracts for difference) nature of trading where profits are a function of price differences. Comparing these two correlations will allow any portfolio manager to understand the degree of diversification and which securities are correlated. In addition it can show the effectiveness of using long-short strategies to diversify portfolios. For example, a portfolio can be highly exposed to equity indices because they are indeed correlated. The European economies, for example, find themselves in turmoil at this present time and that is affecting the US and Asian markets because many banks and companies share funding and of course collaborate through trade meaning they are exposed to each other in one way or another. As may be seen in Table 1.2, the correlations of the profits generated show how using the selected combination of securities as defined by the maximum RAP from the program, reduces the correlations even more. Despite prices being highly correlated, the algorithm output for the two instruments will not be as instruments' positions will not necessarily be in the same long/short position during the history. Hence, this approach may be viewed as a black box which decouples the structural correlation that exists between the securities by using back testing and taking long or short positions accordingly to maximize the diversification effects, and hence the portfolio performance. It should be noted that the Dax-Cac spread is considered in the post correlation as the program runs the spread. The pre correlation however considers the two indexes separately in order to give a better understanding of how the two are related to each other. On the other hand, the WTI-Brent spread is a price which is procured as is. This means the price of the spread was constructed by the exchange. The emboldened correlations represent levels above 15%, the threshold chosen to differentiate significant and insignificant correlations in this study.

1.4.3 Correlations

Correlations for Absolute Price Change

Pre									
	Copper	**Oats**	**Cocoa**	**Dax**	**Cac**	**Nasdaq**	**EurUsd**	**Natural Gas**	**WTI-Brent**
Copper	100.00%								
Oats	**29.10%**	100.00%							
Cocoa	**29.40%**	14.30%	100.00%						
Dax	**52.10%**	**21.60%**	**23.30%**	100.00%					
Cac	**53.60%**	**25.50%**	**24.30%**	**92.80%**	100.00%				
Nasdaq	**32.50%**	16.60%	15.80%	**59.50%**	**56.50%**	100.00%			
EurUsd	**34.50%**	**22.90%**	**28.10%**	**33.60%**	**33.50%**	**31.40%**	100.00%		
Natural Gas	14.40%	15.90%	10.90%	11.90%	11.40%	9.80%	13.90%	100.00%	
WTI-Brent	**50.50%**	**28.00%**	**26.20%**	**39.90%**	**41.10%**	**33.50%**	**32.30%**	**23.30%**	100.00%

Correlations are chosen to be significant at the 15% level and these are emboldened

(15% chosen due to desirability within portfolios of two instruments not having correlation greater than 1 in 6)

(a)

From the correlations estimated on the absolute price changes it is clear there is a significant amount of correlation between many of the securities, for example, EURUSD seems to be quite correlated to all the securities considered. Reasons for this relationship with respect to the agriculturals may arise from the significance of import and export markets of these commodities and their consumption by the European Union. EURUSD is also expected to have a certain degree of correlation with its primary economic indexes and this will in turn spill over to some degree to the agricultural commodities. Copper prices tend to be an economic indicator since copper is a primary base metal used in most electronic equipment and wiring. Its relationships with the oil spread and the indexes may therefore be justified. The indices themselves are expected to have a certain degree of correlation between them, given the structure of financial systems worldwide where countries share debt and trade and this is especially visible by the very significant correlations between Dax, Cac and Nasdaq.

Correlations for Algorithm Profit Change

Post								
	Copper	**WTI-Brent**	**Natural Gas**	**Dax-Cac**	**Nasdaq**	**Oats**	**Cocoa**	**EurUsd**
Copper	100.00%							
WTI-Brent	-1.00%	100.00%						
Natural Gas	-0.10%	-10.10%	100.00%					
Dax-Cac	-5.80%	0.30%	-1.20%	100.00%				
Nasdaq	6.50%	-0.90%	-1.80%	6.30%	100.00%			
Oats	-3.70%	0.50%	-2.20%	-0.40%	-14.80%	100.00%		
Cocoa	**27.80%**	2.50%	-3.60%	**-26.70%**	**21.10%**	-2.10%	100.00%	
EurUsd	**20.50%**	0.40%	-0.20%	-9.40%	12.40%	-4.60%	13.30%	100.00%

Correlations are chosen to be significant at the 15% level and these are emboldened

(b)

Table 1.2 Correlation Matrices for (a) Absolute Price Changes and (b) Algorithm Profit Changes

From the final correlation shown above it is clear that the correlations of the price returns that exist become insignificant once they have been processed by the trading system (see Table 1.2(b)). The correlations seem to be insignificant across the table with a few exceptions as there are far fewer pairs with correlation magnitudes greater than 15%. This demonstrates an important effect of correlation dilution that exists by virtue of the trading strategy. The fact that trading allows one to take long/short positions means that profits can be made on both increases and decreases in price of a security. Even though the prices for various securities are linked (correlated), the algorithm is not necessarily in the same position across these securities, and historical back-testing is utilised to offset and hence smooth portfolio profit profiles taking into account historical scenarios of behaviour. Therefore it can be concluded that the diversification impact in such a portfolio in algorithmic trading has substantial impact on the portfolio performance.

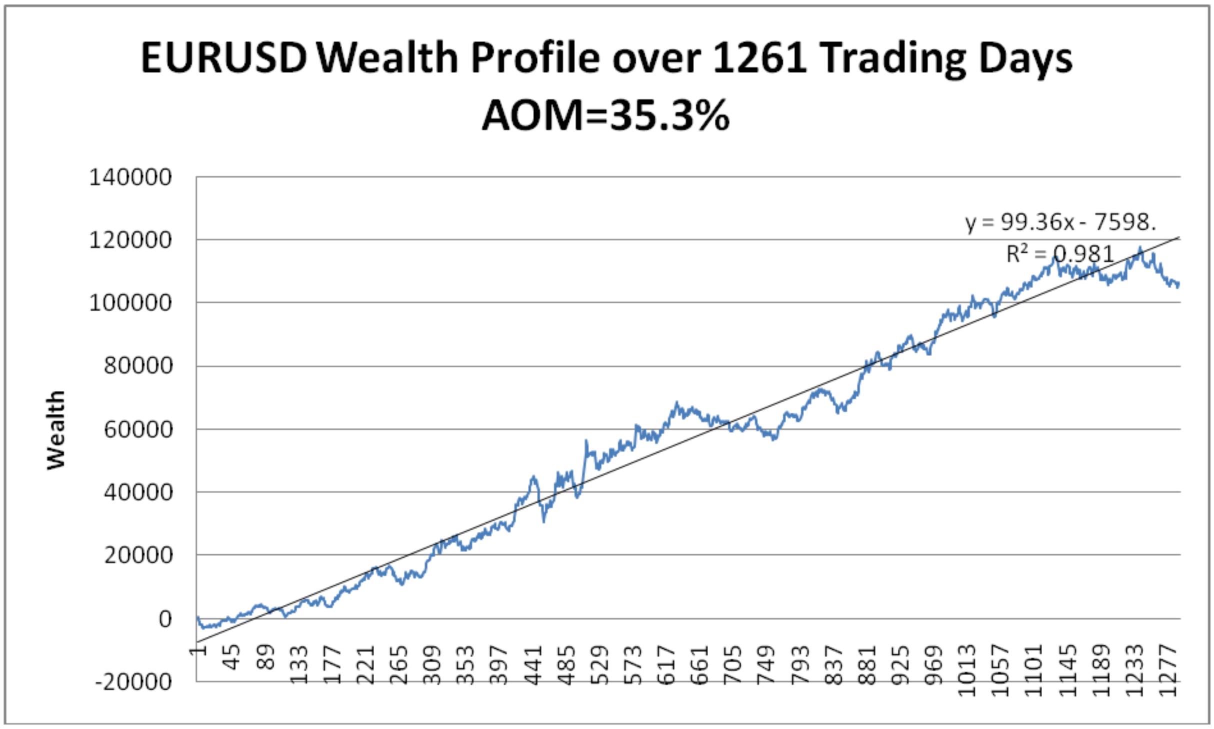
1.4.4 Acknowledgements: The authors would like to thank RGZ Ltd. for the use of their Nixon-class Algorithm outputs.

1.4.5 Conclusions

This study shows a portfolio containing both spreads and single securities reduces exposure to certain markets by reducing ‘noise’ and smoothing portfolio performance, while the PSI can be instrumental in establishing how stable an algorithm will be in generating consistent profits. Other findings show that a truly diversified portfolio over many different asset classes yields superior performance and this can include both securities and security pairs, which in turn can diversify risk by hedging against holding outright positions in securities.

Also significant was the alignment of data with respect to date, which was shown to be vital in establishing real-life traded portfolio weightings and meaningful correlation matrices. This study also allows us to conclude that correlations of daily price returns are significantly different to those of the output profit changes due to the effect of correlation dilution by virtue of the trading strategy or algorithm. This is because there are differences in the long/short positions across component instruments over the time history. Finally it may be concluded that optimising a portfolio according to the maximum RAP and AOM criterion leads to superior performance, particularly when compared to that of other criteria such as a maximum RR and minimum variance. Utilising the RAP and AOM in this instance (as well as other algorithmic systems governing portfolios or more simple portfolios comprised of a basket of stocks) can result in more profit generated and yield a far more desirable PnL profile.

Appendix


EURUSD Wealth Profile over 1261 Trading Days
AOM=35.3%
Wealth
y = 99.36x - 7598.
R² = 0.981
140000
120000
100000
80000
60000
40000
20000
0
-20000
1
45
89
133
177
221
265
309
353
397
441
485
529
573
617
661
705
749
793
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969
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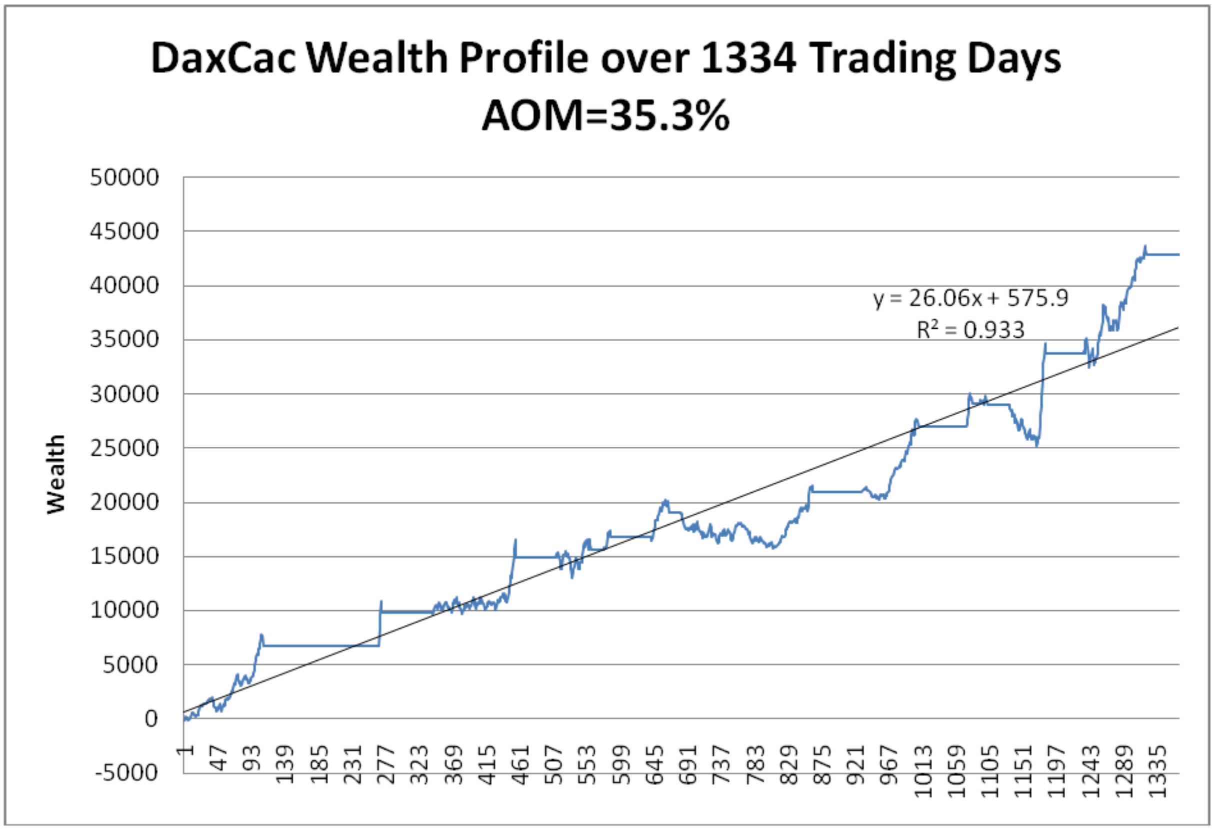
DaxCac Wealth Profile over 1334 Trading Days
AOM=35.3%
Wealth
y = 26.06x + 575.9
R² = 0.933
50000
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
-5000
1
47
93
139
185
231
277
323
369
415
461
507
553
599
645
691
737
783
829
875
921
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1013
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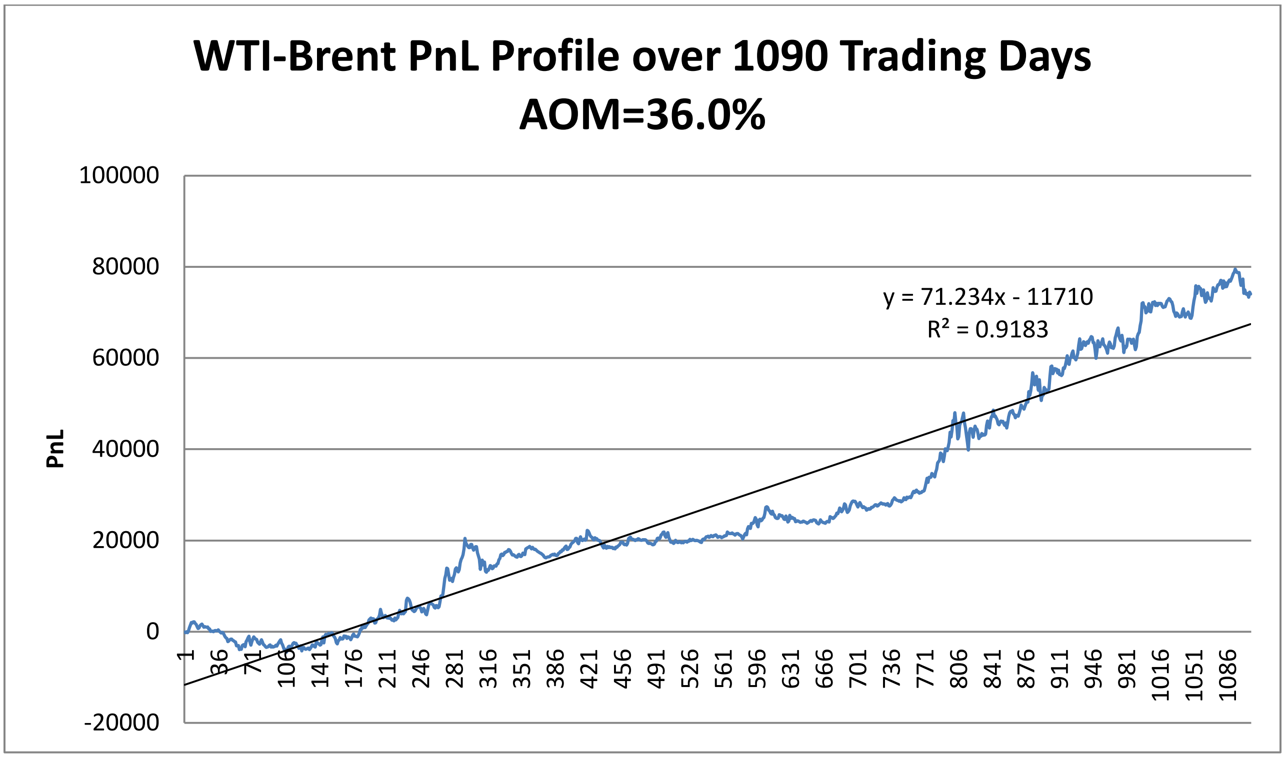
1105
1151
1197
1243
1289
1335



WTI-Brent PnL Profile over 1090 Trading Days
AOM=36.0%
100000
80000
60000
40000
20000
0
-20000
PnL
y = 71.234x - 11710
R² = 0.9183
1
36
71
106
141
176
211
246
281
316
351
386
421
456
491
526
561
596
631
666
701
736
771
806
841
876
911
946
981
1016
1051
1086

Chapter 2: The significance of day of Rollover and Contract Volumes of Commodity Futures in Algorithmic Trading

Chapter 2 is joint work with R.B. Nath, G.S. Metallinos & M.G. Karanasos titled 'The significance of day of Rollover and Contract Volumes of Commodity Futures in Algorithmic-Trading'. R.B. Nath, G.S. Metallinos & M.G. Karanasos contributed in some of the data collection and mapping with a combined contribution of 10% to the chapter (approx. 3% each).

The remaining contributions are by Z.N.P. Margaronis for significant contribution (90%) in data-collection, data processing, data analysis, results & discussion and write-up throughout the Chapter.

Keywords: commodity, futures, price slippage, limit locks, ADV, market liquidity, VWAP, roll day, rollover, FND

2.1. Introduction

Traded contract volumes for commodity futures differ from day to day. Generally, an average daily volume (ADV) is considered however this is slightly erroneous in less liquid securities. This is due to the fact that futures markets with lower liquidity are subject to 'price shocks' as a single buyer or seller may enter the market and impact the price with a large order. In order to carry out a rigorous analysis, the daily volumes for a number of commodities were analysed over a period of a number of years. Data was acquired for certain commodities, both in liquid and illiquid markets and comparisons were carried out along with an analysis of an algorithmic trading system whose PnL profiles for different roll days were acquired for eight different commodities.

This study aims to show how (for various instruments) the point at which the contract is rolled from the expiring contract to the newly active one in a single time series for a single instrument can be significant to the performance of trading algorithms which use these time-series as their back-tested input for optimisation. Various measures are employed to show the significance of altering the day of roll prior to expiry with respect to the time series. These include some standard measures such as the variation of daily returns, the mean return of returns and the coefficient of variation of returns. The study also employs some portfolio specific measures including the percentage change in PnL of the portfolio and the percentage change in AOM (Algorithm Optimisation Metric, see Margaronis et al. 2015) and DC (drawdown coefficient).

Showing this variation is significant to anyone needing to utilise a time series which considers the front month active contract of futures. This ranges from econometricians who are researching real life trading scenarios to wealth managers and algorithmic traders. The basis can differ significantly from rollover day to rollover day as can be seen from the results. The contract volume data of the active contracts is also illustrated to show how the optimised rollover day is usually prior to the volume dropping below the ADV (average daily volume) or in the case of highly liquid instruments, below a significant level.

2.1.1 First Notice Day (FND)

An important consideration and problem associated with trading is that of the first notice day (FND). The FND is notice of the first day in which anyone can hold contracts before agreeing to take delivery of the raw commodity. Given that most people and institutions trade commodities for financial gain and not to take delivery of it at contract expiry, it is clear that most will not trade beyond the FND. Hence, logically, volumes of contracts traded should drop after FND. FNDs vary from commodity to commodity and this has also been considered in the analysis carried out. For the metals the FND is much earlier than the expiry date, whereas for energies the FND is actually after the last trading day. In the interest of the chapter and the wider trading community, the chapter has analysed expiries prior to, and beyond the FND.

2.1.2 Volume Weighted Average Price & Price Slippage

The problems associated with trading are therefore becoming apparent as there are many aspects of the trading world which are not considered in conventional studies in economics and finance where time series are used. Contract volumes in markets can be seen to have an impact on the price and therefore price change in any given security. The extent to which the price will be impacted depends on the proportion of volume traded in any given position (buy or sell) which is the ratio of the order of contracts to the contracts traded that particular day. The greater the proportion, the greater the impact on the price for that given security. This volume weighted price is known as Volume Weighted Average Price or VWAP.

In the case of algorithmic trading, the ADV is a factor that must be considered before applying an algorithm or trading model to a time series especially as profits grow increasing the number of positions taken. This is associated with the parameter sensitivity of the trading model of RGZ Ltd. by Margaronis et al. (2015). This is due to the sentimental aspect of trading of commodities where liquidity may be low, which suggests that any large trade made by anyone could move the market in any given direction. The VWAP is then greatly impacted. The problem arises when taking a position. In the case that you are trading an instrument with low ADV, there will usually be a price slippage associated with taking the position. The larger the position taken, the greater the price slippage. For this reason, traders have developed methods such as "ice-berging" where the trader will enter the market in stages by placing smaller numbers of orders at any one moment, allowing orders to be filled before progressing and placing the next order. This allows for lower average price slippage for the entire position taken.

Price slippage is significant in illiquid markets. When a trade is placed that contributes to a larger proportion of the market, the price is expected to slip as the 'bid-ask' for the security in question is widened. This can have a catastrophic effect on trading algorithms where the liquidity of the market has not been analysed beforehand. Since the back testing of the system will most likely incorporate time series from which the price slip is not known at any given time for any given trade, making the price at which the trader is filled erroneous. This means that the price at which the trade is bought or sold is higher or lower respectively. This can erode the profit of any particular trade and therefore deem a successful trading algorithm flawed in practice. The mechanism by which this happens is shown below in Figure 1. As a result, it is highly desirable to avoid price slippage (by trading when the market is liquid) in order for real-life trading to be as similar to the back-testing as possible and this is done through the process of selecting the optimal rollover day.

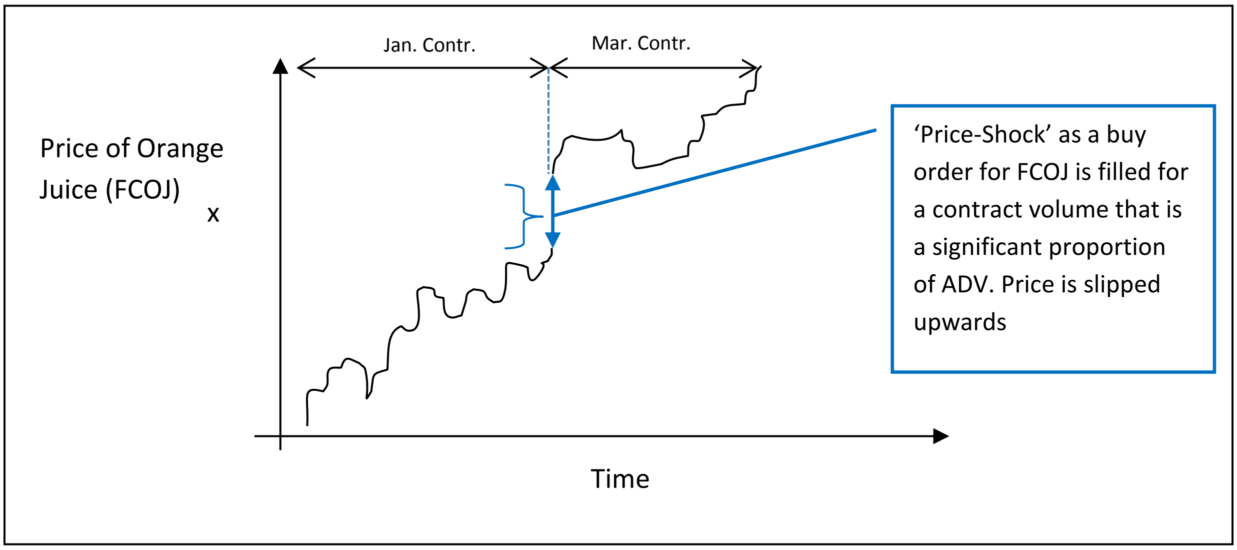


Figure 2.1 A representation of 'price slip' as a buy order of FCOJ is filled where the order is a significant proportion of ADV. This is a result of widening of 'bid-ask' for Frozen Concentrate Orange Juice (FCOJ) due to its low liquidity.

(This diagram is not representative of the real FCOJ market)

In Figure 2.1 the price slip value represented as 'x' is the loss in value of the trade as the price of orange juice (FCOJ) moves upwards due to the basis which exists between the two contracts in the Frozen Concentrate Orange Juice (FCOJ) market. This shows more clearly how the profit of a trading algorithm can be eroded by the introduction of a significant player in the market. This mechanism is also in effect when shorting or selling.

The 'new price' after the order has been filled is calculated and this is known as the volume weighted average price or VWAP. The VWAP is calculated by the exchange the commodity is traded on and incorporates the dollars traded for every transaction (number of contracts multiplied by price) divided by the total shares traded for the day.

2.1.3 Limit Locks

Limit locks can also pose a serious problem for those trading futures. Limit locks occur in the futures market and happen when the trading price of an instrument is predetermined at the exchange's limit price. Limit locks occur mainly in the grains market and are usually the result of unexpected news due to weather or crop yields. They are in place to protect investors from the volatility exhibited in futures markets. When a limit lock occurs, trades above or below the lock price issued are not executed. For traders therefore, this situation is either very beneficial, as they are trapped in a trade that is moving in the correct direction with respect to their position (buy or sell), or very detrimental as they are trapped in a trade which keeps moving in the opposite direction to their respective position. Limit locks can therefore have an impact on the number of contracts traded on the days they occur. It is also worth mentioning that limit locks can occur for consecutive days. This is significant as the limit lock may cause an investor to perhaps refrain from trading that particular day or on the contrary impulse them to take even more positions in the market as a crop yield report may reveal information about what the price may do after the limit lock is removed.

It is therefore expected for volumes on days where commodities limit lock to be significantly lower than usual as traders may enjoy the benefits of being locked in and place orders to be executed when the lock is removed or may be in a position where they are reducing their trades to reduce risk to market exposure and turn to other products such as options.

The chapter is split into 10 main sections. The first and second sections include the introduction and Procedures for Data & Results Preparation which give a general overview of the purpose the chapter and of course the preparation of the data and how it is used. Section 3 details the literature review. Sections 4 to 7 detail the results and discussion of altering the roll day with respect to the measures mentioned earlier while Section 8 is dedicated to the representation and discussion of the volumes data. Section 9 includes the conclusion and Section 10 is comprised of the references.

2.2. Procedures for Data & Results Preparation

The raw data of each contract (as obtained from Bloomberg) is organised into a single file such that all contracts for each instrument are in order in individual files. Each individual file (for each specific instrument) is then mapped using a mapping program (whose process is detailed below). This is done a number of times for each instrument in order to gain a set of time series for various rollover days for each instrument.

The mapped time series for each instrument is then input to the trading algorithm once optimised, then PnL and certain metrics for each instrument and rollover day are evaluated. The post analysis involves the evaluation of measures used in this study as explained earlier and detailed later.

2.2.1 Mapping and Rollover

The mapping procedure involves the use of a computer program. The input for the program is the entire set of monthly futures contracts obtained as explained earlier, in order, in a series. The data itself are daily settlement prices for each contract along with the date for the past 6 years. The program then takes the last price of each contract, being the price on expiry of the contract, and lines it up by date to the price of the second month contract. The program uses a counter for both the price series and the date series. When the counters match on the day before expiry, mapping occurs. The front and second month prices on that date are then lined up and their difference gives the basis or rollover for that contract. This is done consistently throughout the entire data set and each roll value or basis value is stored and accumulated in order for a calculation of the cumulative roll or basis to be made. The roll is then accounted for in the time series. Mapping data can have a significant impact on a price series if the roll value or basis value is significant. It is less significant in instruments which do not exhibit large rolls. However given that the cumulative roll is required, especially when a trading algorithm is applied, even if the roll values are not significant the fact that it accumulates over time makes the mapping procedure imperative no matter the magnitude of the roll or basis.

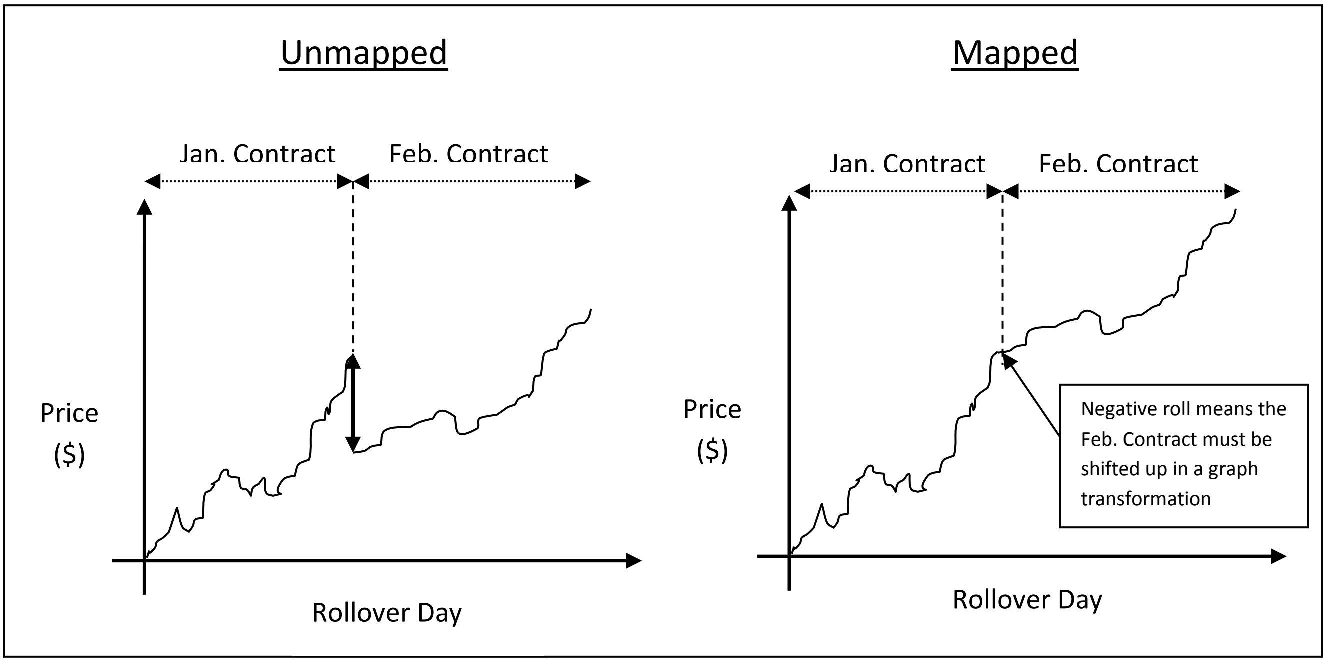


Figure 2.2 A representation of the mapping procedure showing how contracts can be rolled and the process used in the computer programs used

2.2.2 Data and Day of Rollover (Roll Day)

In the interest of this chapter, eight commodities were selected and analysed (two softs, two grains, two metals and two energies). The commodities selected were chosen based on their sector (range of sectors analysed), their liquidity and the size of their roll.

Each set of price data used in the trading algorithms was mapped according to an optimal performance given by the performance indicators employed. Of course the optimal is restricted by certain issues such as FND. For example, the optimal day to roll the oats trading algorithm may be one day before expiry however; its FND is many days before that. Hence, it cannot be rolled a day before in practice unless delivery of the commodity is taken on expiry.

The optimal roll day for all commodities has been found to be a few trading days before the FND.

The price data for each commodity was then constructed for different roll days. This means mapping the price from one contract to the next happens on different days from expiry in each data set. Once different sets of price data for different roll days were available, each set was input into the trading algorithm. The trading algorithm uses the price data to apply its trading rule and strategy, then output a PnL profile and performance indicators thereof.

Given the difference in roll day it is clear there will be differences in the algorithm's performance and the aim of this chapter is to determine how significant this difference is and perhaps show the reasons for this. The indicators employed include the AOM (Algorithm Optimisation Metric), DC (Drawdown Coefficient) and PnL (trading gains made during back-tested period), as defined by Margaronis et al. (2011).

Once the PnL profiles for different roll days is produced, the PnL returns for each profile were calculated in order for standard deviation, mean return (with respect to margin requirement) and CV (coefficient of variation) to be evaluated. It is also evident that due to altering roll day, these values will differ from PnL profile to PnL profile for the same commodity.

The results are presented as percentage changes in order for comparisons inter sector to be made.

2.3. Literature Review

Groot et al. (2014) study the term-structure information of novel momentum strategies for commodities futures. They show that the momentum strategies that invest in contracts with the largest expected roll yield the greatest returns. They show that traditional strategies which utilise the nearest contracts earn lower returns but nonetheless it is clear from the analysis that the basis from contract to contract in commodities exists and that it can significantly alter returns when it is incorporated into the time series.

Theories of storage are often used, as in the study by Symeonidis et al. (2012) where 21 different commodities are considered. The study focuses on the relationship between the inventory and forward curve while also considering price volatility as a function of inventory. The findings show that low inventory is associated with forward curves in backwardation. Also, the findings show that as inventory decreases, so the price volatility increases. This is very much in line with the findings of this study where we show the decrease in volumes (associated with inventories) can induce volatility in the returns via the metrics used.

An interesting study by Yang (2012) identifies a factor which explains most of the average excess returns of commodity futures sorted by basis. This compliments the study by Margaronis et al. 2011 where the significance of basis was investigated for various commodities and of course this study where it is found that lower volumes can result in induced volatility as the FND approaches.

Although the literature may not be completely relevant to the study, it is still very interesting to see how many different factors there are which can impact the volatility through basis and volumes. Even though the studies considered do not consider the exact same factors, it is clear that these factors are related and that the findings are therefore relevant. Due to the nature of this study, and unexplored area within the commodities futures sector being analysed, there are no completely related studies which delve into the relationship between basis, contract volumes and the impact from an algorithmic trading point of view.

2.4. Softs

The softs is a sector that is very useful in diversifying the risk of trading energy, or metals weighted portfolios. Also, given the nature of the liquidity, there can be large price jumps which can be taken advantage of if a strategy is able to predict them.

In order to analyse the two softs, Frozen Concentrate Orange Juice (OJE) and Lumber (LBS) as with CQG Trading Platform, the FND must be used as well as the most optimal day prior to expiry to roll. The optimal expiry day is imperative to evaluating percentage changes as it is used as the benchmark.

After applying the procedures detailed in section 2, the following results were observed.

