An Investigation into the Dynamic Relationship Between Gold,

Silver and Oil: An Intra-day Analysis

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a sustained extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Den Stanford

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Abstract

In this research, the long-run relationships between gold, silver and oil were studied using cointegration analysis. Their dynamic cointegration was also examined. Despite economic recession and crises, cointegration did not disappear, and the strength of dynamic cointegration rose and fell. Price leadership was also investigated by studying impulse response functions. It was found that in periods of weak or no cointegration, gold was led by silver (to a greater extent) and oil (to a lesser extent). It appears that in the periods when there is cointegration, gold is led by silver and oil, and oil is led by silver. The magnitude of responses may appear small, however, they are high in frequency, and low levels of impulse response functions may still be economically significant. Determinants of long-run relationships were also studied by analysing the impact of the stock and bond markets' returns and volatility on gold, silver and oil cointegration strength. It appears that both markets impact the commodities. Cointegration strength between gold and silver, gold and oil, and silver and oil falls during periods of crisis, recession and market turbulence in the stock and bond markets. Economic recovery was not found to have any impact on cointegration strength between the commodities. This could mean that commodities' price relationships are unaffected by the stock and bond markets during recovery periods, and are probably explained by other factors. It is also possible that although the economy seemed to be growing, this was a period of uncertainty with no real trends, in which case there are no meaningful results of the regression.

Chapter 1: Introduction

Gold and silver were used as currencies for many years. Although today they are no longer commonly used this way, they are still used as a measure of wealth, and are widely used in industry (Knapp, 1996). Today, oil is the main fuel that enables our civilisation to prosper. It provides light and warmth, and the ability to cook. Using oil's energy, metals can be extracted from ores and cast into various forms. Oil is used to run our engines and it also produces electricity (Wicks, 2009).

It is found that gold, silver and oil commodities 'move together' in the long-run and share a common trend; therefore they are *cointegrated* (Escribano & Granger, 1998; Lucey & Tully, 2006a; Zhang & Wei, 2010). If these commodities share a common trend, then an important question is whether one commodity drives this trend and whether one of them is likely to lead the others. Finding the leader makes it possible to better understand the relationship between gold, silver and oil markets, and to forecast the price of each. It is acknowledged that such investigation should be conducted using intra-day data, given the fast-paced nature of modern markets (Khalifa, Miao, & Ramchander, 2011; Zhang & Wei, 2010).

Former studies have found that there is a long-run relationship between gold and silver, and between gold and oil (Escribano & Granger, 1998; Lucey & Tully, 2006a; Zhang & Wei, 2010). However, it has also been found that cointegration studies give different results, suggesting that the relationship

between each pair is not constant; they change over time. Therefore, the possibility of *dynamic cointegration* was considered, and it was indeed found that the cointegration strength changes over time (Lucey & Tully, 2006a). Because cointegration strength was not constant, price leadership was put to question. Previous research suggests that oil leads gold in the long run (Zhang & Wei, 2010), however, it is not entirely clear whether oil and silver commodities exhibit the same behaviour as oil and gold. Also, it is not known for certain how gold and silver relate to each other during different economic conditions. This puts to question the determinants of the long-run relationship.

Modern markets are very fast paced, and therefore it is important to use high-frequency data – because not only is it very rich in information, but it also allows us to understand the rapid nature of modern markets better. While many aspects of gold, silver and oil have been thoroughly studied, research on high-frequency interaction of the three markets is scarce (Khalifa et al., 2011; Zhang & Wei, 2010). Currently, other areas are given more focus – for example, Khalifa et al. (2011) investigate gold and silver returns distribution and volatility forecasting; Lucey and Tully (2006a, 2006b) look at gold and silver seasonality, risk and return, and evolving relationships; Wahab and Cohn (1994), and Liu and Chou (2003), investigate gold–silver spread; Cortazar and Eterovic (2010) study whether oil prices can help with estimating commodities futures prices; and Zhang and Wei (2010) look into the long-term relationship of gold and oil. From the above we can conclude

that current research does not appear to examine the long-run relationship of the three commodities using information-rich, high-frequency data.

This research focuses on dynamic changes in the strength of relationships between gold, silver and oil, similar to the approach of Lucey and Tully (2006a). However, the effort and focus of this study is to fill the existing knowledge gap by focusing on intra-day dynamic interactions between gold, silver and oil prices to ascertain which market is leading the others. This is investigated by impulse response function analysis. By answering the gold, silver and oil price leadership question, this research makes it possible to understand how commodities prices interact and react to market shocks, as well as studying their ability to be forecast.

Because gold, silver and oil are used for speculative and hedge trading, they become correlated to the stock and bond markets. This study examines the determinants of long-run relationships by analysing the impact of the stock and bond markets' returns and volatility on gold, silver and oil cointegration strength.

For this study I obtained prices for gold, silver and oil futures contracts traded on the Chicago Mercantile Exchange (CME) from 6 September 2007 to 20 January 2012, at 1 minute frequency, from the Thomson Reuters Tick History (TRTH) via the Sirca database. The data was tested for validity and a common sample of gold, silver and oil prices was prepared for analysis.

I analysed dynamic cointegration following Lucey and Tully's approach (2006a), and studied the price leadership between gold, silver and oil by analysing impulse response functions. I also investigated the determinants of long-run relationships by analysing the stock and bond markets' returns and volatility impact on gold, silver and oil cointegration strength, by employing regression analysis.

I found that long-run relationships between gold and silver, gold and oil, and silver and oil during the research period do exist. However, the global economy crisis and the global financial crisis weakened this relationship during certain periods. Dynamic cointegration analysis shows that the cointegration strength between gold and silver, gold and oil, and silver and oil fluctuates, but does not disappear. We see that in some periods there is cointegration, but in some periods it appears to be absent. Price leadership analysis shows that in periods when there is no cointegration, gold is led by silver to a greater extent, and by oil to a lesser extent. I observed that in the periods when there was cointegration, gold is led by silver and oil, and oil is led by silver. The magnitude of responses may appear small, however, they occur on a high-frequency basis, and such levels of impulse response functions may be economically significant. To verify this would require further research.

I also found that the cointegration strength between gold and silver, gold and oil, and silver and oil, fell during periods of crisis, recession and market

turbulence in the stock and bond markets. I could not confirm that recovery had any impact on the cointegration strength between gold and silver, gold and oil, and silver and oil. This could mean that these price relationships are unaffected by the stock and bond markets during a recovery period and probably are explained by other factors. It is also possible that although the economy seems to be growing, this is a period of uncertainty with no real trends, in which case there is no meaningful output of the regression and further research is required to understand this relationship better.

Chapter 2: Literature Review

This chapter provides a review of the existing literature on the dynamic relationship of gold, silver and oil. It discusses the background and history on these commodities, and their use and importance; the stock and bond markets and their relationship with gold, silver and oil; the trade of gold, silver and oil; and it reports on the cointegration research conducted in recent years.

2.1 Background

Commodities markets are large, and amongst all commodities there are three that stand out: gold, silver and oil. Gold and silver stand out because of their historical inter-relation as currencies, and their "safe haven" attributes (particularly gold) for stabilising returns and reducing risk in investors' portfolios (especially during market shocks and economic downturns (Baur & McDermott, 2010; Lucey & Tully, 2006a; Quinn, 1996)). Oil, an essential raw material for global industry, stands out because it has a strong influence on other commodities' prices, as well as on the global economy itself (Adelman, 2002; Cortazar & Eterovic, 2010; Zhang & Wei, 2010). Given the importance of these three markets globally, understanding their interactions is also of importance.

2.2 History of Gold, Silver and Oil, and Their Use and Importance

2.2.1 Gold

Gold has been known to mankind since our earliest recorded history. *Aurum,* the Latin word for gold, is a chemical element with the symbol Au. It is among the rarest elements on earth, it is extremely resistant to corrosion, and it almost always occurs in pure form – making it possible to use without refining. The largest amount of gold on earth is in sea water, from where it is too hard to collect due to its wide dispersion. On land, gold is found in gold-bearing veins in rocks, as small fragments in the ground, on shore sands and in river beds (Knapp, 1996).

The history of gold being used as a currency goes back to ancient Egyptian times, nearly 6000 years ago. In the 19th century there were several major gold rushes when it was discovered in the United States, Russia, Canada, Australia and South Africa. Today, although gold is no longer used as currency, it still serves as a means of showing wealth, and gold is widely used in jewellery. Because gold is almost nonreactive, it is also useful in industry – for example, in the medical industry gold is used in dental fillings. Because gold does not oxidise, it is a good conductor of electricity, and it can be drawn into fine wires or turned into very thin sheets, it is widely used in micro-electronics, connectors and switches. Gold is also used in chemical and physical processes where it resists corrosion and heat (Knapp, 1996).

Financialisation of gold started in 1970, and gold futures first opened for trading on 31 December 1974 on Commodity Exchange Inc. (COMEX, a division of the New York Mercantile Exchange (NYMEX) (CME, 2012a)).

This coincided with the lifting of a 41-year ban on the private ownership of gold by US citizens, which was imposed in the early days of President Franklin Roosevelt's administration during the Great Depression (CME, 2011).

Gold futures provide an alternative to investing in gold mining companies' shares, gold coins and bars, or gold bullion. Also, gold futures are useful tools for a wide variety of companies involved in the gold industry, like mining companies, manufacturers and others.

Gold is known for its "safe haven" attribute, as gold is argued to be an effective hedging tool against the stock market, inflation, market turbulence and crashes, and political instability (Lucey & Tully, 2006b).

2.2.2 Silver

Silver, like gold, has been known since ancient times. *Argentum* in Latin, meaning "white and shining", it is a chemical element with the symbol Ag. It was known to, and used by, ancient Egyptians almost 5000 years ago (Knapp, 1996). Not only is silver a precious metal, it is also widely used in industry.

Silver is known as a better conductor of electricity and heat than any other metal. In the past, the main use of silver was in coinage and jewellery. Today

up to 40% of silver is used in photography and film making. In contrast, only 16% of silver is now used for coins and jewellery. Silver is also used in mirror manufacturing – from common household mirrors to high-precision scientific mirrors. It is also used in the medical industry, for example in dental amalgam fillings (Knapp, 1996).

In 1792, silver took a key role in the US monetary system when the US Congress based the currency on the value of the silver dollar. It was used in the US coinage until 1965, when silver was demonetised (CME, 2011).

Silver futures opened for trading on 5 July 1933 (CME, 2012a). Silver futures, like gold, provide alternatives to direct silver investments. In addition, silver futures are useful tools for companies involved in the silver industry, like jewellery, medical equipment and electronic manufacturers. Silver, together with gold, is argued to be an effective hedging tool against short- and long-run inflation (Lucey & Tully, 2006b).

2.2.3 Oil

Fire has always played a crucial role in human civilisation, allowing us to populate colder regions. It gives light and heat, and the ability to cook. With fire, metals can be extracted from ores and cast into various shapes. Fire runs engines and produces electricity. However, fire needs fuel, and today oil is

the main fuel that helps our civilisation to prosper (Wicks, 2009). People tried many other fuels before oil was discovered, and coal was once widely used in industry and households.

Oil was accidentally found in Petrolia, Ontario (USA) in 1858. The first commercial oil well was established in August 1859 (Jones, 1978), and petroleum was extracted from this well on 27 August 1859 (Wicks, 2009). However, the era of oil globalisation only started in 1974 (Bina, 2006), and the abundance of inexpensive oil as fuel instigated its wide use. For example, in Russia in the early 1880s, a ton of oil was 30–40 times cheaper than a ton of coal (Jones, 1978). Of the larger markets, only in the UK was there initial resistance to using oil as fuel, as per ton, between 1902 and 1910, it was two- (steam coal, the best) to four- (average price for coal raised at pit) times more expensive than coal. Eventually however, even in the UK, coal was replaced with oil. Interestingly, coal burners can be converted to burn oil, sometimes in a matter of a few hours (Jones, 1978).

Oil has significant advantages over coal: ships and trains can reach higher speeds using oil; it occupies less storage space; it can reach full heat very quickly and can be easily maintained at full capacity; it gives greater control over temperatures; it is much easier to handle and it also requires less labour. Even in old diesel engines, burning 1 ton of oil is equivalent to burning 4–5 tons of coal. Oil is also used in the chemical industry for production of various substances, from plastics to asphalt (Jones, 1978). Therefore, today oil is

widely used as an energy source for households and industry; it drives present-day civilisation and so is of global importance.

While gold and silver have a relatively long-standing financial history, crude oil did not even have a global price before World War II. When the oil market was established, oil prices were relatively stable until the 1970s. Since then they have become very unstable (Adelman, 2002).

Oil futures opened for trading on 30 March 1983 (CME, 2012a). "Light sweet crude" oil serves as the benchmark for nearly 10 million barrels of daily North American production. It is also the most efficient hedging tool for numerous commercial oil companies. Light sweet crude oil futures are one of the most actively traded energy contracts in the world, and have been sought out for price discovery and risk management around the world for more than 25 years (CME, 2012b).

2.3 Trading

Trading commodities evolved from an ancient barter exchange system to present-day modern sophisticated electronic trading. Today, trading in gold, silver and oil using futures contracts is important for buyers, sellers and the economy, because it allows for fast and efficient trading, exiting from a contract, and because it reduces the risk of non-performance. Futures

contracts and forward contracts are called 'derivative contracts', because their value is derived from the value of an underlying asset (Elali, 2009). Futures contracts are similar to forward contracts, which are discussed first to provide an example of how these contracts work.

2.3.1 Forward contracts

Forward contracts are important tools for trading commodities, as they are contracts to buy or sell an underlying asset at a future date at the price and quantity specified in the contract (Bodie & Marcus, 2011). This gives buyers and sellers certainty. It is easy to provide an example of how forward contracts work.

Consider a company that mines oil. The company's revenue solely depends on the oil price, since the company is only mining oil and is unable to diversify. Now suppose there is a refining company that uses oil to produce petrol. This company's revenue is also uncertain, because of the future cost of oil. Both companies can reduce their risks by entering into a forward contract, which would require the mining company to deliver oil at an agreed price in an agreed quantity, regardless of the future market price of oil.

Forward contracts are usually customised and it is not easy to exit the contract, unless the other party agrees. It is much easier to trade standardised

contracts with multiple parties to diversify the risk of non-delivery and simplify the exiting procedures. These standardised contracts are called futures contracts (Bodie & Marcus, 2011).

2.3.2 Futures contracts

Futures contracts are like forward contracts, but they are standardised and traded centrally on an exchange (Ross, Westerfield, & Jaffe, 2005). An exchange would guarantee the performance of parties to contract. For traders this means that the other party's obligations under the contract will be fulfilled. Therefore the trading is less risky, as well as less costly, since there is no need to perform credit checks. Traders are required to keep a *maintenance margin*, which is an amount of equity as a percentage of the current market value of securities held in their account, to guarantee their performance (Bodie & Marcus, 2011). If the market makes an adverse move, affected traders will receive a margin call from their broker or exchange to deposit additional funds, so that the maintenance margin is kept. Otherwise, part of the trader's assets have to be sold.

There are numerous exchanges that support futures contracts trading. Two of the biggest are NYMEX and CME. The data from these exchanges is used in this research, and will be discussed later in the text.

Commodities traded on exchanges sometimes show similar patterns in their price movements. Some of these patterns are spontaneous and do not last long. In this case the commodities follow similar price trends for some time, for example, upward, and then their prices diverge. However, there are commodities which follow similar trends for a long time, like gold, silver and oil. These three commodities follow similar trends for so long that it is reasonable to assume that they have a long-run relationship. If gold, silver and oil indeed have such a relationship, it could be found and studied using certain techniques. One of these techniques is cointegration analysis.

2.4 Cointegration

Cointegration is basically a long-term relationship, or equilibrium, from which variables may deviate, but to which they would return in the long run (Brooks, 2008). As discussed previously, gold, silver and oil are found to be related in the long run. This was first noticed with gold and silver, and later it was found with gold and oil as oil become a very important commodity for the global economy. The relationships of the three markets are neither periodic nor spontaneous, nor recently discovered; they developed over time. Gold and silver have a longer relationship history than oil does with either of these metals.

Gold and silver have been closely examined as a pair for hundreds of years – from when they acted as currencies, to today when they are attractive to

people as alternatives to currencies or stocks in times of economic downturn (Lucey & Tully, 2006b; Quinn, 1996). It was hypothesised by various researchers that silver and gold prices were bound together in the long run, so attempts were made to estimate the extent of this relationship. Indeed, it was found that the ratio of gold-to-silver prices in the long run tends to be within certain boundaries, which are not exact. Some researchers argue for a wide range between 1:8 (gold:silver) and 1:20 (Escribano & Granger, 1998), and some researchers narrow it down to a more precise figure of 1:16 (Lucey & Tully, 2006b). The ratios are different, but they suggest that gold and silver stay within certain boundaries over long periods. This is important because these boundaries can be compared with the outcome of this research, as well as being a guideline for future research – since it can be expected that in the long run, gold and silver prices will stay within these ratio boundaries.

In 2002 (a decade ago at the time of writing) worldwide inflation and other events led oil and gold markets to boom, due to the depreciation of the US dollar. This boom continued until 2008, when both markets collapsed and then regained momentum in 2009. Zhang and Wei (2010) found that during this time gold and oil prices showed strong cointegration. They also found that while the linear Granger causality was significant, the non-linear Granger causality between oil and gold was insignificant, which suggests that interaction between the markets is not simple. Moreover, they found that information contribution to price formation appears to be larger for oil than for gold, which means that oil plays a more significant role in the price

formation of a greater commodities market. Finally, Zhang and Wei also identified opportunities for future study, saying that dynamic interactions between markets were not yet well-researched.

Silver appears to follow the gold and oil price trend, and it is found that gold and silver prices are cointegrated; however, it appears that over the past decade, especially more recently, research on silver's price relationships is scarce. We will now discuss the cointegration research to show what has been found by academia so far.

As different sample frequencies have been studied, it appears that cointegration at higher frequencies holds stronger. One explanation could be that the higher the sampling frequency, the more information is available to explain cointegration. It was found that between the 1970s and the 1990s, both metals' prices were cointegrated at a monthly frequency during some periods, and especially during the 1979 and 1980s economic bubbles (Escribano & Granger, 1998). At a weekly frequency between 1978 and 2002 this relationship became stronger, with only a few weakenings (Lucey & Tully, 2006b). At a daily frequency, between 1983 and 1995 the relationship was strong enough to be used for highly accurate forecasting of the gold–silver price spread, and could be used by metal traders (Liu & Chou, 2003) and hedgers (Worthington & Pahlavani, 2007). Using intra-day frequency sampling provides the most information-rich data and is therefore used in this research.

While metals have a long history of price relationship, crude oil has not been traded as long as gold or silver, and it did not even have a global price before World War II. Once the oil market had been established, the price was stable until the 1970s – since then it has become very unstable (Adelman, 2002). The oil price rose and fell, peaking at almost $150 per barrel and then falling to $30 at the end of 2008. Since then the oil price has been rising again, exceeding $100 per barrel. However, oil has become one of the most important commodities in driving the global economy, and it appears that over the last decade its role has become even more important than the roles of gold or silver.

Zhang and Wei (2010) found that between 2000 and 2008, oil and gold were cointegrated, and generally oil was leading gold – except for highly turbulent situations where speculators were very active on the market.

Granger and Newbold (1974) stressed the importance of choosing a proper approach and model when analysing time series relationships using regression. It was Granger (Engle & Granger, 1987) who came up with the idea of using regression in estimating cointegration vectors (relationships) in a study of nonstationary time series. This approach worked well and was later used by many other researchers, providing good estimations and test statistics (Johansen, 1988). An error-correction term was also introduced as a measure

of how quickly related time series corrected to equilibrium (Engle & Granger, 1987).

Later, Escribano and Granger (1998) used this method to test the relationship between gold and silver, with an emphasis on forecasting. They analysed monthly prices for the period between 1971 and 1990, and found that cointegration was present in the entire sample for both level and log prices, and that intercept dummies greatly strengthen cointegration (which shows a medium level without them). Escribano and Granger found that in-sample, the models they used performed well in forecasting, but the performance dropped in out-of-sample forecasting. They found that for gold, non-linear models performed best in both in-sample and out-of-sample forecasting. The performance drops if models are logs.

Since Escribano and Granger's research, many scholars have used cointegration analysis and error-correction modelling to approach long-run relationships research[1].

Recent studies use the same approach. Zhang and Wei (2010) investigated the relationship between gold and oil using the vector error correction modelling approach. For inputs they used logarithmic difference of the

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[1] The research using cointegration analysis finds its applications in commodities markets and in other areas. For example, An-Sing and James Wuh (2004) used cointegration analysis to examine lead spot and futures prices on the London Metal Exchange (LME), three-month UK Treasury bills, and inventory (quantity) of lead in LME-approved warehouses. Baillie and Bollerslev (1994), and Diebold, Gardeazabal and Yilmaz (1994), conducted their research on seven currencies' long-run relationship using cointegration analysis. Christoffersen, Jacobs, Ornthanalai and Wang (2008) studied options using cointegration analysis. There are many other studies that employ cointegration analysis where it is required to examine long-run relationships.

original daily time series. Another study by Lucey and Tully (2006a) used Johansen and Juselius's technique (1990), which endeavours to establish a rank of cointegrating matrix in the Vector Error Correction Model (VECM). The authors use two approaches, which they call the *global* approach and the *rolling* approach. The difference between the approaches is in the time window used for estimating the VECM. The global approach uses increasing samples, adding new data into the equation every time it is run. The rolling approach uses the same time window every time the equation is run. This research shows dynamic changes in cointegration, and is of interest because applying this technique at high-frequency in a crisis period would show dynamic changes in cointegration in modern, fast-paced markets.

Price relationship studies generally use cointegration analysis with different specific models, depending on the research focus. Recent research stresses that understanding commodities' price leadership has crucial practical significance (Zhang & Wei, 2010). Also, given the fast-paced nature of modern markets, a good level of price leadership understanding can only be achieved by analysing intra-day data, that is, high-frequency data, because commodity prices respond very quickly to each other. Therefore, gold, silver and oil price leadership investigation should be conducted using high-frequency data.

There are different approaches used by researchers regarding how they prepare the data and what interval they use: from tick-by-tick data to readily

available 1, 2, 5 and 15 minute observations. However, Khalifa et al. (2011), who were working from tick-by-tick raw data downwards to lower frequencies, say that increasing frequency, in general, does not improve the forecasting performance of the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) (1,1) model, which they used for their research. This, however, may not be the case for cointegration analysis and is yet to be confirmed or rejected.

Previous research suggests that oil is leading gold in the long run, because of its greater economic impact – although gold is likely to take leadership during rapid market changes (Zhang & Wei, 2010). However, it is not clear whether oil and silver share the same behaviour. Also, while gold has greater safe haven properties (as investors who flee the stock market will first consider gold as an alternative investment) it is not known for certain how gold and silver relate during different economic conditions. Moreover, it appears that research on gold, silver and oil using high-frequency data is scarce.

2.5 Research on Gold, Silver and Oil Cointegration Using High-frequency Data

Most studies published in financial literature deal with low-frequency data (Dacorogna, 2001). This is due to various reasons, such as cost and time involved with collecting, storing and working with high-frequency data. However, today computer technology and data availability make it possible

to study high-frequency data. Modern markets are very fast paced, and hundreds of thousands of trades take place every day. Every trade is one unit of information. Therefore, high-frequency data analysis can explore new information, which is only available at the high-frequency level. In addition, the more observations, the more statistical precision in estimating models (Dacorogna, 2001). The availability of high-frequency data helps researchers to study the gold, silver and oil market interactions in more depth.

Recent research on interaction between the gold, silver and oil markets is scarce (Khalifa et al., 2011; Zhang & Wei, 2010). Khalifa et al. (2011) investigated gold and silver returns distribution and volatility forecasting. They confirmed the scarcity of research on price interaction as well as noting that price formation and price reaction to market news is an area of interest for further research.

Lucey and Tully (2006a, 2006b) investigated gold and silver seasonality, risk and return, and evolving relationship. They found seasonality in silver prices and confirm that it is very similar to the seasonality of gold prices, which suggests similar price movement patterns and long-run relationship between the time series. They also acknowledge some controversies in research on gold-silver price relationship of that time: some researchers claim that since 1990 there has been no long-run relationship, while others claim the opposite. However, in their research they confirm that long-run relationship holds strong in terms of dynamic cointegration. Moreover, they argue that a big

chunk of research from that time can be critiqued for its static nature, therefore implying that research on dynamic interactions is important.

Wahab and Cohn (1994) and Liu and Chou (2003) investigated the gold-silver spread. Wahab and Cohn found that a lag relationship between gold and silver markets exists, and Liu and Chou found that re-examination of previously researched gold-silver parities was required. They also suggested that more general cointegration methods are better tools to examine the asset price dynamics, rather than very specific ones. One such method is vector error correction modelling.

Cortazar and Eterovic (2010) studied whether oil prices can help in estimating commodities' futures prices. They found that oil prices can help estimate commodities' futures prices, but the model they propose requires comparison with other models, like the VECM, and this research is yet to be done.

Zhang and Wei (2010) investigated the gold and oil long-term relationship. They found that gold and oil are related in the long run, however, while the linear Granger causality between the two is significant, the non-linear Granger causality is insignificant, which suggests that interaction between the markets is not simple. They also found that information contribution to price formation appears to be larger for oil than for gold, which means that oil plays a more significant role in price formation of the wider commodities market.

Moreover, Zhang and Wei identified opportunities for future research, saying that dynamic interactions between markets are not well-researched.

Generally, existing research shows that gold, silver and oil prices move together in the long run – that is, they show a common trend. Such research uses low-frequency sampling; quarterly, monthly or weekly (Escribano & Granger, 1998; Lucey & Tully, 2006a; Zhang & Wei, 2010). These low-frequency studies suggest that gold, silver and oil prices are connected. It is worth examining this relationship because one of the three markets is likely to be leading the others. Therefore, finding such a leader makes it possible to study lead–lag interactions, forecasting of gold, silver and oil prices, and price discovery. Price discovery can be looked at from two angles: one is the price determination mechanism or process, which examines the contribution of other commodities in the price forming of a given commodity; the other is the impact of new information from different markets when a security is traded on multiple sites (e.g., see Hasbrouck, 1995).

Given the research already done, it appears that we still do not fully understand this long-run relationship. This study will use the approach of Lucey and Tully (2006a), incorporating the Johansen-Juselius technique (1990). However, the focus is to fill the existing research gap by concentrating on intra-day dynamic interactions between gold, silver and oil prices, to learn which market is leading the others. By answering the price leadership question, this research makes it possible to understand how commodities

prices are formed, and how they interact and react to market shocks, as well as studying their forecastability.

Chapter 3: Hypotheses

This chapter introduces the four hypotheses used in this research. It discusses cointegration and the nature of the long-run relationship between commodities; dynamic cointegration and ongoing changes in the strength of the long-run relationship between gold, silver and oil; price leadership in long-run relationships; and regression analysis and the determinants of long-run relationships.

3.1 Cointegration

Researchers have found that over the past two decades cointegration is present between gold and silver (Escribano & Granger, 1998; Lucey & Tully, 2006b), and between gold and oil (Zhang & Wei, 2010). Because cointegration is a long-term property, it can be assumed that it did not disappear during the sampling period of this research. Moreover, because gold and silver and gold and oil are cointegrated, it is assumed that oil and silver are cointegrated as well. Given the scarcity of oil and silver cointegration research, I concentrated on narrowing this knowledge gap, and therefore tested the following hypothesis:

Hypothesis 1: over the sample period there is cointegration between gold and silver, gold and oil, and silver and oil.

3.2 Dynamic Cointegration

Researchers have found that while cointegration is present, its strength varies over time (Lucey & Tully, 2006a). Therefore, a dynamic cointegration study is required for understanding the nature of changes in this relationship. It is assumed that during crises and market turbulence, cointegration between commodities becomes weaker, but does not disappear, because it is a long-term relationship. To study dynamic cointegration I tested the following hypothesis:

Hypothesis 2: over the sample period cointegration strength between gold and silver, gold and oil, and silver and oil fluctuates, but cointegration does not disappear.

3.3 Price Leadership

Researchers have found that in the long run, oil prices lead gold prices (Zhang & Wei, 2010). However, it appears that we do not yet fully understand price leadership between gold and silver, and silver and oil. Moreover, given the fast-paced nature of modern markets, it appears that we do not fully understand price leadership at high-frequency sample rates. It is assumed that given the results of previous research, and because cointegration is a long-term relationship, that oil is leading gold over the sample period. Because we do not fully understand the behaviour of silver, it can be assumed that since

gold appears to play a more important role in the economy, it leads silver. If oil leads gold, and we assume that gold leads silver, we assume that oil leads silver as well. Therefore, I tested the following hypothesis:

Hypothesis 3: over the sample period, oil leads gold and silver, and gold leads silver.

3.4 Determinants of Long-run Relationship

Because gold, silver and oil are used for speculative or hedge trading, they become correlated with the stock market. Given the safe haven attribute of gold, it is used as a safe investment – and therefore may be correlated with the bond market. Because the global financial crisis was initiated by the bond market crisis, it is assumed that the bond market has an impact on the gold and silver and gold and oil relationships. Moreover, since oil is used for speculative trading, it is assumed that the stock market has an impact on the relationship of gold and oil, and silver and oil. In addition, recession and recovery periods should have different impacts on gold, silver and oil cointegration strength. During a recession, the stock and bond markets' returns fall, turbulence increases and traders flee from the stock market and invest in gold. Therefore, it is assumed that during crises and recessions cointegration strength falls – since long-term equilibrium is disrupted by short-term changes. During the recovery period it is assumed that the opposite occurs, and cointegration strength rises. However, because there may not be

a real recovery over the research period, it is wise to test the recession assumptions. Given these assumptions I tested the following hypothesis:

Hypothesis 4: over the sample period, cointegration strength between gold and silver, gold and oil, and silver and oil falls during periods of crisis, recession and market turbulence in the stock and bond markets.

Chapter 4: Methodology

This chapter addresses the methodology used to test the four hypotheses introduced in Chapter 3. It discusses the Error Correction Model (ECM), which is a model for estimating long-run relationship between commodities; the Johansen-Juselius technique, which uses the VECM (a further development of the ECM) for estimating the strength of long-run relationships; the impulse-response functions, which are used to study price leadership in long-run relationships; and regression analysis of the stock and bond markets.