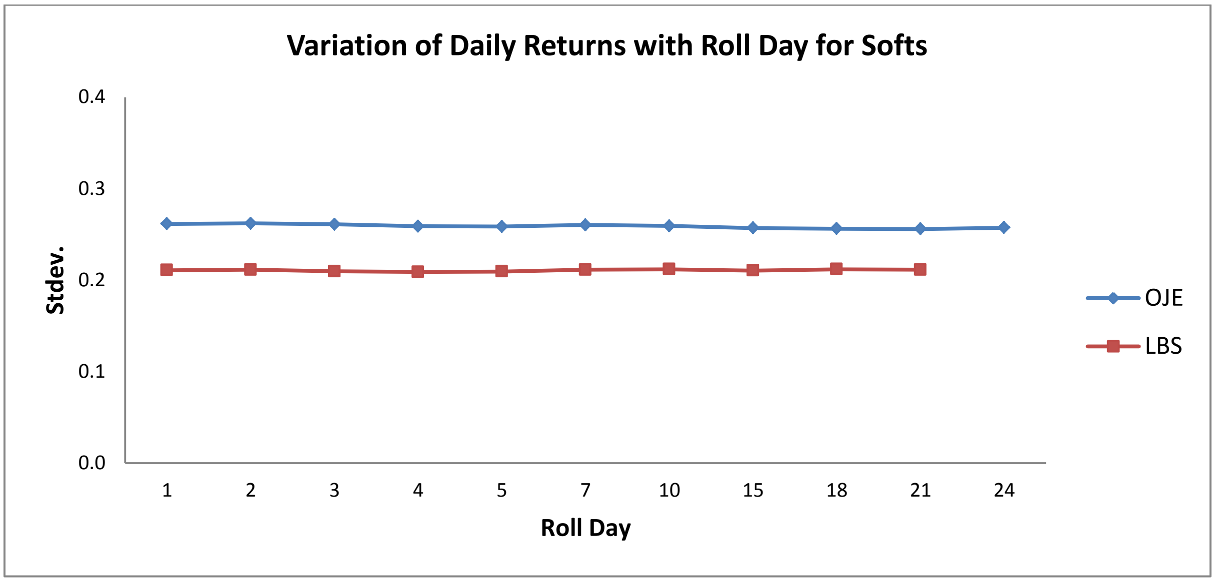


Figure 2.3

From Figure 2.3 it is clear that altering the day the price data is rolled has minimal impact on the standard deviation of the PnL profile's returns. However, it can be inferred that the LBS algorithms are more stable than the OJE algorithms as their PnLs exhibit significantly lower standard deviations across the roll day range.

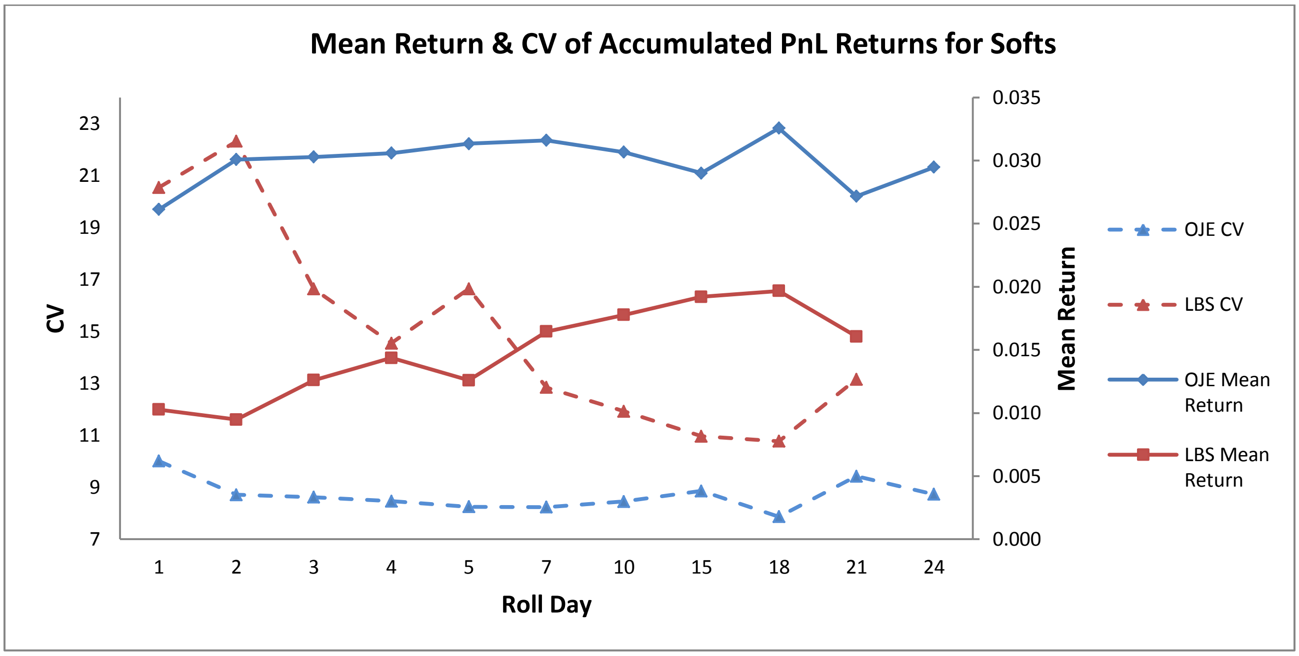


Figure 2.4

From Figure 2.4 it is possible to see that the mean returns for OJE PnL returns are significantly higher than those of LBS. Despite the LBS PnL returns exhibiting lower standard deviations (as seen in Figure 2.3), overall, the OJE algorithms seem to have both a more stable mean return characteristic, and higher mean returns. It can therefore be said also that altering the day of roll for OJE will not significantly impact the PnL returns or coefficient of variation.

On the other hand, the LBS results show that changing the day the prices are rolled can have a more significant impact on both CV and the mean returns. Figure 2.4 suggests that generally, increasing the number of days before expiry that the contracts are rolled will reduce the CV for LBS, and increase its mean returns but by a less than proportional amount. i.e. the drop of CV is greater than the increase in mean return. The reason for this effect may be due to the impact of the FND. The FND for lumber is after the expiry hence it is traded non-speculatively until expiry. Despite this, volumes are generally low as the trading hours for LBS are long. This makes LBS subject to price shocks which may create the instability seen. These price shocks are likely to become more and more significant as the expiry day nears since the volumes reduce further. This phenomenon may explain the instability shown.

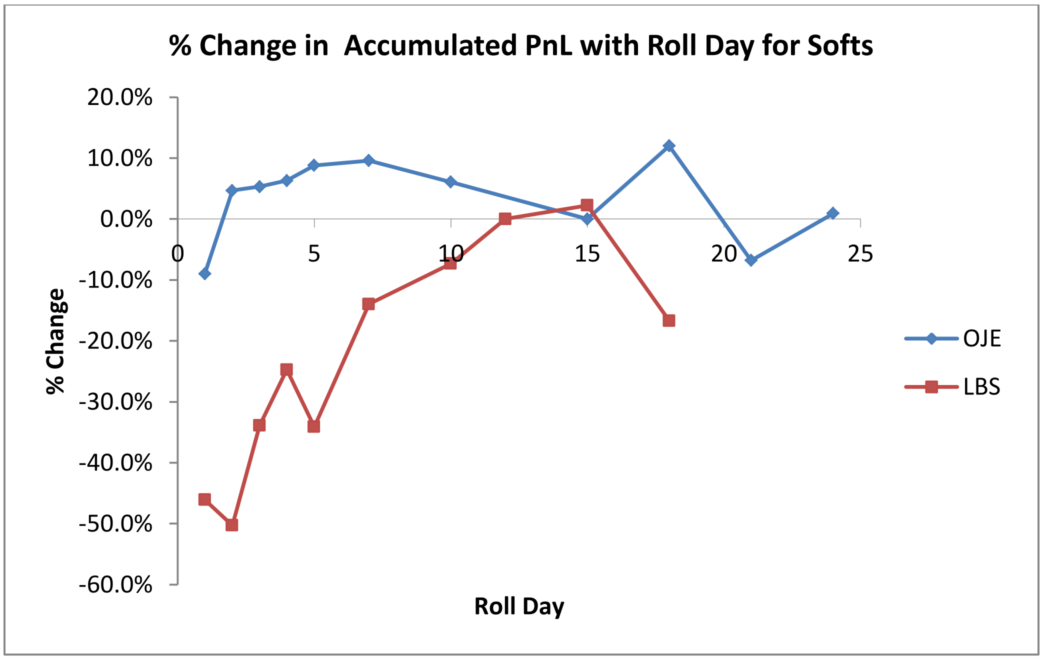


Figure 2.5

(Note: optimal roll day is 15 days prior to expiry for OJE and 12 days prior to expiry for LBS)

Figure 2.5 shows how the accumulated PnL varies with respect to roll day, where percentage changes are with respect to optimal accumulated PnL being day 15 for OJE and day 12 for LBS. As can be seen, OJE is significantly more stable and is not actually being operated at the most optimal level. The reason for this is due to the FND for OJE. As a precaution, traders will roll contracts earlier to avoid price volatility and price slippage due to reduced volumes. It is clear that after day 15, there is instability whereas before day 15 the percentage change is minimal roll day to roll day. As a result, given the instability after day 15, and the precaution to roll before FND and avoid price slippage from low volumes, day 15 was selected as the best balance of performance and stability.

In the case of LBS, it is clear that the change in PnL is far more significant than that of OJE throughout the range. There are significant drops in PnL as expiry is approached. This may be due to reduced volumes as expiry looms and traders move into the next contracts. The effect in the case of the LBS market is accentuated due to the long trading hours and low liquidity. This means price slippage will be even more significant. Despite this however, increases in PnL could be experienced if the data was rolled slightly earlier.

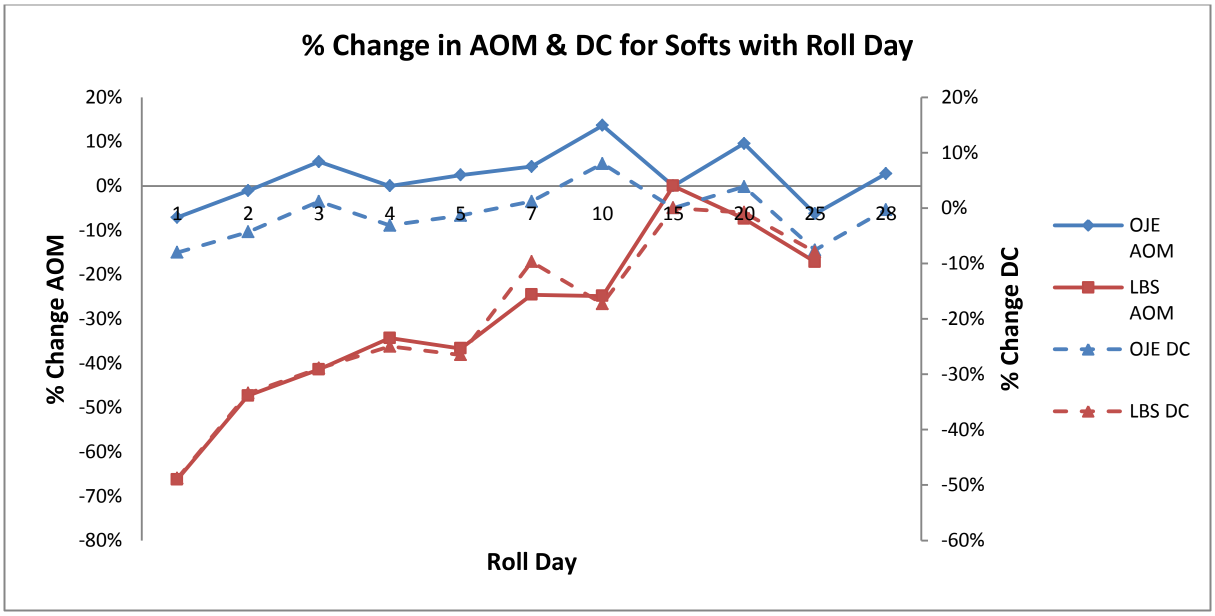


Figure 2.6

(Note: optimal roll day is 15 days prior to expiry for OJE and 12 days prior to expiry for LBS)

Figure 2.6 shows how altering the day of roll can significantly impact the AOM and DC. In the case of OJE there is a hint of stability. The AOM and DC seem to fluctuate between values while also having periods of stability. As expected, the AOM and DC drop as expiry nears and this is once again due to the reasons stated earlier regarding volumes and price slippage. On the other hand the LBS AOM and DC drop significantly as the roll day is altered which shows that LBS has a far more sensitive algorithm. Significant changes in performance could be experienced as a result of rolling on a different day. This drop in performance will also be magnified by the price slippage that would be experienced due to the low volumes and longer trading hours.

These variations could also be attributed to the size of the roll because a greater roll has a greater error attributed to it in absolute terms which is supported by Karanasos and Margaronis et al. (2011).

2.5. Grains

The grains are a sector that has varying liquidities. Grains are however present in most commodity portfolios. Their significant price changes can yield impressive returns but also makes them very risky. In the interest of this chapter, ZSE (Soybeans) and ZOE (Oats) were selected. The reason for the selection is because ZSE is very liquid and ZOE is very illiquid, hence the significance of volume may be made clearer.

Generally, the grains are subject to the same issue as the OJE market. When expiry is looming, the liquidity in the active contract drops as traders move into the next contract to avoid price slippage. This effect is even more prominent in the grains. The FND is 10 days prior to expiry but in order to avoid any price slippage, the optimised roll day is 15 days before the expiry date.

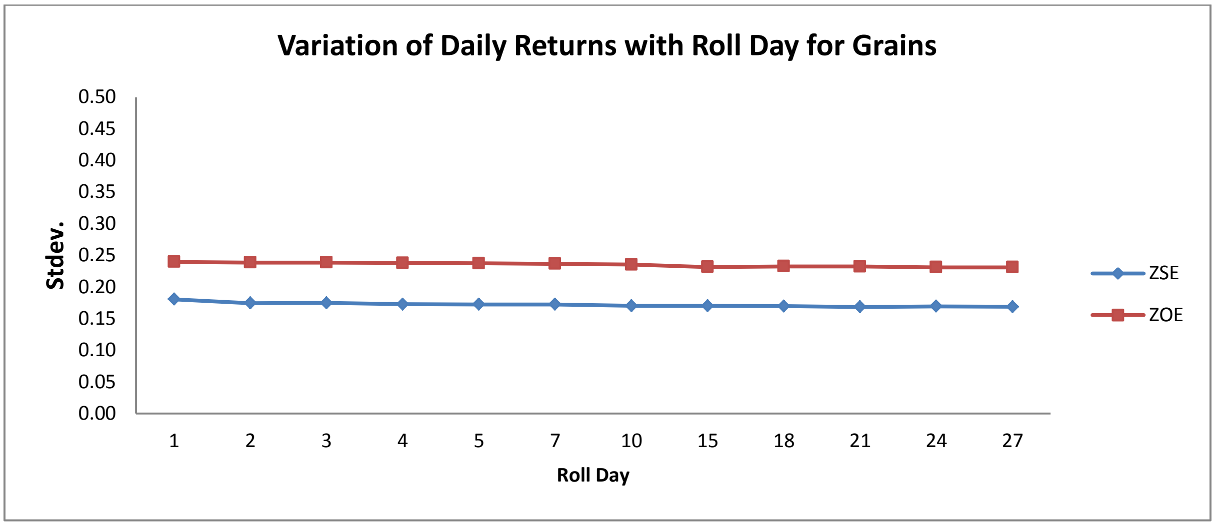


Figure 2.7

From Figure 2.7 it is clear once again, that altering the day the price data is rolled has minimal impact on the standard deviation of the PnL profile's returns. However, it is clear from the results that the ZOE algorithms exhibit lower standard deviations across the range of roll days than the ZSE algorithms.

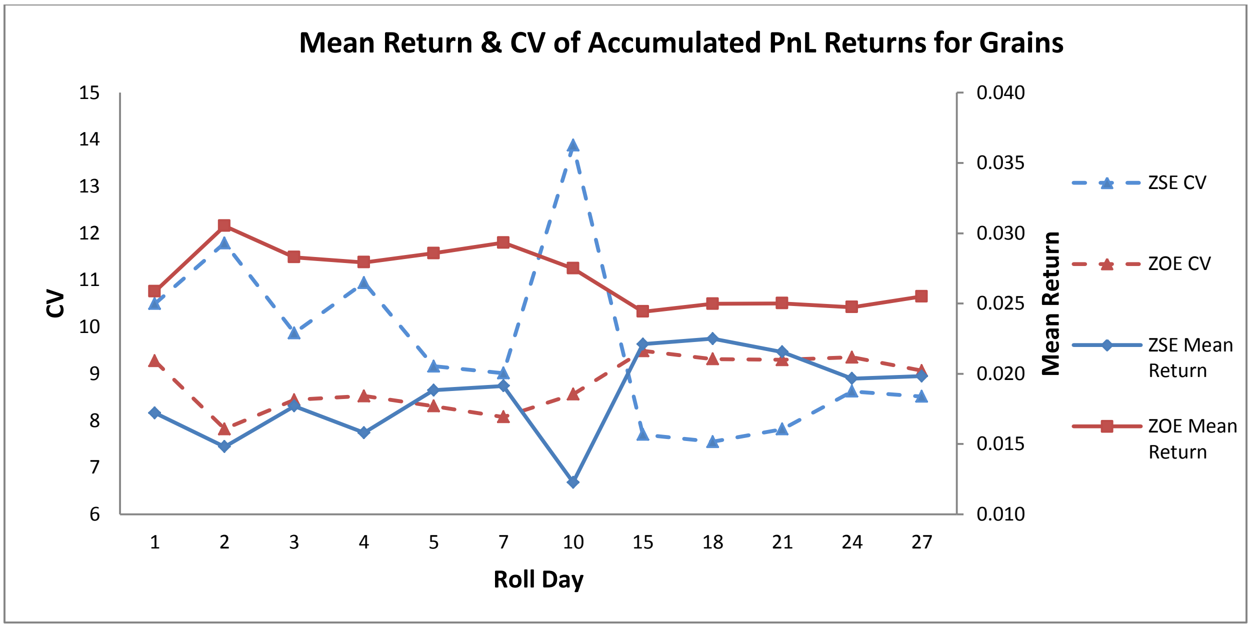


Figure 2.8

From Figure 2.8 it can immediately be seen that the ZOE mean return and CV are far more stable than that of ZSE. Despite this however, the CV for ZOE is consistently greater than ZSE's suggesting that the PnL returns of ZOE are more volatile. Both the CV and mean return for ZSE have very unstable profiles with respect to roll day around the 10th day. Hence, the FND for the grains is 10 days before expiry. The instability of the profiles shown may be attributed to effect of FND as traders close out positions in the active contract to open positions in forward contracts (that will become the active soon). Figure 2.8 also shows that one day from expiry, both ZSE and ZOE experience significant changes in CV and mean return. In the case of ZSE, the CV drops while the mean return rises, suggesting any extra volatility due to lower volumes is favoured by the ZSE algorithms. On the other hand, the ZOE algorithms do not favour the same scenario as the CV rises and mean return drops. These differences may be due to the fact that ZSE volumes are generally an order of magnitude larger than ZOE volumes.

From the results it may be inferred that rolling 15 or more roll days before expiry would yield the most stable profiles and therefore algorithms.

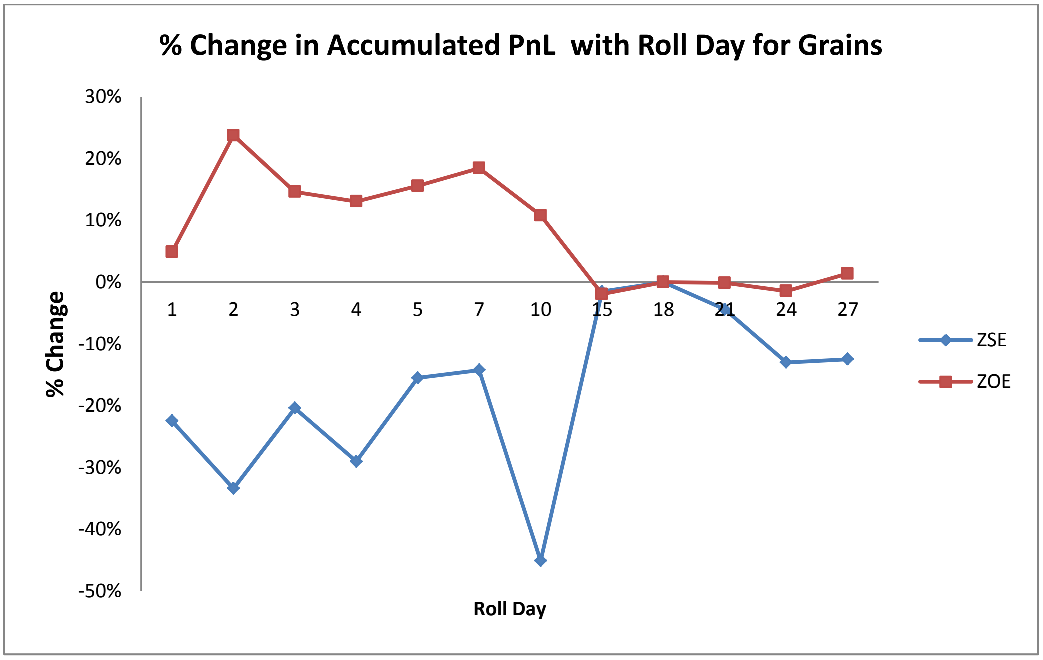


Figure 2.9

(Note: optimal roll day is 15 days prior to expiry for ZSE and ZOE)

Figure 2.9 details the percentage change in PnL with roll days. Any day after the optimised roll day (15 days prior to expiry) seems to be more stable than prior to it. ZOE PnLs are very insensitive to roll days greater than the optimised. ZSE PnLs are far more sensitive as can be seen. Once again on the FND 10 (10 days prior to expiry) the percentage change in PnL drops significantly. The reasons for this were discussed above. Also, it is interesting to see how ZOE PnLs significantly increase as expiry nears. This shows that the ZOE PnL favours the volatility associated with the price as volumes reduce closer to expiry. There is however a significant drop on roll day one suggesting instability. Despite the increase in PnL for ZOE, it would be impossible to make these gains in practice as it is not advisable to keep trading the same contract after FND. Also given the lower volumes, the price slippages that would be experienced after FND would greatly erode PnL. This is also the case for ZSE however, it would also not be advisable based on the results shown as PnL significantly drops as expiry is approached.

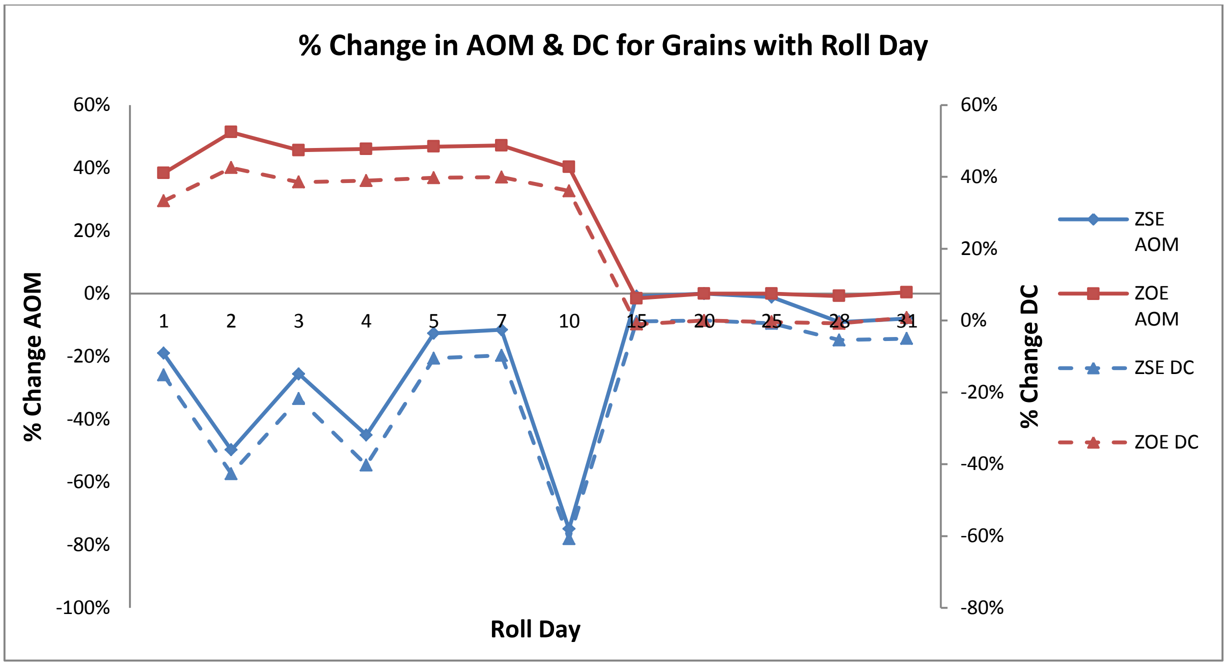


Figure 2.10

(Note: optimal roll day is 15 days prior to expiry for ZSE and ZOE)

Figure 2.10 shows the variation of AOM and DC with varying roll days. From the graph it is clear that any roll day closer to the expiry than the optimised for ZSE (15 days prior to expiry) will result in catastrophic effects on AOM and DC. On the other hand ZOE gains from significantly greater AOM and DC. It has also be discussed how this would not be possible in practice due to the FND. Also that the price slippage would be significant and may harm performance characteristics in real time practice. However, rolling any day before the optimised day i.e.>15days, it is clear that the AOM and DC for both instruments are quite stable (more so for ZOE though). Generally however, the extra stability seen in ZOE would be eroded in reality by the price slippage as ZOE ADVs are consistently an order of magnitude lower than those of ZSE.

2.6. Metals

Metals is a sector that is common in many portfolios not just commodity portfolios. Metals are non-perishable and therefore are not subject to price-shocks unlike the grains and softs. In the interest of this chapter, two metals were considered, Copper (CPE) and Gold (GCE). The reason for this selection is to include a base metal (CPE) used in manufacturing and industry, and a precious metal (GCE) used as an investment, base currency and other reasons. Unlike the grains and softs also, the metals sector is not subject to low volumes however, when it comes to contract expiry, the volumes can be seen to drop significantly. This is because traders and investors may not be interested in taking delivery of the actual commodity.

The CPE and GCE contracts have been optimally rolled 28 days prior to expiry while the FND is 18 days prior to expiry.

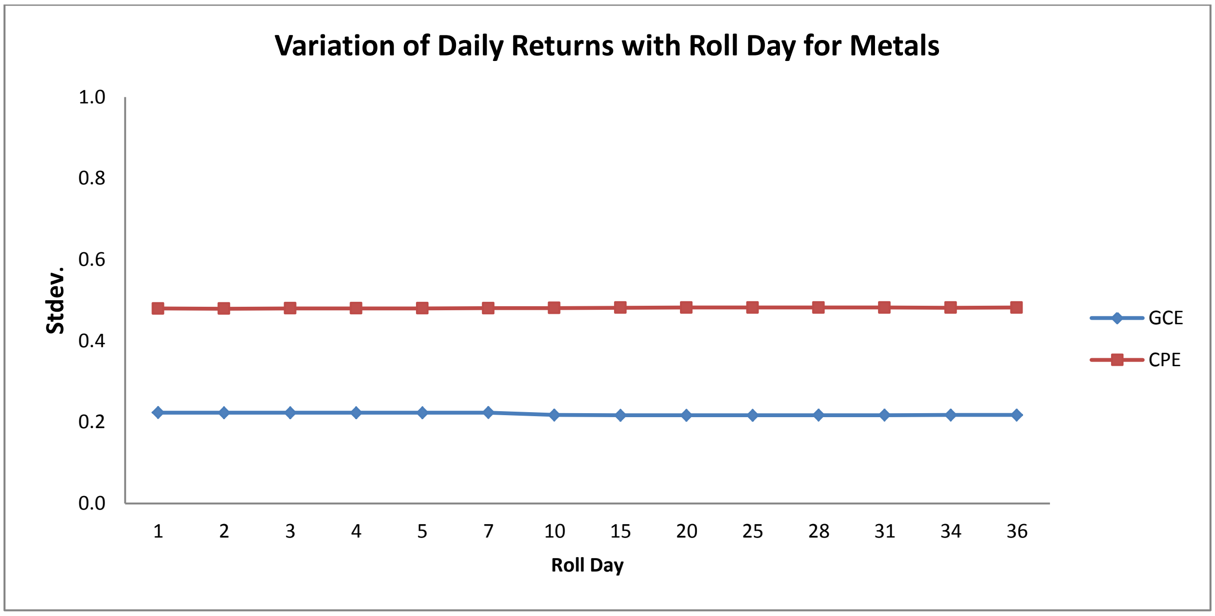


Figure 2.11

Similarly with the previous results, Figure 2.11 shows there being virtually no variation with roll day of the standard deviation. This is true for both GCE and CPE. Although it can be inferred from the graph that the GCE algorithms are more stable with respect to PnL returns over the roll day range as they exhibit lower standard deviations.

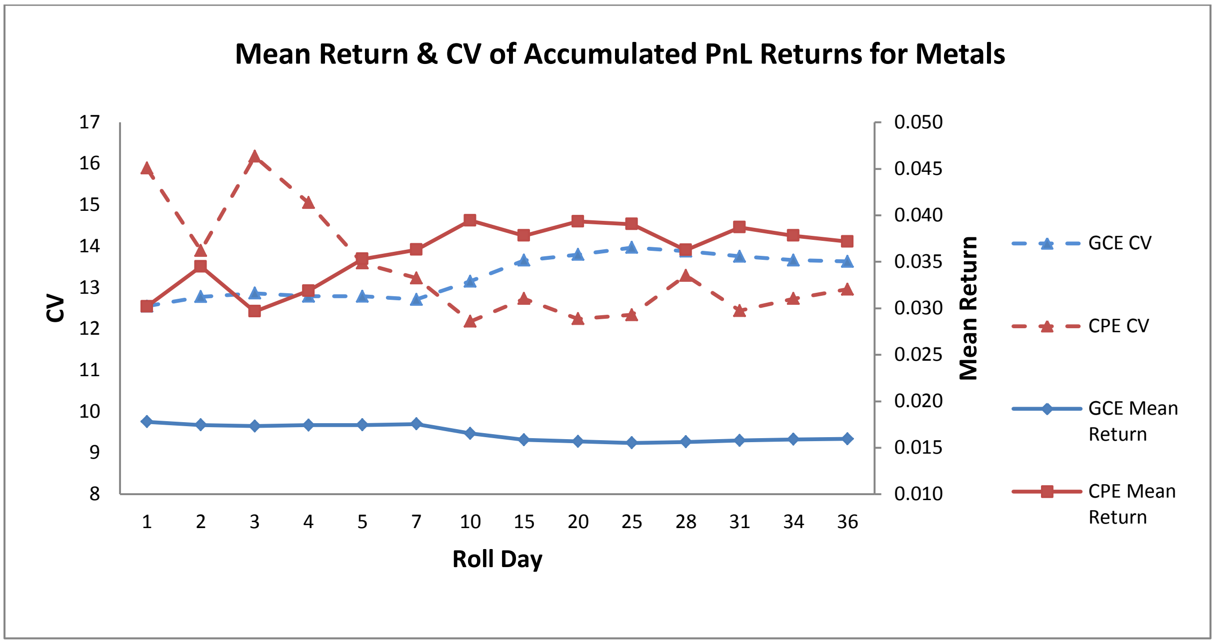


Figure 2.12

From Figure 2.12 it is clear that the GCE mean return and CV is very stable across varying roll days. This means that whether the price data is rolled on expiry, or 7 weeks before expiry, the CV and mean return should not change significantly for GCE. In the case of CPE there is slightly more variation, especially as expiry nears. There are a number of reasons that could explain this. Firstly, CPE, although not perishable, is used and is not considered 'precious' as GCE is. GCE also does not have the storage costs associated with it as CPE does. This means as FND approaches, CPE traders will be far more vigilant of their open positions than GCE traders. Secondly, although both metals are very liquid, GCE is far more liquid than CPE by an order of magnitude. This suggests that the price volatility associated with the drop in volume may be proportionally more for CPE. This can also be inferred from the behaviour of CPE as it approaches expiry.

Generally however, in practice this is not an issue as metals contracts' FND is 18 days prior to expiry. This means that those who do not want to take delivery of the commodities must not be trading them the 18 days before expiry and must therefore have rolled their positions to the next forward contract.

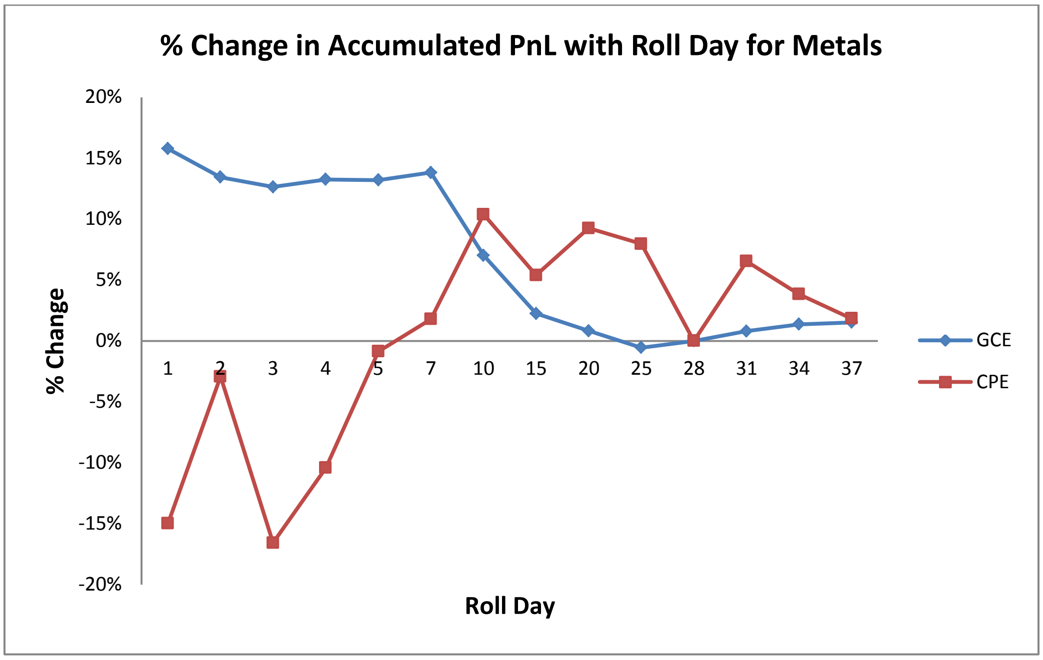


Figure 2.13

(Note: optimal roll day is 28 days prior to expiry for GCE and CPE)

From Figure 2.13 it is clear that the PnLs for both metals vary significantly as roll day tends to expiry. In the case of GCE, the PnL changes are not significant until the FND of 18 days. It is clear that after that day, traders remove positions they may have and begin to trade the next contracts. There is another region of stability between the FND and expiry which may exist due to very high volumes (liquidity) of GCE as many traders take delivery. In the case of CPE, once again after FND and on approach to expiry, the changes in PnL are significant but in this case they drop rapidly. The drop may be associated with the decrease in volume as traders roll their contracts and price volatility is established due to the huge ‘dumping’ of contracts.

Compared to the grains and softs however, it is obvious (by comparing scales) that the metals market is much less affected by the day the data is rolled, proportionately.