4.1 The Error Correction Model

The main methodology used in this research is cointegration analysis. This methodology will help in testing the first hypothesis, that over the sample period there is cointegration between gold and silver, gold and oil, and silver and oil. If there is a common trend in these commodities' prices, then, according to Engle and Granger (1987), there is cointegration. Cointegration may be seen as a long-term relationship between commodities' prices. In the short run there may be deviations, but in the long run, the prices return to equilibrium. Cointegration can be assessed using an error-correction model (Brooks, 2008). A 1 lag specific error-correction model for gold is:

$\Delta g_t = \beta_1 \Delta s_{t-1} + \beta_2 \Delta o_{t-1} + \beta_3(g_{t-1} - \gamma_1 s_{t-1} - \gamma_2 o_{t-1}) + u_t$.   Equation (1)

Where:

g is the price of gold

s is the price of silver

o is the price of oil

β_1 and β_2 are the coefficients capturing the short-run dynamics of s, o and

g.

β_3 is the coefficient measuring how much of the final period's

disequilibrium (or error) has been corrected. In other words, it measures

how quickly the error is corrected.

u_t is price movement unexplained by the model.

Equation (1) is a one lag specific error-correction model, explaining changes

in the price of gold (Δg_t), based on changes in the prices of silver (Δs_{t-1}) and

oil (Δo_{t-1}). The model can be understood as follows. Silver (s) and oil (o), the

independent variables, change between times t-2 and t-1. As a result of such

change, gold (g), the dependent variable, changes between t-1 and t. Also,

gold is supposed to adjust, or 'correct' for disequilibrium existing in the

previous period. Correction is described by ($g_{t-1} - \gamma_1 s_{t-1} - \gamma_2 o_{t-1}$), the error-

correction term, where γ_1 and γ_2 are the cointegrating coefficients defining

the long-run relationship between gold, silver and oil. The error-correction

term has a lag, t-1. This is because gold changes between time t-1 and t in

response to disequilibrium at time t-1. Equation (1) says that changes in the

gold price are determined by changes in the silver and oil prices, plus correction from the final period's disequilibrium, plus unexplained price movement. Similar models can be constructed for silver and oil.

To make use of the information available from the intra-day data, 1 minute closing futures prices bid-ask midpoints for each commodity were used. This time period allows testing of the speed of the error-correction with high precision. Then, Engle and Granger error-correction models were applied to test for the long-run relationship. Also, forecasting was performed for all available information (in-sample forecasting) and then for the model without all available information (out-of sample forecasting), which was then compared with real futures prices to see how accurate the model was.

4.2 Johansen-Juselius Technique

Main methodologies involve the Johansen-Juselius technique (1990), which endeavours to establish a rank of cointegrating matrix in the VECM. The relationship represented in equation (1) above can be more generally represented in the VECM:

$$\Delta E_t = \Gamma_1 \Delta E_{t-1} + \Gamma_2 \Delta E_{t-2} + \ldots + \Gamma_{l-1} \Delta E_{t-l} + \Pi E_{t-l} + \mu_t \qquad \text{Equation (2)}$$

The Johansen-Juselius technique endeavours to estimate the rank of matrix Π in equation 2 above. The rank gives the number of stable cointegrating vectors

in the system. The Johansen-Juselius technique uses maximum likelihood tests on reducing the rank of matrix Π (the long-run impact matrix) (Johansen & Juselius, 1990).

Main outputs are the λ_{trace} and λ_{max} statistics. The λ statistics are called *eigenvalues* of matrix Π. In German the word *eigen* means (among others) "characteristic" (Shores, 2007). For example, let Π be a square *k x k* matrix. An eigenvector of Π is a nonzero vector **x** in rational or complex numbers, such that for some scalar λ we have $A\mathbf{x} = \lambda\mathbf{x}$. The scalar λ is called an eigenvalue of the matrix Π, and vector **x** is an eigenvector belonging to the eigenvalue λ. The pair [λ, **x**] is an eigenpair for the matrix Π (Shores, 2007).

Note that λ can be the 0 scalar, but **x** is never the **0** vector. If λ is 0, then the system $A\mathbf{x} = 0\mathbf{x} = \mathbf{0}$ has a nontrivial solution **x**, meaning that matrix Π is noninvertible (or singular). This is important, because this helps in tracing the existence of cointegrating vectors as a general linear system with the *k x m* coefficient matrix Π. A right-hand-side vector **c** and augmented matrix $\widetilde{\Pi} =$ [$\Pi \mid$ **c**] is consistent if, and only if, rank Π = rank $\widetilde{\Pi}$ – in which case either rank $\widetilde{\Pi} = m$ and the system has a unique solution, or $\widetilde{\Pi} < m$ and the system has an infinite number of solutions (Shores, 2007). Singular matrix Π would yield errors when testing for cointegration in vector autoregression models, meaning no cointegration or problems with input data.

The output λ_{trace} statistic shows whether one or more cointegrating vectors exist, and λ_{max} shows the exact number of cointegrating vectors. Lucey and Tully (2006a) used the Johansen-Juselius technique and plotted λ_{trace} statistics over time to represent dynamic changes in cointegrating relationships on different time windows. The representation is as follows. In equation 2, the λ_{trace} statistic is a measure of Π matrix rank. The equation estimates over a specific time window. Then the λ_{trace} statistic is compared to its critical value at the 5% significance level. If the λ_{trace} statistic is equal to or greater than its critical value, the null hypothesis – that there are no cointegrating equations – can be rejected; and the alternative hypothesis – that there is at most one cointegrating equation – can be accepted.

The λ_{trace} statistic is also converted to a ratio with its critical value and then represented graphically. This shows dynamic changes in cointegration strength and dynamic cointegration. Because we can see the dynamic changes in the strength of cointegration, we can better understand the commodities' behaviours in different circumstances – for example during market crises and periods of turbulence, during recessions and recoveries in the economy, and during specific events of interest. Studying dynamic cointegration is important because it allows the long period over which the cointegration is estimated to be broken down into shorter study periods. While general non-dynamic cointegration may not be found during such periods, dynamic cointegration analysis may show that cointegration is still present, as well as the strength of cointegration. This is where the technique used by Lucey and

Tully (2006a) is particularly useful, as it employs two approaches to time windows, allowing the study of dynamic cointegration from different angles.

The first approach, called *global* analysis by Lucey and Tully (2006a), consists of estimation of the Johansen-Juselius approach on the initial dataset. Then another subset of data is added, and the Johansen-Juselius approach is estimated again on the new sample. Under this approach, data accumulates until all data is included in the sample. This approach enables the researcher to see the evolution of cointegration over time.

The second approach, called *rolling* analysis, consists of dividing the data into a number of non-overlapping samples and the Johansen-Juselius approach is estimated on each of those samples. Once again, this approach allows the researcher to see how the cointegration dynamic changes over time.

For comparison purposes, the λ_{trace} statistic was converted into a ratio with its critical value and represented graphically. When the ratio is equal to 1, the λ_{trace} statistic equals the critical value and the null hypothesis of no cointegration is rejected. When the ratio is above 1, cointegration is stronger. When the ratio is below 1, cointegration is weaker.

One should note that λ_{max} and λ_{trace} are interpreted differently and may provide different results. The λ_{max} tests for *r* cointegrating vectors against the *r+1*

alternative hypothesis, while $\lambda_{trace,}$ tests whether the number of vectors is less than *r*. While it is argued that λ_{max} is more accurate when testing for a specific hypothesis (as with the research of Lucey and Tully (2006a)), two-time series (gold-silver, gold-oil and silver-oil) can only have at most 1 cointegrating vector, so λ_{trace} is used.

In this study the Lucey and Tully (2006a) technique will be used to investigate gold, silver and oil dynamic cointegration. Both global and rolling approaches will be used to study the evolution of cointegration over time, as well as how the cointegration dynamic changes over time.

If the λ_{trace} statistic as a ratio to its critical value is greater than or equal to 1, it can be concluded that there is cointegration, and the strength of the relationship can also be seen. This would allow us to accept or reject our first and second hypotheses: whether there is cointegration between gold, silver and oil, and whether it fluctuates, but does not disappear.

4.3 Impulse Response Functions

In the presence of cointegration, investigation of price leadership can proceed. This is achieved by impulse response tests, which are performed to investigate how commodities react to market shocks. Impulse response tests are used to trace how dependent variables react to shock from each variable in the model. To perform the impulse response test, a unit shock is applied to the error term

of every equation, and effects on the dependent variables are noted. This shows which commodity price change has the greatest influence and therefore, which commodity is leading.

Equation (2) is used:

$$\Delta E_t = \Gamma_1 \Delta E_{t-1} + \Gamma_2 \Delta E_{t-2} + \ldots + \Gamma_{l-1} \Delta E_{t-l} + \Pi E_{t-l} + \mu_t$$

First, a unit shock is applied to μ_t – the residuals. Then the effect of the shock on the matrix ΔE_t is observed. This shows which commodity price change has the greatest impact on the other commodities. Regarding the long-run perspective, this tells us which commodity is leading. In this study, if we see that the impact of oil is the greatest on all commodities, and the impact of silver is the smallest on all commodities, we can conclude that hypothesis 3 is correct: over the sample period, oil leads gold and silver, and gold leads silver.

4.4 Regression Analysis: Determinants of Long-run Relationships

Because gold, silver and oil are used for speculative or hedge trading, they become correlated with the stock and bond markets. Therefore, it is interesting to study how the gold, silver and oil relationships are affected by the stock and bond markets. This investigation tested the impact of the stock and bond markets on the gold-silver, gold-oil and silver-oil commodity pairs'

cointegration strength. The assumption is that such relationships are linear. Therefore, Ordinary Least Squares (OLS) regression is a sufficient tool to perform such investigation. The relevant outputs are independent variable coefficients and their probabilities, as well as R^2 coefficients. For this study, a sub-sample and a whole sample investigation were undertaken.

A sub-sample analysis was carried out to determine relationship between commodities' price cointegration and the stock and bond markets during different economic periods. The first sample was taken up until the easing of the global energy crisis in late 2008. The second sample was taken from 2009 to 2012, when markets and cointegration grew stronger.

To perform the investigation, daily returns and volatility information were produced for the S&P 500 and the Barclays Global Aggregate Bond Index. It was anticipated that research on the bond market would be particularly interesting, since the global financial crisis was initiated by the bond market crisis. Daily returns and volatility for the S&P 500 and the Barclays Global Aggregate Bond Index, and gold-silver, gold-oil, and silver-oil λ-trace statistics, are stationary time series. Therefore, stationarity requirements for the purposes of performing OLS regression were met. A linear regression was performed for each price pair λ-trace statistic, the S&P 500 and the Barclays Global Aggregate Bond Index.

The general form of the equation is:

$$\lambda_t = \alpha + x_1\beta_1 r\_sp_t + x_2\beta_2 v\_sp_t + x_3\beta_3 r\_b_t + x_4\beta_4 v\_b_t + \varepsilon_t \qquad \text{Equation (3)}$$

Where:

λ_t is a commodity pair λ-trace statistic as a ratio to 5% level critical value

α is a constant term

β is an independent variable coefficient

r_sp_t is the return on the S&P 500

v_sp_t is the volatility of the S&P 500

r_b_t is the return on the Barclays Global Aggregate Bond Index

v_b_t is the volatility of the Barclays Global Aggregate Bond Index

ε_t is a residual term, unexplained by the equation

If the probability statistics for the S&P 500 and the Barclays Global Aggregate Bond Index are equal to or less than 0.1, we can conclude that hypothesis 4 is correct: over the sample period, cointegration strength between gold and silver, gold and oil, and silver and oil falls during periods of crises, recessions and market turbulence in the stock and bond markets.

Chapter 5: Data

This chapter discusses the exchanges where gold, silver and oil futures are traded, and their history, key milestones and mechanisms; gold, silver and oil futures contract specifications, contract naming conventions, trading and delivery rules, and trading hours; databases, including which data is obtained, and collection practices and validation; data obtained from the databases; and data properties.

5.1 Exchanges

There are numerous exchanges in the world where futures contracts are traded. These exchanges are found in North and South America, in Europe and Asia, Oceania and Africa. The largest exchange where gold and silver futures are traded is CME, which is also the world's first futures exchange, created in 1848 (Hull, 2005). The largest exchange where oil futures are traded is NYMEX. Both exchanges are now part of CME Group (CME, 2012c).

In the last decade a number of important events took place, resulting in key improvements in gold, silver and oil futures trading. In 2006 the Chicago Board of Trade (CBOT) and CME signed an agreement to merge into a single company. Pending regulatory and shareholder approval, CBOT launched electronic agricultural futures trading. Also, NYMEX products became

available for trading on CME Globex, the electronic trading platform. CME and Reuters agreed to form the first centrally cleared global forex (FX) platform for the over-the-counter (OTC) market – FXMarketSpace (FXMS). In 2007, CME and CBOT officially merged to form CME Group Inc., the world's leading and most diverse derivatives marketplace (CME, 2012c). In 2009 CME Group completed its New York trading floor integration, a key milestone following its 2008 acquisition of NYMEX. The integration included the reconfiguration of the energy trading floor and combined the energy and metals futures and options trading rings onto one trading floor (CME, 2012c).

5.2 Trading

The mechanism of trading is two-fold. One is open outcry, which means trading on the exchange floor. The other is trading through the CME Globex electronic trading platform. Trading is cleared through the CME ClearPort clearing service. For each mechanism trading hours are different, and trading through electronic platforms encompasses a wider range of trading hours.

CME Globex is an electronic trading platform that allows users to enter, view, modify or cancel electronic orders during the daily CME Globex sessions. The sessions are 5 days a week. Several trading types are possible: side-by-side, where contracts trade on CME Globex and, when available, through open outcry on the trading floor; electronic only, where contracts are only

traded on CME Globex; and after-hours electronic, where contracts are traded electronically only when open outcry trading for a given contract stops (CME, 2013b).

CME ClearPort is a clearing service available to all who need clearing services, like traders or hedge fund managers. It uses collateral called margin, which is deposited by the given parties and ensures that parties perform their obligations under the contract. Contracts are marked to market each day, so that an additional deposit may be required to maintain the trading margin (CME, 2013a).

5.3 Contracts

5.3.1 Gold

Gold futures contracts use the "GC" ticker symbol. The ticker symbol is a letter codified symbol that represents an instrument on the ticker – the information board that shows price changes every "tick", that is, every trade conducted. When traded, futures contracts also show the delivery month after the ticker symbol. The combination of the ticker symbol and the delivery month follow the format "GC_Z9", where "GC" stands for gold futures, "Z"

stands for the delivery month of December, and "9" stands for the year 2009. Table 5.1 shows the codes for each month.

Table 5.1: Month Codes

Month	Letter
January	F
February	G
March	H
April	J
May	K
June	M
July	N
August	Q
September	U
October	V
November	X
December	Z

The contract size is for 100 troy ounces, with physical settlement (delivery). The minimum tick size is $0.10 per troy ounce. Trading is conducted for delivery during the current calendar month; the next two calendar months; any February, April, August, and October falling within a 23-month period; and any June and December falling within a 72-month period beginning with the current month. Trading terminates on the third to last business day of the delivery month.

CME Globex/CME ClearPort trading hours for gold futures are Sunday–Friday 6:00 p.m.–5:15 p.m. New York time (5:00 p.m.–4:15 p.m. Chicago Time/CT), with a 45-minute break each day beginning at 5:15 p.m. (4:15 p.m. CT). Open outcry trading hours for gold futures are Monday–Friday 8:20 a.m.–1:30 p.m. New York time (7:20 a.m.–12:30 p.m. CT).

5.3.2 Silver

Silver futures contracts have the "SI" ticker symbol. The contract size is for 5,000 troy ounces with physical settlement. The minimum tick size for outright transactions including Exchange for Physical (EFP) is $0.005 per troy ounce. An outright transaction is a privately negotiated trade negotiated outside of the competitive marketplace, but submitted for clearing through the CME Clearing House. An EFP transaction, being an outright type of transaction, is a privately negotiated and simultaneous exchange of a futures position for a corresponding position in the underlying physical. Exchange for Physical is one of the Exchange for Related Positions (EFRP) transactions, which also includes Exchange for Risk (EFR) and Exchange of Options for Options (EOO). These transactions are privately negotiated trades transacted outside of the competitive marketplace, but submitted for clearing through the CME Clearing House (CME, 2013c).

Silver futures contracts also have a minimum tick size for spread transactions and settlement prices, which is $0.001 per troy ounce. A spread transaction is a trade inside the competitive market and is the simultaneous purchase and sale of silver futures with different delivery months. It is also known as a *straddle* (CME, 2011).

Trading is conducted for delivery during the current calendar month; the next two calendar months; any January, March, May, and September falling within a 23-month period; and any July and December falling within a 60-month

period beginning with the current month. Trading terminates on the third to last business day of the delivery month.

CME Globex/CME ClearPort trading for silver futures hours are the same as the trading hours for gold futures: Sunday–Friday 6:00 p.m.–5:15 p.m. New York time (5:00 p.m.–4:15 p.m. CT), with a 45-minute break each day beginning at 5:15 p.m. New York time (4:15 p.m. CT). Open outcry trading hours for silver futures are very close to gold futures trading hours: trading starts 5 minutes later and finishes 5 minutes earlier, than for gold. The open outcry trading hours for silver futures are Monday–Friday 8:25 a.m.–1:25 p.m. New York time (7:25 a.m.–12:25 p.m. CT).

5.3.3 Oil

Oil futures contracts use the "CL" ticker symbol, which stands for "crude light". The contract size is for 1,000 barrels with physical settlement. The minimum tick size is $0.01 per barrel.

Crude oil futures are listed nine years forward using the following listing schedule: consecutive months are listed for the current year and the next five years; in addition, the June and December contract months are listed beyond the sixth year.

Additional months are added on an annual basis after the December contract expires, so that an additional June and December contract would be added nine years forward, and the consecutive months in the sixth calendar year will be filled in. Additionally, trading can be executed at an average differential to the previous day's settlement prices for periods of two to thirty consecutive months in a single transaction. These calendar strips are executed during open outcry trading hours.

Trading in the current delivery month ceases on the third business day prior to the twenty-fifth calendar day of the month preceding the delivery month. If the twenty-fifth calendar day of the month is a non-business day, trading ceases on the third business day prior to the last business day preceding the twenty-fifth calendar day.

In the event that the official Exchange holiday schedule changes subsequent to the listing of a crude oil futures contract, the originally listed expiration date shall remain in effect. In the event that the originally listed expiration day is declared a holiday, expiration will move to the business day immediately prior.

CME Globex/CME ClearPort trading hours for oil futures are the same as for gold and silver futures: Sunday–Friday 6:00 p.m.–5:15 p.m. New York time (5:00 p.m.–4:15 p.m. CT) with a 45-minute break each day beginning at 5:15 p.m. (4:15 p.m. CT). Oil futures start and finish trading almost two hours later

than gold or silver futures. Open outcry trading hours for oil futures are Monday–Friday 9:00 a.m.–2:30 p.m. New York time (8:00 a.m.–1:30 p.m. CT) (CME, 2012b). Gold, silver and oil futures contracts details are summarised in Table 5.2.

Table 5.2: Gold, Silver and Oil Futures Contracts Summary (CME, 2011, 2012b)

	Gold Futures	Silver Futures	Oil Futures
Contract Size	100 troy oz.	5,000 troy oz.	1,000 Barrels
Ticker Symbol	GC	SI	CL
Settlement Type	Physical	Physical	Physical
Minimum Tick Size	$0.10 per troy oz.	$0.005 per troy oz. $0.001 per troy oz.	$0.01 per barrel
Listed Contracts	Trading is conducted for delivery during the current calendar month; the next two calendar months; any February, April, August, and October falling within a 23-month period; and any June and December falling within a 72-month period beginning with the current month.	Trading is conducted for delivery during the current calendar month; the next two calendar months; any January, March, May, and September falling within a 23-month period; and any July and December falling within a 60-month period beginning with the current month.	Crude oil futures are listed nine years forward using the following listing schedule: consecutive months are listed for the current year and the next five years; in addition, the June and December contract months are listed beyond the sixth year. Additional months will be added on an annual basis after the December contract expires, so that an additional June and December contract would be added nine years forward, and the consecutive months in the sixth calendar year will be filled in. Additionally, trading can be executed at an average differential to the previous day's settlement prices for periods of two to 30 consecutive months in a single transaction. These calendar strips are executed during open outcry trading hours.
Termination of Trading	Trading terminates on the third last business day of the delivery month.	Trading terminates on the third last business day of the delivery month.	Trading in the current delivery month shall cease on the third business day prior to the twenty-fifth calendar day of the month preceding the delivery month. If the twenty-fifth calendar day of the month is a non-business day, trading shall cease on the third business day prior to the last business day preceding the twenty-fifth calendar day. In the event that the official Exchange holiday schedule changes subsequent to the listing of a Crude Oil futures contract, the originally listed expiration date shall remain in effect. In the event that the originally listed expiration day is declared a holiday, expiration will move to the business day immediately prior.
Trading Hours (All times listed are New York time)	**CME Globex/CME ClearPort**: Sunday – Friday 6:00 p.m. – 5:15 p.m. (5:00 p.m. – 4:15 p.m. Chicago Time/CT) with a 45-minute break each day beginning at 5:15 p.m. (4:15 p.m. CT) **Open Outcry**: Monday – Friday 8:20 a.m. – 1:30	**CME Globex/CME ClearPort**: Sunday – Friday 6:00 p.m. – 5:15 p.m. (5:00 p.m. – 4:15 p.m. Chicago Time/CT) with a 45-minute break each day beginning at 5:15 p.m. (4:15 p.m. CT) **Open Outcry**: Monday – Friday 8:25 a.m. – 1:25 p.m. (7:25 a.m. – 12:25 p.m. CT)	**CME Globex/CME ClearPort**: Sunday – Friday 6:00 p.m. – 5:15 p.m. (5:00 p.m. – 4:15 p.m. Chicago Time/CT) with a 45-minute break each day beginning at 5:15 p.m. (4:15 p.m. CT) **Open Outcry**: Monday – Friday 9:00 a.m. – 2:30 p.m. (8:00 a.m. – 1:30 p.m. CT)

	p.m. (7:20 a.m.–12:30 p.m. CT)		

5.4 Data Collection

Data was collected from TRTH via the Securities Industry Research Centre of Asia-Pacific (Sirca) database.

5.4.1 Securities Industry Research Centre of Asia-Pacific database

To support the needs of academic researchers, Sirca was created by a group of Australian and New Zealand universities in 1997 as a not for profit organisation. Its mission is to develop and provide global data and tools for financial research. The original group of founding universities has been expanded and currently includes, as members and customers, over 30 universities in Australia and New Zealand, many other international universities, central banks, regulators and public sector agencies. The organisation is a leader in many areas such as helping members to understand financial instrument data structures, managing the grasping of important financial market-data streams, and managing large-scale archives of financial market data sets. Numerous global organisations seek Sirca's help for their largest and most complex data processing challenges (SIRCA, 2013a).

5.4.2 Thomson Reuters tick history

Sirca provides access to the TRTH for academics and regulators of non-commercial research of the financial markets. TRTH is able to provide tick data at millisecond frequency back to January 1996, and covers 45 million active OTC and exchange-traded instruments globally (the total pool is greater than 140 million active and inactive instruments). TRTH currently updates at a rate of 1 million messages per second and is around 3 Petabytes, uncompressed. It is a comprehensive, accurate, and precise historical record of market behaviour and can be accessed using the following methods: a Java enabled web browser, the Application Programming Interface (API), or File Transfer Protocol (FTP) (SIRCA, 2013b).

As discussed in Chapter 4 on methodology, VECM estimates long-run relationships, therefore data is required over a long time period to achieve robust results. For this study the data was collected from the TRTH database from Sirca over the past five years (2007 – 2012), a time period that allows for analysing the price leadership question during different economic events, including the 2008 global financial crisis and the broader global economic crisis of 2007–2012.

The commodities futures contracts have fixed delivery dates and, therefore, a limited lifespan. However, VECM requires a continuous time series, so contracts need to be combined. To achieve this, the initial daily data was

obtained from the Datastream database and processed to identify days on which a contract was most actively traded. Those days become the rollover days, on which separate time series were joined into one continuous time series. It was necessary to do this because the main research method, Vector Error Correction Model (VECM), requires a continuous time series for its application.

Next, separate time series with 1 minute frequencies were obtained from the Sirca database. The extracted fields were contract name, date, time, close bid price, close ask price, and number of trades. The bid price is always lower than the ask price, except for in rare circumstances, under which the prices are not considered to be true bid and ask prices (Dacorogna, 2001). Because bid and ask closing prices are continually rising and falling, this introduces autocorrelations (Andersen, Bollerslev, Diebold, & Labys, 2003). In finance literature this is called bid-ask bounce, and is known for introducing negative lag-1 serial correlation (or autocorrelation) in an asset return (Tsay, 2005). The way to mitigate this is to use the midpoint price, and for this analysis the close bid and close ask prices were used to calculate the midpoint price. The local exchange time was used and time series were synchronised to New York time.

To check whether constructed time series matched real prices, continuous time series with daily frequency were obtained from Datastream for the same period. Then closing daily prices were captured from the 1 minute constructed

time series. Logarithmic returns time series were made from all level time series. Large outliers were excluded. On average there was 1 large outlier per 1,000 observations. Then constructed time series logarithmic returns were regressed on real time series logarithmic returns: R^2 for gold was 0.9712, R^2 for silver was 0.9821, and R^2 for oil was 0.6538. Given that the two time series captured data at different times of the day, the constructed continuous gold and silver time series closely match the real time series because the time series logarithmic returns are highly correlated. Oil returns' constructed continuous time series are correlated to oil real returns time series at a moderate level. However, there are several factors to consider. First, it is unknown when Datastream close prices are collected: for example at the end of open outcry session, at the end of the day at 5 p.m. or at the end of a 24-hour period at 23:59. It is also unknown whether Datastream uses electronic trading prices. The constructed time series are open outcry close prices only. Second, because oil is traded significantly later than gold and silver on open outcry, the constructed oil time series was trimmed to achieve a common sample with gold and silver. Third, it is unknown how Datastream constructs continuous time series for futures contracts, as futures contracts do not have naturally continuous time series, and continuous time series for futures contracts have to be constructed. Given these factors, R^2 for oil being 0.6538 is high enough to support the usability of the constructed time series for the research. Therefore, gold, silver and oil constructed time series are all fit for use in this research.

The individual time series were joined into two data sets for a continuous time series: one for open outcry trading hours and one for platform trading hours, which includes open outcry trading hours. Each dataset has data for the three futures contracts. The time series for open outcry was trimmed to 9:00 a.m.– 1:25 p.m. This is when prices were available for all three contracts. Furthermore, the time series was trimmed to 9:05 a.m.–1:20 p.m. to eliminate opening and closing effects. The time for trading through the platform was the same for all contracts, therefore it did not require adjustments. Because trading outside of open outcry hours is less active and periods of no trading are frequent, it was assumed that the most information was contained in prices observed during open outcry sessions, and therefore analysis was performed on prices for these periods.

The data for the three contracts was then checked for integrity. There were only three instances identified where price was equal to zero for the open outcry data set. This was corrected by taking the price from a previous observation and using it instead of zero, as suggested by Andersen et al. (2007).

5.5 Data Description

One-minute bid-ask midpoint closing prices from 6 September 2007 to 20 January 2012 (a total of 289,024 observations for each time series) were used in this study. The commodities markets trends are shown in Figure 5.1.
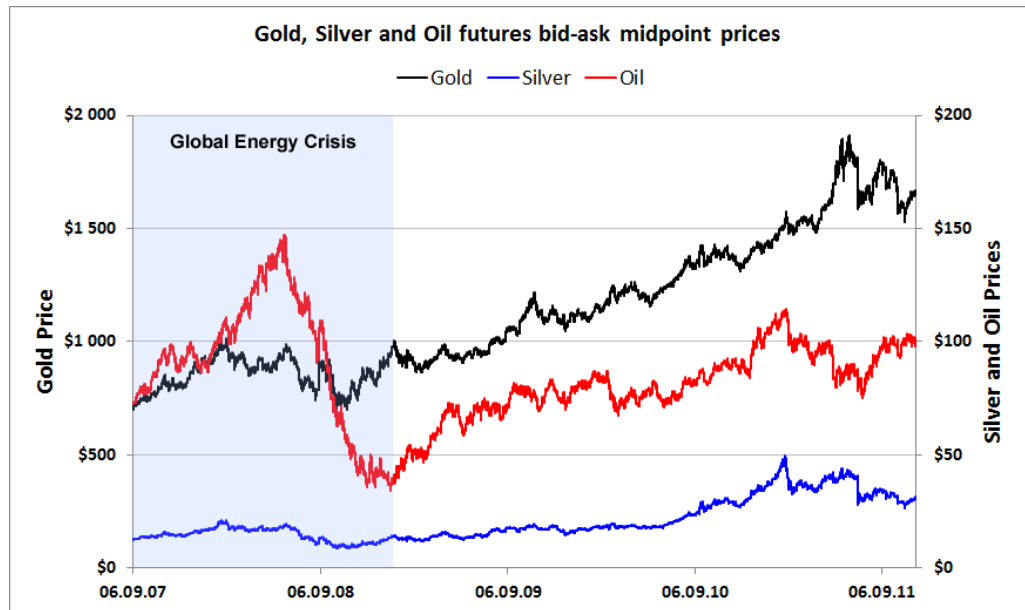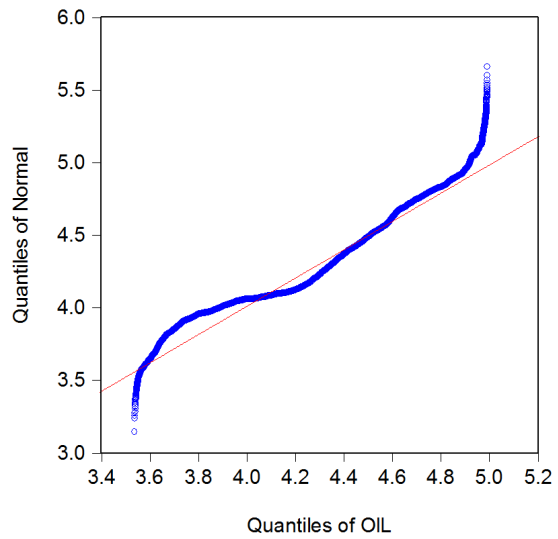

Figure 5.1: Gold, Silver and Oil Price Levels

All three commodities are traded in US dollars, therefore no price conversion or exchange rate adjustments were required. Because the price of gold is significantly higher, the secondary axis is used to show silver and oil prices. All three commodities markets were consistent with price trends. Note that during the global energy crisis, which eased in late 2008, oil prices show a greater relative range, which I define as the difference between the highest and lowest price values, relative to price mean.
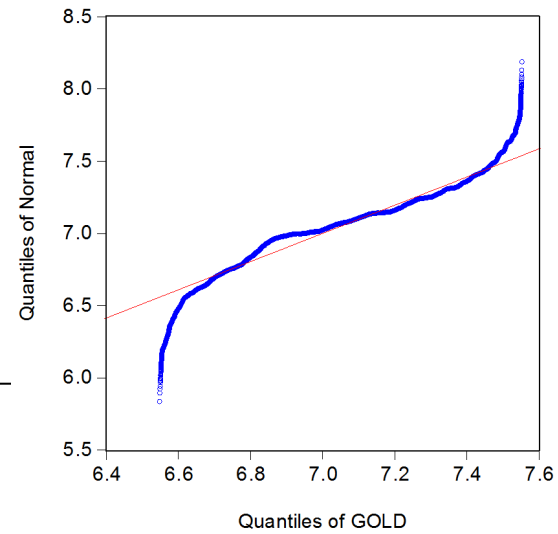
The dramatic price change is represented by the spike between 2007 and 2008, when the price of oil rose from $100 to $150 per barrel and then dropped back again to $50 per barrel. Gold prices followed a similar pattern, rising from $700 to $1,000 and reversing to $700 again in late 2008. Silver prices also rose, starting at $12 and rising to $21, and then falling to $9. After 2008, all prices showed an upward trend with common spikes in late 2009 and 2010, which could relate to the easing of the financial crisis and increased activity on the commodities markets.