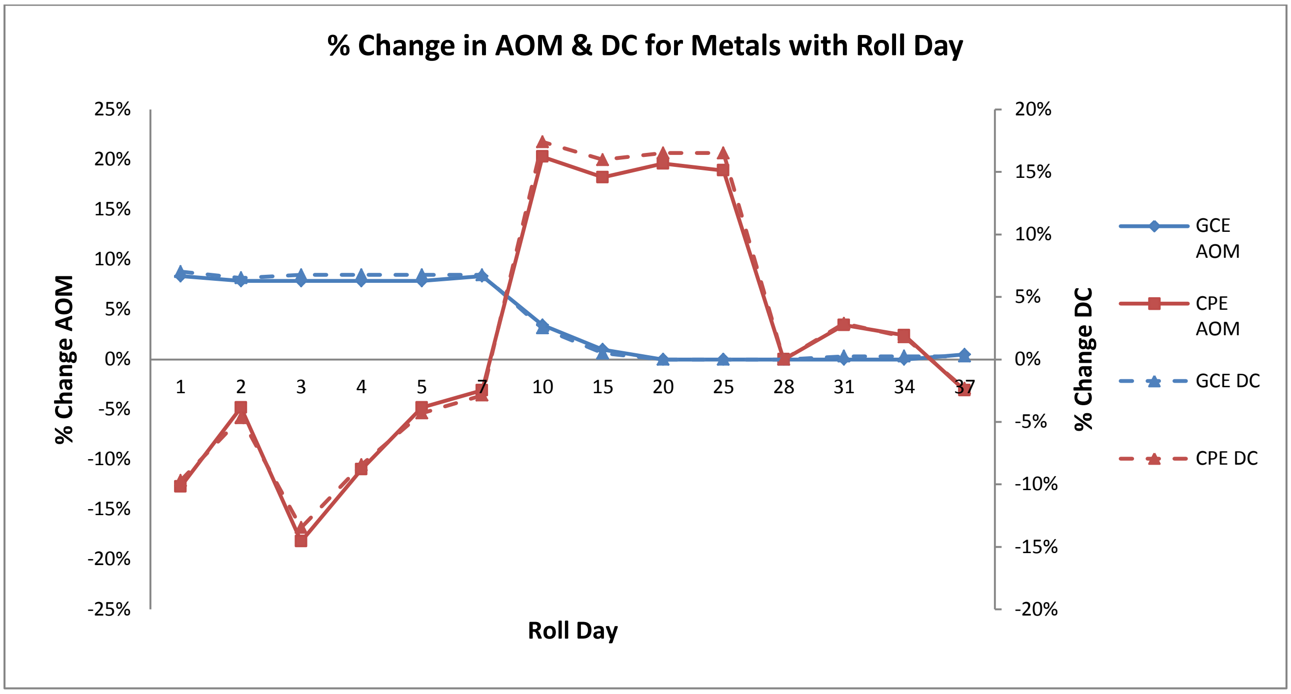


Figure 2.14

(Note: optimal roll day is 28 days prior to expiry for GCE and CPE)

From Figure 2.14 it is apparent that the AOM and DC for GCE are very stable across roll days with slight increases as the roll day tends to expiry. On the other hand the CPE is far more unstable with both AOM and DC fluctuating throughout the roll day range. Interestingly, as expiry nears, the AOM and DC drop dramatically and this may be due to the illiquidity phenomenon discussed earlier however compared to both the grains and softs, the fluctuations in AOM and Dc are far lower proportionately, making both metals algorithms stable with respect to roll day. Even though there are changes in performance, the size of the changes for the metals is not as significant as with the other sectors. Also it is important to consider the fact that most traders do not hold positions past FND, and that contracts held after the FND are subject to delivery.

2.7. Energies

The energy sector is the largest sector with commodities. Energies are traded in very high volumes and their FND is after the date of expiry due to this liquidity. In order to analyse the energies sector fairly against the other sectors, two energies were selected to be subject to the procedures and analysis to determine whether their algorithmic performance is compromised with respect to roll day; Heating Oil (HOE) and Natural Gas (NGE). Due to the same phenomenon of volumes dropping as expiry nears the energy algorithms are optimised to roll 3 days before expiry. The FND (as mentioned earlier) is not of importance as it occurs after expiry.

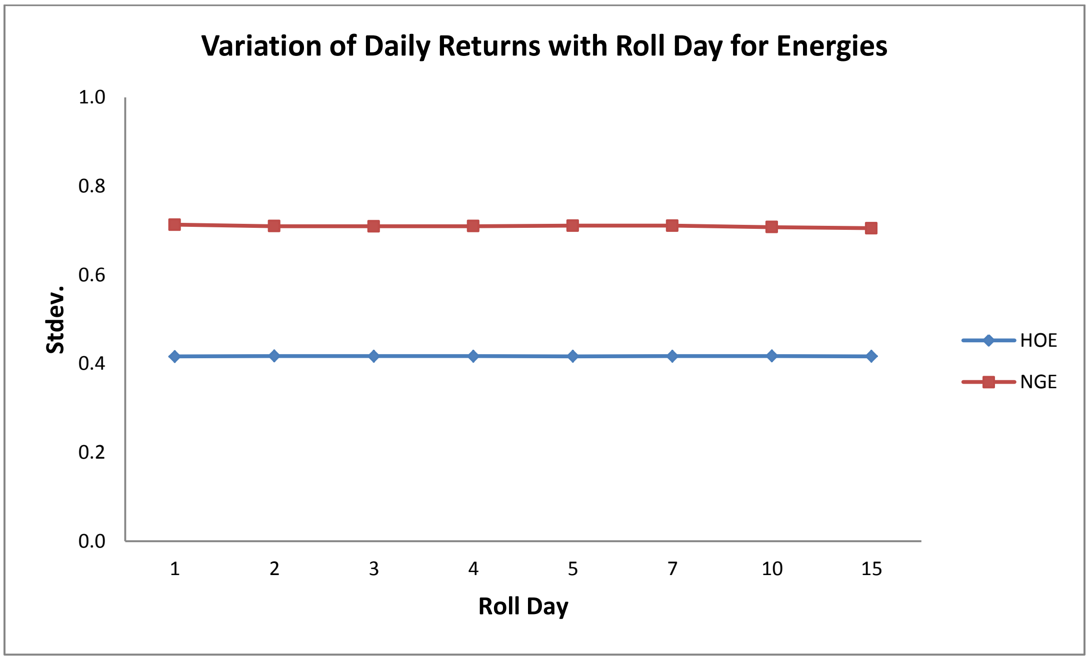


Figure 2.15

From Figure 2.15, as with all other sectors, the standard deviation of PnL returns remains constant as the roll day is altered. Generally, compared with the other sectors, the standard deviation of the PnL returns are very high suggesting greater price volatility associated with the energies. In relation to each other though, the HOE standard deviation is far lower than that of NGE and this may be due to the famous issue of storage problems associated with gas which makes it susceptible to price shocks.

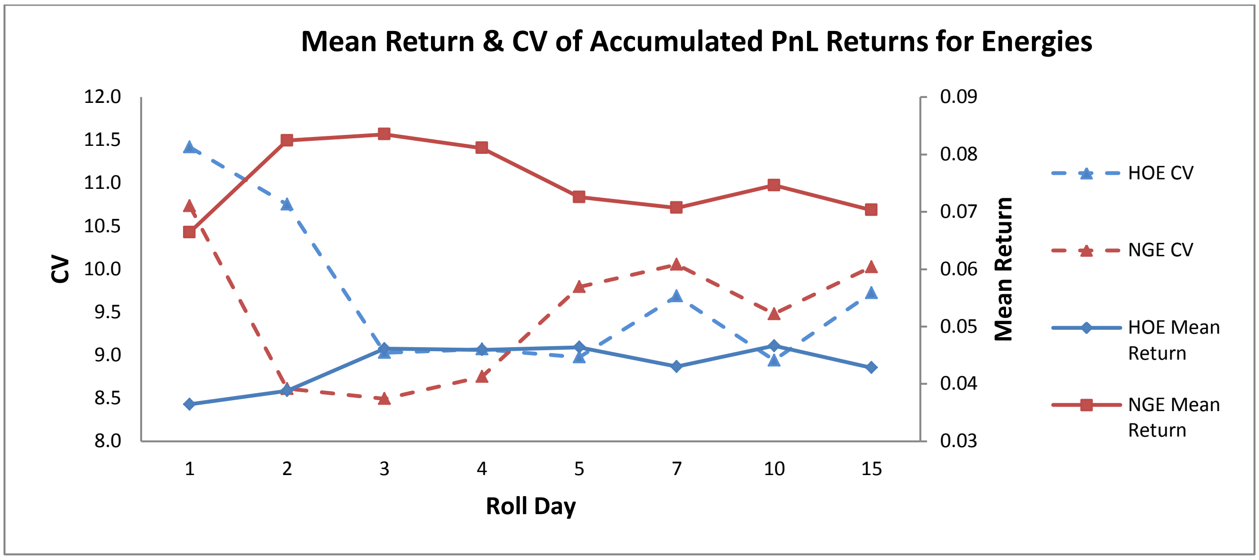


Figure 2.16

From Figure 2.16 it is apparent that the mean return for both NGE and HOE are quite stable. The mean return however of HOE is far lower and more stable than NGE's. The reason for this may be the problem associated with the storage of gas making the price more volatile as expiry nears. This suggests why the mean return for NGE is stable up until 4 days prior to expiry. On the other hand the CV's of both NGE and HOE exhibit very similar trends with an almost sinusoidal characteristic. It is quite clear though that as expiry nears more and more, the CV will rise for all energies as the storage of both is an issue for whoever is taking delivery. There is also a drop in volumes of both NGE and HOE as expiry nears.

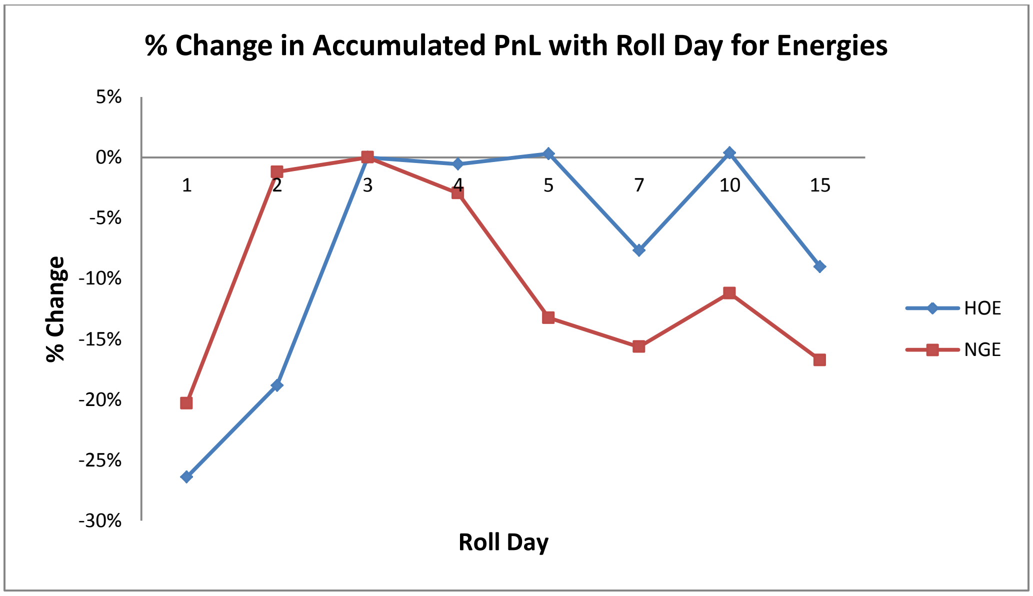


Figure 2.17

(Note: optimal roll day is 3 days prior to expiry for HOE and NGE)

From Figure 2.17 it is clear that both energies have a greater stability of PnL across roll days compared to the softs and grains, similar to the metals. In the case of the energies there are sharp drops 1 or 2 days from expiry. Reasons for this could be the fact that energies' FND is after expiry, so traders are rushed to "dump" contracts closer to expiry resulting in an increase in price volatility, hence the drop in PnL. The other reason for the instability shown could be the size of the roll for energies. Energies (unlike metals) have famously large roll values which mean mapped algorithm prices have larger margins for error, hence there could be a larger discrepancy of PnL.

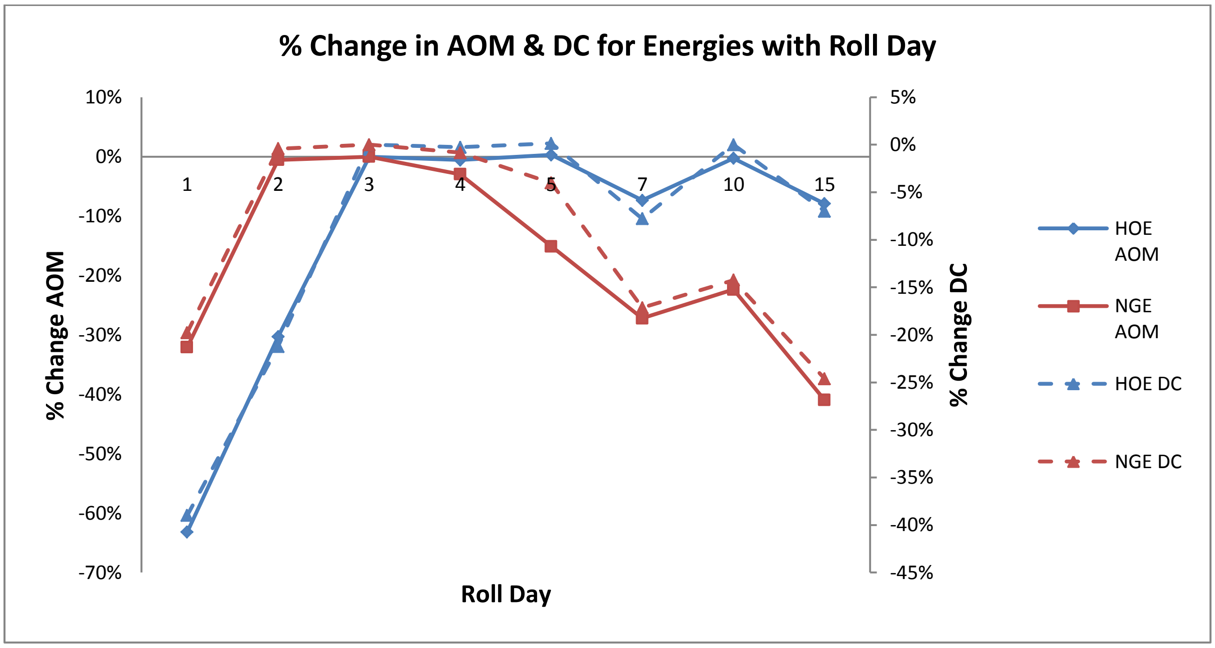


Figure 2.18

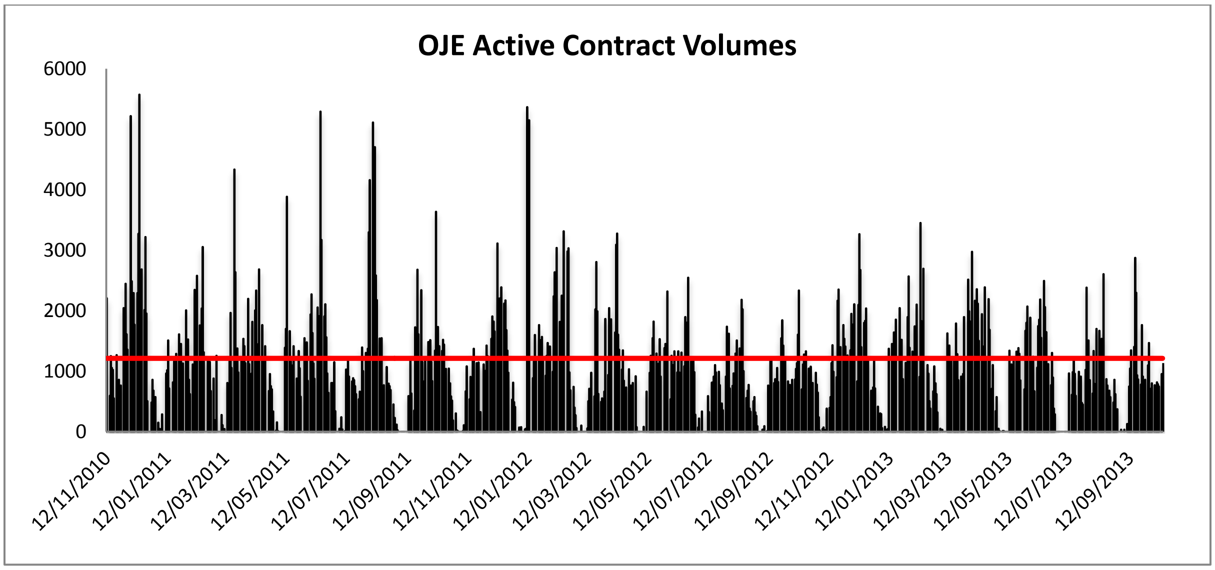
(Note: optimal roll day is 3 days prior to expiry for HOE and NGE)

Figure 2.18 shows how the AOM and DC for HOE and NGE change with respect to the day the data is rolled (days from expiry contracts are mapped). From the graph it is apparent that both energies suffer from instability in both AOM and DC. As expiry nears, the algorithms AOM and DC collapse suggesting that the price volatility associated with the lower volumes and storage issues are significant. Also the FND is after expiry so contracts may be held longer by traders compared to commodities in other sectors. The major drops occur as expiry nears with HOE performance characteristics falling more violently. The reason for this may be due to the lower liquidity associated with HOE compared with NGE, especially as expiry nears.

2.8. Volume Data

Volume data was acquired for all the commodities considered in this analysis in order to show that volumes reduce towards expiry. In the interest of the chapter, the last three years of volume data have been considered in order to make the diagrams legible to the reader. The red lines throughout represent the ADV.

2.8.1 Softs



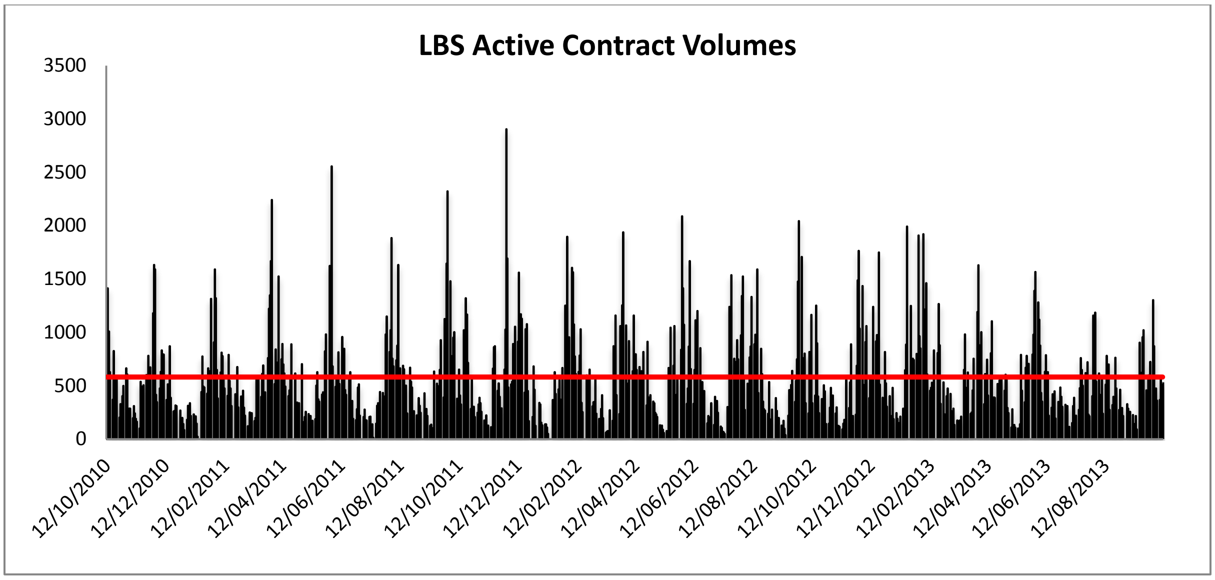
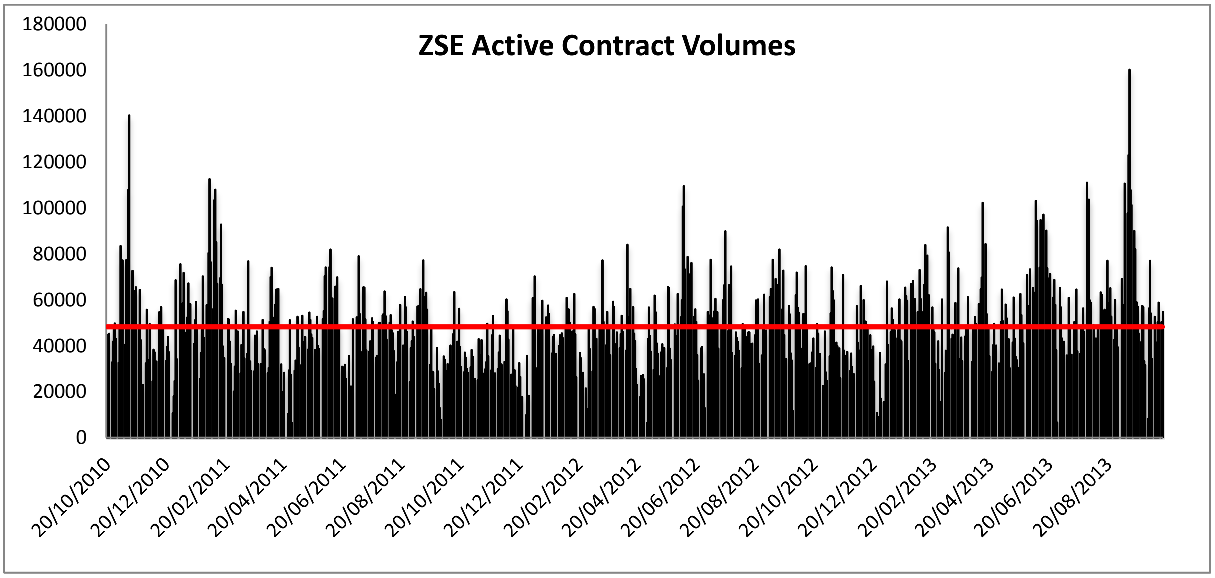


Figure 2.19

From Figure 2.19 it is clear that both LBS and OJE follow contract cycles as explained earlier. There is an apparent drop as contracts near expiry for both softs which consolidates the findings made in section 4. The ADVs shown support this, while also making it easier to understand. The reason for changes in PnL, CV, mean return and performance characteristics can therefore be supported. The drops in volume suggest traders are rolling their positions due to FND.

2.8.2 Grains



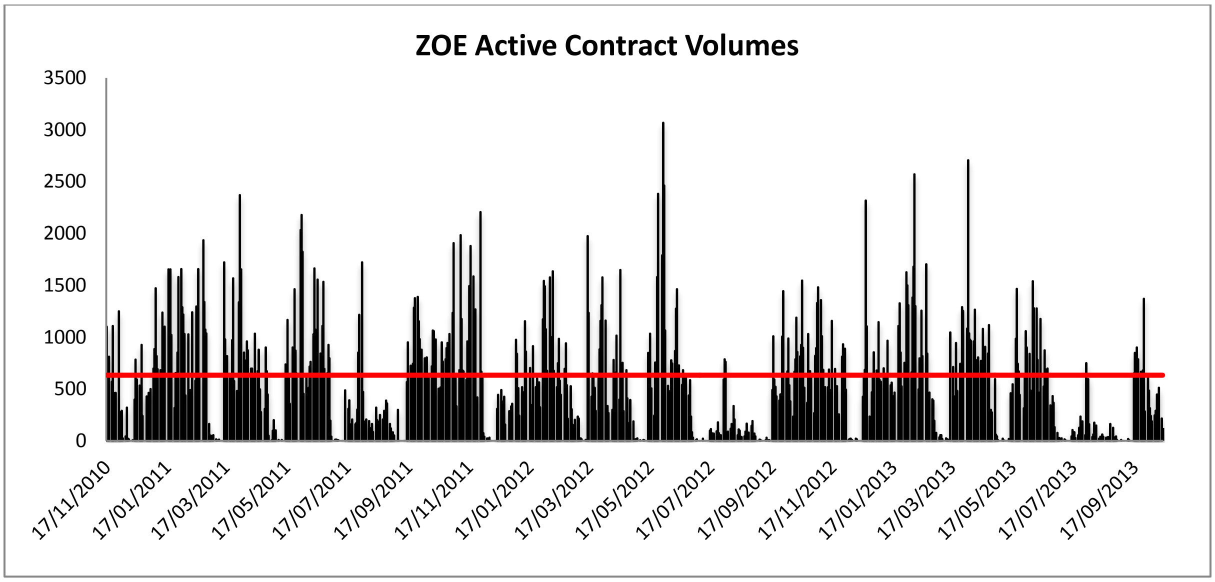
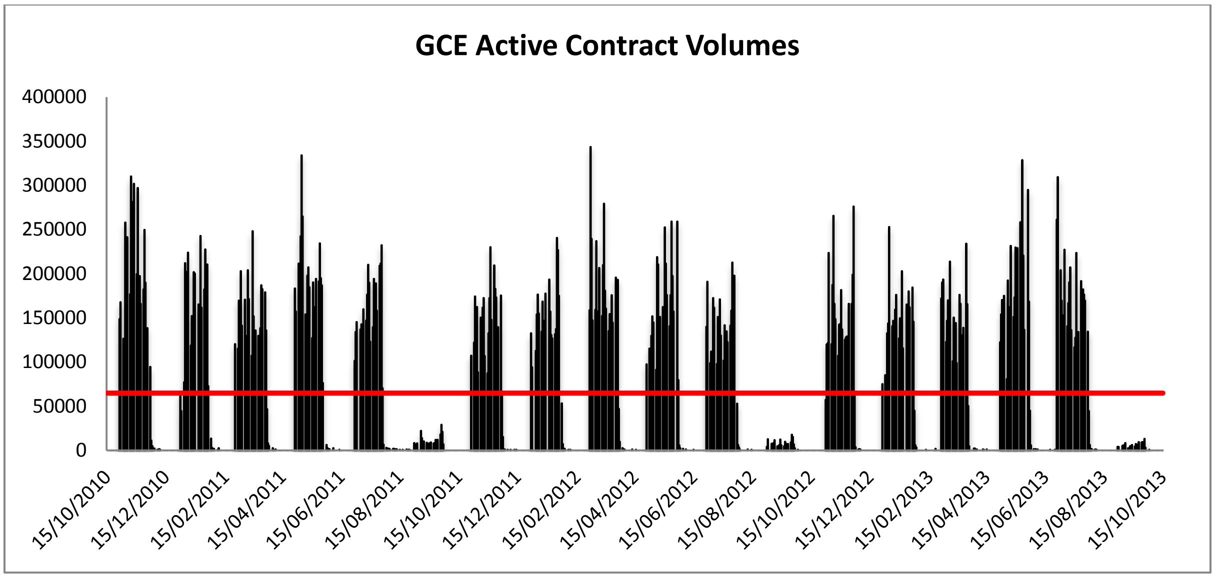


Figure 2.20

From Figure 2.20, just by looking at the scales and ADVs it is clear that ZSE volumes are an order of magnitude larger than ZOE's. This in itself may be a reason for the difference seen earlier in section 5. The proportional decrease should be considered also. In the case of ZSE, the contract cycle is less prominent but still nevertheless exists.

2.8.3 Metals



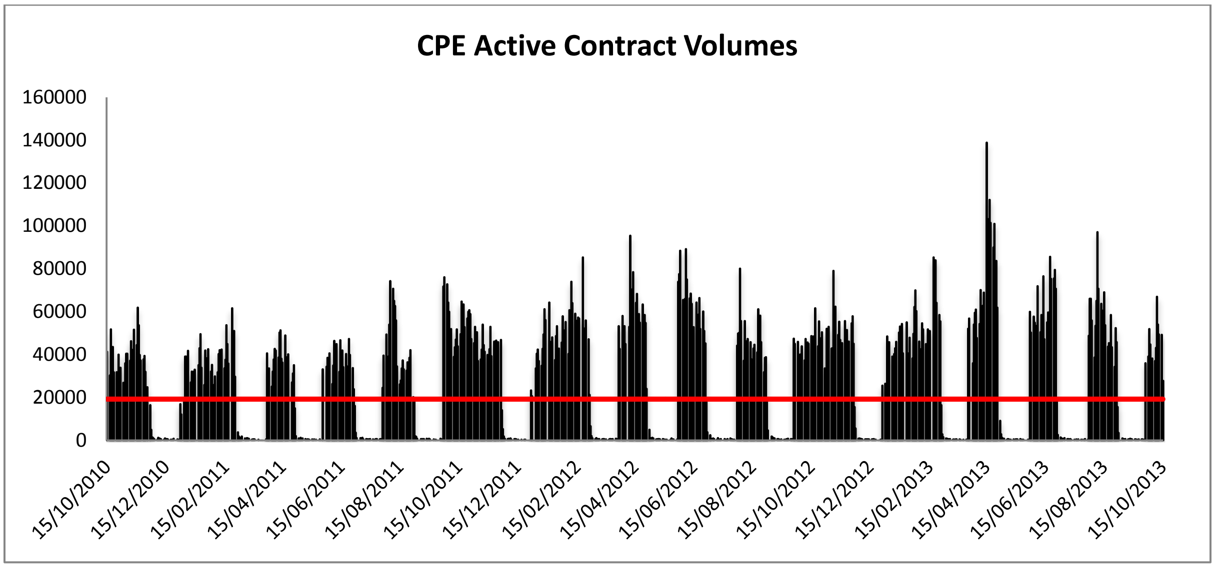
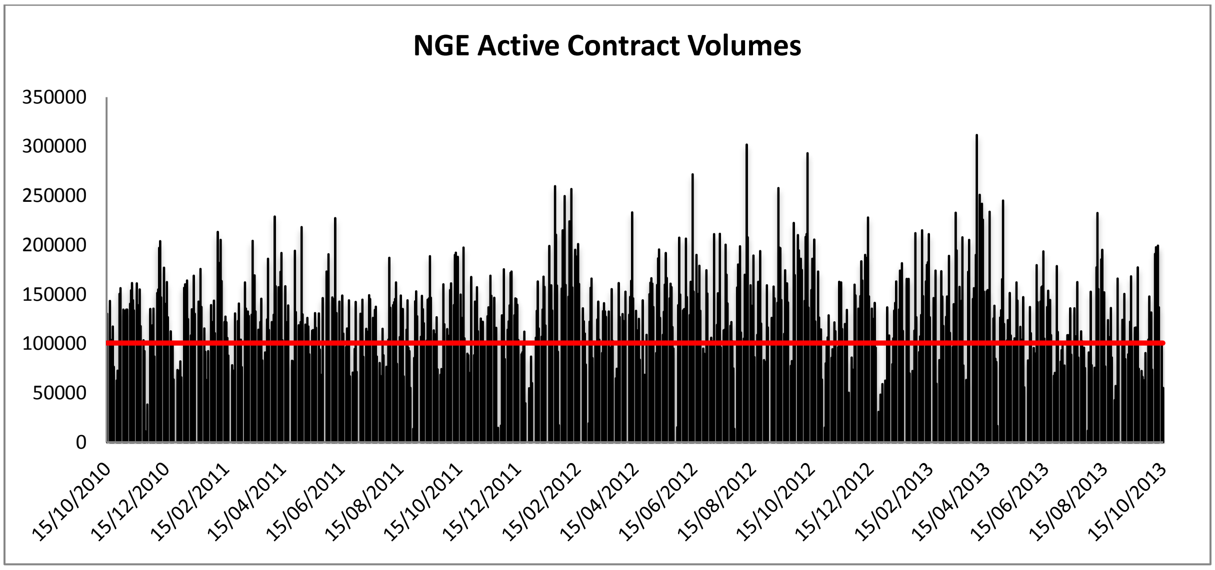


Figure 2.21

From Figure 2.21 it is clear that both metals experience lower volumes as expiry nears for each liquid contract shown. In the representation shown, intermediate contracts for the metals have also been plotted for entirety. These contracts in practice are ‘dead’ contracts and only exist for those who want to trade on Globex and take delivery at the end of the month. These contracts have not been considered in the analysis carried out earlier. However in the interest of this chapter, a number of contracts for each metal are shown with clearly falling volumes towards expiry and clearly rising volumes from the beginning of the cycle.

2.8.4 Energies



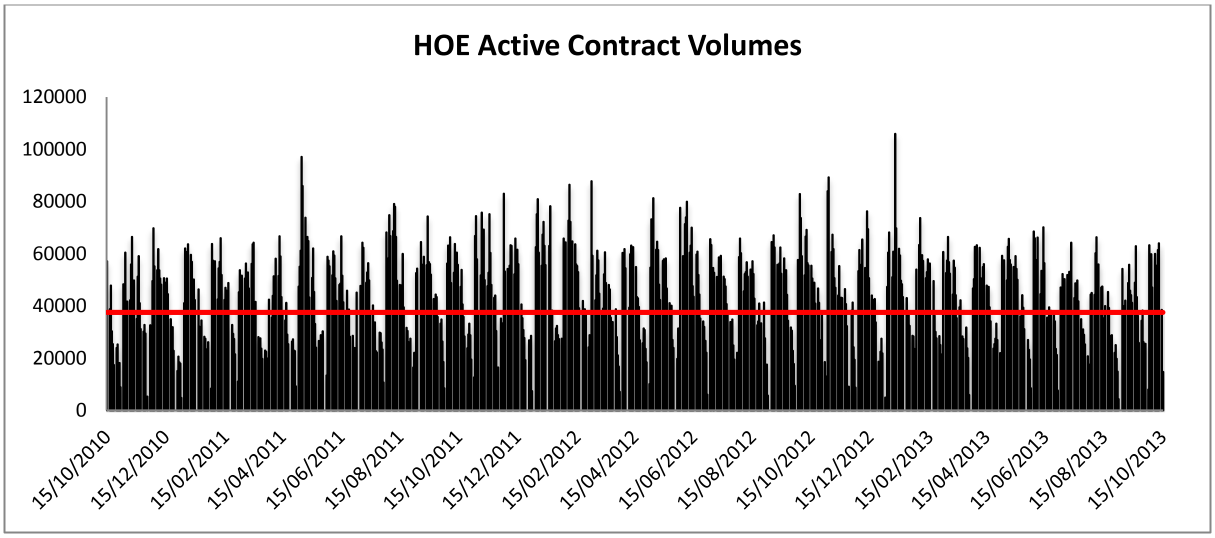


Figure 2.22

Figure 2.22 shows the volumes for the energies selected for the past 3 years, daily. The data clearly shows that both NGE and HOE follow monthly cycles with drops in volumes towards the expiry of the contracts. The ADV lines make it easier to distinguish what is to be deemed 'lower than average volume' and 'higher than average volume'. It is however apparent that the volumes for HOE are less than half those for NGE. This along with the storage issue and the fact FND is after expiry day may attribute to the results shown in section 7. All results are presented in graphical form.

2.9. Conclusions

From the results it is clear that altering the roll day of price data used to optimise a trading algorithm can greatly impact the performance characteristics of the algorithm, while also impacting mean PnL returns and coefficients of variation. It is apparent also that altering roll day in trading algorithms will not impact standard deviation significantly and this was clear throughout the analysis across all sectors.

The volume data supports the theories of lower volumes towards expiry throughout the sectors. In the case of GCE where performance indicators were stable near expiry, it is clear that the volumes are so large that it is not possible to have volatility induced by reduced liquidity. Also it must be remembered that GCE is a non-perishable 'precious' commodity and does not have the storage costs associated with it of other commodities. This is supported by Margaronis et al. (2011). Also, it can be held indefinitely in its raw form much like a currency meaning traders may not rush to come out of positions in it. These are all reasons supporting the stability of GCE throughout the roll day range.