Overall, gold prices rose steadily and more than doubled from $700 per ounce to levels surpassing $1,500 per ounce. Silver rose from $12.61 to almost $50 ($49.52), and then reversed to the $30–$35 level. After the oil market collapse and crisis relief, oil prices also rose steadily from $35 to $100. To summarise, gold, silver and oil commodities prices achieved continuous growth and at least doubled their values as at the beginning of the period.
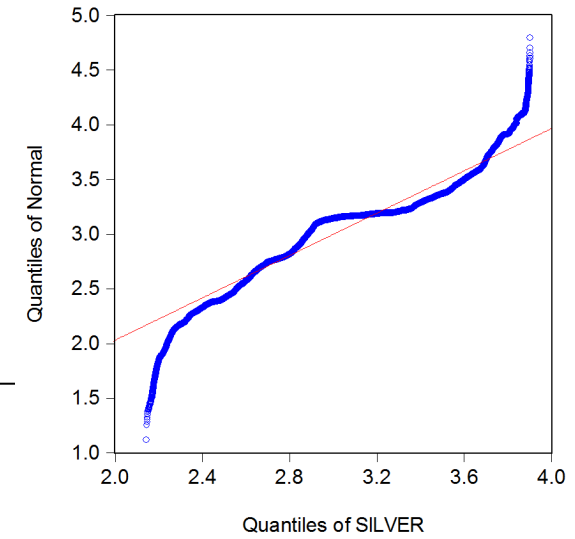
It is expected that prices are not normally distributed. Non-normality can be seen from Quantile–Quantile (Q–Q) plots, which show how closely two distributions match. If they match, then the Q–Q plot is a straight line (Easton & McCulloch, 1990). Figure 5.2 below shows gold, silver and oil logarithmic prices on Q–Q graphs, and from the Q–Q figures we can see that gold, silver and oil prices do not follow normal distribution. Use of logarithmic prices is discussed later in the text.

Panel A: Logarithmic oil prices   **Panel B: Logarithmic gold prices**   **Panel C: Logarithmic silver prices**

Figure 5.2: Logarithmic Prices Using Quantile-Quantile Figures

Table 5.3: Gold, Silver and Oil Logarithmic Prices Descriptive Statistics

Prices			
	Gold	Silver	Oil
Mean	7.0064	2.9573	4.4034
Median	6.9870	2.8668	4.4261
Std. Dev.	0.2533	0.3960	0.2714
Skewness	0.3191	0.4851	-0.7700
Kurtosis	1.9566	2.2614	3.7755
Jarque-Bera	18079	17969	35933
Probability	0.0000	0.0000	0.0000
Coefficient of Variance	27.6659	7.4671	16.2226
Coefficient of Variance Ratio	3.7050	1.0000	2.1725
Probability of Unit Root	0.1349	0.6874	0.7834

From Table 5.3 we see that commodities are priced at different levels: the natural logarithmic gold, silver and oil time series prices have means of 7.0064, 2.9573 and 4.4034 respectively. Medians vary little from the means and almost match them: gold, silver and oil price medians are 6.9870, 2.8668 and 4.4261 respectively. Gold and silver means are slightly higher than their medians, while the oil mean is slightly lower than median. This suggests skewness in the data, which is supported by the skewness statistics: 0.3191, 0.4851, and -0.7700 for gold, silver and oil respectively. From the skewness data we can see that the gold and silver data is skewed to the right, and oil data is skewed to the left. Standard deviations are 0.2533, 0.3960, and 0.2714 for gold, silver and oil respectively. From the commodities prices' descriptive

statistics we see that their prices are not normally distributed, based on their statistically significant Jarque-Bera, kurtosis and skewness tests. For normal distribution, the Jarque-Bera test should be close to 0, kurtosis should be close to 3, and skewness should be close to zero. Note that silver has the least volatility in magnitude, based on its coefficient of variance, which is the sample mean divided by the sample standard deviation (Zhang & Wei, 2010). Interestingly, oil has twice the magnitude of volatility of silver, while gold has twice the magnitude of volaltility of oil. Gold-oil-silver volatility magnitudes can be approximately represented as 4–2–1 or, more precisely as 3.7–2.2–1: gold (27.6659), oil (16.2226), and silver (7.4671).

Cointegration research uses logarithmic values of the original prices to arrive at a comparable scale. Therefore, original gold, silver and oil prices are converted to their natural logarithmic values and tested for stationarity using the Augmented Dickey-Fuller Unit Root test for a unit root in levels assuming intercept and trend. Lag length was selected using the Schwarz Information Criterion (SIC). The null hypothesis is that each time series has a unit root. The results of the test, as well as other statistics are outlined in Table 5.3.

From Table 5.3 we can see the probability of the null hypothesis that gold, silver and oil logarithmic price time series have unit roots of 13.49%, 68.74% and 78.34% respectively. So at the 5% significance level we cannot reject the null hypothesis, which suggests that each time series has a unit root. Therefore, all three commodities' price time series have a unit root and they

are not stationary. Because there are unit roots at level prices, we can proceed with examination of the possible cointegration relationships (Lucey & Tully, 2006a).

While prices are not normally distributed and not stationary, it is expected that returns are normally distributed and stationary. Therefore, next we test the assumption that returns on each commodity are stationary and normally distributed. For this we generate a natural logarithmic returns time series using equation 4:

$$R_1 = \log_e P_2 - \log_e P_1 \qquad \text{Equation (4)}$$

Where:

R_1 is the return in period 1 (1 minute)

P_1 and P_2 are prices at periods 1 and 2

Note from Figure 5.3 that gold returns are the least volatile of the three commodities. Also, note the volatility clustering in all of the time series. The first clustering is evident in 2008 during the peak of the global energy and global financial crises. The second clustering is in 2011, the new wave of global recession – also called the global economic crisis.
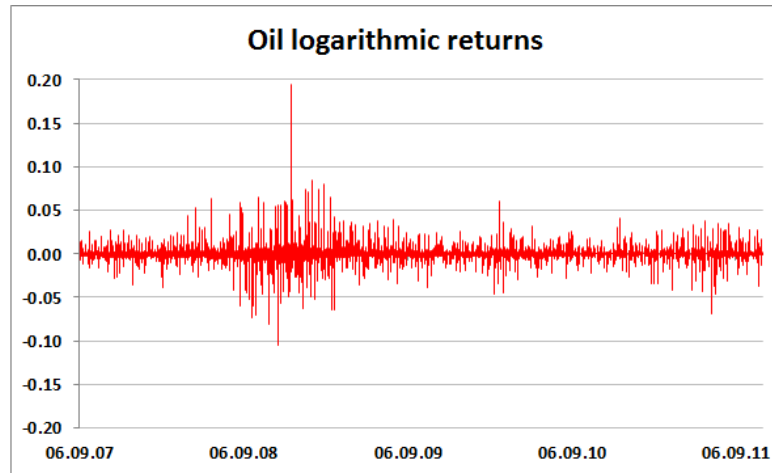
Panel A: Oil returns
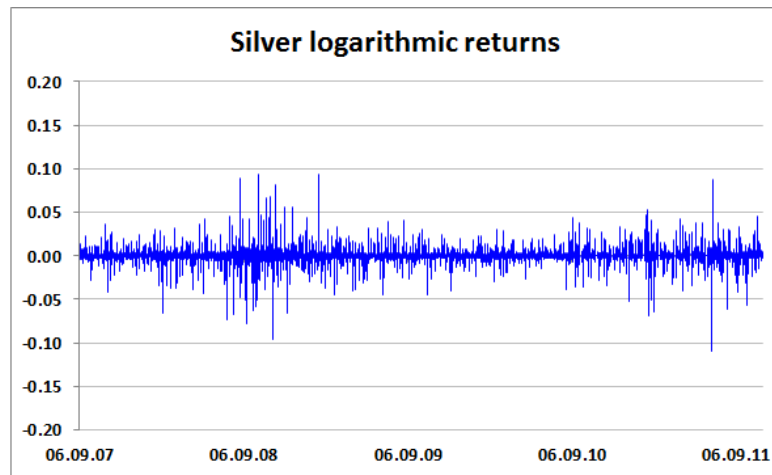
Panel B: Silver returns
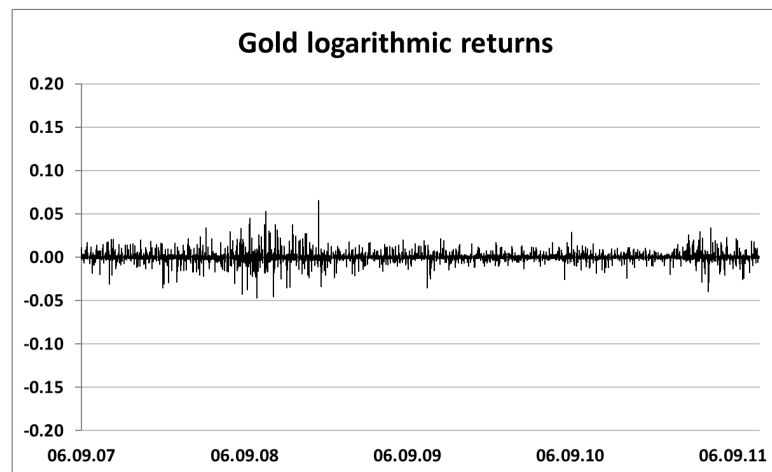
Panel C: Gold returns

Figure 5.3: Gold, Silver and Oil Returns

Table 5.4: Gold, Silver and Oil Logarithmic Returns Descriptive Statistics

Returns			
	Gold	**Silver**	**Oil**
Mean	0.0000	0.0000	0.0000
Median	0.0000	0.0000	0.0000
Std. Dev.	0.0009	0.0016	0.0017
Skewness	1.8004	-2.1162	5.7817
Kurtosis	557.6323	636.7060	1070.2390
Jarque-Bera	3720000000	4850000000	13800000000
Probability	0.0000	0.0000	0.0000
Coefficient of Variance	0.0033	0.0020	0.0006
Coefficient of Variance Ratio	5.3522	3.1636	1.0000
Probability of Unit Root	0.0001	0.0001	0.0001
Correlations			
	Gold	**Silver**	**Oil**
Gold	1.0000	0.7764	0.3186
Silver	0.7764	1.0000	0.4027
Oil	0.3186	0.4027	1.0000

From Table 5.4 we can see that commodities returns have means and medians of zero. We cannot see whether gold, silver and oil means are higher or lower than medians to check for skewness, however skewness statistics shows that gold and oil returns data are right skewed, and silver returns data are left skewed; the skewness statistics are 1.8004, -2.1162 and 5.7817, for gold,

silver and oil respectively. Standard deviations are 0.0009, 0.0016, and 0.0017 for gold, silver and oil respectively. From the commodities' prices descriptive statistics, we see that returns are not normally distributed, based on their significant Jarque-Bera, kurtosis and skewness statistics. Note that the Jarque-Bera statistics are expected to be high due to high-frequency data and numerous cases of no price change during quiet periods on the markets.

Also note that oil returns have the least volatility magnitude, based on oil's coefficient of variance. Interestingly, silver returns are triple the magnitude of oil, and gold returns are five times that of oil returns. Gold-silver-oil returns' volatility magnitudes can be represented approximately as 5–3–1 or, more precisely, 5.4–3.2–1: gold (0.0033), silver (0.0020), oil (0.0006).

Time series were tested for stationarity using the Augmented Dickey-Fuller Unit Root test for a unit root in levels assuming intercept and trend. Lag length was selected using the SIC. The null hypothesis is that each time series has a unit root. The results of the test, as well as other statistics, are outlined in Table 5.4.

From Table 5.4 we see that at the 5% significance level we can reject the null hypothesis that each time series has a unit root. Therefore, all three commodities' returns price time series have no unit root and they are stationary.
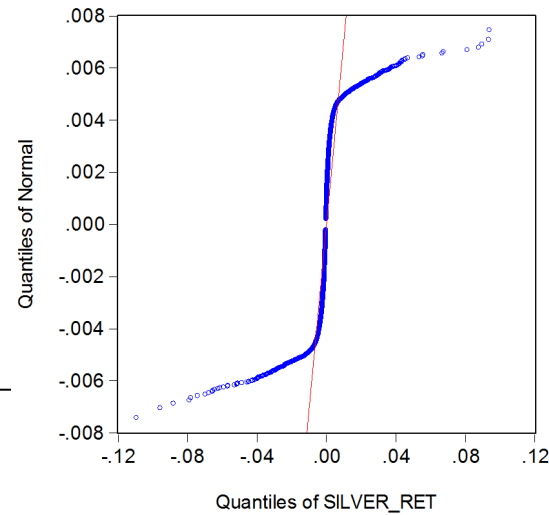
The commodities' returns show correlation: gold and silver returns are reasonably highly correlated (0.7764), and again, oil returns have higher correlation with silver returns (0.4027) than with gold returns (0.3186). This may support the speculative behaviour of investors hypothesis, stated earlier: if oil and silver are used more for speculation, while gold is more often used for hedging, then returns on oil and silver would show a higher correlation.

Returns histograms for this data are not normal distribution histograms and are not even close to a bell shape. Returns histograms in Appendix 1 support the descriptive statistics showing that gold, silver and oil returns are not normally distributed.
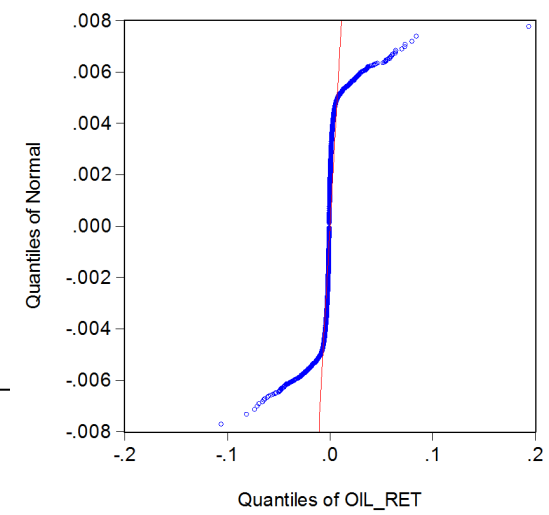
In addition, non-normality can be seen from the Q–Q plots. From Figure 5.4 we can see that gold, silver and oil returns (GOLD_RET, SILVER_RET and OIL_RET respectively) do not follow normal distribution.
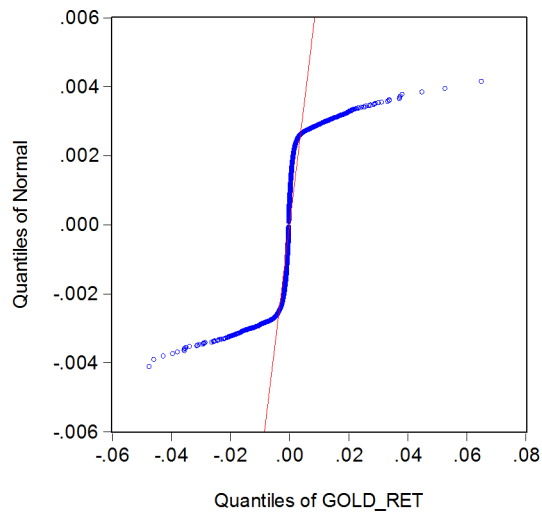
Panel A: Gold logarithmic returns   **Panel B: Silver logarithmic returns**   **Panel C: Oil logarithmic returns**

Figure 5.4: Logarithmic Returns Quantile-Quantile Figures

Chapter 6: Results

This chapter discusses the results of the cointegration analysis, including different approaches and their outcomes; impulse response functions analysis and related findings; and the relationship between the stock and bond markets and gold, silver and oil futures markets using the S&P 500 as a proxy for the stock market, and the Barclays Global Aggregate Bond Index as a proxy for the bond market.

6.1 Cointegration

Researchers have found that over the past two decades cointegration is present between gold and silver (Escribano & Granger, 1998; Lucey & Tully, 2006b) and between gold and oil (Zhang & Wei, 2010). Because cointegration is a long-term relationship, it was assumed that it did not disappear during the sampling period of this research. Moreover, because gold and silver and gold and oil are cointegrated, it was assumed that oil and silver are cointegrated as well. Also, other researchers have found that while cointegration is present, its strength varies over time (Lucey & Tully, 2006a). Therefore, it was concluded that a dynamic cointegration study was required for understanding the nature of changes in this relationship. It was assumed that during crises and market turbulence, cointegration between the commodities becomes weaker, but does not disappear – because it is a long-term relationship.

To estimate cointegration, a similar approach to that used by Lucey and Tully (2006a) was employed in this study. This approach confirmed the presence of cointegration between all three commodity pairs: gold-silver, gold-oil and silver-oil.

For comparison purposes, daily estimated λ-trace statistics for gold-silver, gold-oil and silver-oil price pairs were converted into ratios to their critical values. When the ratio equals 1, the λ-trace statistic equals the critical value at the 5% significance level, and the null hypothesis of no cointegration is rejected. Table 6.1 shows a summary of the Johansen-Juselius approach.

Table 6.1: Johansen-Juselius Approach Summary

Johansen - Juselius approach summary			
	Gold - Silver	Gold - Oil	Silver - Oil
Average ratio of λ-trace statistic to its critical value	0.9073	0.8826	0.8720
Number of times when ratio of λ-trace statistic to its critical value is above 1	434	392	386
Number of times when ratio of λ-trace statistic to its critical value is above 1 *as a % of total results*	38.44%	34.72%	34.19%

From Table 6.1 we can see that the average λ-trace statistic is 0.9073 for gold and silver, 0.8826 for gold and oil, and 0.8720 for silver and oil. Cointegration was found in 38.44%, 34.72% and 34.19% of days for gold-silver, gold-oil and silver-oil commodity pairs respectively. This is similar to Lucey and Tully's (2006a) findings, where cointegration was present approximately 50% of the time. There are differences however, because Lucey and Tully's (2006a) research was conducted on an earlier sample, and did not include the global financial crisis. Moreover, Lucey and Tully (2006a) used a 52-week window, while this study uses a daily window. However, given that the outputs of the two studies are so close, we can say that cointegration did not disappear during the sample period. Therefore, we can conclude that hypothesis 1 is correct: over the research sample there is cointegration between gold and silver, gold and oil, and silver and oil.

6.1.1 Dynamic cointegration

Dynamic cointegration research was conducted following Lucey and Tully's (2006a) approach. For each commodity pair, a daily VECM was estimated. Following the Johansen-Juselius (Johansen & Juselius, 1990) methodology, the λ-trace statistic (at most 1) for gold – silver, gold – oil and silver – oil price pairs was calculated on a daily basis. The assumption was that there was an intercept and no trend. The appropriate lag structure was initially assumed to be not more than several minutes, due to the fast-paced nature of modern markets. This was supported by extensive Akaike Information Criterion

(AIC) and SIC modelling and testing. As a result of the modelling and testing, a lag of 2 (2 minutes) was suggested by both the AIC and the SIC.

The first approach, called global analysis by Lucey and Tully (2006a), consists of estimation of the Johansen-Juselius approach on an initial set of data (1 day). Then another subset of data is added (1 day), and the Johansen-Juselius approach is estimated again on a new sample (2 days). Under this approach, data keeps adding until all data is included in the sample. This approach allows observation of the evolution of cointegration over time.

The second approach, called rolling analysis, consists of dividing the data in a number of non-overlapping samples (a period of 1 day in this study) and the Johansen-Juselius approach is estimated on each of those samples. This approach allows us to see how the cointegration dynamic changes over time.

It can be noted that during 2007–2012 cointegration was stronger in some periods and weaker in other periods. Figure 6.2 shows that for all price pairs the λ-trace statistic as a ratio to the critical value revolves around 1, which is supported by the data in Table 6.1. Representing the λ-trace statistic for gold-silver, gold-oil and silver-oil commodity pairs as a ratio to critical values graphically, following Lucey and Tully's (2006a) global and rolling approaches, supports the findings outlined in Table 6.1. See Figures 6.1 and 6.2, which follow.
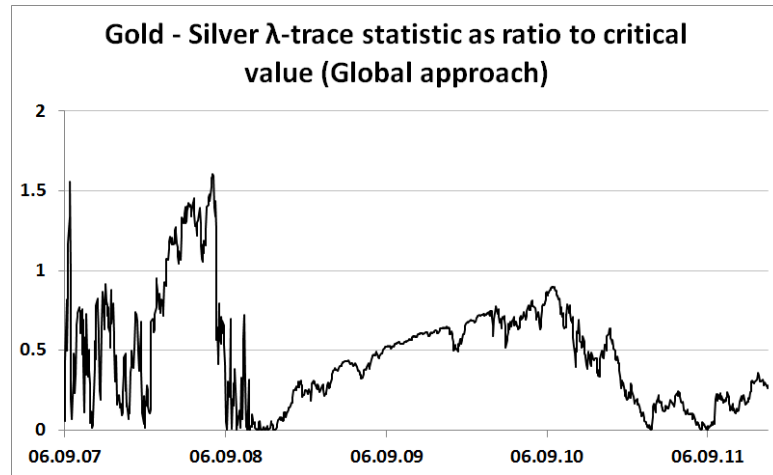
Panel A
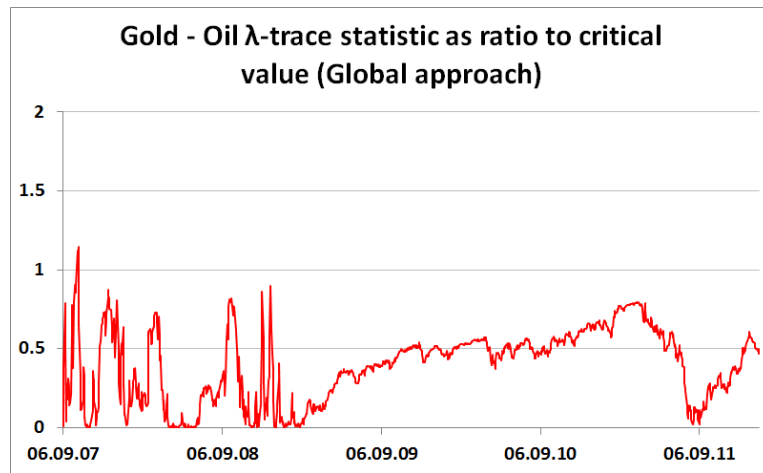
Panel B
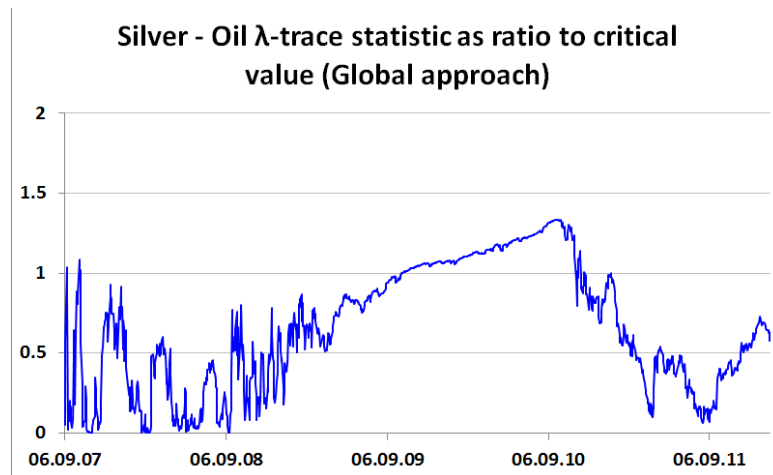
Panel C

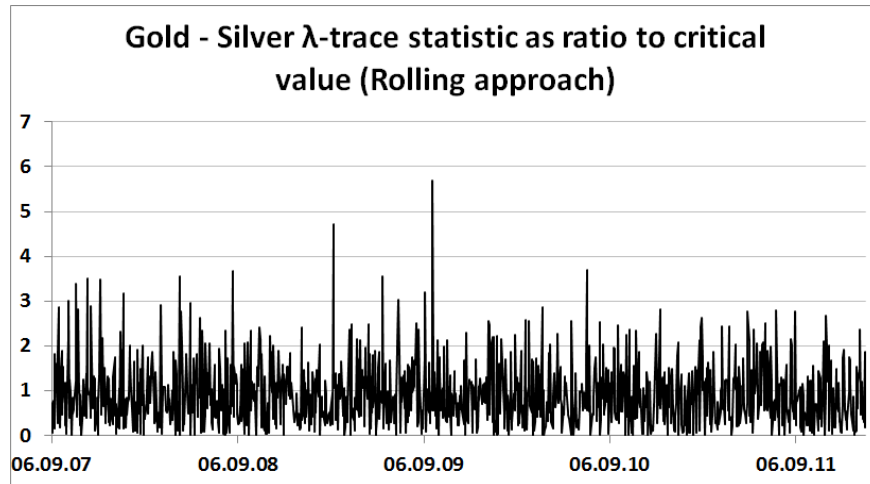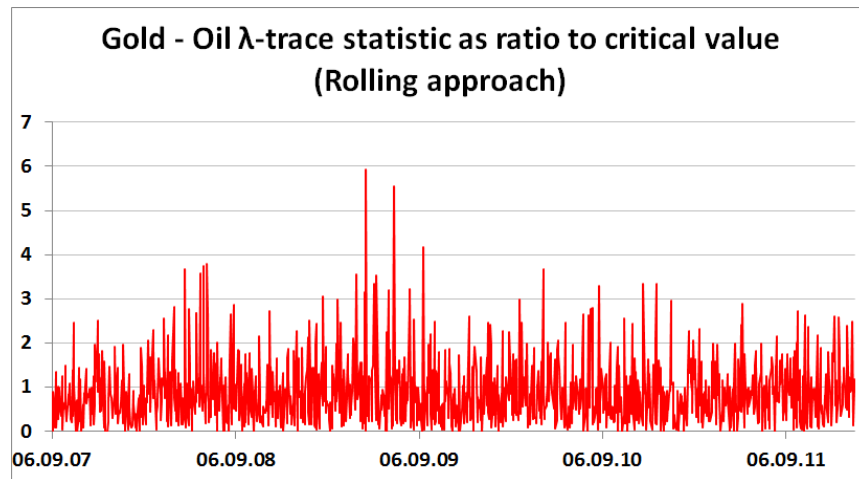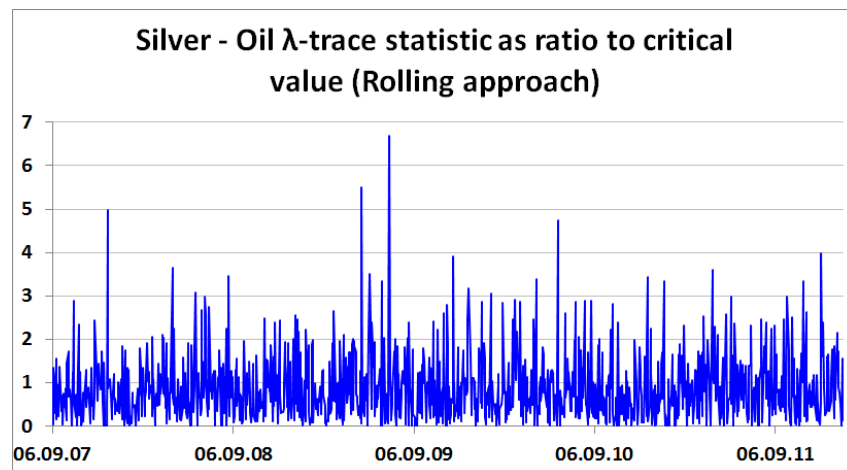**Figure 6.1: Gold, Silver and Oil λ-trace Statistics as a Ratio to Critical Value (Global Approach)**

Panel A

Panel B

Panel C

Figure 6.2: Gold, Silver and Oil λ-trace Statistics as a Ratio to Critical Value (Rolling Approach)

Figure 6.1 (global approach) shows that in some periods cointegration was strong and in some periods it was weak. In periods of strong cointegration we can observe ratios in excess of 1, similar to what Lucey and Tully (2006a) observed. This could be explained by speculative market activity, which causes cointegration to weaken in the short-term. During 2009–2011 cointegration was near-strong for gold and silver, moderate to near-strong for gold and oil, and moderate-to-strong for silver and oil. The case of silver and oil is particularly interesting, as strong cointegration during crisis and market turbulence may be explained by the fact that silver is not considered a speculative asset, and therefore is less exposed to cointegration disruption as a result of market speculation.

The spike of gold and silver cointegration in late 2007–mid 2008 could be explained by the beginning of the global financial crisis, when many investors fled from stocks and invested in metals.

Interestingly, for the period 2009–2011, when cointegration for all price pairs was steadily growing, the global Gross Domestic Product shows a major decrease. This is found to be related to the stock and bond market crashes (Bran, Rădulescu, Ioan, & Bălu, 2011), which is supported by findings that will be reported in section 6.3, "Stock and bond markets and commodities". In this research, the λ-trace statistic is used as an estimate of cointegration strength, rather than evidence of presence or absence of cointegration.