In the case of ZSE, positive changes are seen as expiry nears. This shows that the ZSE algorithms favour the volatility induced by the reduction in volumes. However, due to FND, ZSE contracts cannot be traded so close to expiry unless delivery it taken (which has storage costs, margin calls and other complexities associated with it).

In the case of the softs, the volumes are low throughout making price-slippage an issue when taking positions and rolling contracts. The softs and grains also have lower numbers of contracts cycles per year. ZOE and the softs experience low volumes making the price volatility as expiry nears greater. This, coupled with price slippage can have a devastating impact on an algorithms performance in live-trading. Also, given the FND none of the grains or softs can be traded beyond this point unless delivery is taken. Hence it is wise to optimise trading algorithms to roll a certain number of days before each instrument's FND.

In the case of the metals, the volumes data is not as conclusive however, the trends can still be seen clearly enough. Also, it is clear that for both the metals and energies sectors, the impact of altering the roll day effected the performance indicators, mean return of PnL returns and CV of PnL returns far less, proportionately than in the softs and grains; the main reason being the differing liquidity of the markets.

For the energies the volumes data showed clearly the monthly cycles with volumes dropping significantly as expiry nears. However, given that the FND for energies is after the expiry date, there is no indicator for traders to start thinking about rolling contracts to the next month. Hence, when expiry nears there is a massive rush for traders to 'dump' contracts that are expiring. This causes instability in the price and therefore volatility since proportionately, volumes decrease more. Another significant reason for the instability of the energy algorithms towards expiry (especially in relation to performance indicators) is the storage issues associated with them. Both NGE and HOE (more so NGE as it is a gas) require a huge amount of infrastructure to be stored, hence as expiry looms (and FND has not been announced as it is after expiry) those trading energies who do not want to take delivery must roll their positions or come out of the trades altogether. Finally, given the contract cycle of the energies, it is clear that they roll more often, meaning there is a greater chance of there being error in rolls and hence greater chances of algorithms being optimised incorrectly due to inaccurate data.

Overall however, the results support the initial theory that altering roll day of price data used to optimise a trading algorithm can impact the trading algorithm's performance criteria among other characteristics. The results supported the theory more so for certain instruments than others but the properties of each instrument could be used to explain these differences, being absolute ADV (liquidity/volume), FND and storage costs.

Chapter 3: The significance of rollover in commodity returns using PARCH models

Chapter 3 is joint work with M.G.Karanasos, P.D. Koutroumpis & R.B. Nath 'The significance of rollover in commodity returns using PARCH models'. M.G.Karanasos, P.D. Koutroumpis & R.B. Nath contributed with mapping of data and interpretation of some of the results with a combined contribution of 10% to the chapter (approx. 3% each).

The remaining contributions are by Z.N.P. Margaronis for significant contribution (90%) in data-collection, data processing, data analysis, results & discussion and write-up throughout the Chapter.

Keywords: Algorithmic trading, forecasting, futures commodities, rollover, mapping, power ARCH models, structural breaks

3.1. Introduction

The most important aspect of any algorithmic system is to ensure the data with which the system is back-tested is correct and completely agrees with the data of the platform which is then used to trade. Generally most studies in econometrics do not specify which type of data is used, whether futures or spot and at which time the data is taken. The application of any of the theoretical models to real life trading situations is rare. Finding the correct prices for back testing is more difficult than initially thought. It is therefore not straightforward to obtain the data required to back test. Such data is obtained from two sources: Bloomberg and Thomson Reuters Datastream. In order for a real time series to be created, one needs to search and download prices available for each individual active (front month) contract for the given security. The data obtained then needs to be mapped (roll/basis accounted for) if futures contracts are being considered which expire on a regular basis. Carrying out an analysis on any data that is not mapped makes it inapplicable to real life trading systems since these are based on continuous data sets. The aim of this study is to show how the unmapped and mapped data differ econometrically. Showing this will confirm that any analysis carried out for the purposes of real life trading requires mapped data to be used because the differences between the mapped and unmapped data can be significant.

The data section describes the data and degrees of homoskedasticity. The main issue with such data sets is that for a trading algorithm to be applied, the data itself must be continuous and contemporaneous for security spreads, if considered. Due to the existence of monthly contracts, expiry of the front month contract means the second month contract then becomes the new front month contract, and since these prices differ, a rollover or basis exists. If this roll is not taken into account, any trading system will misestimate profits generated. The value and significance of the roll differs greatly from instrument to instrument. In order for a traded continuous data set to be meaningful, the data must be mapped in order to account for roll. The only data that does not require mapping is foreign exchange data and any contracts such as those for equity indices that take spot prices and do not involve contracts and hence rollover.

This chapter will analyse the differences, econometrically, between data that has been mapped and data that is unmapped. This is significant for algorithmic trading because the roll that exists can significantly change a data set. When a model is optimised based on the data, it is clear how having incorrect data with respect to real life trading situations can lead to a very erroneous and wrong optimised algorithm parameters. It will be seen that the significance of roll is greater in some data sets than in others. The significance of the rollover will be compared econometrically by running PARCH (Power Autoregressive Conditional Homoskedasticity) models and the various coefficients within models will be analysed across securities. If coefficients change significantly between a single time series, one that has been mapped and one that is unmapped, then it will be concluded the impact of roll is large. The impact of the roll is found to be significant for most instruments, greatest of all in energies and least of all in metals, considered as a percentage of price.

3.2. Literature Review

Tansuchat et al. (2009) carry out an impressive analysis modelling long memory volatility in a number of agricultural futures returns and find that the fractionally integrated GARCH and EGARCH models outperform the conventional GARCH and EGARCH models. This is an in-depth analysis looking into many agriculturals but mapping was not considered at any point throughout the analysis and by looking at the results of this chapter, it will be made clear that the model which best fits a time series can significantly change when rollover is accounted for and mapped data is introduced. Of course this analysis appears to be concentrating more on the theoretical side of the science rather than the more practical trading aspects considered in this chapter.

Chatrath et al. (2001) show commodity prices to be chaotic to a certain degree. This chapter only considers the prices of four agricultural commodities that tend to ‘spike’ more often since they are less liquid markets. They use ARCH processes to explain the non-linearity in data however given the stability of trading algorithms in terms of their returns, the extra volatility obtained in certain seasons exists but is not significant for a trading system which trades at a low frequency. This is because the optimisation of the algorithm takes into account any extra volatility obtained even if it is seasonal.

Vivian and Wohar (2012) mention that the increased volatility exhibited by commodities in the recent financial crisis was not significant and that there are no real resulting volatility breaks. This is however not true for other financial crises where the volatility breaks are more obvious. For this chapter the recent financial crisis is more of interest as the optimisations are carried out over 5 years of data. The fact that their findings show no real evidence of volatility breaks, despite the financial crisis, is important. This is because the profits obtained from the trading algorithms also show no structural breaks in volatility even during the financial crisis. This was confirmed from the homoscedastic nature of the profit profiles obtained.

Ji and Fan (2012) tell us that the impacts of the oil market spillover into other commodity markets. This may indeed be true in terms of price, however it is clear that after applying a trading strategy to many instruments, the way in which the algorithm trades and is optimised for different securities varies. It is important to remember the significance of diversification along with the idea of trading spreads which reduces the exposure to any single commodity. This is linked to the analysis of correlation between securities where the prices and daily returns may be correlated, but the returns of the algorithms are not by virtue of the important fact that algorithms will not predict securities to be in the same buy/sell positions. Margaronis et al**.** (2011) have already demonstrated the fundamental effect of correlation dilution of a diversified trading system which uses securities that are highly correlated, especially intra-sector.

Cheung et al. (2010) agree that diversification benefits can be gained by investing in commodities and also that the diversification benefit of commodities is far more complex than is generally understood in finance. The fact that commodities regimes are constantly changing is also interesting as we see a significant amount of heteroscedasticity throughout our analysis. However diversifying into portfolios with commodities yielding a positive risk-return relationship compared to international equities is in line with what the authors believe, given that commodities' low volatility leads to lower returns. The RGZ algorithms (2010) have shown however that being diversified correctly can lead to a superior portfolio performance even in times of a bearish commodity environment. This is due to the inclusion of security spreads, single securities in different sectors and asset classes in the portfolio, as well as dilution effect on daily return correlations mentioned earlier which generate a profit profile that is truly diversified and offers a superior return-risk characteristic.

Guida and Matringe (2005) show that stock indices time series are easier to predict using econometric models, however mapping of data was not employed at any point throughout the analysis. The reason for their agricultural commodities model not giving the results expected may be because the roll was not accounted for or even because the data used was not exactly the front month contract. Also given the large sample of data used, structural breaks were included in the analysis that would not help the model in its prediction. They suggest the use of continuous futures which do not entail rollover. It is however very difficult to find exchanges where these types of futures are available to trade making the practicality of the models slightly difficult to see in a real life situation. The results however will be very interesting to compare against mapped and unmapped time series and see which is most alike.

3.3. Data

This particular study is based on trading the front month contract based on daily prices at 2100 hrs GMT (for most instruments) or at the close of business for each respective instrument. All data was obtained from Thomson Reuters Datastream and Bloomberg and the prices are daily for the front month futures contract at that particular time. For example, on May 5th 2008, the active contract that was trading on that particular date needs to be obtained so that back testing for that time is carried out on correct data. This will require knowledge of the correct ticker corresponding to that month. Tickers are defined by the security, month and year, so a three part code is required for every contract search. This results in a large number of contracts required to generate a time series. Given the hours of trading of certain securities, the time to algorithmically trade varies. In the case of Wheat, the daily closing price is at the close of 1900 hrs GMT since it is traded on a US Exchange only. So if any new positions in the portfolio need to be taken or changed, in most cases, it should happen at 2100 hrs on the trading day. For most time series the sample size is from January 2007, for five years.

3.3.1. Mapping Procedure

The mapping procedure involves the use of a program. The input for the program is the entire set of front month contracts obtained as explained earlier in order in a series (front month contract from January 2007, 5 years of daily settlement data). The program then takes the last price of each contract, being the price on expiry of the contract, and lines up by date to the price of the second month contract. The program uses a counter for both the price series and the date series. When the counters match on the day of expiry, mapping occurs. The front and second month prices on that date are then lined up and their difference gives the basis or rollover for that contract. This is done consistently throughout the entire data set and each roll value or basis value is stored and accumulated in order for a calculation of the cumulative roll or basis to be made. Mapping data can have a huge impact on a price series if the roll value or basis value is significant. It is less significant in instruments which do not exhibit large rolls. However given that the cumulative roll is required, especially when a trading algorithm is applied, even if the roll values are not significant the fact that it accumulates over time makes the mapping procedure imperative no matter the magnitude of the roll or basis.

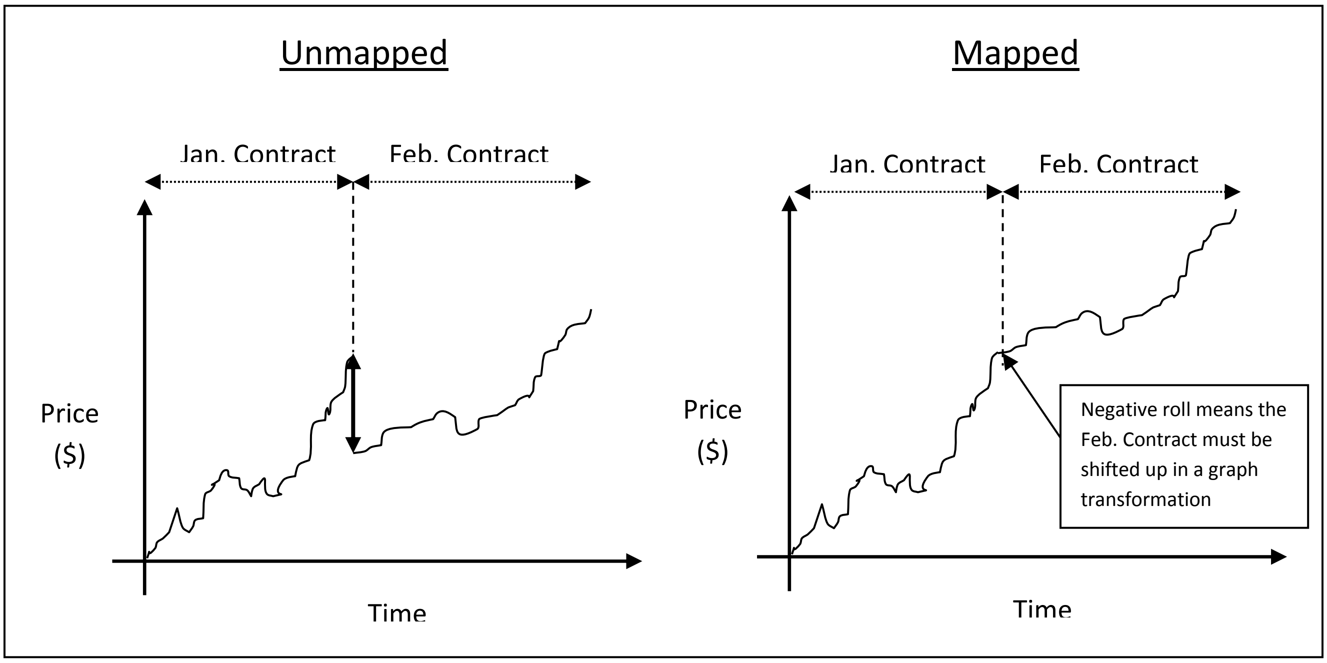


Figure 3.1 Diagram representing mechanism of mapping procedure

3.3.2. Grains

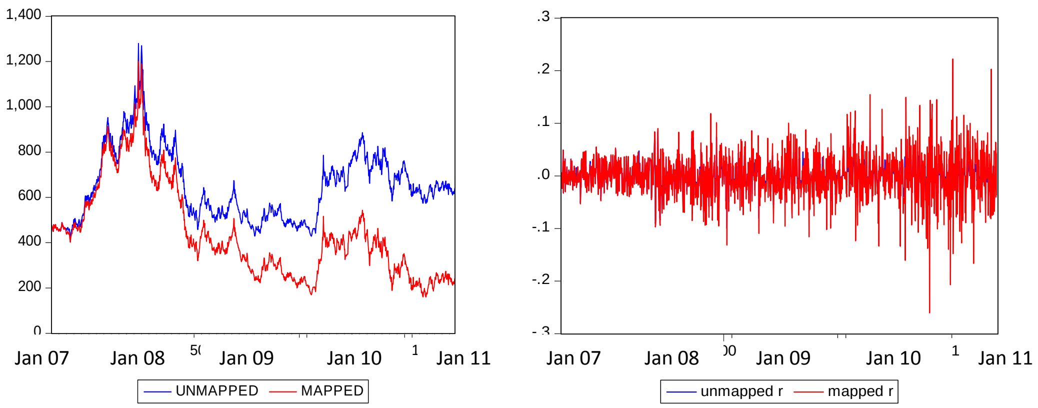


Figure 3.2 Mapped and unmapped prices and returns for Wheat

In figure 3.2, 3.3 and 3.4 the time series for the past five years of mapped and unmapped grains have been plotted. The grains prices are more heteroskedastic than those for copper (figure 3.5) as the degree of volatility throughout the time series seems to change with greater levels of volatility around the beginning of 2008 and 2010 days. In this case, the size of the roll is greater hence there is a far greater impact on the data of carrying out the mapping procedure. The returns are shown in figure 3.2, 3.3 and 3.4 where it is clear that the grains prices, more so visible for wheat figure 3.2, have gained a greater level of volatility in the last year or so. Given the larger level of roll in this sector it is predicted that the coefficients of the PARCH model run should differ more than those for copper. This same regime can be seen in oats and corn. The reason is the similar behaviour and roll within the grains sector.

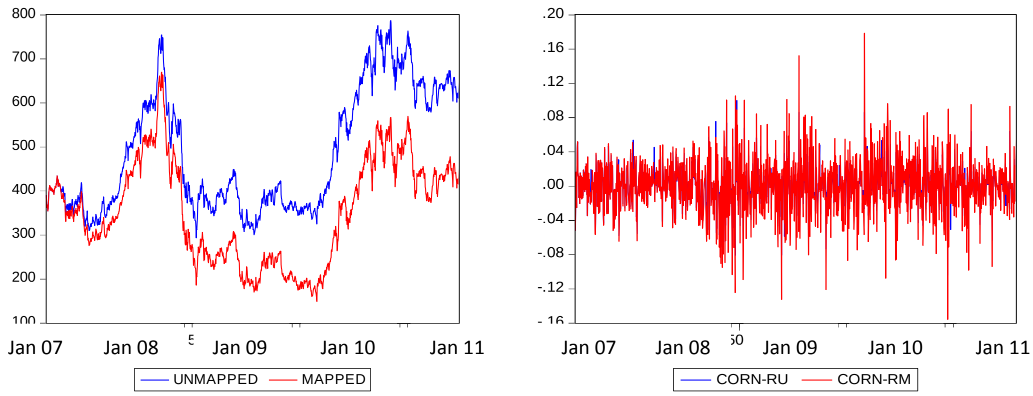


Figure 3.3 Mapped and unmapped prices and returns for Corn

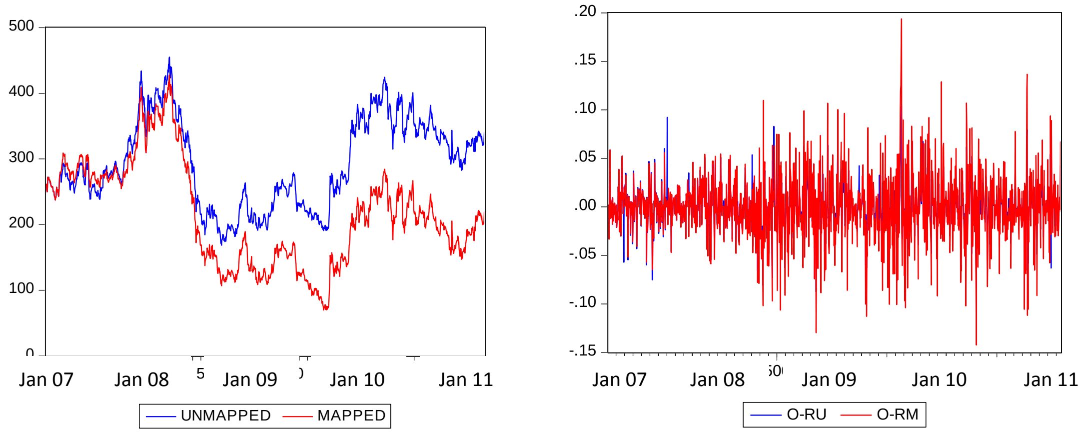


Figure 3.4 Mapped and unmapped prices and returns for Oats

3.3.3. Metals

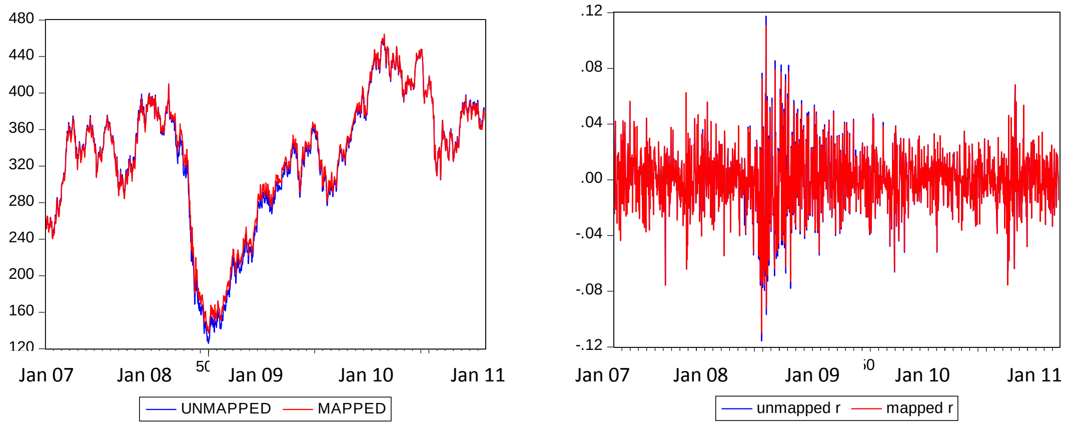


Figure 3.5 Mapped and unmapped prices and returns for Copper

Figure 3.5 shows the price of copper for the past five years. Generally there is a degree of homoskedasticity. The copper price seems to possess homoskedasticity throughout the time series. From the plot it is clear that there is a slight difference between the mapped and unmapped prices. The differences can also be seen in the logarithmic returns for unmapped and mapped prices are shown. These graphs prove that inclusion of rollover in any time series can impact the data and as predicted earlier given the smaller level of roll in metals, the effect of mapping might be not as significant for the time series. This will be further investigated in the analysis section. Platinum is also show in figure 3.6 where the less significant roll in metals can again be seen despite differences in heteroskedasticity.

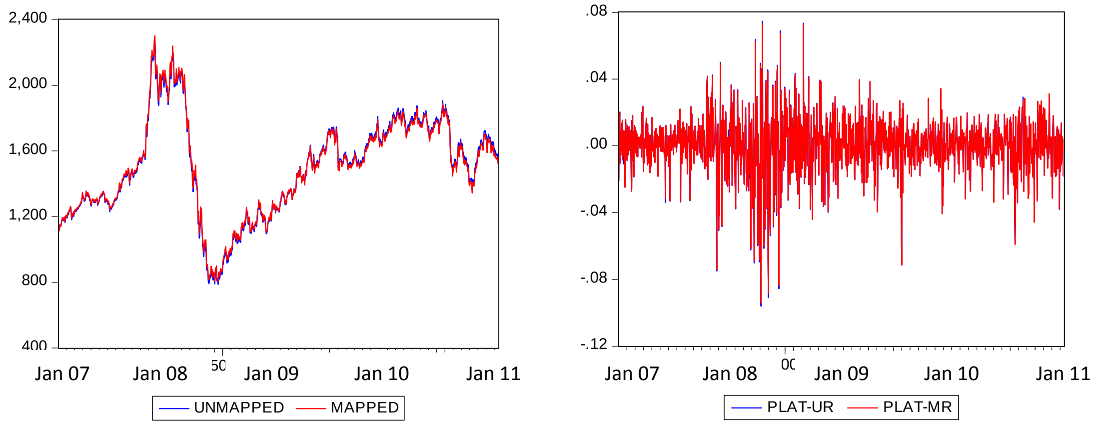


Figure 3.6 Mapped and unmapped prices and returns for Platinum

3.3.4. Energies

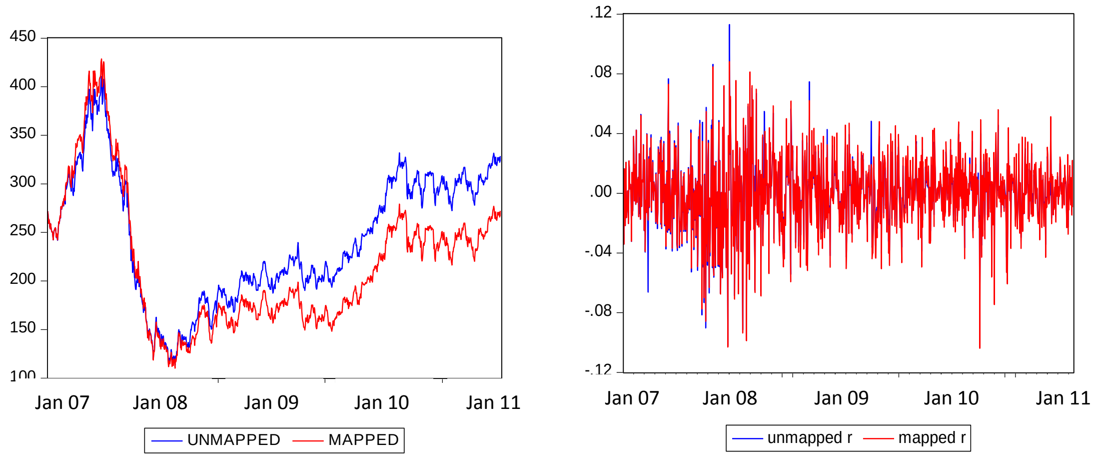


Figure 3.7 Mapped and unmapped prices and returns for Heating oil

The level of roll for energies such as heating oil is generally very significant. Energies' futures cannot be traded algorithmically unless some kind of data manipulation is carried out. The graph of figure 3.7 shows how significant the impact of mapping is for the price of heating oil is and the returns for heating oil (mapped and unmapped). Generally, the entire time series seems to be very homoscedastic over the five year period. There seems to be far more irregularity in the returns of this particular commodity since a greater proportion of the unmapped returns plot (blue) can be seen to be larger than the corresponding mapped returns (red). This means that there is an artificial return in the data due to the roll. Very similar behaviour can be seen in the plot of RBOB in figure 3.8. The energy commodities seem to have increased volatility in similar periods while also having quite a significant roll. Heating oil returns seem to be slightly more volatile, however the level of heteroscedasticity for both instruments is similar with both enduring more volatile returns around the end of 2007 and beginning of 2008.

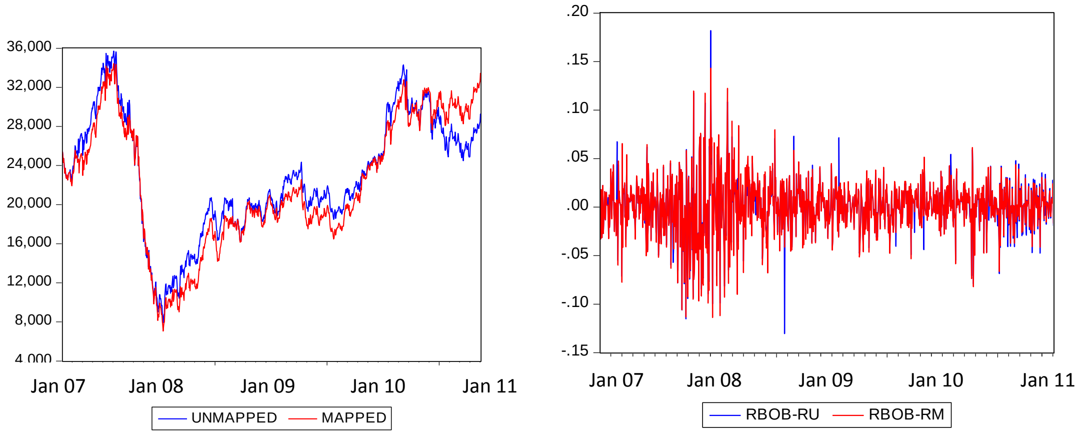


Figure 3.8 Mapped and unmapped prices and returns for RBOB

In the case of WTI it is clear there is a significant difference between the mapped and unmapped prices, as can be seen in figure 3.9. Despite the very large decline in price between the end of 2008 and the beginning of 2009, the data is quite homoscedastic throughout the sample period, except during the decline. The crisis in 2008 caused a volatility in the oil price which is evident however the price resumed its original behaviour by 2009. In the case of the returns, there is evidence that the mapping procedure has created a series that is different to the original due to the rolls that have now been accounted for. These observations are generally quite consistent with what has been seen earlier in figures 3.7 & 3.8.

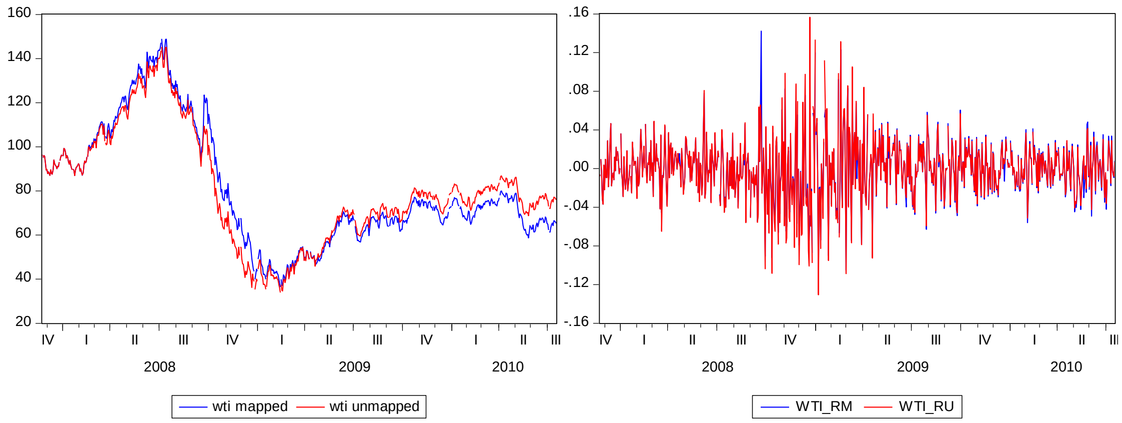


Figure 3.9 Mapped and unmapped prices and returns for WTI

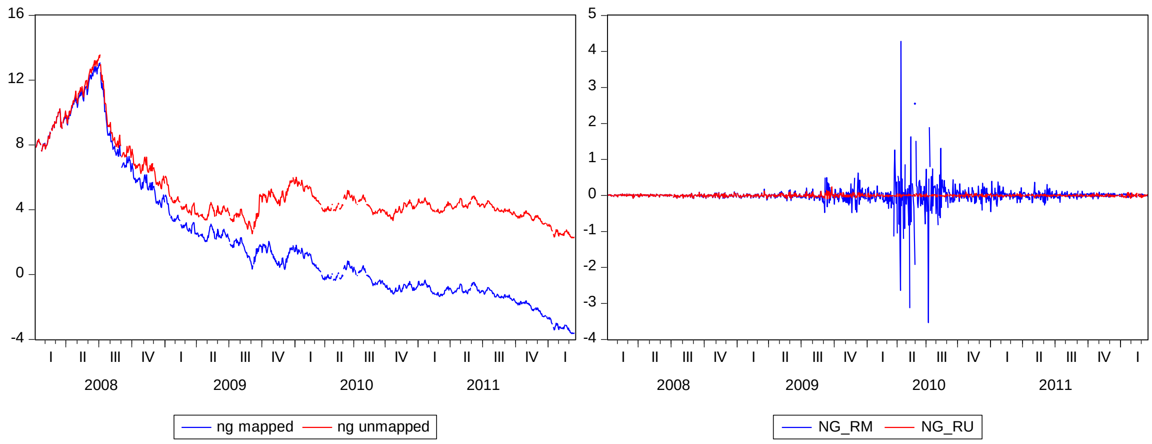


Figure 3.10 Mapped and unmapped prices and returns for Natural Gas

In figure 3.10 there is a very large inconsistency between the mapped and unmapped data sets for natural gas. Unfortunately it is not possible to understand these difference between mapped and unmapped data sets until the analysis is concluded. By the end of 2009 and beginning of 2010, there is a three quarter period of increased volatility. The reason for the very large differences between mapped and unmapped prices in this case may be due to the significant and sudden loss of homoscedastcity. Generally however, the time series is consistent with the presumption that the energy sector of commodities yields significantly different series after being mapped.

3.3.5. Softs

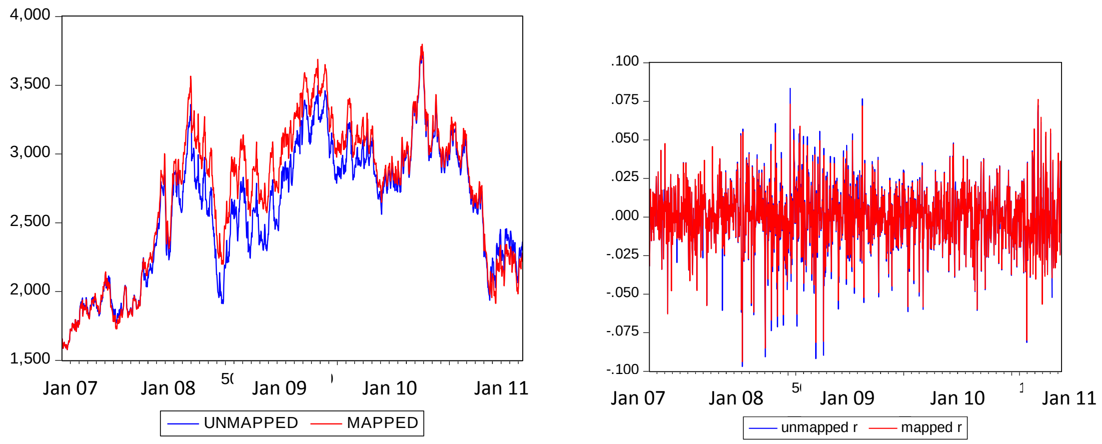


Figure 3.11 Mapped and unmapped prices and returns for Cocoa

Cocoa seems to be another commodity whose price seems very different after being mapped (figure 3.11). Cocoa prices have a large amount of volatility however it can be seen that the mapping of cocoa prices reduces exposure to some of it. The level of volatility seems generally quite high given the price fluctuations but nonetheless it still exhibits a degree of homoskedasticity. In the case of coffee, there seems to be a great deal of heteroscedasticity around the beginning of 2010 where there seems to be a structural break in the data as the coffee price obtains a greater volatility suddenly (figure 3.12). The impact on the coffee price of accounting for roll is significant as expected however this will be considered more in-depth when analysing the results later.

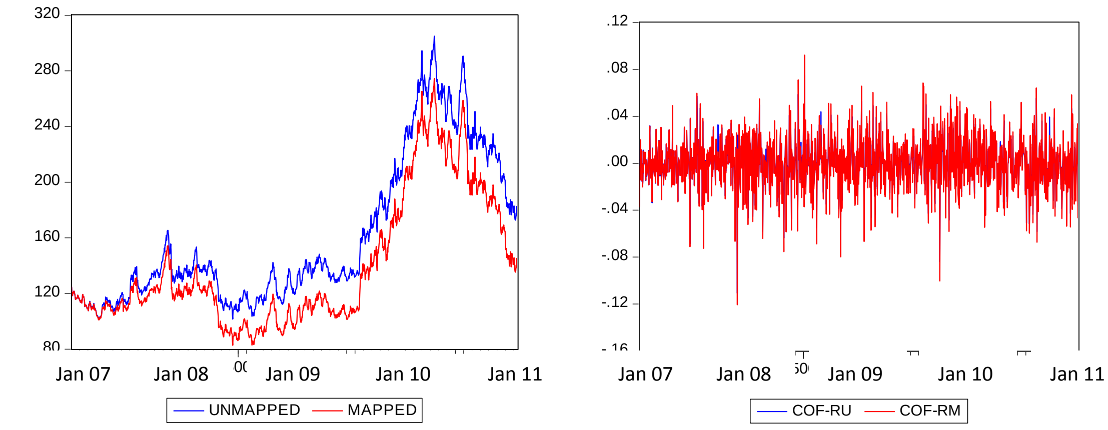


Figure 3.12 Mapped and unmapped prices and returns for Coffee

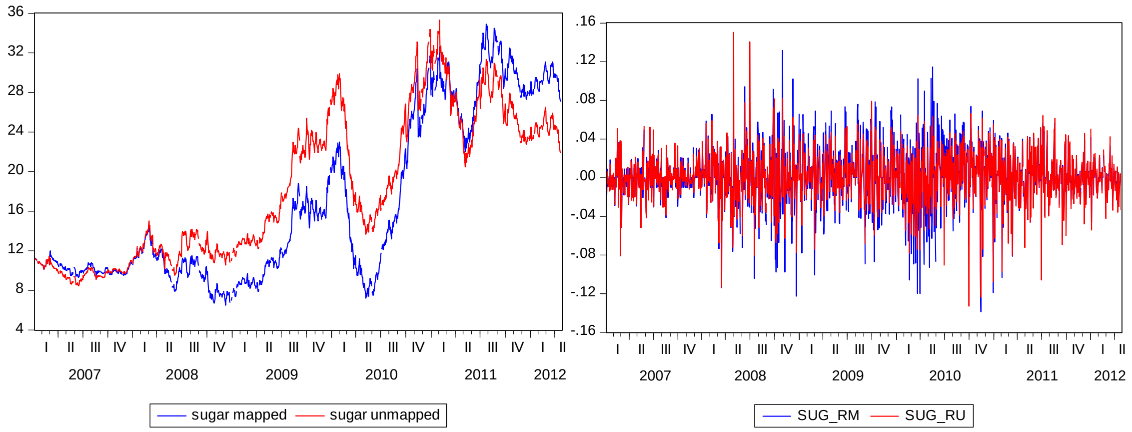


Figure 3.13 Mapped and unmapped prices and returns for Sugar

From figure 3.13 it is apparent that mapping the sugar price can have a significant impact on the time series which results. There also seems to be a lack of homoskedasticity throughout. Similarly it also has a profound impact on the returns for sugar where it is evident, especially between 2008 and the beginning of 2010, that mapping of commodities such as sugar is imperative if a trading system is to be created around the time series.