Because it was established by previous researchers that there is cointegration, and because cointegration is a long-term property, we cannot say that cointegration suddenly disappears if the λ-trace statistic is below its critical value. During turbulent periods the long-run relationship, while still present, may be overwhelmed by short-run dynamics, therefore we can assume that when the λ-trace statistic ratio to its critical value is above 1, cointegration is stronger. When the ratio is below 1, cointegration is weaker. Therefore, we can conclude that hypothesis 2 is correct: over the sample period, cointegration strength between gold and silver, gold and oil, and silver and oil fluctuates, but cointegration does not disappear.

6.2 Impulse Responses

It is found that in the long run oil leads gold (Zhang & Wei, 2010). However, it appears that the price leadership between gold and silver and silver and oil is not yet fully understood; neither is price leadership at high frequencies, given the fast-paced nature of modern markets. Below I discuss hypothesis 3, which suggests that oil leads gold and silver, and gold leads silver.

Because there is cointegration between the commodities, and from this and previous research it is concluded that cointegration did not disappear, it was only slightly weakened, price leadership analysis can now proceed. This is done by analysing impulse response functions. As discussed in Chapter 4 on methodology, impulse response analysis looks at changes in dependent

variables when a unit of shock is applied to the residuals of the equation. Because cointegration strength fluctuates, and the λ-trace statistic as a ratio to its critical value sometimes falls below 1, to be accurate, we assume that there is no cointegration, and we use VAR instead of VECM on the entire sample. Figure 6.3 shows cumulative responses of gold, silver and oil to one unit shock on the residuals of VAR. Interestingly, the gold response to oil is half of the gold response to silver.

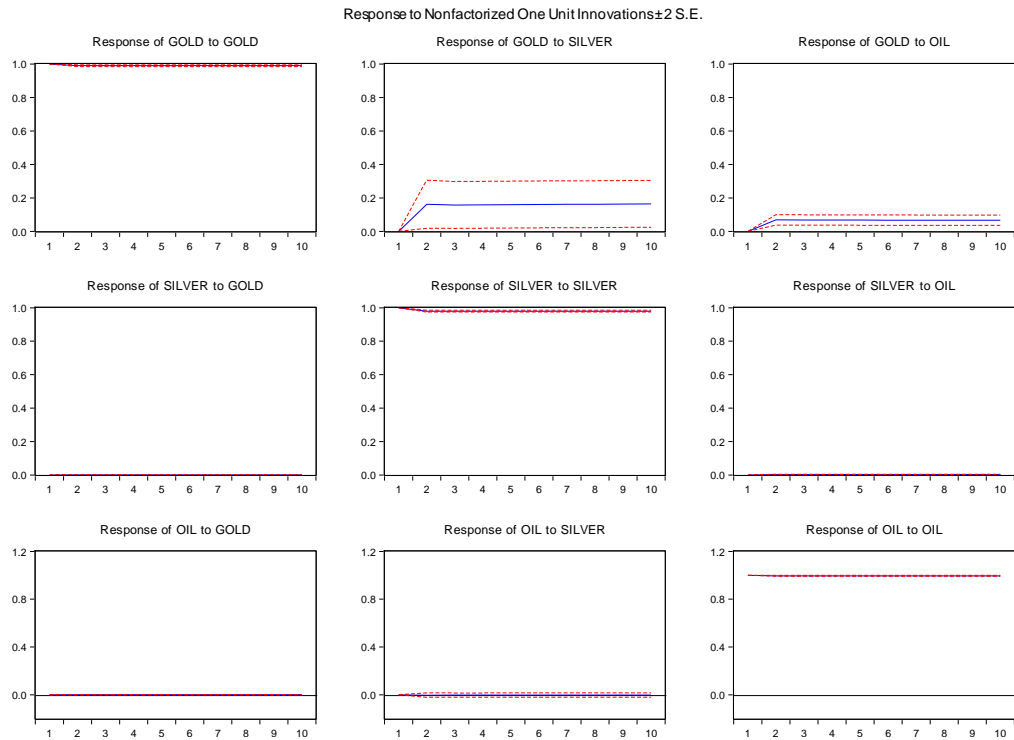Response to Nonfactorized One Unit Innovations±2 S.E.

Figure 6.3: Vector AutoRegression Impulse Response Functions: Entire Sample

The results are almost the same if the sample is cointegrated, as per the approach using the λ-trace statistic as a ratio to the critical value. It appears that of the three commodities, only gold is responsive to changes in the others.

Impulse response functions support the proposition that during financial crises gold acts as a safe haven, as the gold price reacts to changes in the silver and oil prices – probably because of the behavioural aspect of finance, where investors shift to gold every time there is a shock in the silver and oil markets. It appears that in the sample period gold is led by silver and oil. Because of the fast-paced nature of modern markets, the gold response is very rapid: within 2 minutes the gold price changes 0.2 units per 1 unit of shock in silver, and 0.1 units per 1 unit of shock in oil. Although the response may appear small, it occurs on a high-frequency basis, and such level of impulse response functions may be economically significant. To verify this would require further research.

If we use VECM in periods when there is cointegration, instead of VAR, the picture is similar; see figures 6.4 and 6.5. The noticeable difference is the greater response of gold to silver and oil, and the response of oil to silver. The responses are very rapid. Within 2 minutes the gold price changes 0.6 units per 1 unit of shock in silver, and 0.2 units per 1 unit of shock in oil. Also, within 2 minutes the oil price changes 0.3 units per 1 unit of shock in silver. It appears that in the periods when there is cointegration, gold is led by silver and oil, and oil is led by silver. In terms of price leadership, silver appears to lead gold and oil. Although the response may appear small, it occurs on a high-frequency basis, and such level of impulse response functions may be economically significant. To verify this would require further research. Therefore, we can conclude that our hypothesis 3 is not fully correct, because

over the research sample price leadership is different from oil leading gold and silver, and gold leading silver.

Response to Nonfactorized One Unit Innovations

Response of GOLD to GOLD	Response of GOLD to SILVER	Response of GOLD to OIL
Response of SILVER to GOLD	Response of SILVER to SILVER	Response of SILVER to OIL
Response of OIL to GOLD	Response of OIL to SILVER	Response of OIL to OIL
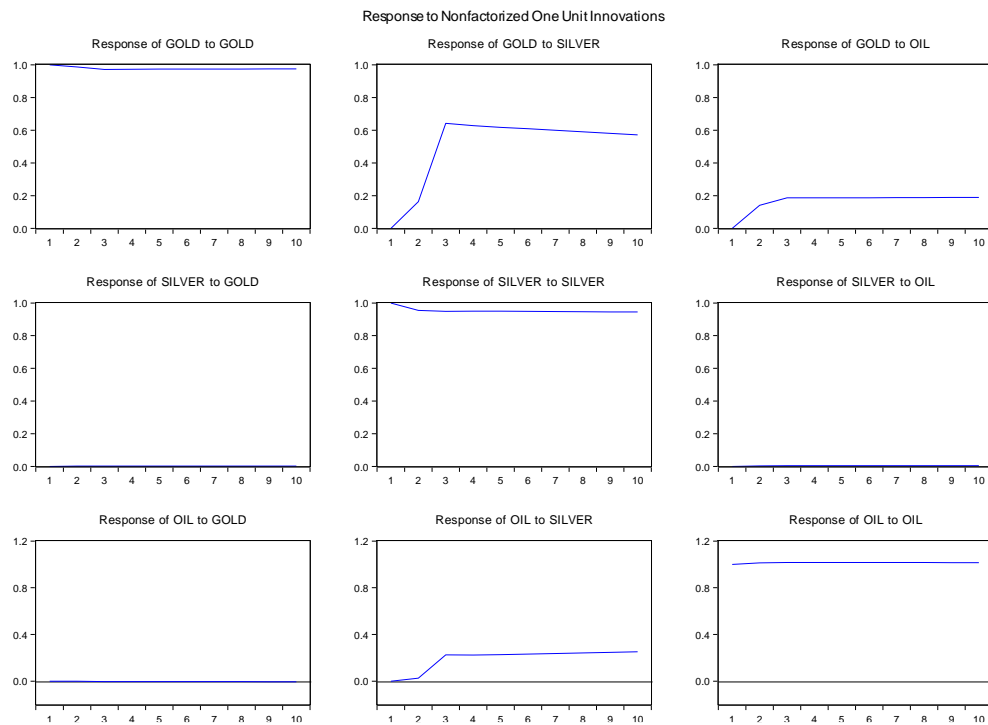
Figure 6.4: Vector Error Correction Model Impulse Response Functions: July 2008 – July 2009

Response of GOLD to GOLD	Response of GOLD to SILVER	Response of GOLD to OIL

Response of SILVER to GOLD	Response of SILVER to SILVER	Response of SILVER to OIL

Response of OIL to GOLD	Response of OIL to SILVER	Response of OIL to OIL
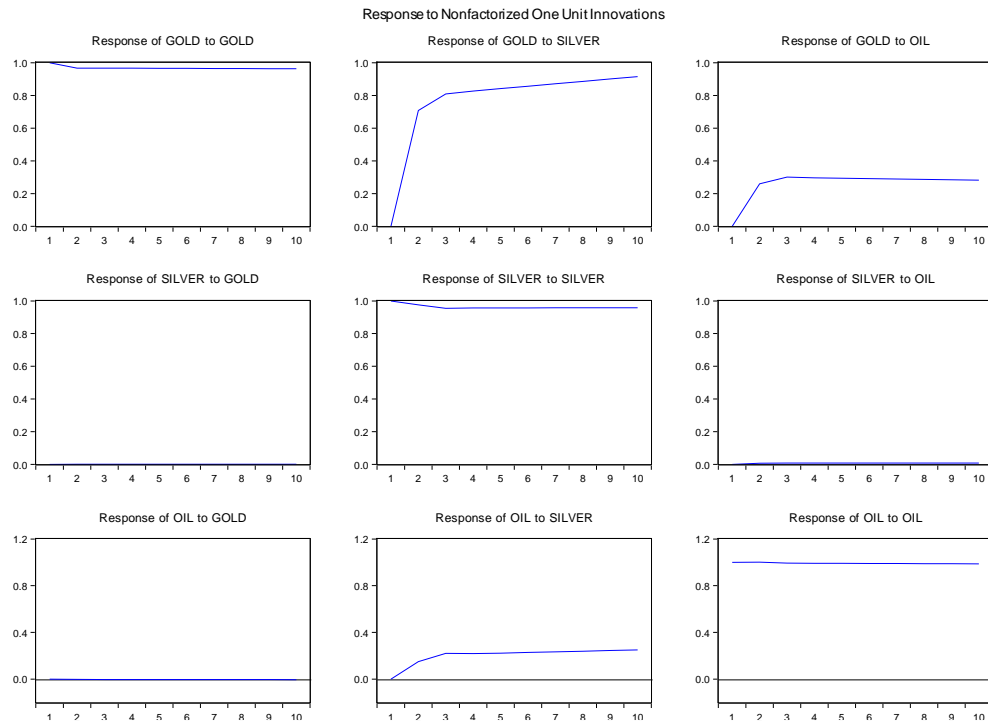
**Figure 6.5: Vector Error Correction Model Impulse Response
Functions: July 2009 – July 2010**

6.3 The Stock and Bond Markets and Commodities

Gold, silver and oil started their transition towards financialisation in the late
1970s, when financial markets made efficient reallocation of money possible
(Fumagalli & Lucarelli, 2012). Because gold, silver and oil are used for
speculative and hedge trading, they are correlated with the stock and bond
markets. Gold is used as a safe haven investment and therefore may be
correlated with the bond market to a greater extent. Because the global
financial crisis was initiated by the bond market crisis, we assumed that the
bond market has an impact on the relationships between gold and silver, and

gold and oil. Moreover, since oil is used for speculative trading, we assumed that the stock market has an impact on the relationship of gold and oil, and silver and oil. In addition, we assumed that recession and recovery periods should have different impacts on gold, silver and oil cointegration strength.

In this research an investigation was carried out to determine the relationship between commodities' price cointegration and the stock and bond markets. For this, daily logarithmic returns and volatility were produced for the S&P 500 and the Barclays Global Aggregate Bond Index. Returns were calculated as the difference between close and open logarithmic prices, and volatility was calculated as the difference between high and low logarithmic prices, similar to the approach of Andersen et al. (2003). The bond market research was particularly interesting, since the global financial crisis was initiated by the bond market crisis. Gold-silver, gold-oil, and silver-oil λ-trace statistics were converted to their logarithmic values to compensate for right skewness in residuals of the regression, as the λ-trace statistics were all positive. All time series were checked for stationarity, which was confirmed to comply with stationarity requirements for the purposes of performing OLS regression. Then a linear regression was performed for each price pair λ-trace statistic returns and the S&P 500 and the Barclays Global Aggregate Bond Index.

The general form equation is:

$$\lambda_t = \alpha + x_1\beta_1 r\_sp_t + x_2\beta_2 v\_sp_t + x_3\beta_3 r\_b_t + x_4\beta_4 v\_b_t + \varepsilon_t$$

Where:

λ_t is a commodity pair λ-trace statistic as ratio to 5% level critical value

α is a constant term

β is an independent variable coefficient

r_sp_t is return on the S&P 500

v_sp_t is volatility of the S&P 500

r_b_t is return on the Barclays Global Aggregate Bond Index

v_b_t is volatility of the Barclays Global Aggregate Bond Index

ε_t is a residual term, unexplained by the equation

Results are shown in Table 6.2.

Table 6.2: Gold-silver, Gold-oil, and Silver-oil λ-trace Statistic Returns on the S&P 500 and the Barclays Global Aggregate Bond Index Regression Results

	Dependent Variable					
	Gold-Silver		Gold-Oil		Silver-Oil	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
S&P500 Returns	3.5004	0.1885	**-4.5729**	**0.0791**	**-5.4167**	**0.0444**
S&P500 Volatility	0.7153	0.8377	1.1356	0.7395	0.8849	0.8023
Barclays Global Aggregate Bond Index Returns	12.0097	0.1050	**17.0079**	**0.0190**	6.6775	0.3729
Barclays Global Aggregate Bond Index Volatility	0.9735	0.8104	-2.4541	0.5365	-2.7288	0.5065
R-squared	0.0039		0.0086		0.0051	

From Table 6.2 we can see that the Barclays Global Aggregate Bond Index returns appear to have some explanatory power over the strength of gold and silver cointegration: the probability is 0.1050, but the number is not significant. The relationship is positive, as the coefficient for the Barclays Global Aggregate Bond Index returns for gold-silver is 12.0097.

This can be explained as follows. When returns on the debt market increase, bonds become more expensive and valuable, as expected, because demand for bonds rises, signalling that the economy is expanding and stabilising (Mishkin, 2001). Market turbulence and speculation decrease, gold and silver prices return to their normal long-run relationship, and cointegration becomes stronger. Conversely, during crisis and contraction, when returns on the debt market decrease, bonds become less expensive and valuable, and, as expected, demand for bonds falls (Mishkin, 2001). This signals that the economy is destabilising. Market turbulence and speculation increase, gold and silver prices deviate from their normal long-run relationship, and cointegration becomes weaker.

The Barclays Global Aggregate Bond Index appears to have a high impact on gold and silver. This could be due to gold's safe haven attributes and the similar properties of debt instruments (which are considered safer than stocks) resulting in a stronger relationship between gold and bonds, than, for example, gold and stocks.