From figure 3.14, the orange juice price and returns can be observed and immediately it becomes apparent that it is far more homoscedastic than the other softs with the exception of a few spikes. The reason for these few spikes is due to supply shocks as orange juice production is based on two major producers. The orange juice price dependant very much upon the weather in the countries of these two producers and can therefore be considered a weather derivative, unlike the other softs. The mapping procedure seems to not have a very significant impact on the data.

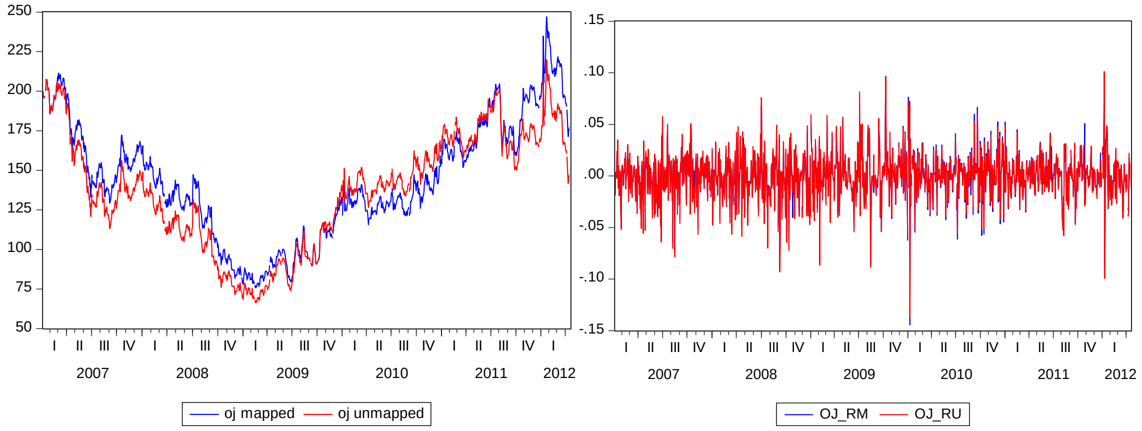


Figure 3.14 Mapped and unmapped prices and returns for Orange juice

3.3.6. Soy Complex

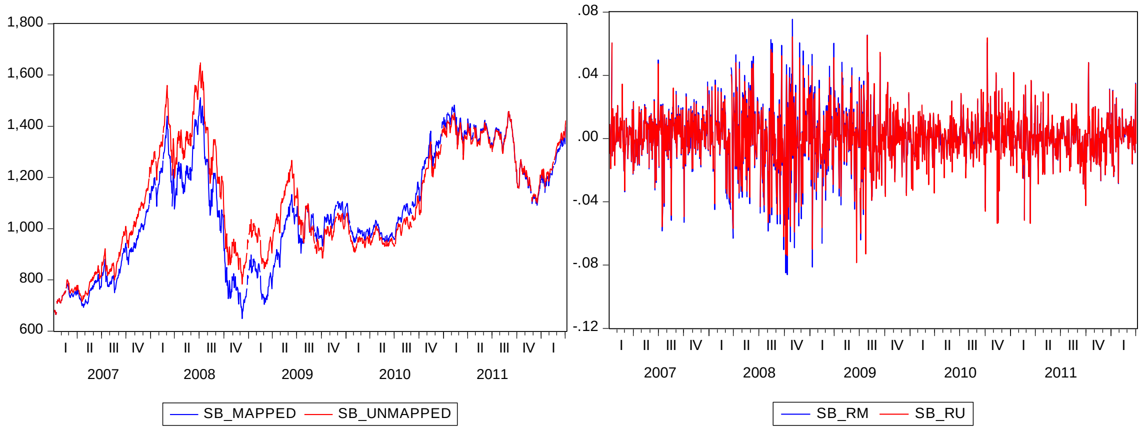


Figure 3.15 Mapped and unmapped prices and returns for Soybeans

The soy complex is a sector that is comprised of soybeans and its processed derivatives. When a soybean is crushed, oil can be extracted known as soy oil and the shell and rest of the bean is known as soy meal. In the case of soybeans, the price seems relatively homoscedastic but at second glance, the returns show a time series that is quite heteroscedastic. Even though the price difference is not significant between mapped and unmapped data sets, there is still a requirement for mapping as there are points with significant differences between mapped and unmapped data sets.

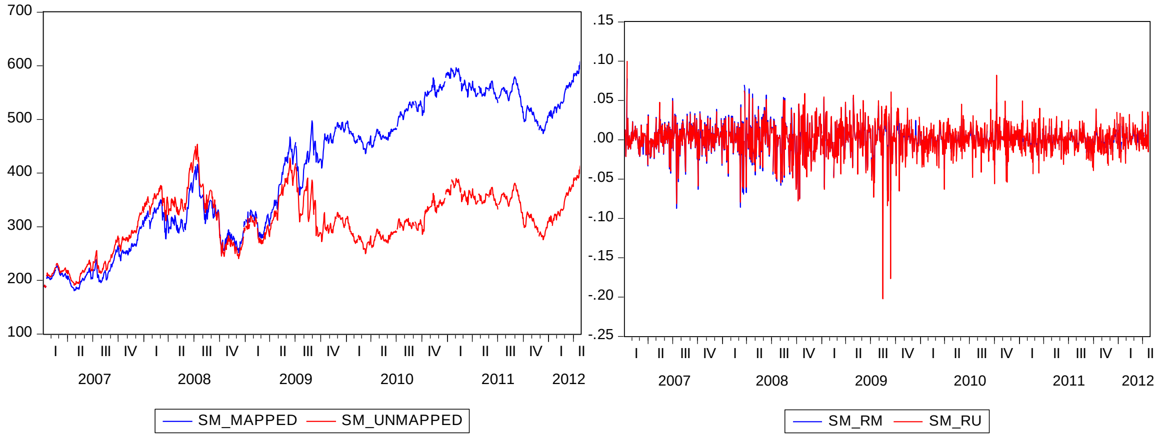


Figure 3.16 Mapped and unmapped prices and returns for Soy meal

The soy meal data shown above in figure 3.16 is surprisingly different from the soy bean data. The returns show a significant degree of homoscdasticity which is not expected if the soybean results are considered and the fact that soy meal is a derivative. However, it is important to remember the uses of these commodities and the fact that soy meal is used primarily as animal feed and hence does not have the same demand characteristic as the rest of the soy complex. Figure 3.17 shows the soy oil price and returns which, as expected, are very similar to those of soybeans with a lower volatility characteristic in 2007 and increasing volatility in 2008 after which it varies.

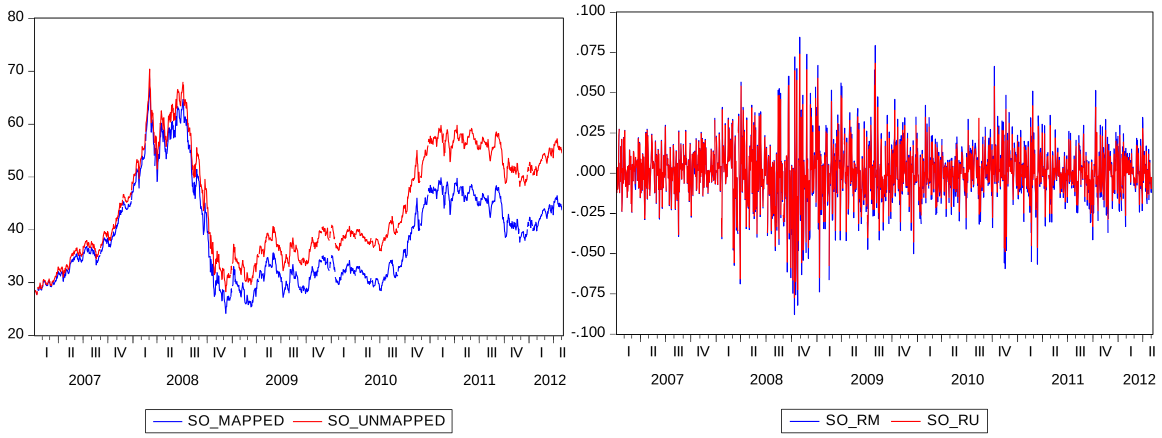


Figure 3.17 Mapped and unmapped prices and returns for Soy oil

From the commodities considered, it is clear that a trading algorithm optimised and back-tested on mapped prices will give different parameters to one optimised on unmapped prices. This is because the price including the roll simply is not the same as when the roll is not included. This systematic "price error" must be accounted for in order for a trading system to be optimised and used in real life. An algorithm optimised on unmapped data will yield far less returns and perhaps even losses as it will include artificial gains from roll that cannot be made in real life trading situations.

3.4. PARCH model

In this Section, for the different commodity returns, we will estimate AR-PARCH models (for applications of the asymmetric PARCH models see among others, Karanasos and Kim, 2006). Since PARCH models require stationary data to be run, the returns of each of the instruments will be considered. The data was summarised briefly in the data summary section. For each instrument, the mapped and unmapped returns will be analysed. The data itself would be run through different PARCH models within the Eviews software. This is because a pre-analysis showed that a PARCH model was far more suited to the data than GARCH models. The reason being the PARCH model allows estimation of the power or an a priori specification of a power. In a GARCH model this power is of course fixed at a value of 2. The pre-analysis also confirmed that the heteroscedasticity consistent covariance (Bollerslev-Wooldridge) option for coefficient covariance was used for robust standard errors. This is due to the nature of the returns as seen earlier in the data summary section. The optimisation algorithm selected was the default Marquardt and the method was chosen to favour accuracy over speed since computational time was not of particular significance.

After running the data for through a number of combinations of models, some very interesting findings were made. The mapped and unmapped data, as predicted, differed in terms of coefficients and sometimes even in terms of the model specification which suited best the data. Throughout the analysis the errors were assumed to be of Gaussian distribution.

Overall, the Akaike information criterion (AIC) was used to measure the relative goodness of fit of each model and this was the final criterion by whish each model for each data set was selected. Throughout the analysis, a level of significance of 0.10 was chosen for the significance of coefficients.

Let commodity returns be denoted by $y_t = (logp_t - logp_{t-1}) \times 100$, where p_t is the commodity futures price at time t. A general AR(1)-PARCH(1,1)-in mean specification is given as:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \zeta h_t + \varepsilon_t,$$

where $\varepsilon_t|\Omega_{t-1}$~N(0, σ_t^2) is the innovation, which is conditionally (as of time t-1) normally distributed with zero mean and conditional variance σ_t^2. In addition, σ_t^δ is specified as a PARCH (1,1) model[1]:

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta,$$

where α and β denote the ARCH and GARCH parameters, γ is the asymmetry coefficient and δ is the power term. The `persistence' in the conditional variance, in the absence of breaks, is given by c=αk+β, where $k = \frac{2^{\frac{\delta}{2}}}{\sqrt{\pi}}\Gamma\left(\frac{\delta+1}{2}\right)$ under normality (see Karanasos and Kim, 2006). All the instruments considered will follow this model however some will differ due to symmetry meaning the asymmetry parameter (γ) will not exist in that particular model. The coefficients of each individual security (mapped and unmapped) are shown later.

3.5. Empirical Analysis

Let it be noted that throughout the analysis the AIC was minimised for each instrument by running different versions of the models.

3.5.1. Grains

Wheat Returns

The wheat returns yielded very interesting results when tested. The mapped and unmapped data gave very different models which is interesting considering the data is essentially the same except that the mapped data accounts for the rollover of contracts. The unmapped returns fitted best with a symmetric (P)ARCH model where the power was fixed at 1.1. Also the in-mean specification was favoured. On the other hand, the mapped data yielded very different

[1] In order to distinguish the general PARCH from a version in which δ is fixed (but not necessarily equal to two) we refer to the latter as (P)ARCH.

estimation results. That is, for the mapped data the power estimation was favoured with δ=0.49.

Corn Returns

The mapped and unmapped data gave very similar models which is interesting considering the significant level of rollover in the grains data on contract expiry. The unmapped corn returns favoured an asymmetric (P)ARCH model with a fixed power at a value of 1.3. In the case of the mapped returns for corn, a very similar model was favoured in that it was once again (P)ARCH with asymmetry, with a fixed power at 1.1 which is similar to the 1.3 output for the unmapped returns.

Oats Returns

The significant roll in oats prices meant the models favoured for the mapped and unmapped returns were quite different. The unmapped returns favoured a symmetric AR-(P)ARCH model where the power was fixed to a value of 1.4. On the other hand the mapped returns agreed with a very different model, once again an AR-(P)ARCH, however the power was favoured to be fixed at a value of 0.87 and the asymmetric term was significant.

Where the unmapped data favoured fixing the power in all three grains, the mapped data preferred power estimation in the case of wheat. Looking at the power terms it is clear there is a considerable difference (between mapped and unmapped data) for wheat and oats. The reason being the rollover can be significant in instruments such as grains. There is also a noticeable difference in some of the other estimated coefficients (for a summary see also the Appendix) confirming that the roll and therefore the mapping of data has a significant impact on how it behaves and how it can be modelled. In the interest of the real life trading situations this can be the difference between making a profit and a loss on a long lasting trade. Most of all, this is crucial to anyone using such data to back test a trading system or algorithm. An algorithm optimised with the unmapped data will yield far different parameters to one optimised on mapped data and this analysis has proved this theory.

Grains									
	Wheat			Corn			Oats		
	Unmapped	Mapped	% change	Unmapped	Mapped	% change	Unmapped	Mapped	% change
α	**0.053 *** (0.016)	**0.035 *** (0.011)	**34.48%**	0.061 * (0.022)	0.075 * (0.021)	-21.85%	0.094 * (0.026)	0.092 * (0.019)	2.12%
β	0.935 * (0.022)	0.972 * (0.008)	-3.91%	0.876 * (0.033)	0.893 * (0.025)	-2.01%	0.854 * (0.044)	0.914 * (0.018)	-7.03%
γ				0.738 * (0.329)	0.748 * (0.230)	-1.43%		**0.257** (0.142)	
δ	**1.100**	**0.491** (0.487)	**55.36%**	1.300	1.100	15.38%	**1.400**	**0.870**	**37.86%**
ζ	**-7.470 (3.891)**								
ϕ_1 (AR1)							0.126 * (0.031)	0.142 * (0.032)	-12.66%

Notes: Table above estimates the following model:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \zeta h_t + \varepsilon_t$$
$$\sigma_t^{\delta} = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta} + \beta\sigma_{t-1}^{\delta}$$

All figures are to 3d.p.
Bold results signify percentage change greater than 30%. Standard errors are shown in brackets
**Coefficient is significant at a 5% level*

Table 3.1 Table of results showing coefficients for unmapped and mapped data and their percentage changes for grains (standard errors shown in brackets)

From Table 3.1 there seems to be a greater percentage change in certain coefficients. The proportional change in AIC is quite similar for corn and oats which may be explained by the lesser volatility these two instruments display in comparison to wheat. Generally the ω, ϕ_0 (not reported) and δ coefficients have the greatest change proportionately. The power coefficient can have a large impact on the model therefore given its large change it is safe to say the mapped and unmapped data are significantly different.

3.5.2. Metals

Copper Returns

For the copper returns we expect the results to differ from the wheat results. The reason for this is that the rollover for metals is generally not very significant. The mapped and unmapped copper returns fitted almost identical models. Both favoured asymmetric AR-(P)ARCH models with very similar fixed powers (0.72 for the mapped and 0.71 for the unmapped).

Platinum Returns

For the platinum returns we expect the results to differ from the grains results. The reason for this is that the rollover for metals is generally not very significant. In the case of the platinum returns the models were actually identical with both mapped and unmapped sets of returns favouring symmetric (P)ARCH models and a fixed power of 1.60.

From the results it is clear that the metals' roll is not significant. The mapped and unmapped data yield very similar results and have almost an identical model. Further, the coefficients are almost exactly the same. This supports the suggestion made earlier that the rollover on metals is less significant. The impact on the results of mapping the data is not crucial in this case. A trading algorithm optimised on unmapped data may therefore not be erroneous in reality with respect to the trades it makes.

Metals						
	Copper			Platinum		
	Unmapped	Mapped	% change	Unmapped	Mapped	% change
α	0.055 * (0.011)	0.057 * (0.012)	-2.96%	0.088 * (0.021)	0.088 * (0.021)	0.08%
β	0.941 * (0.013)	0.937 * (0.014)	0.37%	0.906 * (0.023)	0.906 * (0.022)	-0.03%
γ	0.806 * (0.167)	0.802 * (0.167)	0.54%			
δ	0.720	0.710	1.39%	1.600	1.600	0.00%
ϕ1 (AR1)	-0.055 * (0.026)	-0.053 * (0.026)	3.35%	0.108 * (0.030)	0.108 * (0.030)	-0.27%

Notes: Table above estimates the following model:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \zeta h_t + \varepsilon_t$$
$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta$$

All figures are to 3d.p.
Bold results signify percentage change greater than 30%. Standard errors are shown in brackets
**Coefficient is significant at a 5% level*

Table 3.2 Table of results showing coefficients for unmapped and mapped data and their percentage changes for metals

In this case the roll is not significant hence the models throughout for each instrument, even if mapping has been carried out, are similar. Since the roll is not large, the data is not transformed as much so similar models should result as expected. The results clearly show this with a maximum percentage change being in α for copper at 2.96%, which is far less than the 30% change tolerance set.

3.5.3. Energies

RBOB Returns

In the case of energy commodities such as heating oil and RBOB, the rollover is considered to be larger than in most other sectors so the differences in model between the mapped and unmapped data are expected to be quite substantial. The mapped and unmapped returns for RBOB have quite a significant roll which explains why the models for the RBOB mapped and unmapped returns differed so much. In the case of the unmapped returns, an asymmetric (P)ARCH model was favoured with a fixed power at 1.10. However for the mapped returns a symmetric GARCH model (that is with a fixed power of 2.00) was favoured.

Heating Oil Returns

For heating oil the values of the roll were also quite significant which explains why the models for the mapped and unmapped returns differed so much. The unmapped heating oil returns favoured an asymmetric (P)ARCH model with a power fixed at 0.92. On the other hand the mapped returns also favoured a (P)ARCH model however in this case symmetry was favoured and the power was fixed at 1.55. Thus the models were very different due to the power values and the presence of asymmetries in the unmapped data.

WTI Returns

The mapped and unmapped returns for WTI favoured models that differed also. In the case of the unmapped returns, an asymmetric (P)ARCH model was favoured with the power fixed at 1.18. In the case of the mapped returns however the same model specifications were favoured with the significant difference that the power was favoured and fixed at 1.42.

Natural Gas

Similar to RBOB, the returns for natural gas yielded favoured very different models for unmapped and mapped returns. The unmapped returns favoured a symmetric AR-GARCH model (power being 2.00). On the other hand, the mapped returns favoured a symmetric (P)ARCH model where the power was fixed at 1.30.

From the results it can be concluded that the roll does in fact have a significant impact on the data in the case of energies. This can be seen clearly from that data as the unmapped data favours a model of asymmetry in three cases, whereas mapped data favours a model of symmetry in two out of the four cases (that is RBOB and heating oil). This suggests that in this particular case, not accounting for roll introduces an asymmetric component to the behaviour of the data over time. There is also a significant change in the value of the power parameter which impacts the model greatly. Interestingly however, the values of the other coefficients are not very different.

Energies						
	RBOB			Heating Oil		
	Unmapped	Mapped	% change	Unmapped	Mapped	% change
α	0.061 * (0.021)	0.059 * (0.017)	2.60%	0.042 * (0.013)	0.040 * (0.011)	5.38%
β	0.931 * (0.023)	0.927 * (0.020)	0.40%	0.958 * (0.013)	0.958 * (0.013)	-0.03%
γ	**0.520 *** (0.250)			**0.642 *** (0.243)		
δ	**1.100**	**2.000**	**-81.82%**	**0.920**	**1.550**	**-68.48%**

Notes: Table above estimates the following model:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \zeta h_t + \varepsilon_t$$
$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta$$

All figures are to 3d.p.

Bold results signify percentage change greater than 30%. Standard errors are shown in brackets

**Coefficient is significant at a 5% level*

Energies						
	WTI			Natural Gas		
	Unmapped	Mapped	% change	Unmapped	Mapped	% change
α	0.047 (0.026)	0.049 (0.028)	-4.26%	**0.065** * (0.017)	**0.204** * (0.037)	**-214%**
β	0.946 * (0.021)	0.939 * (0.021)	0.74%	0.918 * (0.018)	0.852 * (0.023)	7.19%
γ	0.887 (0.594)	0.685 (0.462)	22.77%			
δ	1.180	1.420	-20.34%	**2.000**	**1.300**	**35%**
ϕ_1 AR(1)				**-0.072*** (0.032)		

Notes: Table above estimates the following model:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \zeta h_t + \varepsilon_t$$
$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta$$

All figures are to 3d.p.

Bold results signify percentage change greater than 30%. Standard errors are shown in brackets

**Coefficient is significant at a 5% level*

Table 3.3 Table of results showing coefficients for unmapped and mapped data and their percentage changes for energies

The reason for the RBOB and natural gas changes being slightly larger may be due to the storage implications in reality. This means there can be very large spikes in prices which can impact the roll if the spike occurs at rollover. This may also be due to larger errors in the data for the same reasons. The results for WTI showed that from all the energies it is the least sensitive to mapping with none of its parameter percentage changes exceeding the tolerance set. On the other hand, the heating oil returns yielded results proving the mapped and unmapped data is significantly different. Generally however, there is a significant difference between mapped and unmapped data for energies and the results prove this.

3.5.4. Softs

Cocoa, coffee, sugar and orange juice (both are the instruments traded on the American exchanges) are commodities that fall into the category of 'softs'. This is a separate sector and is often confused with the 'grains' sector. However like the grains, the softs' time series can exhibit a significant roll. This will be seen from the results yielded having run the models.

Cocoa Returns

The unmapped cocoa returns favoured an asymmetric AR- (P)ARCH model with asymmetry and a power fixed at 1.46. On the other hand the mapped cocoa returns favoured a (P)ARCH model too however in this case symmetry was favoured and the power was fixed at a value of 0.48.

Coffee Returns

In the case of the coffee returns the models were quite similar despite the roll being quite significant. Both mapped and unmapped returns for coffee favoured asymmetric (P)ARCH models. The only differences between the models was the fixed power, which for the unmapped coffee returns was favoured at 0.68 and for the mapped coffee returns was favoured at 0.54.

Sugar Returns

For the sugar returns there was a significant difference between the models favoured by the mapped and unmapped series. The unmapped returns favoured asymmetry and a (P)ARCH model with a fixed power of 0.55. On the other hand, the mapped returns favoured a very different model, that is a symmetric GARCH model.

Orange Juice Returns

For the orange juice returns the models favoured by both unmapped and mapped returns were quite similar. This is in line with the fact that the rollover values or basis for orange juice is not very significant; hence it is not expected to observe a large difference between mapped and unmapped data. Both mapped and unmapped returns favoured asymmetric AR-(P)ARCH models with fixed power. The unmapped data favoured a fixed power of 1.89 while the mapped data favoured a power of 1.96.

From the results it can be concluded that the mapped and unmapped data for softs is indeed different, with the exception of orange juice. This can be seen from the significant changes in coefficients between the models and the models themselves as mapped data prefers a symmetric model and unmapped prefers asymmetric models in the case of cocoa and sugar. Given that the mapped an unmapped data differ quite substantially in most of the cases, the models within a certain instrument differ too. Overall, it is clear that there is an importance to the mapping procedure in accounting for roll when trading these securities, even for orange juice where the roll is not significant since the accumulation of rolls over time will end up being significant. In order to quantify this effect, the following table was drawn up (Table 3.4).

Softs						
	Cocoa			Coffee		
	Unmapped	Mapped	% change	Unmapped	Mapped	% change
α	0.032 * (0.012)	0.026 * (0.011)	18.41%	0.036 * (0.014)	0.040 * (0.014)	-12.08%
β	0.963 * (0.014)	0.974 * (0.014)	-1.12%	0.947 * (0.024)	0.952 * (0.020)	-0.52%
γ	**-0.395** (0.280)			-0.612 (0.321)	-0.479 (0.276)	21.68%
δ	**1.460**	**0.480**	**67.12%**	0.680	0.540	20.59%
ϕ1 (AR1)	**0.047** (0.026)					
Softs						
	Sugar			Orange Juice		
	Unmapped	Mapped	% change	Unmapped	Mapped	% change
α	0.049 * (0.016)	0.047 * (0.012)	4.08%	0.161 * (0.038)	0.162 * (0.045)	-0.62%
β	0.948 * (0.019)	0.951* (0.012)	-0.32%	0.705 * (0.060)	0.593 * (0.093)	15.89%
γ	**-0.377** (0.259)			-0.247 * (0.091)	-0.297 * (0.103)	16.84%
δ	**0.550**	**2.000**	**-263.63%**	1.89	1.96	-3.7%
ϕ1 (AR1)				0.140 * (0.031)	0.134 * (0.031)	0.60%

Notes: Table above estimates the following model:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \zeta h_t + \varepsilon_t$$
$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta$$

All figures are to 3d.p.

Bold results signify percentage change greater than 30%. Standard errors are shown in brackets

**Coefficient is significant at a 5% level*

Table 3.4 Table of results showing coefficients for unmapped and mapped data and their percentage changes for softs

In reality the link between soft commodities is not as strong as it may be in other sectors. This is important when considering this set of results. The mapped and unmapped series in this case do have significant differences however the changes are not similar in all cases. The proportional changes in cocoa and sugar returns for the influential coefficients are far greater than those for coffee and orange juice. For example, the models are very different with the mapped and unmapped returns demanding very different power parameters. This may be explained by the structural break that may exist in the coffee data (see figure 3.12). Perhaps if the coffee returns were more homoscedastic the results would yield more similar percentage changes. The orange juice returns on the other hand yield very similar models for both unmapped and mapped data which may be due to the low roll values. However, the rolls accumulate and will impact the data in the long run.

3.5.5 Soy Complex

Soybean Returns

In the case of the soy complex the results are very interesting. At first glance, all three soy derived commodities are expected to have a very similar behaviour with respect to both price and returns given the fact that both soy oil and meal are derivatives of soybeans. However, in reality the soy meal exhibits very different behaviour and this is reflected in the results. The roll characteristics throughout the soy complex, despite the behavioural differences in soy meal, are quite similar. In the case of soybeans returns, the model favoured by the unmapped returns was a symmetric (P)ARCH model of fixed power 1.56. In the case of the mapped returns, the model favoured was again a (P)ARCH model of fixed power 1.36 and again no asymmetry.

Soy meal Returns

For the soy meal returns the model favoured by the returns for the unmapped data was a symmetric (P)ARCH model of fixed power 1.31. In the case of the mapped returns, once again a symmetric (P)ARCH model was favoured but this time with a fixed power of 1.51.

Soy oil Returns

In the case of soy oil returns the models favoured were quite similar. In both cases a symmetric (P)ARCH model was favoured with very similar powers (fixed at 2.15 and 2.12 respectively).

The models themselves have been summarised in table 3.5 below.

Soy Complex									
	Soybeans			Soy meal			Soy oil		
	Unmapped	Mapped	% change	Unmapped	Mapped	% change	Unmapped	Mapped	% change
α	0.065 * (0.015)	0.070 * (0.016)	7.69%	0.063 * (0.015)	0.073 * (0.017)	15.87%	0.062 * (0.015)	0.063 * (0.015)	-1.61%
β	0.934 * (0.016)	0.935 * (0.015)	0.12%	0.941 * (0.019)	0.934 * (0.015)	0.74%	0.924 (0.017)	0.923 * (0.017)	0.11%
δ	1.56	1.36	12.82%	1.31	1.51	-15.27%	2.15	2.12	1.40%

Notes: Table above estimates the following model:

$y_t = \varphi_0 + \varphi_1 y_{t-1} + \zeta h_t + \varepsilon_t$
$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta$

All figures are to 3d.p.
Bold results signify percentage change greater than 30%. Standard errors are shown in brackets
**Coefficient is significant at a 5% level*

Table 3.5 Table of results showing coefficients for unmapped and mapped data and their percentage changes for the Soy Complex (standard errors shown in brackets)

From the soy complex results it is clear that the models between the mapped an unmapped returns do not differ significantly suggesting that mapping is not as imperative when considering applying a trading model or algorithm to the soy complex. The results for soybeans and soy oil are significantly below the threshold making them relatively insensitive to the mapping procedure. On the other hand, the soy meal returns favour models which differ to a greater degree, but still not at a level where it can be considered significant. Having said this however, the (fixed) powers within the (P)ARCH models do change, especially in the cases of soybean and soy meal. Overall however, it can be concluded that the soy complex is not very sensitive with respect to mapping. In reality, all soy complex data would be subject to mapping if it were to be used in a trading model or algorithm as the rolls can accumulate and become large even if they are individually small. Also, in the case of trading in reality, it is clear that the most accurate possible model will be desired; hence it is likely that a mapping procedure is employed.

3.6 Structural Breaks

This Section, reports the baseline results provided by the conditional maximum likelihood estimates of the (P)ARCH(1,1) model allowing the conditional means and variances to switch across the breakpoints identified by the Bai and Perron (2003) procedure. First, we present the breakpoints that we obtained from Bai-Perron and discuss the potential major economic events that are associated with them. Then we focus our analysis based on these breaks to discuss the findings produced from our univariate models in Table 4.

3.6.1 Estimated Breakpoints

An analysis of breakpoints was conducted for each series of returns (Table 2 below) and squared returns/ ’variance’ (Table 3 below). The breakpoints are detailed in the two tables shown and using the dates of past events, the reasons behind the breaks will be explained where possible. The dates in bold indicate break dates for which, at least one dummy variable is significant in either the mean or the variance equation of each commodity series [for instance for oats 08/01/2010 breakpoint ϕ_1^3 is significant, see Table 4 below]. In the following breakpoint analysis we will focus on the significant break dates. Five primary commodities in each sector were considered to show how break impacts change depending on sector.

By applying the Bai-Perron breakpoint estimation procedure on commodity and squared commodity returns we identify five breaks during the sample period. Furthermore, there are several cases where the breaks are either identical or very close to one another, which clearly show the significant impact that some economic events had on the commodities returns under consideration. The main finding supports that the financial crisis of 2007-2008, and the European sovereign-debt crisis that followed are reflected in all commodity returns and squared returns series. However, despite the sharp down-turn in prices during 2008 and early 2009 in most of the series, prices began to rise again from late 2009 to mid-2010 (a resounding exception is the case of natural gas where prices are still falling since 2008 causing significant problems in exporting countries such as Russia).

3.6.2 Oats

The beginning of 2010 saw Greece to unveil its financial problems and the EU pledge its support. The crisis in Greece has caused a huge change in consumer confidence worldwide due to the exposure of the banking sector, which causes knock on effects into other markets. Additionally, Greece itself produces grains including oats (2nd largest European producer), and the crisis may have impacted the production of grains within Greece, hence introducing the break seen in the time series (8^{th} January 2010, see the first row in Table 2).

As far as the breaks in the squared returns are concerned (see the first row in Table 3), the Bai-Perron test identifies three significant break dates, namely 3^{rd} of October 2008, 15^{th} of March 2010 and 2^{nd} of August 2010. October the 2^{nd} 2008 saw the US Senate pass their bailout bill, which would increase stability within the world economy however the economic confidence would still be uncertain due to the need for government intervention in the private sector and this may be a very good explanation for the first break seen in the oats squared returns. This also might be due to consumer confidence being impacted, hence affecting demand for grains. The other two breaks occurred (15^{th} of March 2010 and 2^{nd} of August 2010) are not directly linked to events however they may be the result of lags from past events or simple demand and supply issues, especially in the grains market where farming factors such as weather and crop yields are significant.

3.6.3 Platinum

The platinum time series saw no significant breaks in the mean equation throughout the period (see Table 2). Metals are non-consumable and recyclable and in the case of precious metals, they can be considered reserve currencies. These are likely the reasons why the metals time series saw no significant breaks in their time series. In the case of breaks in the ‘variance’ (see the second row in Table 3), where the squared returns are utilised, the platinum series experiences two breaks. One occurred late August 2008 and shortly before the Fannie Mae, Freddie Mac and Ginnie Mae takeover by the Federal Reserve Bank (FRB) and the other early January 2009 when the FRB began purchasing mortgage backed securities guaranteed by the same companies. This may be explained by the use of precious metals in times of financial turmoil as reserve currencies, where a sudden surge of demand for them, manifests as confidence in other securities falls.

3.6.4 Natural Gas

The natural gas time series saw no breaks in the mean equation throughout the period (see Table 2). In the case of breaks in the variance, there are two significant breaks dates; one on the 9th of October 2008 and one on the 26th of February 2009 (see the third row in Table 3). The first break occurred during the worst week for the stock market in 75 years, meaning economic confidence and stability would be at historical low level, and hence possibly affecting demand for consumables such as natural gas. Additionally, another factor that might explain the break in October of 2008 could be the start of the winter months in Europe, where natural gas is used for household heating. The second break (26th of February 2009) took place when the Federal Deposit Insurance Corporation (FDIC) announced its list of `problem banks', as well as huge losses being announced by Fannie Mae. Once more the economic confidence would be affected by these two events. Furthermore, the end of February marks the end of the harsh winter in many parts of Europe where natural gas is used to heat households, adding a reason that might explain the displayed break.

3.6.5 Coffee

Similarly coffee shows a significant break only for its squared return early March 2008 (see the fourth rows in Tables 2 and 3). This period is during the time Bear Stearns was taken over by JP Morgan for a fraction of its previous year's price. Furthermore a recession is beginning to become more and more evident and consumer and economic confidence as well as stability started to decrease.

3.6.6 Soybeans

The soybeans saw no significant breaks for the returns, however when the squared returns were considered, a number of breaks occurred. The first break for soybeans on the 14th of June 2007, took place shortly after large banks began to show signs of instability and profit warnings and given their involvement in the trading of soy contracts, it is possible that the volumes for such perishable commodities might be adversely effected, hence affecting their demand and price. The second break on the 31st of July 2008 occurred, shortly after consumer sentiment was measured to be the lowest in 28 years, which would of course impact demand for goods (and services) involving the soybeans industry. Additionally, gasoline reached $4 per gallon, hence machinery and vehicles used to process and transport soybeans would become more expensive to run, altering price due to cost changes.

Table 2. The break points (commodity returns)

	1^{st} Break	2^{nd} Break	3^{rd} Break	4^{th} Break	5^{th} Break
Grains					
Oats	04/07/2008	20/02/2009	**08/01/2010**	28/05/2010	15/10/2010
Metals					
Platinum	03/09/2007	05/03/2008	24/07/2008	12/12/2008	12/05/2009
Energies					
Natural Gas	22/05/2008	09/10/2008	26/02/2009	16/07/2009	03/12/2009
Softs					
Coffee	02/07/2008	05/12/2008	01/06/2009	07/06/2010	09/03/2011
Soya Complex					
Soybean	04/07/2008	05/12/2008	11/06/2009	22/07/2011	09/12/2011

Notes: The dates in bold indicate breakdates for which, at least one dummy variable is significant in the mean equation of each commodity series (for instance for oats 08/01/2010 breakpoint φ_1^3 is significant).

Figure 3.18 The Break Points (commodity returns)

Table 3. The break points (squared commodity returns)

	1^{st} Break	2^{nd} Break	3^{rd} Break	4^{th} Break	5^{th} Break
Grains					
Oats	**03/10/2008**	**15/03/2010**	**02/08/2010**	21/02/2011	16/11/2011
Metals					
Platinum	06/02/2008	**20/08/2008**	**07/01/2009**	12/07/2010	10/11/2011
Energies					
Natural Gas	22/05/2008	**09/10/2008**	**26/02/2009**	16/07/2009	03/12/2009
Softs					
Coffee	**05/03/2008**	16/11/2009	09/06/2010	18/11/2010	08/09/2011
Soya Complex					
Soybean	**14/06/2007**	03/03/2008	**31/07/2008**	12/01/2009	15/09/2009

Notes: The dates in bold indicate breakdates for which, at least one dummy variable is significant in the variance equation of each commodity series (for instance for coffee 05/03/2008 breakpoint β^1 is significant).

Figure 3.19 The Break Points (squared commodity returns)

3.7 PARCH Models with Breaks

In this Section, for the five different commodity returns, we will estimate AR-PARCH models with structural breaks (for applications of GARCH models with structural breaks see Karanasos et al., 2014 and the references therein).

The mean equation is defined as:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_1^3 D_t^3 y_{t-1} + \varepsilon_t, \tag{1}$$

where D^τ are dummy variables defined as 0 in the period before each break and 1 after the break. The breakpoints τ=1 are given in Table 2 above. In addition σ_t^δ is specified as a PARCH(1,1):

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| + \gamma\varepsilon_{t-1})^\delta + \sum_{\tau=1}^{3} \alpha^\tau D_t^\tau \varepsilon_{t-1}^\delta + (\beta + \sum_{\tau=1}^{3} \beta^\tau D_t^\tau)\sigma_{t-1}^\delta, \tag{2}$$

Tables 4 below, reports the baseline results provided by the conditional maximum likelihood estimates of the (P)ARCH(1,1) model[2] allowing the conditional means and variances to switch across the breakpoints [see Eq. (1) and (2) above] identified by the Bai and Perron procedure. Moreover, the tests for remaining serial correlation suggest that all the models are seem to be well-specified since there is no remaining autocorrelation in either the standardized residuals or squared standardized residuals at 5% statistical significance level. In the case of the two constants (φ_0, ω) the effects of breaks are insignificant in all the cases, whereas for the autoregressive coefficients there seems to exist a statistically significant impact of the breaks only in the case of oats. In particular, the parameters of the mean equation show time varying characteristics across one break (in the case of oats). As far as the conditional variance is concerned, the ARCH parameter (α) shows significant time varying behavior with either one or two breaks in the case of platinum and soybean respectively. The GARCH parameter (β) shows either three (oats), two (platinum and natural gas) or one (coffee and soybeans) significant. In the case of soybeans GARCH parameter does not show time varying behavior. As far as the power parameter is concerned it is fixed, and equal to 1.20 (oats and coffee), 1.30 (natural gas and soybeans) and 1.60 (platinum); different from either zero or unity. Finally, the asymmetry

[2] In order to distinguish the general PARCH from a version in which δ is fixed (but not necessarily equal to two) we refer to the latter as (P)ARCH.

parameter displays significant and positive leverage effects when oats and soybeans are under examination.

Table 4. The estimated univariate (P)ARCH(1,1) allowing for breaks in the mean and in the variance

	Oats	Platinum	Natural Gas	Coffee	Soybean
Mean Equation					
φ_0	-0.001 (-1.02)	0.001^{***} (2.62)	-0.002 (-1.05)	-0.0001 (-0.14)	0.001^{**} (2.06)
φ_1	–	0.11^{***} (3.75)	–	–	–
φ_1^3	0.16^{***} (3.79)	–	–	–	–
Variance Equation					
ω	0.002^{***} (3.61)	0.0001^{***} (3.58)	0.004^{***} (3.77)	0.001 (1.25)	0.00001^{***} (2.63)
α	0.04^{**} (2.01)	0.17^{***} (3.63)	0.18^{***} (5.22)	0.07^{**} (2.27)	0.04^{**} (2.29)
β	0.68^{***} (9.58)	0.83^{***} (22.07)	0.50^{***} (4.74)	0.88^{***} (16.27)	0.93^{***} (75.54)
α^1	–	–	–	-0.04 (-1.19)	0.02^{*} (1.73)
α^2	–	-0.09^{**} (-1.97)	–	–	–
α^3	–	–	–	–	-0.01^{*} (-1.78)
β^1	0.17^{***} (3.48)	–	–	0.05^{**} (2.03)	–
β^2	0.03^{**} (1.59)	0.10^{***} (2.77)	0.15^{**} (2.34)	–	–
β^3	-0.04^{**} (-2.07)	-0.03^{***} (-2.33)	0.16^{**} (2.70)	–	–
δ	1.20	1.60	1.30	1.20	1.30
γ	0.15^{***} (5.71)	–	–	–	0.03^{**} (1.96)
$LB(1)$	2.88 [0.09]	0.09 [0.75]	2.40 [0.12]	0.31 [0.57]	0.26 [0.61]
$MCL(1)$	1.54 [0.21]	0.83 [0.36]	3.31 [0.07]	0.06 [0.80]	1.33 [0.25]

Notes: Table 5 reports parameter estimates for the following model:

$$y_t = \phi_0 + \varphi_1 y_{t-1} + \varphi_1^3 D_t^3 y_{t-1} + \varepsilon_t$$

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| + \gamma\varepsilon_{t-1})^\delta + \sum_{\tau=1}^{3} \alpha^\tau D_t^\tau \varepsilon_{t-1}^\delta + (\beta + \sum_{\tau=1}^{3} \beta^\tau D_t^\tau)\sigma_{t-1}^\delta$$

The number in parentheses represent t-statistics. LB and MCL represent Ljung-Box and McLeod-Li tests for serial correlations of one lag on the standardized and squared standardized residuals, respectively (p-values reported in brackets).

***, **, *, indicates significance at the 1%, 5%, 10%, level respectively.

Figure 3.20 The estimated univariate (P)ARCH (1,1) allowing for breaks in the mean and in the variance

3.7.1 Forecasting using spectral techniques

In this section we employ spectral techniques in order to forecast the commodity prices of oats, platinum, natural gas, coffee and soybean (to the best of our knowledge, this is the first time that forecasting using spectral techniques is employed in commodity prices data). In particular we implement an algorithm suggested by Geweke and Porter-Hudak (1983). The basis of the method is the moving average representation:

$$Y_t = c(L)\varepsilon_t,$$

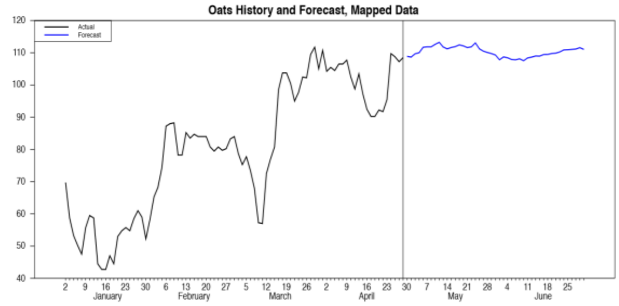
where $c(L)=1-c_1L-...-c^p L^p$ is polynomial in L of order p, c(0)=1 and ε is fundamental for Y. Spectral techniques permit us to compute an estimate of the Fourier transform of c, which in turn can be employed to compute forecasts. In this study we will attempt to forecast the prices of oats, platinum, coffee and soybean from 30th of April 2012 (end of our original dataset) to 29th of June of 2012 or for 45 steps ahead. In the case of natural gas we will forecast the price for 117 steps ahead since the end of our original dataset is 18th of January 2012. The reason behind the choice of that period (end of June 2012) lies to the fact that during the first quarter of 2012 United Kingdom (UK) announced for a second consecutive time a negative growth rate, formally entering a recession, while euro zone showed negative growth rates for three consecutive quarters (2011Q4 to 2012Q2) since the last recession of 2009. It would be only some months later were euro zone would experience a double dip recession. Hence it would be interesting to investigate whether or not the forecasting technique would be able to capture the effects of this negative economic atmosphere that dominated the European economy on the commodity prices.

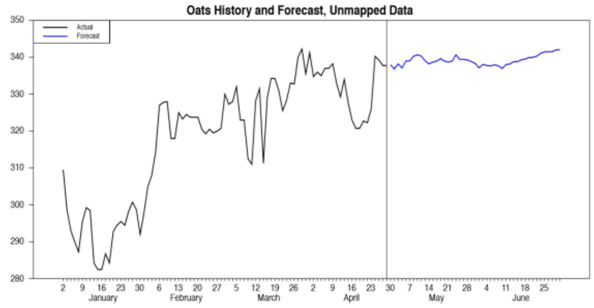
During the period under consideration (daily data covering a period from January 2007 to April 2012) the commodity prices have gone through many variations due to the financial and the EU sovereign debt crisis of 2007-2008 and 2009-present respectively. Hence employment of forecasting methods that are not sensitive to dynamical variations such as the aforementioned is a vital stage of the estimation procedure. Therefore, taking under consideration the properties of spectral forecasting method, the latter could be considered as an appropriate technique for predicting the commodity prices.

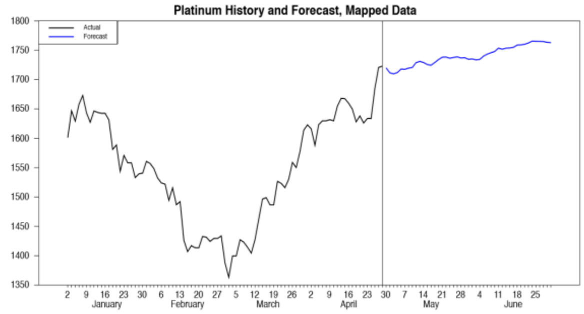
Figure 2 below displays the history and the forecast for each of both the mapped and unmapped commodity prices[3]. First notice, that regardless of whether the data for each commodity are mapped or unmapped the trend (blue line in Figure 2 below) is approximately the same. Specifying the results, in the case of the oats, platinum and soybeans the forecasting algorithm predicts that the prices in overall will increase the period from 30th of April 2012 to 29th of June 2012. In contrast, the predicted prices of natural gas and coffee show a declining trend. To check the validity of our results and the accuracy of the forecasting algorithm we compared the predicted prices (for the unmapped data) with those of the actual prices during the period under examination and we found that the way they behave (both predicted and actual series) is very

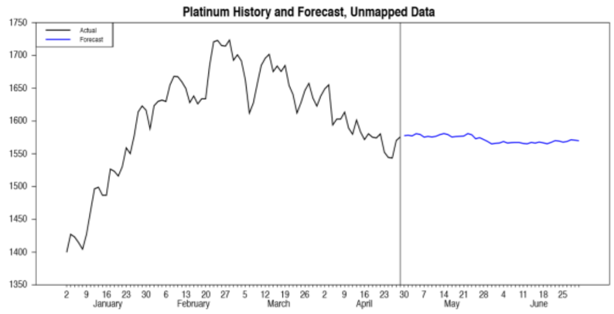
[3] For oats, platinum, coffee and soybeans the forecasting period is 30/04/2012-29/06/2012, whereas for natural gas is 18/01/2012 to 29/06/2012.

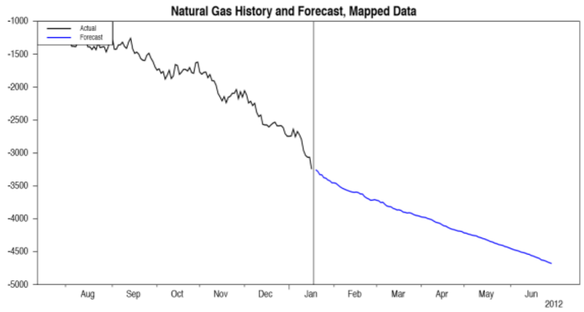
similar[4]. Hence spectral methods could be a reliable tool for predicting the future prices of commodities.

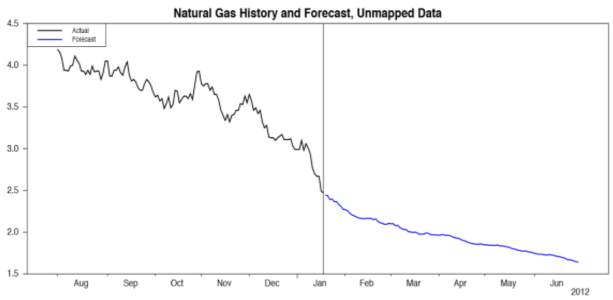


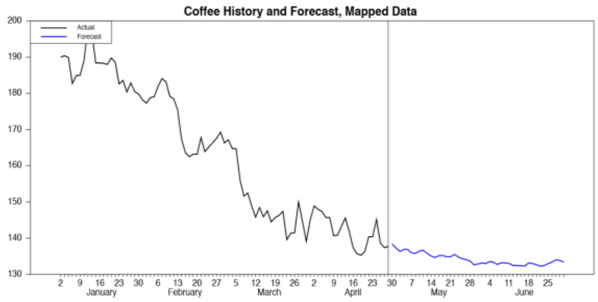


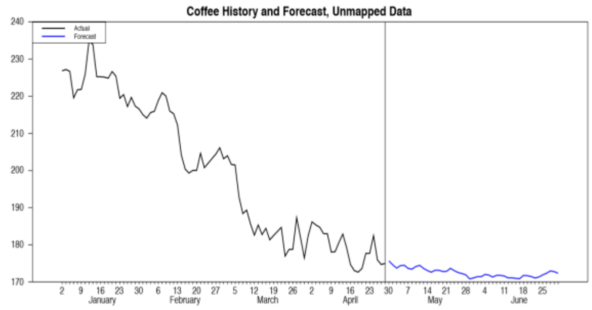












4 Actual data during the first two quarters of 2012 for the commodities under investigation are not plotted graphically, graphs upon request.

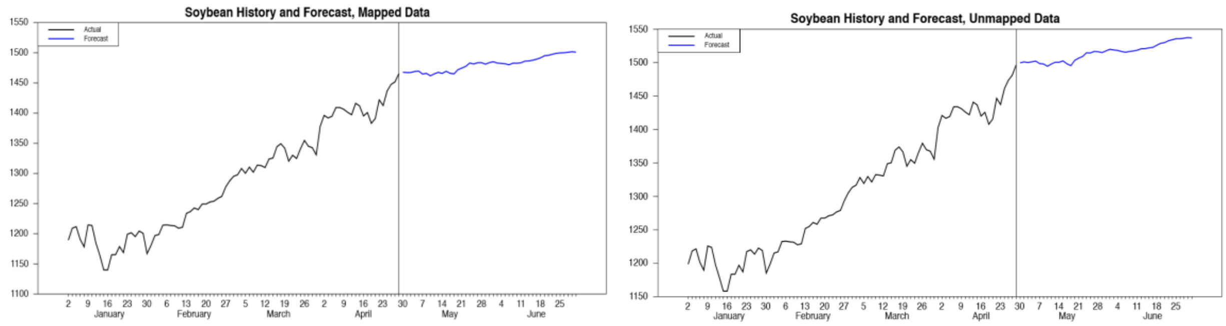


Figure 3.21. History and Forecast of commodity prices, mapped and unmapped daily data

3.8 Conclusion

From the results presented it can be concluded that some data sets are more sensitive than others when it comes to data mapping. The analysis was carried out over a range of commodities in different sectors in order to capture the significance of rollover in each. The metals results showed how copper prices and platinum prices have a small rollover and therefore mapping the data does not significantly change its behaviour. The model which best fits the data therefore remains very similar for mapped and unmapped data. This was also seen within the Soy Complex. On the other hand, the grains' results showed how significant the impact of rollover can be on a time series. The rollover for grains' prices from contract to contract is more substantial and this was projected in the results where the mapped and unmapped time series for grains fitted very different models. This was also observed in most of the softs and energy results.

The impact of the roll may not seem substantial however in the world of real life trading where the front month contract of any instrument is the active contract, the inclusion of roll into prices used to back test could be the difference between a trading strategy being successful or not. Therefore it must be concluded that data mapping be an essential pre-analysis carried out before back-testing any trading system. Just as a PARCH models' coefficients differ as data is mapped or unmapped, so much so may the parameters of a trading algorithm differ. The more significant the roll for a given commodity, the larger was the observed difference in model coefficients and general specification. The significance of the current approach is that the creation of time series that account for roll will allow more accurate back testing of any algorithmic trading system that is proposed including those of RGZ Ltd. This finding is in contrast to that of Chatrath et al. (2001) who show commodity prices to be chaotic to a certain degree.

In addition by applying the Bai-Perron breakpoint estimation procedure on commodity and squared commodity returns we identify five breaks during the sample period. The main finding supports that the financial crisis of 2007-2008, and the European sovereign-debt crisis that followed are reflected in all commodity returns and squared returns series. Having obtained the breaks we applied (P)ARCH models allowing for breaks both in the conditional mean and variance. The tests for remaining serial correlation suggest that all the models seem to be well-specified.

The main results suggested that for the two constants (φ_0, ω) the effects of breaks are insignificant in all the cases, whereas for the autoregressive coefficients a statistically significant impact of the breaks exist only in the case of oats. As far as the ARCH parameters is concerned there is a time varying behavior only in the case of platinum and soybean. Regarding the β coefficient there are significant breaks in all cases apart from soybean. Finally, leverage effects are observed only for oats and soybean while the power parameter δ is fixed and different from either zero or unity.

Concluding we used spectral methods in order to predict the futures prices of five commodities (in both mapped and unmapped data). The results indicated that in the case of the oats, platinum and soybeans the predicted prices in overall will increase. In contrast, the predicted prices of natural gas and coffee showed a declining trend.

The authors would like to thank RGZ Ltd. for the use of their Reagan–class Mapping Algorithm and its output.

3.9. Appendix

Summary Tables

<u>*Grains*</u>

Wheat

	Unmapped	Mapped
PARCH	√	√
Power	1.10	0.41 (Estimated)
Asymmetry	x	x
In-mean	√	x
AR	x	x

Corn

	Unmapped	Mapped
(P)ARCH	√	√
Power	1.30	1.10
Asymmetry	0.74	0.75
In-mean	x	x
AR	x	x

Oats

	Unmapped	Mapped
(P)ARCH	√	√
Power	1.40	0.87
Asymmetry	x	√
In-mean	x	x
AR	0.13	0.14

<u>*Metals*</u>

Copper

	Unmapped	Mapped
(P)ARCH	√	√
Power	0.72	0.71
Asymmetry	0.81	0.80
In-mean	x	x
AR	-0.05	-0.05

Platinum

	Unmapped	Mapped
(P)ARCH	√	√
Power	1.60	1.60
Asymmetry	x	x
In-mean	x	x
AR	x	x

Energies

Heating Oil

	Unmapped	Mapped
(P)ARCH	√	√
Power	0.92	1.55
Asymmetry	√	x
In-mean	x	x
AR	x	x

RBOB

	Unmapped	Mapped
(P)ARCH	√	x
Power	1.10	2.00
Asymmetry	√	x
In-mean	x	x
AR	x	x

WTI

	Unmapped	Mapped
(P)ARCH	√	√
Power	1.18	1.42
Asymmetry	0.89	0.68
In-mean	x	x
AR	x	x

Natural Gas

	Unmapped	Mapped
(P)ARCH	x	√
Power	2.00	1.30
Asymmetry	x	x
In-mean	x	x
AR	√	x

Softs

Cocoa

	Unmapped	Mapped
(P)ARCH	√	√
Power	1.46	0.48
Asymmetry	√	x
In-mean	x	x
AR	√	x

Coffee

	Unmapped	Mapped
(P)ARCH	√	√
Power	0.68	0.54
Asymmetry	-0.61	-0.48
In-mean	x	x
AR	x	x

Sugar

	Unmapped	Mapped
(P)ARCH	√	x
Power	0.55	2.00
Asymmetry	√	x
In-mean	x	x
AR	x	x

Orange Juice

	Unmapped	Mapped
(P)ARCH	√	x
Power	1.89	1.96
Asymmetry	-0.25	-0.30
In-mean	x	x
AR	0.14	0.13

<u>Soy Complex</u>

Soybeans

	Unmapped	Mapped
(P)ARCH	√	√
Power	1.56	1.36
Asymmetry	x	x
In-mean	x	x
AR	x	x

Soy meal

	Unmapped	Mapped
(P)ARCH	√	√
Power	1.31	1.51
Asymmetry	x	x
In-mean	x	x
AR	x	x

Soy oil

	Unmapped	Mapped
(P)ARCH	√	√
Power	2.15	2.12
Asymmetry	x	x
In-mean	x	x
AR	x	x

Chapter 4: Modelling Time Varying Volatility Spillovers and Conditional Correlations Across Commodity Metal Futures

Chapter 4 is joint work with M.G. Karanasos, F.M. Ali & P.D. Koutroumpis 'Modelling Time Varying Volatility Spillovers and Conditional Correlations Across Commodity Metal Futures'. M.G. Karanasos, F.M. Ali & P.D. Koutroumpis helped in the model specification and contributed to some of the interpretation of the results with a combined contribution of 20% to the chapter (approx. 7% each).

The remaining contributions are by Z.N.P. Margaronis for significant contribution (80%) in data-collection, data processing, data analysis, results & discussion and write-up throughout the Chapter.

Keywords: Financial crisis, metal futures, structural break, time-varying volatility spillovers

JEL Classification Codes: C32; Q02

4.1 Introduction

The financial crisis of 2007-08 and the European sovereign-debt crisis that occurred afterwards sent a wave of panic throughout financial and commodity markets around the globe. Given the macroeconomic slowdown and the widespread fear of an international systemic financial collapse, an interesting issue is whether the main stochastic properties of the underlying financial time series of these markets and their cross-shock and volatility spillovers have been affected by the crisis. Karanasos et al. (2014) do indeed find a time varying pattern in the persistence of the volatility of stock market returns, as well as their correlations, cross-shock and volatility spillovers during the period.

Surprisingly, the aforementioned impact in relation to the commodity futures markets has drawn less attention. To the best of our knowledge, the studies by Vivian and Wohar (2012) and Sensoy (2013) are the only ones to date to have examined the impact of the recent crisis on the volatility of commodity returns, even though they consider spot price data. Moreover, such studies have limitations in that they ignore the impact of the crisis on the cross-shock and volatility spillovers between the corresponding returns.

This chapter, by contrast, considers two metals futures: copper and gold. These metal futures are considered due to their sheer daily volumes. Gold is the main precious metal and has mixed demand characteristics. Its demand is determined by financial factors as it is a reserve currency for the world, as well as being a traded commodity whose price is longed and shorted continually in huge volumes. Gold is also affected by its pure consumer and market application in jewellery and electronics. Copper, on the other hand, is the main industrial metal, with huge applications in electronics, mainly in wiring. It is far more abundant in comparison to other metals, and hence it is a useful candidate metal to be considered for this analysis.[1]

Consequently, there are several broad contributions to the existing literature that we make, which we outline following the structure of the chapter. More specifically, we make use of several modern econometric approaches for univariate and multivariate time series modelling, which we also condition on the possibility of breaks in the volatility dynamics taking place in the returns of these metal futures. That is, we use a battery of tests to identify the number and estimate the timing of breaks both in the mean and volatility dynamics. Then, we use these breaks in the univariate context by adopting an asymmetric generalised autoregressive conditional heteroscedasticity (AGARCH) model to determine changes in the persistence of volatility, and in the multivariate one by employing the recently developed unrestricted extended dynamic conditional correlation (UEDCC) AGARCH model of Karanasos et al. (2014) to analyse the volatility transmission and the correlation structure.

We also examine how the persistence of volatility of the two considered returns is affected by their corresponding positive (e.g. increases in these metal futures) and negative (e.g. declines in these metal futures) returns. Finally, we investigate the regime dependent volatility spillovers between these metal futures returns to discern shock and volatility spillovers associated with the exact movements of each metal future (e.g. upward or downward) to the other, and vice versa. Knowledge of the spillovers mechanism adopted in this chapter could prove to be very valuable to investors since such spillovers in addition to the associated structural changes could give rise to trading strategies, thereby minimising the risk exposure and maximising the returns.

It is also important to consider the manipulation the data has undergone in this chapter. The unmapped data is comprised of prices that have not been adjusted for differences in prices due to rollover or 'basis'.[2]

The use of mapped data will allow us to observe the true interactions between the commodities. Taking into account the roll or basis alters the time series in such a way that econometric models' best fit may change as a result. The use of the front month contract prices (at the time of trading in real time) indicates the time series as it would appear to a trader at the particular point in time. The differences in the time series (mapped and unmapped) may be large or small and sometimes cancel each other out. However, they should be considered if a true 'live' trading time-series is to be created.

[1] See also Conrad and Karanasos (2014) for an application to inflation-growth link

Our results suggest that both copper and gold futures returns exhibit time varying persistence in their corresponding conditional variances over the recent crisis. The results of the bivariate UEDCC- AGARCH(1;1) model also show the existence of time varying shock and volatility spillovers between these returns during the different stages of the financial crisis. In particular, there is a bidirectional mixed feedback between the two volatilities. That is, the conditional variance of copper affects gold negatively whereas the reverse effect is of the opposite sign. This mixed feedback between the volatilities of copper and gold is consistent with the fact that these two metals are so different in their values and uses.

The results also suggest that the volatility transmission from gold returns to those of copper has shifted after the European sovereign-debt crisis and the downgrade of the US government debt status. The regime-dependent volatility spillovers analysis, by contrast, suggests that declines in copper prices induce positive volatility spillovers to gold returns. These results are broadly robust irrespective of whether mapped or unmapped data are employed.

The remainder of this chapter is as follows. Section 2 reviews the relevant literature. Section 3 describes our employed data and methodology. Sections 4 and 5 present our empirical results and a discussion. The final Section contains the summary and our concluding remarks.

[2] Rollover, or roll, occurs when the current contract of a commodity instrument expires and the next month contract then becomes the new front month contract. As this happens, the price of the instrument may 'jump' since the front month contract and next month contract do not have the same price at the time of rollover. In this first analysis, therefore, the data have not been mapped to account for the rollover values. It has been discovered that taking into account the roll can significantly change the time series since these roll values can be signi…cant in the commodities considered (Margaronis et al.,2014).

4.2 A Review of the Relevant Literature

Modelling the stochastic properties of financial and commodity returns as well as their cross-shock and volatility spillovers has drawn much attention to the fields of financial and energy economics, given their important practical implications for investors. For example, understanding the stochastic properties of returns may help investors in terms of forecasting market movements, while strong linkages between financial and/or commodity returns would imply limited portfolio diversification opportunities for them. Although there is a large body of literature that has examined the interactions between international financial markets such as those of equity, foreign exchange, and bond, and their returns properties, a growing literature has also been examining the dynamic linkages between commodity markets as well as their return characteristics.

Recent studies on exploring the stochastic properties of commodity returns include Watkins and McAleer (2008), Hammoudeh and Yuan (2008), Choi and Hammoudeh (2010), Vivian and Wohar (2012), Arouri et al. (2012), Sensoy (2013), and Demiralay and Ulusoy (2014) among others. Using a rolling AR(1)-GARCH(1,1) model, Watkins and McAleer (2008) found that the conditional volatility of aluminium and copper returns have been time-varying when analysed over a long horizon. By contrast, Choi and Hammoudeh (2010), using a Markov-switching specification and data over the January period.

Vivian and Wohar (2012), using daily data over the period January 1990 to July 2010, concluded that the volatility persistence of spot commodity returns, including those of precious metals, remains very high even when structural breaks are accounted for. More recently, Sensoy (2013) revealed that the volatility of palladium and platinum, unlike that of gold and silver, exhibited an upward shift during the turbulent year 2008 using spot price data over the period January 1999 to April 2013. His results also provided evidence that gold has a uni-directional volatility shift contagion effect on all other precious metals while silver has a similar effect on platinum and palladium.

Empirical studies that have examined the linkages across commodity prices and their returns and volatility include Ciner (2001), Xu and Fung (2005), Erb and Harvery (2006), Hammoudeh et al. (2010), and Sensoy (2013) among many others. Ciner (2001) reported that gold and silver futures contracts traded in Japan are not cointegrated using daily data over the period 1992 to 1998. Erb and Harvery (2006) further provided evidence that commodity futures returns have been largely uncorrelated with one another, especially across the different sectors. However, using daily futures data of gold, platinum, and silver futures contracts traded in both the US and Japanese markets, Xu and Fung (2005) found evidence of strong volatility feedback between these precious metals across both markets over the period November 1994 to March 2001. Choi and Hammoudeh (2010), using a dynamic conditional correlation model and data over the period January 1990 to May 2006, also found evidence of increasing correlations between all the considered spot commodity returns (Brent oil, WTI oil, copper, gold and silver) over recent years.

The ongoing literature has also been exploring the dynamic linkages across both financial and commodity markets (e.g., Choi and Hammoudeh, 2010; Mensi et al., 2013; among others). Choi and Hammoudeh (2010) found evidence of decreasing correlations between spot commodity returns (Brent oil, WTI oil, copper, gold and silver) and the US' S&P 500 stock market returns over recent years. However, Mensi et al. (2013), using a VAR GARCH model over the period January 2000 to December 2011, showed that there are significant spillovers in terms of shock and volatility between the S&P stock returns and spot commodity market returns. In particular, their results revealed that the past shock and volatility of the S&P stock returns strongly influence the oil and gold market returns. Cochran et al. (2010), on the other hand, showed that the VIX index is an important factor in the determination of metal returns and return volatility using spot price data on copper, gold, platinum, and silver over the period January 1999 to March 2009.

The impact of the macroeconomic performance on commodity prices and their returns and volatility has also drawn much attention (e.g., Tulley and Lucey, 2007;

Hammoudeh and Yuan, 2008; Sari et al., 2009; Batten et al., 2010; among others). Tulley and Lucey (2007) confirmed that the US dollar is the main macroeconomic variable which affects gold. Sari et al. (2009) further found that spot metal prices (gold, silver, platinum, and palladium) are strongly related to the dollar-euro exchange rates. Hammoudeh and Yuan (2008), on the other hand, provided evidence that rising interest rates are found to dampen futures precious metals volatilities. Using monthly data over the period January 1986 and May 2006, Batten et al. (2010) examined the macroeconomic determinants of four precious metals (gold, silver, platinum and palladium prices) and found that gold prices are greatly influenced by monetary variables, but silver prices are not. Their results also provided supporting evidence of volatility feedback between the precious metals.

To the best of our knowledge, analysing the stochastic properties of metal futures returns and their time varying cross-shock and volatility spillovers during the recent financial crisis has yet to be undertaken. This chapter aims to fill this gap by considering copper and gold futures, with two types of data: mapped and unmapped.

4.3 Data and Methodology

This Section overviews the data we have used and outlines the methodology we have employed to study the different properties of the stochastic processes associated with gold and copper futures returns over the 2007-8 crisis. First, we provide a brief description of our data and the break identification method which we have adopted. Then we describe the univariate and bivariate models we have estimated.

4.4 Data Description and Breaks Detection

We use daily (mapped and unmapped) data on gold and copper futures prices which span the period January 3, 2007 to April 27, 2012. The unmapped data have been retrieved from Bloomberg.

4.4.1 Gold vs. Copper

The precious metals are, and for many years have been, used as a reserve currency in times of financial turmoil where uncertainty lingers within economies. When consumers are not confident in their currency they often buy gold or other precious metals. The reason for this is the precious metals' value and demand. The increased volatility, liquidity and use as a reserve currency mean that gold prices will react to the market with little to no lag time. Precious metals are not really consumed (and if they are it is usually a small percentage which is often recycled e.g. jewellery, watches, and used as wiring in expensive earphones or sound systems) and neither do they tarnish or rust. They also have value and demand worldwide, making them a very good substitute for a currency. Their price is therefore very difficult to be determined as it is traded very frequently by countless companies and individuals. The use of gold to hedge currencies has become increasingly popular lately, which adds yet another demand dynamic to its already complex demand characteristic. The induced demand that results from uncertainty in financial markets can cause behavioural changes in the price, hence impacting volatility.

In the case of copper and its heavy industrial use, the demand characteristics are very different. Rather than being exposed to many market participants who trade lower volumes each, the copper market tends to consist of fewer market participants who trade larger volumes each, e.g. mining companies, electronics companies, of which there are limited numbers. Financial instability can be a major factor influencing the price of copper. Decreased demand for copper as world demand falls (especially for consumer goods in which copper is a major raw material) is therefore expected but as the non-industrial utilisation of copper rises, its demand characteristics are also subject to major changes. Over the years, the copper price has been subject to a huge amount of speculative trading (although far less significant than in the gold market) and this, combined with the uncertainty of financial markets, which typically causes the demand for copper to fall, can induce significant levels of volatility in the copper price. With a lower number of market participants, despite the very large volumes, the net positions placed in the copper market will differ significantly from those of gold due to the lower speculative nature and far less complex demand characteristics of the copper market. The recyclable nature of copper also makes it an interesting prospect to be analysed.

4.4.2 Mapping Procedures

The mapping procedure in these metal futures is achieved by a specialist computer program (mapping program) where the input for the program is the entire set of monthly futures contracts. The program then takes the last (expiry) price of each contract and lines it up by date to the price of the second month contract. As the program uses a counter for both the price series and date series, mapping occurs when the counters match on the day before expiry as this represents the true traded time series. The front and second month prices on that date are then lined up and their difference gives the basis or rollover for that contract. Each roll value or basis value is stored and accumulated in order for a calculation of the cumulative roll or basis to be made (see, for details, Margaronis et al., 2014). Finally, we use continuously compounded returns (r_t) on these metal futures calculated as $r_t = (\log p_t - \log p_{t-1}) \times 100$; where p_t is the metal futures price at time t (Table C.1 in the additional Appendix provides a summary of the statistical properties of metal futures returns (mapped and unmapped).