For gold and oil, the S&P 500 and the Barclays Global Aggregate Bond Index returns appear to have strong explanatory power: probabilities are 0.0791 and 0.0190 respectively. The relationship is negative for S&P 500 returns: - 4.5729; but positive for Barclays Global Aggregate Bond Index returns: 17.0079.

The explanation of the positive relationship between gold and oil cointegration and returns on the Barclays Global Aggregate Bond Index is similar to the previous explanation. When returns on the debt market increase, demand for bonds rises, the bond market becomes stronger and the economy grows (Mishkin, 2001). Market turbulence and speculation decrease, gold and oil prices return to their normal long-run relationship, and cointegration becomes stronger. The negative relationship between gold and oil cointegration and returns on the S&P 500 may mean that when returns on the stock market increase, stocks become more expensive and valuable, and demand for stocks rises, signalling that the economy is growing. Market speculation increases, gold and oil prices deviate from their normal long-run relationship, and cointegration becomes weaker because oil is used for speculation more than gold, and market players invest heavily in oil. On the other hand, during crises when returns on the stock market drop, market players invest more in gold due to its safe haven attributes (Lucey & Tully, 2006b). This balances investments in gold and oil, which leads to the gold and oil relationship returning to its long-run equilibrium. Interestingly, it appears that the Barclays Global Aggregate Bond Index has greater absolute

impact, 4.5729 vs. 17.0079, and greater significance than the S&P 500, 0.0791 vs. 0.0190. This could be due to gold's safe haven attributes and the similar attributes of debt instruments, which are considered safer than stocks, resulting in a stronger relationship between gold and bonds, than gold and stocks.

For silver and oil it appears that S&P 500 returns have strong explanatory power over the strength of silver and oil cointegration: the statistical probability is 0.0444, and the relationship is negative: -5.4167. This could be explained by silver not being used as heavily as oil for speculations, and therefore in a good economic climate, when stock market volatility decreases, returns increase and the price relationship between silver and oil becomes weaker. However, in a bad economic climate, when stock market volatility increases, returns decrease and the price relationship between silver and oil becomes stronger, as oil becomes a less speculative asset.

6.3.1 Sub-sample analysis

A sub-sample analysis was carried out to determine the relationship between commodities' price cointegration and the stock and bond markets during different periods in the economy. There is no clear distinction between the recession and recovery periods to enable selection of an exact date to separate samples. Therefore, a year end was selected as a separator between the

recession and recovery periods. This is supported by the S&P 500 daily closing prices, shown in Figure 6.6. The samples in the figure are separated between the end of 2008 and the beginning of 2009. The first sample is from 6 September 2007 to 31 December 2008, where two events took place: the easing of the global energy crisis, and the easing of the stock market recession. The second sample is from 1 January 2009 to 20 January 2012; during this period the stock market experienced recovery and commodities' cointegration grew stronger. Regression results for the first sample are shown in Table 6.3.
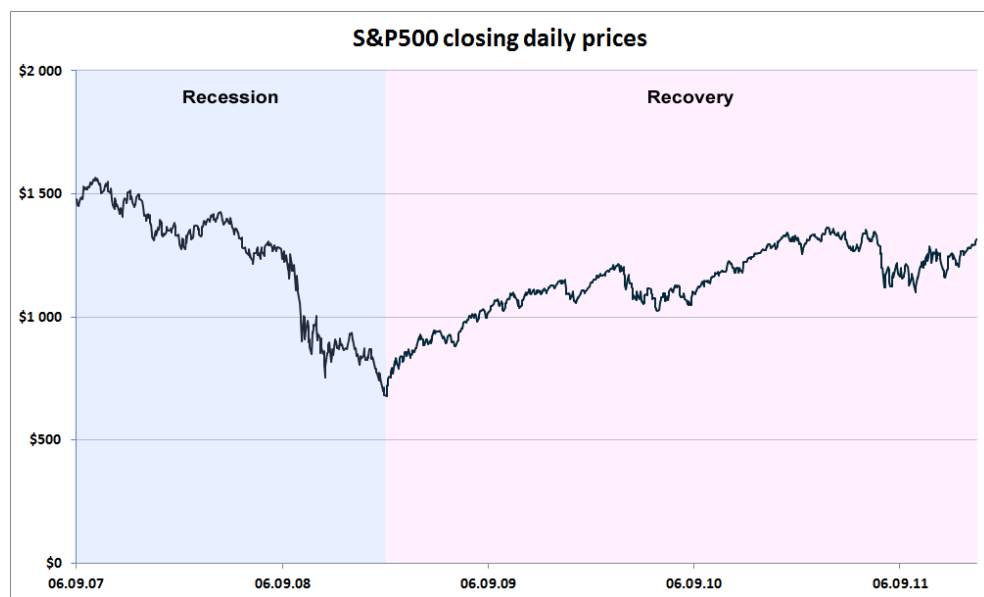

Figure 6.6: S&P 500 Closing Daily Prices

Table 6.3: Gold-silver, Gold-oil, and Silver-oil λ-trace Statistic Returns on the S&P 500 and the Barclays Global Aggregate Bond Index Regression

	Dependent Variable					
	Gold-Silver		Gold-Oil		Silver-Oil	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
S&P500 Returns	0.8092	0.7965	**-8.1384**	**0.0344**	**-6.2367**	**0.0470**
S&P500 Volatility	3.3662	0.4125	0.7041	0.8884	1.6580	0.6857
Barclays Global Aggregate Bond Index Returns	**14.9581**	**0.0412**	**21.1769**	**0.0182**	8.4802	0.2451
Barclays Global Aggregate Bond Index Volatility	-0.1896	0.9611	-1.0056	0.8322	-2.0221	0.6018
R-squared	0.0138		0.0080		0.0163	

Results shown are for the period 6 September 2007 to 31 December 2008

From Table 6.3 we can see that during the first sample period the Barclays Global Aggregate Bond Index returns appear to have strong explanatory power over the strength of gold and silver cointegration; statistical probability is 0.0412 and the relationship is positive: 14.9581. Note that these numbers are stronger than for the whole sample period outlined in Table 6.2.

During this period returns on the debt market decreased, bonds became less expensive and valuable, and the economy was destabilising. Market turbulence and speculation increased, gold and silver prices deviated from their normal long-run relationship, and cointegration became weaker.

The Barclays Global Aggregate Bond Index appears to have high impact on gold and silver, with a coefficient of 14.9581. This supports gold's safe haven attributes and the similar properties of debt instruments, especially during crises.

For gold and oil, the S&P 500 and the Barclays Global Aggregate Bond Index returns appear to have strong explanatory power: probabilities are 0.0344 and 0.0182 respectively. The relationship is negative for S&P 500 returns: -8.1384; but positive for the Barclays Global Aggregate Bond Index returns: 21.1769. Again, note that these numbers are stronger than for the whole sample period outlined in Table 6.2.

The explanation of a positive relationship between gold and oil cointegration and returns on the Barclays Global Aggregate Bond Index is similar to the previous explanation. During this period, returns on the debt market went down, bonds became cheaper, and the economy was slowing down. Market turbulence and speculation increased, gold and oil prices deviated from their normal long-run relationship, and cointegration became weaker. The negative relationship between gold and oil cointegration and returns on the S&P 500 is supported by returns on the stock market decreasing, and stocks becoming less expensive and valuable – signaling that the economy was shrinking. During the crisis, when returns on the stock market dropped, market players invested more in gold, balancing investments to gold and oil – which lead to the gold and oil relationship returning to its long-run equilibrium.

Interestingly, it appears that the Barclays Global Aggregate Bond Index has greater absolute impact than the S&P 500, 8.1384 vs. 21.1769, and greater significance, 0.0344 vs. 0.0182. This could mean that gold's safe haven attributes have more economical weight than oil's speculative features.

For silver and oil it appears that S&P 500 returns have strong explanatory power over the strength of silver and oil cointegration: statistical probability is 0.0470, and the relationship is negative: -6.2367. This supports the assumption that in a bad economic climate, when stock market volatility increases, returns decrease – and the price relationship between silver and oil becomes stronger, as oil becomes a less speculative asset.

Table 6.4 shows results of the second sample. Interestingly, it appears that during this period neither the S&P 500 nor the Barclays Global Aggregate Bond Index have strong explanatory power over the cointegration strength of gold and silver, gold and oil, and silver and oil. It appears that the S&P 500 returns have some explanatory power over the strength of gold and silver cointegration: statistical probability is 0.1136, but the number is not significant. Also, there are a number of cases where probabilities are approaching 0.2000 – 0.3000 levels, but do not appear to be significant. This could mean that gold and silver, gold and oil, and silver and oil price relationships are unaffected by both the stock and bond markets during this period, and are probably explained by other factors. It is possible that although the economy seemed to be growing, it was a period of uncertainty

with no real trends – in which case there is no meaningful output of the regression. Further research is required to understand this relationship better.

In summary, we can conclude that hypothesis 4 is correct: over the sample period, cointegration strength between gold and silver, gold and oil, and silver and oil falls during periods of crises, recessions and market turbulence in the stock and bond markets.

Table 6.4: Gold-silver, Gold-oil, and Silver-oil λ-trace Statistic Returns on the S&P 500 and the Barclays Global Aggregate Bond Index Regression Results

	Dependent Variable					
	Gold-Silver		Gold-Oil		Silver-Oil	
Variable	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
S&P500 Returns	6.7670	0.1136	-0.8105	0.8305	-4.4565	0.3058
S&P500 Volatility	-4.3632	0.4603	4.6051	0.3793	0.0344	0.9954
Barclays Global Aggregate Bond Index Returns	3.1165	0.8606	4.2499	0.7870	-1.1341	0.9500
Barclays Global Aggregate Bond Index Volatility	-4.5615	0.7444	-9.9221	0.4237	-16.7703	0.2393
R-squared	0.0049		0.0017		0.0036	

Results shown are for the period from 1 January 2009 to 20 January 2012

Chapter 7: Conclusions

This chapter provides a summary of the findings of this study.

The research investigates the long-run relationship between gold, silver and oil from 6 September 2007 to 20 January 2012 at 1 minute frequency; dynamic cointegration following the approach of Lucey & Tully (2006a); the price leadership between gold, silver and oil by studying impulse response functions; and the determinants of long-run relationships by analysing the impact of stock and bond markets' returns and volatility on the strength of cointegration between gold, silver and oil.

Overall, looking at the λ-trace statistics as a ratio to their critical values, the findings show that on some days there is cointegration and on some days there is no cointegration. However, because the average λ-trace statistic was approximately 0.9, and in approximately 40% of days the λ-trace statistic as a ratio to the critical value was at least 1 for all commodity pairs (with numerous days exceeding 2), we can conclude that the long-run relationships between gold and silver, gold and oil, and silver and oil have been maintained during the research period. The global economic and financial crises weakened this relationship during certain times, but did not destroy it.

The dynamic method allows examination of the evolution of cointegration over time. Cointegration strength between gold and silver, gold and oil, and silver and oil fluctuates, but cointegration is still present. This also means that

when used in a portfolio, the three commodities may at times offer diversification benefits.

Price leadership analysis shows that in periods when there is no cointegration, gold is led by silver to a greater extent and oil to a lesser extent. It appears that in the periods when there is cointegration, gold is led by silver and oil, and oil is led by silver. The magnitude of responses may appear small, however, they occur on a high-frequency basis, and such levels of impulse response functions may be economically significant. This would require further research.

It appears that not only does the stock market impact the commodities, but also the bond market, especially in the case of gold and silver. Cointegration strength between gold and silver, gold and oil, and silver and oil falls during periods of crises, recessions and market turbulence in the stock and bond markets. Recovery was not found to have any impact on the cointegration strength between gold and silver, gold and oil, and silver and oil. This could mean that these price relationships are unaffected by the stock and bond markets during a recovery period, and probably are explained by other factors. It is also possible that although the economy seemed to be growing, this was a period of uncertainty with no real trends, in which case there was no meaningful output of the regression. Further research is required to understand this relationship better.

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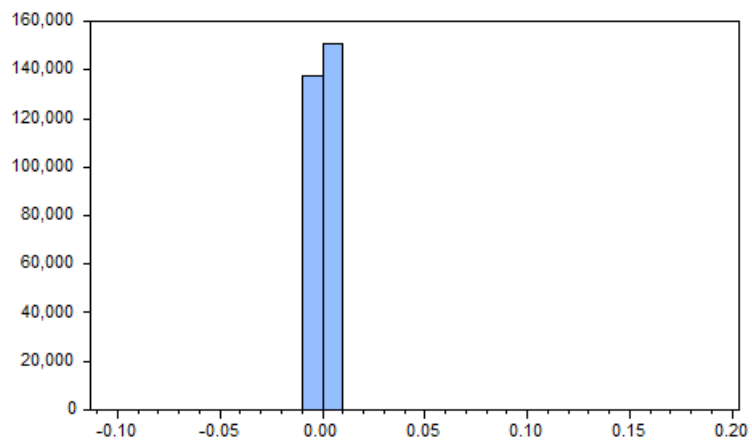
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Appendix A: Gold, Silver and Oil Returns Histograms
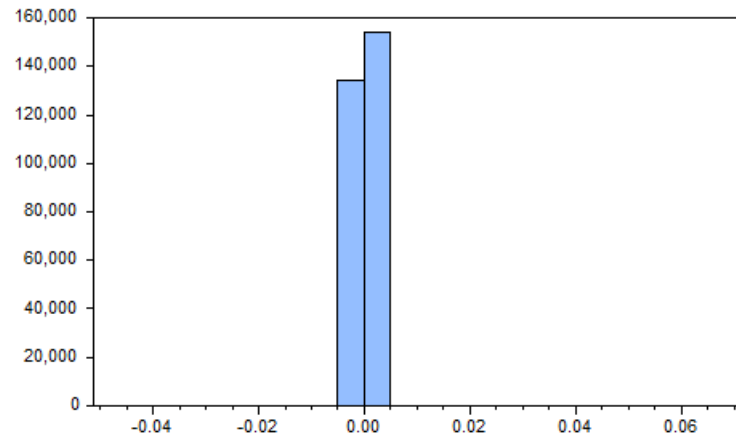
Panel A: Gold Returns Histogram
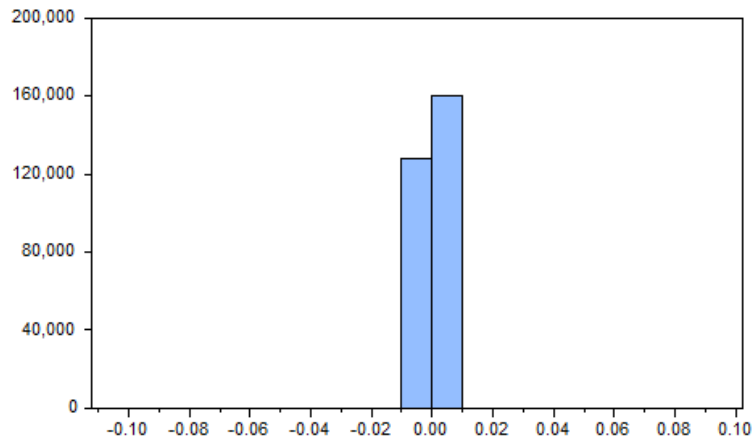
Panel B: Silver Returns Histogram

Panel C: Oil Returns Histogram