4.4.3 Structural Breaks

Since the employed data span includes various economic and financial events causing behavioural changes due to confidence alterations in economies as a result of the financial crisis, the considered return series are likely to contain breaks associated with such events. Examples may include the collapse of Lehman Brothers, the collapse and buy-out of Bearn Sterns and the AIG, increased unemployment, quantitative easing and many more.

To account for the possibility of breaks in the mean and/or volatility dynamics of these returns we use a set of parametric and non-parametric data-driven methods to identify the number and timing of the potential structural breaks. In particular, we employ the procedures in Bai and Perron (2003) and Lavielle and Moulines (2000).[3]

From applying these procedures on gold and copper futures returns we find the stochastic behaviour of both returns yields four breaks during the sample period, roughly one every one and a half years on average. The predominant feature of the underlying segments is that it is mainly changes in variance that are found to be statistically significant. Moreover, all four break dates for the two series are very close to one another, which apparently signify economic events with a global impact (see Table C.2 in the additional Appendix). It follows that the detected breaks contrast to those of Vivian and Wohar (2012), who found limited evidence of common breaks for spot precious and industrial metals using the AIT (adjusted Inclan and Tiao, 1994) test statistic.

Figure 1 displays the identified four break points (see Table 1) and the associated regimes for each metal futures (unmapped) returns series.[4] Overall, events such as the Troubled Asset Relief Program (TARP) in the US, capital purchase program by the US Treasury Department, the European sovereign- debt crisis and the downgrade of US sovereign debt have been associated with such break points.[5] In particular, the first break for gold returns observed on July 22, 2008 may be explained by the stock markets having suffered their steepest fall since January 2001 causing the Federal Reserve to make an emergency significant cut in rates soon after. This act to help recovery by the Federal Reserve mixed with their efforts to aid JP Morgan Chase in their offer to buy Bear Sterns, and the government assistance offered to the two largest mortgage lenders in the US, may explain the break observed. By contrast, the first break for copper returns observed on September 29, 2008 can almost certainly be attributed to the rejection of the $700bn US banking sector rescue plan. Although this was revised soon afterwards, it caused the stock markets worldwide to collapse and instilled a great deal of fear and uncertainty into the world economies again.

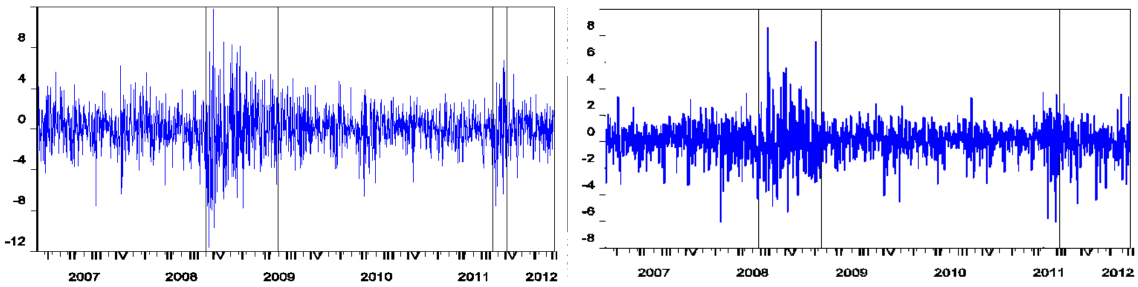


Figure 4.1 Daily (unmapped) copper (left panel) and gold (right panel) metal futures returns over the sample period with breaks.

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[3] Alternatively, we have also adopted the two-stage Nominating-Awarding procedure of Karoglou (2010) (see also Karanasos et al., 2014 and Karanasos et al., 2015) to identify breaks that might be associated either to structural changes in the mean and/or volatility dynamics or to latent non-linearities that may manifest themselves as dramatic changes in the mean and/or volatility dynamics and might bias our analysis. The details of the two stages in the Nominating-Awarding procedure are contained in an additional Appendix, which is available up on request.

[4] The graphs (available up on request) of the corresponding mapped returns exhibit a similar pattern.

[5] Table C.3 in the additional Appendix provides a detailed account of the possible associations that can be drawn between each breakdate for metal futures returns and a major economic event that took place at or around the breakdate period in the world. Table C.4 in the additional Appendix presents a summary of the descriptive statistics of each segment for the metal futures returns.

In 2009 after the largest first-quarter loss ever announced in US history by AIG, the group received a significant amount in government rescue funds. This was followed by the Federal Reserve's plans to buy $1.2tn of mortgage and government debt. This series of events may explain the observed break on March 10, 2009 in gold returns as fear and uncertainty in financial markets were moderated after the rescue plans by the Federal Reserve and the US government were implemented. The same phenomenon is observed on June 25, 2009 (the second break for copper), where ten of the large banks receive TARP rescue funds, again showing how the intervention to aid the financial markets by propping up its major institutions instils confidence in the world economy which therefore undeniably impacts on the commodity markets, especially the metals studied in this chapter.

While the observed breaks on June 13, 2011 and August 10, 2011 in gold returns could be the result of respectively the European sovereign debt crisis and the downgrade of the US government debt status, the observed break on September 09, 2011 in copper returns may also be due to the effects of the unexpected rating reduction which may have taken a few weeks to be expressed in some commodity prices such as those of copper. The break seen on November 03, 2011, by contrast, does not exactly coincide with a specific event. However, given the significance of the events prior to this, it is clear that at some point the economies of the world would begin recovering from the global financial crisis. This date may represent the beginning of this recovery, and hence the start of a new low volatility regime.

4.5 Time Series Modelling

4.5.1 Univariate Models

The conditional mean equation of the considered metal futures returns is specified as:

$$r_t = \mu + \varepsilon_t , \qquad \varepsilon_t = \sqrt{h_t} e_t$$

where the innovation $\varepsilon_t \quad \mathcal{F}_{t-1} \sim N(0, h_t)$ is conditionally normal with zero mean and variance h_t and $e_t \overset{i.i.d}{\sim} N(0,1)^6$.

Next, the dynamic structure of the conditional variance is specified as an AGARCH (1, 1) process of Glosten et al. (1993) (one could also employ the asymmetric power GARCH (APGARCH) as in Karanasos and Kim, 2006). Moreover, Karanasos et al. (2014) found that the persistence of the conditional variances of financial returns such as those of equity indices are significantly affected by structural changes associated with financial crises and economic events over the last two decades. To this end, in order to examine the impact of the breaks on the persistence of the conditional variances of these metal futures returns, the equation is specified as follows:

$$h_t = \omega + \sum_{i=1}^{4} \omega_l D_l + \alpha \varepsilon_{t-1}^2 + \sum_{i=1}^{4} \alpha_l D_l \varepsilon_{t-1}^2 + \gamma S_{t-1}^{-} \varepsilon_{t-1}^2 + \sum_{i=1}^{4} \gamma_l D_l S_{t-1}^{-} \varepsilon_{t-1}^2 + \beta h_{t-1} + \sum_{i=1}^{4} \beta_l D_l h_{t-1} ,$$

Where $S_{t-1}^{-} = 1$ if $\varepsilon_{t-1} < 0$, and 0 otherwise. Note that failure to reject $H_o : \gamma = 0 \; and \; \gamma_l = 0, l = 1, \ldots, 4$, implies that the conditional variance follows a simple GARCH (1,1) process. Furthermore, the stationarity conditions require $\alpha + \beta + \frac{\gamma}{2} < 1$ for the AGARCH (1,1) model, and hence $\alpha + \beta < 1$ for the simple GARCH (1,1) process. The breaks $l = 1, \ldots, 4$ are given in Table 1 for metals futures returns, and D_l are dummy variables defined as 0 in the period before each break, and 1 after the break.

In order to examine how the persistence of the conditional variances is affected by upward and downward trends in these metal futures, we consider the simple GARCH (1,1) model which allows the dynamics of the conditional variances to switch across positive and negative returns. This is given by:

$$h_t = \omega + \omega^{-} D_{t-1}^{-} + \alpha \varepsilon_{t-1}^{2} + \alpha^{-} D_{t-1}^{-} \varepsilon_{t-1}^{2} + \beta h_{t-1} + \beta^{-} D_{t-1}^{-} h_{t-1},$$

Where $D_{t-1}^{-} = 1$ if $r_{t-1} < 0$, and 0 otherwise.

4.5.2 Bivariate Models

Having defined the univariate modelling, in this Section we use a bivariate model to simultaneously estimate the conditional means, variances, and covariances of returns. Let $y_t = (r_{1,t} r_{2,t})'$ represent the

2x1 vector with the two returns of metal futures. As before $\mathcal{F}_{t-1} = \sigma(y_{t-1}, y_{t-2}, \dots)$ is the filtration generated by the information available up through time *t-1*. That is, we estimate the following bivariate AGARCH(1,1) model:

$$y_t = \mu + \varepsilon_t ,$$

where $\mu = [\mu_i]_{i=1,2}$ is a 2x1 vector of drifts.

Let $h_t = (h_{1,t}\ h_{2,t})'$ denote the 2x1 vector of $\mathcal{F}_{t-1}$ measurable conditional variances. The residual vector is defined as $\varepsilon_t = (\varepsilon_{1,t}\ \varepsilon_{2,t})' = \boldsymbol{e}_t \odot h_t^{\wedge 1/2}$, Where the symbols Θ and ^ denote the Hadamard product and the elementwise exponentiation, respectively. The stochastic vector $\boldsymbol{e_t} = (e_{1,t} e_{2,t})'$ is assumed to be independently and identically distributed *(i.i.d.)* with mean zero, finite second moments, and 2x2 correlation matrix $\mathrm{R}_{\boldsymbol{t}} = diag\{\mathrm{Q}_{\boldsymbol{t}}\}^{-1/2}\mathrm{Q}_{\boldsymbol{t}} diag\{\mathrm{Q}_{\boldsymbol{t}}\}^{-1/2}$ with diagonal elements equal to one and off-diagonal elements absolutely less than one. $\mathrm{Q}_{\boldsymbol{t}}$ is specified as follows (see Engle, 2002):

$$\mathrm{Q}_{\boldsymbol{t}} = [q_{\boldsymbol{ij,t}}]_{\boldsymbol{i,j=1,2}} = (1 - \alpha^{DCC} - \beta^{DCC})\bar{\mathrm{Q}} + \alpha^{DCC}\varepsilon_t\varepsilon_t' + \beta^{DCC}\mathrm{Q}_{t-1}$$

Where $\bar{\mathrm{Q}}$ is the unconditional covariance matrix of ε_t and α^{DCC} and β^{DCC} are non-negative scalars fulfilling $\alpha^{DCC} + \beta^{DCC} < 1$. A typical element of $\mathrm{R}_{\boldsymbol{t}}$ takes the form $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}\ for\ i,j = 1,2\ \ and\ i \neq j.$

Following Conrad and Karanasos (2010, 2014) and Karanasos et al. (2014), we impose the UEDCC-AGARCH(1,1) structure on the conditional variances (one could also use multivariate fractionally integrated APARCH models as in Karanasos et al., 2014):

$$h_t = \omega + \mathrm{A}\hat{\varepsilon}_{t-1}^2 + \sum_{l=1}^{n} \mathrm{A}_l D_l \hat{\varepsilon}_{t-1}^2 + \mathrm{B}h_{t-1} + \sum_{l=1}^{n} \mathrm{B}_l D_l h_{t-1} + \Gamma S_{t-1}\hat{\varepsilon}_{t-1}^2$$

Where $\omega = [\omega_i]_{i=1,2,}$ $\mathrm{A} = [\alpha_{ij}]_{i,j=1,2,}$ $\mathrm{B} = [\beta_{ij}]_{i,j=1,2}$; $\mathrm{A}_l, l = 1, \dots, n$ $(and\ n = 0,1, \dots, 4)$ is a cross diagonal matrix with nonzero elements $\alpha_{ij}^l, i, j\ 1,2, i \neq j, and$ B_l is a cross diagonal matrix with nonzero elements $\beta_{ij}^l, i, j\ 1,2, i \neq j, and\ \Gamma$ is a diagonal matrix with elements $\gamma_{ii}, i = 1,2, and\ \boldsymbol{S}_{t-1}$ is a diagonal matrix with elements

$\boldsymbol{S}_{i,t-1}^{-} = 1\ if\ \ e_{i,t-1} < 0, and\ 0\ otherwise.$

The model without the breaks for the shock and volatility spillovers and the asymmetries, that is $h_t = \omega + \mathrm{A}\hat{\varepsilon}_{t-1}^2 + \mathrm{B}h_{t-1}$, is minimal in the sense of Jeantheau (1998, Definition 3.3) and invertible (see Assumption 2 in Conrad and Karanasos, 2010). The invertibility condition implies that the inverse roots of $|\mathrm{I} - \mathrm{B}L|$, denoted by $\varphi_1$and φ_2, lie inside the unit circle. Following Conrad and Karanasos (2010) we also impose the four conditions which are necessary and sufficient for $h_t \to 0\ for\ all\ t$: $(i)(1 - b_{22})\omega_1 + b_{12}\omega_2 > 0\ and\ (1 - b_{11})\omega_2 + b_{21}\omega_1 > 0$, $(ii)\varphi_1 is\ real\ and\ \varphi_1 > |\varphi_2|$, $(iii)\ \mathrm{A} \to 0\ \ and\ (iv)\ [\mathrm{B} - \max(\varphi_2, 0)\ \mathrm{I}]\mathrm{A} \to 0$, where the $\to$ denotes the elementwise inequality operator. Note that these constraints do not place any a priori restrictions on the signs of the coefficients in the B matrix. In particular, these constraints imply that negative volatility spillovers are possible. When the conditional correlations are constant, the model reduces to the UECCC-GARCH(1,1) specification of Conrad and Karanasos (2010).

Moreover, we also amend the UECCC-GARCH(1,1) model by allowing shock and volatility spillovers to vary across positive and negative returns:

$$h_t = \omega + A^* \varepsilon_{t-1}^{\wedge 2} + \mathrm{B}^* h_{t-1}$$

Where $A^* = \mathrm{A} + \Gamma S_{t-1} + A^- D_{t-1}^-$ and $\mathrm{B}^* = \mathrm{B} + \mathrm{B}^+ D_{t-1}^+$; $A^-(\mathrm{B}^+)$ is a cross diagonal matrix with nonzero elements $\alpha_{ij}^-(\beta_{ij}^+), i, j = 1,2, i \neq j$; $D_t^-(D_t^+)$ is a diagonal matrix with elements $d_{it}^-(d_{it}^+), i = 1,2,$ where $d_{it}^-(d_{it}^+)$ $is\ one\ if\ r_{it} < 0\ (r_{it} > 0)\ and\ zero\ otherwise.$

The quasi-maximum likelihood method of Bollerslev and Wooldridge (1992) is used in the estimation of the above univariate and bivariate specifications[7]. Finally, we check the standardized residuals and their squares to determine, respectively, the adequacy of the conditional means and the conditional variances in these specifications to capture their associated dynamics.

The estimation of these models was implemented in RATS 8.1 with a convergence criterion of 0.00001.

4.6 Empirical Results

In this Section we condition our analysis based on the breaks that we have identified to discuss first the findings from the univariate modelling and then from the bivariate modelling.

4.6.1 Univariate Results

The quasi-maximum likelihood estimates of the AGARCH(1,1) model for copper and gold returns using mapped and unmapped data are displayed in Table 2. We allow the 'unconditional variance' (as well as the ARCH and GARCH parameters to switch across the breaks as in eq. (2). The estimated models, at the 5% level, appear to be well-defined, there is no evidence of further linear or nonlinear dynamics to be captured. In a broad sense, the results seem not to be dissimilar with regard to the type of data used, mapped or unmapped. Margaronis et al. (2014) found that small rolls or basis prove to yield similar time series for mapped and unmapped data sets. The differences in the results may be due to the explanations expressed in this chapter whereby small compensations required over time to map data sets can accumulate to, and result in, large cumulative changes in the time series. The unmapped data are likely to include artificial 'price jumps' when contract roll over occurs, which are of course reflected in the returns. Furthermore, while copper returns are shown to exhibit asymmetric responses regardless of using mapped or unmapped data, this is not the case for gold returns (the insignificant parameters are excluded). This finding is consistent with that of Hammoudeh and Yuan (2008) using the EGARCH model over the period January 1990 to May 2006.

As far as the impact of the breaks is concerned, the results suggest that the 'unconditional variance' (the ω's) for both types of metals is not significantly accepted by the breaks. However, the dynamics of the conditional variances especially the ARCH (α) and GARCH (β) parameters are shown to be time varying, in line with Vivian and Wohar (2012) who used spot price data. That is, the ARCH parameter in copper returns becomes significant after the first break (September 29, 2008) (see the α_1 coefficients), whilst this parameter in the case of gold returns decreases after the second break (March 10, 2009) (α_2 is significant at the 1% level). With regard to the GARCH parameter, it exhibits time varying pattern across the second (June 25, 2009), third (September 09, 2011) and fourth (November 03, 2011) break for copper returns and across the first (July 22, 2008), third (June 13, 2011), and fourth (August 10, 2011) break for gold returns (see the β_ι coefficients in Table 2). Moreover, as is evident from Table 3, the time variation of the ARCH and GARCH parameters is also observed by allowing the dynamics of a GARCH (1, 1) process to switch across positive and negative metal futures returns (see the α^- and β^- coefficients).

Table 4 reports the persistence of the conditional variances of the two types of metal futures returns. It is evident that both returns show time varying persistence in their corresponding conditional variances irrespective of whether mapped and unmapped data are used. In particular, the persistence of the conditional variance of copper returns increases from 0:95 to 0:98 over the financial market uncertainty created as a result of the rejection of the $700bn US banking sector rescue plan in the US. Nonetheless, such persistence declines to 0:93 over the TARP rescue funds and then increases to 0:99 over the period followed the downgrade of the US sovereign debt status before falling back to 0:93 over the break in late 2011. With regard to gold returns, the persistence of its corresponding conditional variance exhibits a similar pattern. It increases from 0:94 to 0:97 over the period of high uncertainty identified by the first break (July 22, 2008), then it declines to 0:91 over the capital purchase program by the US Treasury Department. However, after the European sovereign-debt crisis there is an increase in the persistence to unity before it declines to 0:94 over the downgrade of the US sovereign debt status.

Table 5, by contrast, reports the time varying pattern of the persistence of the conditional variances by allowing the GARCH (1, 1) process to switch across positive and negative futures returns. The results suggest that the persistence of the conditional variances originating from negative returns is higher than those of the positive counterparts, especially for copper returns, using mapped and unmapped data. In particular, negative returns are shown to increase the persistence of the conditional variances from 0:91 and 0:97 to around 0:98 and 0:99 for copper and gold returns, respectively.

It is clear that the persistence of the conditional variances increases during periods of high volatility compared with low volatility. That is, such persistence of both metals responds to common factor such as events induced high uncertainty in financial markets, even though the identified break points for each return series have slight differences in timing which can be explained of how quick these metals react to such events. In a broad sense, our result of the time-varying persistence of the conditional volatility corroborates the findings of Watkins and McAleer (2008) and Choi and Hammoudeh (2010) who used rolling AR(1)-GARCH and Markov-switching specifications, respectively. However, the finding is not consistent with that of Sensoy (2013), who concluded that gold volatility was not accepted by the turbulent year 2008 using spot price data.[8]

[8] In a related vein, Ewing and Malik (2010) observed a stronger reduction in the ppersistence of oil returns volatility once structural breaks are accounted for.

4.6.2 Bivariate Results

We also apply the bivariate UEDCC-AGARCH(1; 1) time varying model to estimate the shock and volatility spillovers structure between copper and gold returns using two types of data, mapped and unmapped. The results, reported in Table 6, provide evidence of strong conditional heteroskedasticty in the two variables, irrespective of using unmapped (left panel) or mapped (right panel) data. The ARCH parameters (α_{11} and α_{22}) are positive and significant. Copper returns exhibit asymmetric responses (the estimated γ_{11} coefficient is positive and highly significant). However, this is not the case for those of gold. These results are in line with those of the univariate ones. Furthermore, the results suggest the existence of bidirectional volatility spillovers between copper and gold returns. Specifically, it is shown that volatility of gold returns affects that of copper returns positively (the estimated β_{12} coefficient is positive and significant at the 10% significance level), whilst the negative sign holds in the reverse direction (the estimated β_{21} coefficient negative and significant at the 10% significance level).[9] The negative volatility spillovers from copper to gold implies that volatility innovations in copper affect gold but they have a less persistent effect than the volatility innovations from gold itself (see Conrad and Weber, 2013).[10]

With regard to the impact of the breaks on the volatility transmission structure between the two returns, the results indicate that there are shifts in the volatility spillovers from gold to copper after the third (June 13, 2011) and the fourth (August 10, 2011) break (see the estimated coefficient β and β), regardless of using mapped or unmapped data. These two shifts correspond to the European sovereign- debt crisis and the downgrade of the US government debt status, respectively.

In other words, the results suggest that the volatility spillovers effect from gold to copper is sensitive to 'structural changes' in which such positive spillovers are shown to have diminished on the onset of the European sovereign debt crisis.

[9] Similar results hold for the conventional (without breaks) model as well (see Table C.5 in the additional Appendix).

[10] The estimation of volatility impulse responses is left for future research.

In particular, for the mapped returns this positive impact has weakened in the period after the sovereign debt crisis and before the downgrade of the US government debt status. Interestingly, for this period for the unmapped returns the effect has turned to be negative. It is clear that the two events can filter through the financial system and impact on the way commodities such as gold and copper behave. The mechanism by which this happens has been detailed elsewhere in this chapter.

Evidently, gold and copper volatility spillovers vary as structural breaks occur. The stabilization of the crisis over the years induced confidence in the world economies. The behaviour of the world economy has a direct impact on commodity markets and the structural breaks seen during this time of turmoil along with the findings of Mensi et al. (2013) support this. This is also complemented by the work of Cochran et al. (2010) where the analysis of the spot metal market and the VIX show similar mechanisms and impacts as this chapter does. The study by Batten et al. (2010), by contrast, showed how influential macroeconomic factors can be on the price behaviour of gold. Batten et al. (2010) also looked into the volatility feedback between precious metals and they found good supporting evidence of its existence. Although not entirely in the scope of this study, the existence of metals volatility spills from one metal to another is reassuring for the findings of this chapter.

Figure 2 shows the evolution of the time varying conditional correlations between the two types of metal futures returns over the sample period. As is evident from Figure 1, the time varying correlations between both returns are shown to be similar using mapped and unmapped data. Furthermore, Tse's (2000) test statistic of the null hypothesis H_0: $\alpha^{DCC} = \beta^{DCC} = 0$ are 0.400 (with p-value of 0.527) and 0.315 (with p-value of 0.574) for unmapped and mapped data, respectively. These test statistics do not reject the constant conditional correlations between the two returns using the two types of data, even though the correlations between the two variables are shown to exhibit transitory shifts over the Lehman Brothers collapse and the phases of the European sovereign-debt crisis.[11]

Finally, the results of the regime dependent volatility spillovers between the two metal futures returns, reported in Table 7, suggest that declines in copper prices generate positive volatility spillovers to gold, using mapped and unmapped data (the estimated coefficient is positive and significant at the 5% level). This result indicates that negative shocks to copper result in an increase in the volatility of gold.

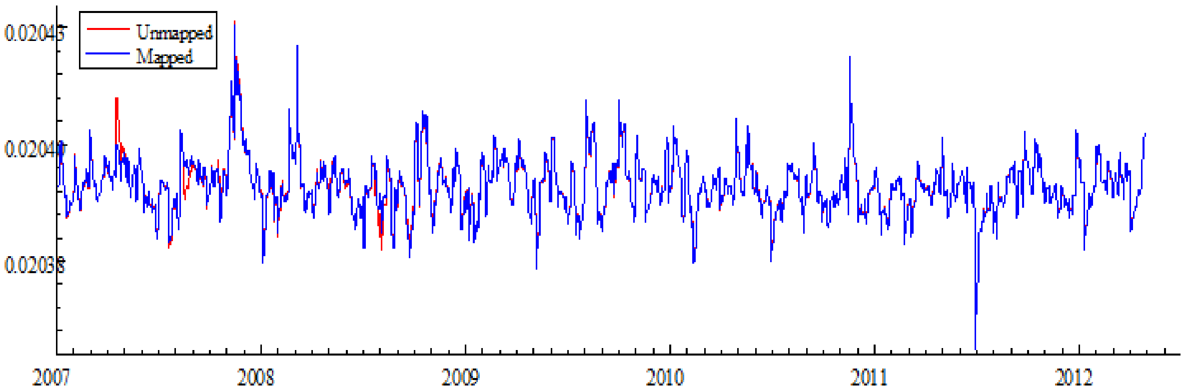

Figure 4.2. Evolution of the dynamic conditional correlation between mapped and unmapped copper and gold returns.

[11] The results (available upon request) of the volatility spillovers were shown to be robust by using the UECCC- AGARCH(1,1) specification.

4.7 Discussion

The conditional variances equations were used to observe cross-volatility effects. From the unmapped data results it is clear that there are bidirectional volatility spillovers between the two metals, where the conditional variance of copper affects gold volatility negatively whereas the effect in the opposite direction is positive. This means that when the price of copper exhibits greater volatility the price of gold becomes more stable and its volatility falls. This is in line with the differences in the demand characteristics between the two metals, explained previously.

During times of financial turmoil, where uncertainty lingers and individuals and organisations tie their capital up in gold as a reserve currency, the price of gold is suddenly influenced more by all the new demand. Rather than trading gold to make pro...t on its price changes, people are suddenly inclined to buy gold and keep it until there is confidence and stability in the economies of the world. Also, the fact that gold is a precious metal and copper is a base, industrial metal suggests that their price fluctuations will differ simply because of the differences in uses and therefore demand and demand characteristics.

This can also be understood by considering the products based on each of the metals. Products based on copper are generally less dear and are replaced with new ones at a much greater rate, which is not the case for products containing gold or made of gold. Since copper prices depend significantly on the state of the Australian mining sector, Chinese and South-East Asian demand and the demand of large world economies, the volatility exhibited can be due to uncertainties in these.

The positive spillovers from the conditional variance of gold to that of copper are consistent with the sheer volume and significance of gold in the world economy. Induced volatility in gold prices will almost certainly influence a wide range of world economic factors. With gold being a reserve currency, a increase in the volatility of gold implies an increased uncertainty in world economies. Copper, being the main industrial metal, is therefore hugely impacted by such uncertainty as industrial demand is based on economic and business confidence worldwide, hence the connection can be made. Uncertainty in such factors does not usually occur when economies are booming. In the case of the gold price, however, the opposite effect is seen due to its establishment as a reserve currency and its non-consumable nature. This could therefore explain the inverse relationship observed in the cross-volatility effects. The use of gold as a hedging tool in times of financial turmoil common and is supported by Beckmann et al. (2014) and Wang and Lee (2011) among others, while the findings by Sensoy (2013) show gold having uni-directional volatility shift contagion on all precious metals. Sensoy (2013) supports the premise that precious metals are used in times of financial turmoil to hedge and diversify portfolios and as alternative investment vehicles.

In the case of the mapped data results the same bidirectional volatility spillovers occur between copper returns and gold returns as was seen in the analysis of unmapped returns. That is, the conditional variance of copper affects gold volatility negatively, while the reverse effect is of the opposite sign. This is consistent with the links between the two metals in terms of their monetary value through foreign exchange rates. It is clear that while the two metals have, for the most part, very different applications, when a significant world event occurs impacting foreign exchange, volatility tends to be induced in most financial securities. However, given the relation of gold with foreign exchange as it is used as a reserve currency, it is clear that it may be accepted with lesser lag than an industrial metal such as copper.

4.8 Summary and Conclusions

In this chapter, we have analysed how the recent financial crisis accepted the principal time series properties of the underlying series of two metal futures: copper and gold. In particular, we have employed several univariate and multivariate models to examine how the volatility dynamics, including the volatility persistence and volatility spillovers structure of these two metal futures returns, have changed due to the recent financial crisis, and conditioned our analysis on non-parametrically identified breaks.

Our findings suggest that the volatility persistence of these metal futures returns exhibit substantial time variation over the recent financial crisis; in particular, such persistence is shown to increase during periods of high volatility compared with low volatility. This time variation appears consistent across metal futures returns and irrespective of whether we allow for positive and negative changes in the underlying asset. The estimation of the bivariate UEDCC-AGARCH (1; 1) model also shows that the volatility transmission from gold returns to those of copper shifted after the European sovereign-debt crisis and the downgrade of the US government debt status. Finally, the regime-dependent volatility spillovers analysis suggests that declines in copper prices induce positive volatility spillovers to gold returns.

From the results it may be concluded that there is indeed a systemic relationship between the two metals in spite of their very different applications and values. The volatilities of copper and gold are inherently linked, proved by the findings of the analyses carried out. The possible explanations for the findings have also been explored deeply, analysing the impacts of one market on the other and of course other factors, including the implications of the financial turmoil for these markets.

Due to the financial crisis, therefore, it is clear that there are significant factors that cause the prices of copper and those of gold to behave as they do and this may be explored in the context of other commodities too. The impact of the financial crisis on the other metals whose characteristics differ significantly by virtue of mixed demand characteristics and lower volumes may show that the metals sector has far more to offer in terms of these relationships. Further to this, the utilisation and comparison of mapped and unmapped time series show how results can differ and this may prove to be far more important as conducted by Margaronis et al. (2015) for the other commodities whose basis can be far more significant.

Table 4.1

Breakpoints ‘dates in copper and gold returns		
Break	Copper	Gold
1	29=9=2008	22=7=2008
2	25=6=2009	10=3=2009
3	09=9=2011	13=6=2011
4	03=11=2011	10=8=2011

Table 4.2

The estimated univariate AGARCH (1,1) models allowing for breaks in the conditional variance

	Unmapped		Mapped	
	Copper	Gold	Copper	Gold
μ	0:063	0:088[a]	0:056	0:085[a]
	(0:047)	(0:026)	(0:050)	(0:023)
ω	0:181[a]	0:098[a]	0:196[a]	0:109[a]
	(0:062)	(0:031)	(0:062)	(0:026)
α		0:069[a]		0:074[a]
		(0:018)		(0:017)
α_1	0:025[b]		0:027[a]	
	(0:011)		(0:011)	
α_2		-0:066[a]		—0:069[a]
		(0:025)		(0:022)
β	0:921[a]	0:874[a]	0:918[a]	0:865[a]
	(0:019)	(0:034)	(0:018)	(0:032)
β_1		0:032[c]		0:038[c]
		(0:017)		(0:020)
β_2	-0:046[a]		-0:043[a]	
	(0:016)		(0:014)	
β_3	0:056[b]	0:109[a]	0:055[b]	0:108[a]
	0:025)	(0:028)	(0:025)	(0:023)
β_4	-0:059[b]	-0:077[a]	—0:054[b]	-0:076[a]
	(0:028)	(0:019)	(0:027)	(0:018)
γ	0:070[a]		0:072[a]	
	(0:017)		(0:017)	

LogL	—2924:8	—2268:9	—2994:5	—2319:5
LB(5)	8:369	3:789	8:086	4:006
	[0:137]	[0:580]	[0:151]	[0:548]
LB^2 (5)	1:543	2:308	1:699	2:093
	[0:908]	[0:805]	[0:889]	[0:836]

Notes: Robust-standard errors are used in parentheses. LB(5) and LB^2 (5) are Ljung–Box tests for serial correlations of five lags on the standardized and squared standardized residuals, respectively (p-values are reported in brackets).

α_1 and β_1 indicate the estimated parameters of the break dummies where the break $l = 1; ::; 4$ (see Table 1). Insignificant parameters are excluded. [a]; [b] and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.3

The estimated univariate GARCH (1, 1) models allowing for switching across positive and negative returns:

$$h_t = \omega + \omega^- D^-_{t-1} + \alpha\varepsilon^2_{t-1} + \alpha^- D^-_{t-1}\varepsilon^2_{t-1} + \beta h_{t-1} + \beta^- D^-_{t-1} h_{t-1}$$

	Unmapped		Mapped	
	Copper	Gold	Copper	Gold
ω	0:034	0:076[b]	0:024	0:071[b]
	(0:048)	(0:030)	(0:050)	(0:030)
ω^-	0:077[a]	0:026[a]	0:088[a]	0:027[a]
	(0:011)	(0:007)	(0:013)	(0:008)
α	0:020[b]	0:072[a]	0:019[b]	0:073[a]
	(0:008)	(0:013)	(0:008)	(0:003)
α^-	0:056[a]	0:056[a]	0:060[a]	0:055[a]
	(0:009)	(0:018)	(0:010)	(0:010)
β	0:891[a]	0:900[a]	0:887[a]	0:900[a]
	(0:002)	(0:004)	(0:002)	(0:006)
β^-	0:090[a]	0:095[a]	0:097[a]	0:093[a]
	(0:011)	(0:014)	(0:009)	(0:002)
LogL	-2929.75	-2277.09	-2998.67	-2327.98
LB(5)	8.688[a]	3.608[a]	8.724[a]	3.788[a]
	(0:122)	(0:607)	(0:120)	(3.788)
LB(5)	1.404[a]	0.558[a]	1.131[a]	0.451[a]
	(0:923)	(0:989)	(0:951)	(0.993)

Notes: Robust-standard errors are used in parentheses. LB(5) and LB^2 (5) are Ljung-Box tests for serial correlation of five lags on the standardized and squared standardized residuals, respectively (p-values are reported in brackets).

[a] and [b] indicate significance at the 1% and 5% levels, respectively.

Table 4.4

The persistence of the AGARCH (1,1) models for copper and gold returns

Panel A. The persistence of the standard (without breaks) AGARCH (1, 1) models

Unmapped		Mapped	
Copper	Gold	Copper	Gold
0:982	0:988	0:981	0:988

Panel B. The persistence of the AGARCH (1, 1) models allowing for breaks in the conditional variance

	Unmapped		Mapped	
0	0:956	0:943	0:954	0:939
1	0:981	0:975	0:981	0:977
2	0:935	0:909	0:938	0:908
3	0:991	1:018	0:993	1:016
4	0:932	0:941	0:939	0:940

Notes: Break 0 covers the pperiod preceding all breaks, while break 1 covers the pperiod bbetween breaks 1 and 2, and break 2 covers the period bbetween breaks 2 and 3, and so on (see Table 1 for the dates of the breaks).

Table 4.5

The persistence of the GARCH (1, 1) models allowing for switching across positive and negative returns

	Unmapped		Mapped	
Returns	Copper	Gold	Copper	Gold
r^+	0:911	0:972	0:906	0:973
r^-	0:984	0:991	0:984	0:992

Notes: $r^+(r^-)$ indicates the persistence of the conditional variance generated from positive (negative) returns. The ppersistence of the p positive returns is calculated as $\alpha+\beta$, while that of the negative returns is calculated as

$$\alpha+\beta+\left(\frac{\alpha^-+\beta^-}{2}\right)$$

Table 4.6

Coefficient estimates of bivariate UEDCC-AGARCH models allowing for shifts in shock and volatility spillovers between copper and gold returns

Unmapped				Mapped			
Conditional Mean Equation							
μ_1	0:060	μ_2	0:075[b]	μ_1	0:052	μ_2	0:072[a]
	(0:042)		(0:029)		(0:047)		(0:027)
Conditional Variance Equation							
ω_1	0:017	β_{12}	0:059[b]	ω_1	0:025	β_{12}	0:060[c]
	(0:036)		(0:029)		(0:037)		(0:026)
ω_2	0:017[b]	β^3_{12}	-0:085[c]	ω_2	0:019[a]	β^3_{12}	-0:051[c]
	(0:007)		(0:050)		(0:009)		(0:030)
α_{11}	0:016[c]	β_{21}^4	0:071[c]	α_{11}	0:016[c]	β^4_{12}	0:071[c]
	(0:008)		(0:038)		(0:009)		(0:040)
α_{22}	0:038[a]	β_{21}	-0:003[c]	α_{22}	0:038[a]	β_{21}	-0:003[c]
	(0:009)		(0:002)		(0:011)		(0:002)
β_{11}	0:929[a]	α^{DCC}	0:010	β_{11}	0:925[a]	α^{DCC}	0:010
	(0:025)		(0:007)		(0:021)		(0:007)
β_{22}	0:960[a]	β^{DCC}	0:906[a]	β_{22}	0:961[a]	β^{DCC}	0:914[a]
	(0:011)		(0:066)		(0:015)		(0:077)

γ_{11}	0.067^{a}			γ_{11}	0.071^{a}		
	(0.024)				(0.022)		
LogL	-5208.3			LogL	-5327.5		
$LB(5)_{Cop}$	9.055	$LB(5)_{Gol}$	3.223	$LB(5)_{Cop}$	3.910	$LB(5)_{Gol}$	3.702
	[0.106]		[0.665]		[0.562]		[0.593]
$LB(5)^2_{Cop}$	0.431	$LB^2(5)_{Gol}$	0.298	$LB(5)^2_{Cop}$	5.972	$LB^2(5)_{Gol}$	3.823
	[0.994]		[0.997]		[0.309]		[0.575]

Notes: Robust-standard errors are used in parentheses, 1= copper, 2=gold. $LB(5)$ and $LB^2(5)$ are Ljung-Box tests for serial correlation of five lags on the standardized and squared standardized residuals, respectively (p-values are reported in brackets). α_{12} (β_{12}) indicates shock (volatility) spillovers from gold to copper, whilst α_{21} (β_{21}) indicates shock (volatility) spillovers in the reverse direction. α^{1}_{12} (β^{1}_{12}) indicates the shift in shock (volatility) spillovers for the break 1 (see Table 1) from gold to copper. Insignificant parameters are excluded.

[a], [b] and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.7

Coefficient estimates of bivariate UEDCC-AGARCH models allowing for different spillovers across positive and negative returns in copper and gold

	Unmapped				Mapped		
			Conditional Mean Equation				
μ_1	0:050	μ_2	0:085[b]	μ_1	0:053	μ_2	0:082[a]
	(0:038)		(0:033)		(0:049)		(0:028)
			Conditional Variance Equation				
ω_1	0:020	γ_{11}	0:073[a]	ω_1	0:023	γ_{11}	0:073[a]
	(0:029)		(0:022)		(0:035)		(0:022)
ω_2	0:039[b]	β_{12}	0:038[b]	ω_2	0:033[a]	β_{12}	0:068[b]
	(0:016)		(0:018)		(0:010)		(0:032)
α_{11}	0:016[c]	β_{21}	-0:017[a]	α_{11}	0:017[c]	β_{21}	-0:018[a]
	(0:009)		(0:005)		(0:010)		(0:005)
α_{22}	0:049[a]	β^{-}_{21}	0:036[a]	α_{22}	0:030[a]	β^{-}_{21}	0:030[b]
	(0:010)		(0:012)		(0:008)		(0:011)
β_{11}	0:931[a]	α^{DCC}	0:006	β_{11}	0:914[a]	α^{DCC}	0:011
	(0:021)		(0:010)		(0:020)		(0:007)
β_{22}	0:929[a]	β^{DCC}	0:792[a]	β_{22}	0:962[a]	β^{DCC}	0:911[a]
	(0:018)		(0:129)		(0:013)		(0:071)
LogL	-5198:2			LogL	-5324:7		
$LB(5)_{Cop}$	8:900	$LB(5)_{Gol}$	4:057	$LB(5)_{Cop}$	8:657	$LB(5)_{Gol}$	3:378
	[0:113]		[0:541]		[0:123]		[0:641]
$LB(5)^2_{Cop}$	0:418	$LB^2(5)_{Gol}$	1:067	$LB(5)^2_{Cop}$	1:292	$LB^2(5)_{Gol}$	0:092
	[0:994]		[0:957]		[0:935]		[0:999]

Notes: Robust-standard errors are used in parentheses, 1= copper, 2=gold. $LB(5)$ and $LB^2(5)$ are Ljung-Box tests for serial correlation of five lags on the standardized and squared standardized residuals, respectively (p-values are reported in brackets). α_{12} (β_{12}) indicates shock (volatility) spillovers from gold to copper, whilst α_{21} (β_{21}) indicate shock (volatility) spillovers in the reverse direction. β^{-}_{21} reports the shift in volatility spillovers from copper to gold (Induced by negative copper returns). Insignificant parameters are excluded. [a], [b] and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

Chapter 5: Time-Varying analysis including Volatility Spillovers for Commodity Futures Metals

Chapter 5 is joint work with M.G. Karanasos, F.M. Ali & P.D. Koutroumpis 'Time-Varying analysis including Volatility Spillovers for Commodity Futures Metals'. M.G. Karanasos, F.M. Ali & P.D. Koutroumpis helped in the model specification and contributed to the interpretation of the results with a combined contribution of 20% to the chapter (approx. 7% each).

The remaining contributions are by Z.N.P. Margaronis for significant contribution (80%) in data-collection, data processing, data analysis, results & discussion and write-up throughout the Chapter.

Keywords: commodity, metals, futures, mapped, unmapped, rollover, spillover, volatility, bivariate, univariate, bidirectional

5.1 Introduction

This study considers the mapped and unmapped time series as defined by Margaronis et al. (2011), for the metals commodities. The methodology applied in Chapter 4 is reapplied to larger range of metals including Gold, Copper, Silver and Platinum. The metals considered include both industrial and precious metals and the aim is to ascertain the cross effects which exist between the various metals and how these cross effects change as the mapped data is considered as opposed to the unmapped data. This is especially interesting because of the large application of metals commodities, both as consumables in an industrial application and precious application, but also as reserve currencies, in hedging financial positions and as sentimentally traded financial securities.

This study will look into the mean cross effects, ARCH spillovers and volatility spillovers for both mapped and unmapped data sets in order to give a complete overview of the metals' interactions throughout the five year, daily data time series [PX_LAST Bloomberg] starting from January 2007.

By considering four different metals, it is clear that there will be a more holistic view of the metals sector and this is especially interesting because we know from Margaronis et al. (2011) that the metals sector has the smallest associated rolls or basis. Hence if we see differences in results between mapped and unmapped data within the metals sector, we can probably expect to see an even more significant difference between the mapped and unmapped relationships of the other commodities.

We expect to see various relationships within the metals sector due to their similarities in use. We also expect to see some effects due to the world economy and its demand in one metal spilling over to another. This is obvious for some metals such as Gold, Silver and Platinum which are all used in everyday jewels. However, there are some less obvious relationships which may exist such as that between Copper and Platinum. Although Platinum is a precious metal, it has a large industrial use in catalytic converters in vehicles so we can expect to see some kind of relationship between Copper and Platinum due to their industrial demand which although different, may go hand-in-hand. These are just a handful of relationships we expect to see but may not actually surface from the analysis and it seems this is also an unexplored area as regards the literature.

5.2 Literature Review

Wang et al. (2010) examine the effectiveness of gold as a hedging tool in the US and Japan, especially during the financial crisis (as a tool against sudden inflation). There has been a large movement into these metals markets, with ETFs and other commodities trading organizations driving this movement especially since the dawn of the financial crisis. Having said this, the analyses available within the metals market of commodities are not substantial although the few analyses that have been carried out are marginally relevant. They detail various aspects of the market including causalities that exist between precious metals and of course causalities stemming from other factors, namely stock markets, which influence metals price behaviour.

This section will review the current studies which are available relating to the metals within the commodities sector.

Mensi et al. (2013) findings support the phenomenon that decreased confidence in the world economy leads to underperformance of stock markets, by looking primarily at the S&P 500. This in turn induces volatility in the metals markets, specifically the precious metals as people turn to them as reserve currencies during times of financial turmoil. Mensi et al. (2013) findings can therefore be considered to support the phenomenon that precious metals markets and industrial metals markets are linked. This may be linked to the findings by Batten et al. (2010) who indicate that gold prices are greatly influenced by macroeconomic variables, specifically monetary variables, which in turn are known to be used as a tool in governing economic growth. Batten et al. (2010) also look closely at the precious metals market including the financial crisis, showing volatility feedback between the precious metals. This is particularly interesting as there are certainly logical mechanisms linking the precious metals due to their substitutability in application and scarcity.

Beckmann et al. (2014) and Wang et al. (2010) support each other in their findings and the initial premise that gold is traditionally used as a hedging tool in portfolios to protect investors against sudden movements in stock prices. This is advantageous as it shows a number of sources agreeing on the same phenomenon which is closely linked to the findings of this chapter.

Smiech et al. (2012) study the causality between metals and find there to be a driving force of causality by copper and later platinum, whereas silver and gold were found to not be the Granger causes. Primarily, Smiech et al. (2012) acknowledge that their approach of using monthly metal prices will yield different findings to one where higher frequency data are considered which is the case for our study. It is of great interest however, that an analysis considering the causalities within the metals market yields results showing significant causal effects between metals during the crisis.

Cochran et al. (2010) also delve into the metals market specifically but utlise spot prices to show how the VIX (implied volatility of the equity market) influences the metals’ returns significantly. Specifically, copper is found to have an indirect relationship with the VIX while other metals are found to have a direct relationship. It is nonetheless hugely important to show that once again, metals prices are influenced not only by each other but by the volatility of the equity markets just as Mensi et al. (2013) suggest.

A major consideration when considering commodities futures is taking account roll or basis when contract expiry nears. In order to create a real life time series, it is important to roll on specific days in order to be trading the active contract whose liquidity and hence volume is greatest. It has been discovered that taking into account the roll can significantly change the time series since these accumulation of roll values can be significant in the commodities considered (Margaronis et al. 2011)

In one paper Hammoudeh et al. (2011) focus on the volatility dynamics in precious metals while also looking into the risk management implications too. Hammoudeh et al. (2011) discover that during the financial crisis in 2008, there is a very high variance and this complements the breaks discovered in this study. The premise that market participants invested in precious metals heavily during this time which suggests why this break occurs. The general conclusion is that during the initial years of their sample, Hammoudeh et al. (2011) find that there is low volatility of returns. This changes as the financial crisis occurs and higher volatilities are experienced causing VaR estimates to diverge. In another paper, Hammoudeh et al. (2010) examine the correlation dependency and interdependency of the precious metals. There seem to be significant short run and long run interdependencies between the precious metals and this is a relationship that becomes stronger when exchange rates are included in the analysis. This is also true of monetary policy effects. As a result, it is clear that the metals behaviour is dependent on news as well as the other metals behaviour. There is also a spill over onto exchange rates from the metals which is interesting given our findings whose explanations are based on this theory.

The purpose of this chapter is to investigate the relationship between the four metals and the impact of considering mapped and unmapped data sets, where we believe there is a significant void in the literature.

5.3 Bivariate Models

5.3.1 Mean Cross Effects

Information criteria and likelihood ratio tests choose the specification with the bidirectional feedback between platinum and either silver or gold returns. As seen in Table 1, when the unmapped data are used (not accounting for roll/basis), there is a mixed bidirectional link between platinum and gold/silver returns. In particular, gold/silver returns affect platinum returns positively [see also entrances in cells 2,3 (second row, third column) and 2,4 of the summary Table 5 below] whereas the reverse effects are of the opposite sign (see also the entries in cells 3,2 and 4,2 of the summary Table). However, the feedback disappears when the mapped data are used. Moreover, the returns of gold have a positive impact on copper returns for both data sets.

5.3.2 Error Correction

As seen in Table 2 Platinum returns have a long run impact on both copper and silver returns. The latter effect disappears when the mapped data are used.

5.4 Spillovers

5.4.1 ARCH Spillovers

There are bidirectional ARCH spillovers between platinum and gold unmapped returns. Moreover, there are unidirectional ARCH cross effects from platinum unmapped returns to those of copper (see Table 3). However, these cross effects disappear for the mapped data. In addition, there are cross ARCH effects from silver unmapped returns to both copper and gold returns. The latter effects disappear when the mapped data are used.

5.4.2 Volatility Spillovers

The results in Table 4 suggest the existence of mixed bidirectional volatility spillovers between copper and gold returns for both mapped and unmapped data. Specifically, it is shown that the volatility of gold returns affect that of copper returns positively (the estimated β_{12} coefficient is positive and significant at the 1% significance level; see also the entries in cell 1,3 of the summary Table below), whilst the negative sign holds in the reverse direction (the estimated coefficient β_{21} is negative and significant at the 10% significance level; see also cell 3,1 of the summary Table). The negative volatility spillovers from copper to gold implies that volatility innovations in copper affect gold but they have a less persistent effect than the volatility innovations from gold itself (see Conrad and Weber, 2013). However, there are no cross effects between copper and gold returns (see Table 1 above).

The empirical evidence also suggests that there is a causal negative effect from the volatilities of platinum and silver returns to the volatility of gold re- turns at the 5% and

1% significance levels, respectively (see also the entries in cells 3,2 and 3,4 of the summary Table). The former impact disappears when the mapped data are used. Interestingly, the volatilities of platinum and silver returns (either mapped or unmapped) are independent of changes in the volatilities of the other two returns.

5.5 Summary

Table 5.1. Bivariate Models: Return (Re), Volatility (Vo) spillovers and Error Correction (Er) effects.

	C	P	G	S
C	x	Er_M: -	Vo_M : +	
P		x	Re: +	Re: +
G	Vo_M: -	Re:- ; Vo:-	x	Vo_M:-
S		Re:-; Er:-	Re_M : +	x

Note: C, P, G and S denote Copper, Platinum, and Gold and Silver respectively The variables in each column are the independent variables.

(+): the effect is negative (positive)

The subscript M indicates that the effect holds for the mapped data as well.

According to the first column of the summary table 5 the returns of copper does not affect the other three returns. The volatility of copper returns has a negative effect on that of gold (see cell 3,1 of the summary table) whereas the volatilities of silver and platinum are independent of changes in the volatility of copper.

Platinum returns affect the three other returns negatively (see the second column). They have a short-run effect on gold returns, a long-run one on copper returns and both a short and long-run effect on silver returns (for the latter effect see cell 4,2). The volatility of platinum returns affects (negatively) only that of gold returns (see cell 3, 2) but not the other two volatilities.

As seen in the third column gold returns have a positive effect on platinum and silver returns (see cells 2, 3 and 4, 3 respectively). Similarly, the volatilities of gold returns affect those of copper returns positively (see cell 1, 3).

Silver returns affect positively the returns on platinum (see cell 2,4 in the fourth column) whereas their volatility has a negative effect on the volatility of gold returns (see cell 3,4). Copper returns are independent of changes in the returns (and their volatility) of silver.

5.6 Discussion

5.6.1 Bidirectional Effects

Copper returns and their volatility are not affected by changes in silver returns and volatilities and vice versa. Copper returns (in the short-run) and their volatility are independent of changes in platinum returns and their volatilities.

There is a mixed bidirectional link between platinum and gold returns. Platinum returns affect gold returns negatively (see cell 3, 2 in Table 5a below) while the positive sign holds in the opposite direction (see cell 2,3). In other words, the mean equation for unmapped time-series shows there is bidirectional causality evident between gold returns and platinum returns where gold returns affect platinum returns positively and the negative sign holds in the opposite direction. The mixed bidirectional causality could be explained by the liquidity difference between the two metals as gold is far more popular (and traded in higher volumes). It will also naturally exhibit higher volatility as it is exposed on more demand fronts than platinum. The increased volatility, liquidity and use as a reserve currency mean that gold prices will react to the market with little or no lag time. On the other hand, platinum, with its much larger demand for industrial applications (catalytic converters) gives this particular metal a very different demand characteristic. Lower liquidities mean there will be a lag between the time of an event and the actual impact on the price which could explain the bidirectional causality found in the analysis.

In a similar way, from the unmapped results of the mean equation, silver returns were seen to affect platinum returns positively while the negative effect holds in the opposite direction (platinum to silver), (see cells 2,4 and 4,2 respectively). In sharp contrast, there is no volatility link between the returns of platinum and silver.

The bivariate conditional variance equations were used to observe cross volatility effects. From the unmapped results it is clear that there are bidirectional volatility spillovers between copper and gold returns where gold volatility affects that of copper positively (see cell 1,3 in Table 5a) and the negative sign holds in the opposite direction (see cell 3,1). This might be explained by the following mechanisms.

The fact that gold is a precious metal and copper is a base, industrial metal suggests the price fluctuations will differ simply because of the differences in uses and therefore demand and demand characteristic. This can also be understood by considering the products based on each of the metals. Products based on copper are generally less dear and are replaced with new ones at a much greater rate which is not the case for products containing gold or made of gold. Since copper prices depend significantly on the state of the Australian mining sector, Chinese and South-East Asian demand and the demand of large world economies, the volatility exhibited can be due to uncertainties in these. During times of financial turmoil, where uncertainty lingers and individuals and organisations tie their capital up into gold as a reserve currency, the price of gold is suddenly influenced more by all the new demand. Rather than trade gold to make profit on its price changes, people are suddenly inclined to buy gold and keep it until there is confidence and stability in the economies of the world.

Gold may influence copper volatility positively due to the sheer volume and significance of gold in the world economy. Induced volatility in gold prices will almost certainly influence a wide range of world economic factors. With gold being a reserve currency, volatility increases in gold show uncertainty in world economies. Copper being the main industrial metal in therefore hugely impacted by such volatility as industrial demand is based on economic and business confidence worldwide, hence the connection can be made. Uncertainty in such factors does not usually occur when economies are booming. In the case of the gold price however, the opposite effect is seen due to its establishment as a reserve currency and its non-consumable nature. This might therefore explain the inverse relationship observed (that is, the negative cross volatility effect from copper to gold returns).

In the case of the mapped returns there is also mixed bidirectional volatility spillovers between copper and gold returns, similar to those for the unmapped returns. This may be due to the links between the two metals in terms of their monetary value through foreign exchange rates. While the two metals have, for the most part, very different applications, when a significant world event occurs impacting foreign exchange, volatility tends to be induced in most financial securities but given the relation of gold with foreign exchange as it is used as a reserve currency it may be affected with lesser lag than an industrial metal such as copper.

In other words, as with the case of the unmapped returns there are reasons to explain this mixed feedback in behaviour which include the fact that copper is a base, industrial metal as oppose to gold and platinum which are precious metals. That is, the mixed bidirectional volatility spillovers between copper and gold returns may also be explained by the fact that the metals are so different in their value and uses. Generally in times of financial turmoil the price of copper falls while the price of gold rises and vice versa for periods of growth.

Table 5.2. Bidirectional Effects

Bivariate Models and Unmapped Data: Return (Re), Volatility (Vo) spillovers

	C	P	G	S
C	x		Vo_M : +	
P		x	Re: +	Re: +
G	Vo_M:-	Re:- ;	x	
S		Re:- ;		x

Note: C, P, G and S denote Copper, Platinum, Gold and Silver respectively The variables in each column are the independent variables.

—(+): the effect is negative (positive)

The subscript M indicates that the effect holds for the mapped data as well.

5.6.2 Unidirectional Effects

There is a long-run causality from platinum returns to copper and silver returns (see cells 1,2 and 4,2 in Table 5b below). This might be explained by the industrial link and uses between these three metals. Platinum and copper are used heavily in industrial applications while platinum has the added demand characteristic of also being desirable as a precious metal. Given the use of platinum as a reserve currency as well it is clear that the platinum prices will 'react' to the markets faster. The efficiency of the platinum market is greater (Kristoufek et al. (2013)) with many participants participating with lower volumes compared to the copper market where there are fewer participants buying and selling large volumes. The causality from platinum to silver may be explained by the industrial applications of the metals however the added demand of platinum as a reserve currency could also be to blame.

In the case of mapped returns, the results indicate that platinum has a long run effect in copper (see cell 1, 2). The long run relationship observed between platinum and copper returns may be due to fact that both metals have significant industrial applications. Platinum, in the use of catalytic converters for vehicles and copper primarily in the use of wiring and electrical equipment. Another explanation could include the uses of platinum as a reserve currency. Increased demands for platinum as a reserve currency may arise from financial instability, which would in turn explain the decreased demand for copper as world demand falls (especially for consumer goods) in which copper is a major raw material. The long run causality from platinum to copper returns is consistent as with the unmapped results.

Gold returns have a positive effect on silver returns (see cell 4, 3 in Table 5b). The positive causality from gold to silver returns may be explained by the similarities of the two metals in their uses. This includes the standard uses of precious metals such as jewellery and of course other applications. Another link between these metals' demand characteristics is the fact that they may both be used as a reserve currency, although this is the case for gold far more than it is for silver. Silver is considered in these circumstances when gold is deemed to be too dear. In supply, both metals are mined and undergo similar processes but again, silver is more abundant, hence its significantly lower price.

For the mapped mean equation results, there was also positive causality from gold to silver returns (see cell 4,3). Given that both metals share a position as reserve currencies and as instruments to hedge currencies (Wang et al. (2010), and Beckmann et al. (2014)) this relationship might be expected. It is also evident that both are subject to similar demand characteristics (although to different degrees) as they are exposed to demand and supplies from mining, financial markets, commercial uses and industrial applications (these applications are much more prominent for platinum). Beckmann et al. (2014) support Wang et al. (2010) in their findings and the initial premise that gold is traditionally used as a hedging tool in portfolios to protect investors against sudden movements in stock prices. Even though this approach is market specific and the models used vary significantly from study to study, it is supported by the findings of Wang et al. (2010) and the results of our study also complement their findings.

The volatilities of platinum and silver returns affect negative that of gold returns (see cells 3, 2 and 3, 4 in Table 5b). That is, negative volatility spillovers also exist from platinum to gold, which as we analysed earlier are linked in more ways than one. Platinum as an industrial metal and due to its more absolute demand characteristic, its volatility may lead that of gold negatively. Platinum has a huge industrial application and as a result, is heavily subject to demand and supply shocks from a single source which can explain its volatility. Given platinum's links to gold in its uses, its volatility might (negatively) spill over into this market too, commercially and financially.

In the case of the negative spillovers from silver returns to gold returns, the phenomenon seen may simply be due to the lag associated with the markets. It was explained earlier that gold is considered a very efficient market (Kristoufek et al. 2013) with respect to number of buyers and sellers and volumes. This is true to a much lesser extent for silver and may be the overriding factor causing the negative volatility spillover in the results. Another factor that might cause this phenomenon may simply be the fact that gold is used in hedging and as a reserve currency. This may also be the case for silver, but to a far lesser extent.

Table 5.3. Unidirectional Effects Bivariate Models and Unmapped Data: Return (Re), Volatility (Vo) spillovers and Error Correction (Er) effects.

	C	P	G	S
C	x	Er_M :-		
P		x		
G		Vo:-	x	Vo_M : -
S		Er: -	Re_M : +	x

Note: C, P, G and S denote Copper, Platinum, Gold and Silver respectively The variables in each column are the independent variables.

—(+): the effect is negative (positive)

The subscript M indicates that the effect holds for the mapped data as well.

5.7 Conclusion

Much of the concluding remarks have been detailed in the discussion however the key findings of this chapter are that many of the relationships found, whether they were volatility spillovers, shock spillovers or mean effects, changed when unmapped and mapped data were employed. This shows that the transformation of the data and accounting for roll, even if roll or basis values are small (as they tend to be in the metals sector), has a significant enough impact on the data that relationships found with unmapped data, do not appear when the mapped data set is considered. It may therefore be concluded that the unmapped data and artificial price-jumps which exist within them, mislead the models into finding relationships which do not really exist in the real-life traded time series.

5.8 TABLES

Bivariate Metals:

Table 5.4. The estimated biavriate cross effects of the conditional mean (ϕ_{ij}).

	Unmapped				Mapped			
	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$
$R_{C,t}$						-0:075^{b}		
						(0:037)		
$R_{P,t}$			0:097^{a}	0:059^{a}				
			(0:031)	(0:014)				
$R_{G,t}$		-0:058^{b}						
		(0:023)						
$R_{S,t}$		-0:081^{b}	0:101^{a}				0:099^{a}	
		(0:040)	(0:027)				(0:028)	

Note: $R_{C,t}$, $R_{P,t}$, $R_{G,t}$; $R_{S,t}$ indicate copper, platinum, gold, and silver returns, respectively. The variables in each column are the independent variables, while those in each row are the dependent variables in the corresponding regression. For example, the coefficient in the row labelled $R_{G,t}$ and in the column labelled $R_{P,t}$ indicates the impact of the $R_{P,t}$ on $R_{G,t}$. Robust standard errors are reported in brackets.

^{a} and ^{b} indicate significance at the 1% and 5% levels, respectively.

Table 5.5. The estimated bivariate error correction terms in the conditional mean (λ_{ii}).

	Unmapped				Mapped			
	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$
$R_{C,t}$								
$R_{P,t}$	$-0{:}808^{a}$			$-0{:}289^{c}$	$-0{:}759^{a}$			
	(0:317)			(0:151)	(0:396)			
R_{Gt}								
$R_{S,t}$								

Note: $R_{C,t}$, $R_{P,t}$, $R_{G,t}$; $R_{S,t}$ indicate copper, platinum, gold, and silver returns, respectively. The variables in each column are the dependent variables in the corresponding regression. For example, the coefficient in the column labelled $R_{C,t}$ and in the row labelled $R_{P,t}$ indicates the adjustment of $R_{C,t}$ to $R_{P,t}$ when the system is shocked away from the equilibrium. Robust standard errors are reported in brackets.

[a] and [c] indicate significance at the 1% and 10% levels, respectively.

Table 5.6. The estimated bivariate cross effects of the conditional variance (α_{ij}).

	Unmapped				Mapped			
	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$
$R_{C,t}$		0:020 [a]		0:006 [b]				
		(0:008)		(0:002)				
$R_{P,t}$			0:044 [b]		0:006 [b]			
			(0:019)		(0:003)			
$R_{G,t}$		0:022 [b]		0:015 [a]				0:016 [a]
		(0:010)		(0:005)				(0:006)
$R_{S,t}$								

Note: $R_{C,t}$, $R_{P,t}$, $R_{G,t}$; $R_{S,t}$ indicate copper, platinum, gold, and silver returns, respectively. The variables in each column are the independent variables, while those in each row are the dependent variables in the corresponding regression. For example, the coefficient in the row labelled $R_{G,t}$ and in the column labelled $R_{P,t}$ indicates the impact of $R_{P,t}$ on $R_{G,t}$. Robust standard errors are reported in brackets.

[a], [b] and [c] indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5.7. The estimated bivariate cross effects of the conditional variance (b_{ij}).

	Unmapped				Mapped			
	$R_{C;t}$	$R_{P;t}$	$R_{G;t}$	$R_{S;t}$	$R_{C;t}$	$R_{P;t}$	$R_{G;t}$	$R_{S;t}$
$R_{C;t}$			0:058 [a]			0:036 [b]	0:061 [a]	0:010 [a]
			(0:020)			(0:018)	(0:022)	(0:004)
$R_{P;t}$							0:041 [c]	
							(0:024)	
$R_{G;t}$	-0:003 [c]	-0:030 [b]		-0:016 [a]	−0:004 [b]			-0:016 [a]
	(0:002)	(0:014)		(0:005)	(0:001)			(0:006)
$R_{S;t}$								

Note: See notes of Table 3.

5.9 ADDITIONAL TABLES

Table 5.8. Summary of descriptive statistics.

	Unmapped				Mapped			
	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$
Mean	0:026	0:023	0:067	0:056	0:019	0:030	0:064	0:053
St. Dev	2:244	1:681	1:363	2:509	2:360	1:666	1:420	2:643
Skewness	—0:132	-0:738	-0:100	-0:803	—0:135	-0:754	-0:084	-0:775
Ex. Kurtosis	5:300	7:102	6:456	8:172	5:233	7:337	6:579	8:255
JB	309:9[a]	1098:8[a]	692:9[a]	1695:2[a]	292:4[a]	1218:8[a]	742:3[a]	1735:3[a]
Q(5)	26:76[a]	16:382[a]	5:307	1:816	24:68[a]	20:97[a]	5:575	1:777
Q^2 (5)	494:7[a]	299:5[a]	122:2[a]	77:38[a]	492:9[a]	258:2[a]	131:9[a]	80:71[a]

Note: $R_{C,t}$, $R_{P,t}$, $R_{G,t}$; $R_{S,t}$ indicate copper, platinum, gold, and silver returns, respectively;

JB is the Jarque-Bera test for normality; Q(5)and Q^2 (5) are respectively the Ljung-Box test of significance of autocorrelations of five lags in the returns and squared returns.

[a] indicates significance at the 1% level.

Table 5.9. The estimated bivariate own effects of the conditional variance (α_{ii})

	Unmapped				Mapped			
	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$
$R_{C,t}$		0:077[a]	0:036[a]	0:101[a]		0:076[a]	0:036[a]	0:101[a]
		(0:022)	(0:009)	(0:034)		(0:021)	(0:010)	(0:034)
$R_{P,t}$	0:057[a]		0:042[a]	0:098[a]	0:072[a]		0:042[a]	0:103[a]
	(0:012)		(0:010)	(0:017)	(0:013)		(0:011)	(0:020)
$R_{G,t}$	0:054[a]	0:066[a]		0:137[a]	0:056[a]	0:076[a]		0:143[a]
	(0:014)	(0:018)		(0:026)	(0:014)	(0:021)		(0:028)
$R_{S,t}$	0:060[a]	0:080[a]	0:036[a]		0:058[a]	0:081[a]	0:036[a]	
	(0:014)	(0:014)	(0:009)		(0:016)	(0:016)	(0:009)	

Note: $R_{C,t}$, $R_{P,t}$, $R_{G,t}$; $R_{S,t}$ indicate copper, platinum, gold, and silver returns, respectively. The variables in each column are the dependent variables in the corresponding regression. For example, the coefficient in the column labelled $R_{C,t}$ and in the row labelled $R_{S,t}$ indicates the own effect of $R_{C,t}$ when the counterpart variable is $R_{S,t}$. Robust standard errors are reported in brackets.[a] indicates significance at the 1% level.

Table 5.10. The estimated bivariate own effects of the conditional variance (b_{ii}).

	Unmapped				Mapped			
	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$	$R_{C,t}$	$R_{P,t}$	$R_{G,t}$	$R_{S,t}$
$R_{C,t}$		$0{:}902^{a}$	$0{:}964^{a}$	$0{:}865^{a}$		$0{:}898^{a}$	$0{:}964^{a}$	$0{:}869^{a}$
		(0:028)	(0:013)	(0:044)		(0:026)	(0:012)	(0:043)
$R_{P,t}$	$0{:}916^{a}$		$0{:}958^{a}$	$0{:}872^{a}$	$0{:}887^{a}$		$0{:}948^{a}$	$0{:}866^{a}$
	(0:014)		(0:017)	(0:024)	(0:018)		(0:013)	(0:026)
$R_{G,t}$	$0{:}916^{a}$	$0{:}896^{a}$		$0{:}835^{a}$	$0{:}913^{a}$	$0{:}889^{a}$		$0{:}837^{a}$
	(0:018)	(0:025)		(0:029)	(0:019)	(0:031)		(0:027)
$R_{S,t}$	$0{:}919^{a}$	$0{:}903^{a}$	$0{:}946^{a}$		$0{:}919^{a}$	$0{:}902^{a}$	$0{:}945^{a}$	
	(0:019)	(0:017)	(0:009)		(0:020)	(0:018)	(0:010)	

Concluding Remarks

In conclusion, it is clear that the AOM/RAP and PSI metric evaluated in Chapter 1 is a far more effective and representative metric for trading algorithm performance for back-tested systems. Along with this, it was also shown that diversification is an effective way to reduce market exposure and reduce risk when utilising such trading algorithms. The metrics developed could be used as the basis for optimisation by attempting to maximise their values when constructing a portfolio.

From Chapter 2 the main conclusions that can be drawn include that altering the roll day of price data used to optimise a trading algorithm can greatly impact the performance characteristics of the algorithm, while also impacting mean PnL returns and coefficients of variation. It is apparent also that altering roll day in trading algorithms will not impact standard deviation significantly and this was clear throughout the analysis across all sectors. Overall however, the results support the initial theory that altering roll day of price data used to optimise a trading algorithm can impact the trading algorithm's performance criteria among other characteristics. The results supported the theory more so for certain instruments than others but the properties of each instrument could be used to explain these differences, being absolute ADV (liquidity/volume), FND and storage costs.

From Chapter 3, it can be concluded that the differences between mapped and unmapped time series can be significant depending on the commodity due to the roll/basis being accounted for in the mapped series. Despite the effect being more significant in some commodities than others, the impact of mapping the data sets always influences the time series in some way and results in different 'best-matching' models (whether they are econometric or algorithmic). This means trading algorithms will have alternate optimal parameters and hence alternate trade decisions.

From Chapter 4, it is evident that there is indeed a systemic relationship between the two metals in spite of their very different applications and values. The volatilities of copper and gold are inherently linked, as evidenced by the findings of the analyses carried out. it is clear that there are significant factors that cause the prices of copper and those of gold to behave as they do and this may be explored in the context of other commodities too. The impact of the financial crisis on the other metals whose characteristics differ significantly by virtue of mixed demand characteristics and lower volumes may show that the metals sector has far more to offer in terms of these relationships. Further to this, the utilisation and comparison of mapped and unmapped time series show how results can differ especially for other commodities whose basis can be more significant.

Chapter 5 also looks at the metals sector more closely and concludes that there are even more complex relationships between the main traded metals despite some being categorised as precious and others being categorised as industrial. The relationships are looked at more closely by considering volatility spillovers, bidirectional and unidirectional effects and of course the effect on these relationships of utilising mapped as oppose to unmapped data where a significant concluding remark was the existence of relationships with unmapped data, and the absence of these relationships when mapped data is considered. This shows that the unmapped data which does not account for rolls, can mislead the models into finding relationships that do not really exist in the traded time series.

Future Work

The research could be extended to other commodities futures and a comparison to spot prices could be done. In addition, improvements could be made to the metrics to increase the number of significant parameters and improve accuracy. This could include a parameter with a memory function that ceases all trading when desired levels of gains have been made. The parameter sensitivity index could also be improved by including more parameters although visually displaying this will be difficult due to the number of dimensions, making this difficult to comprehend.

The volumes data could be analysed in more detail where the deceleration or proportional drops of volumes from day to day could be matched to the optimised day of roll. This will give a more quantitative measure of the way contract volumes link to the day of roll and evaluating when the optimal roll day should be.

Another area where the research could be extended is to consider the other commodity sectors using the methodology of Chapters 4 and 5 to see if the larger rolls associated with the other commodities do indeed result in spillovers which vary between the mapped and umapped data sets.

The significance of using mapped time series will have a significant amount of applications throughout the science of time series analysis of commodities futures. This is however only if the study is focused on considering the true traded time series (which represents the real-life trading prices used by financial institutions). And this is indeed realistic because the contract volume data proves it to be.

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