ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ
ΤΜΗΜΑ ΧΡΗΜΑΤΟΟΙΚΟΝΟΜΙΚΗΣ
& ΤΡΑΠΕΖΙΚΗΣ ΔΙΟΙΚΗΤΙΚΗΣ

UNIVERSITY OF PIRAEUS
DEPARTMENT OF BANKING
& FINANCIAL MANAGEMENT

M.Sc. in Banking and Finance

Specialization: Financial Analysis for Executives

Master's Thesis

"Flight to Quality? Macroeconomic and Financial Market events and portfolio flows between stocks and commodities"

Student: Anastasi Nikoleta (MXAN1505)

Supervisor: Associate Professor Tsiritakis Emmanouel

Committee

Associate Professor Tsiritakis Emmanouel

Lecturer Anthropelos Michail

Assistant Professor Voliotis Dimitrios

February 2017

Acknowledgements

I would like to thank my supervisor, Professor Emmanouel Tsiritakis, for his guidance and advice he provided as I was writing my thesis. My sincere gratitude goes out to Dr. Christos Bouras for his unlimited amount of support throughout my whole studies and for his critical reviews of this master thesis. I would also like to extend my thanks to the Eurobank group who granted me the scholarship in memory of G. Gontikas in order to pursue my goal of obtaining an MSc. Last but not least, I would like to express my gratitude to my family who offered me their total support whenever I needed it.

Abstract

This thesis analyzes the existence of flight-to-quality from equities to commodities. Flight-to-quality is present if correlations between equities and commodities decrease in falling stock markets. In the literature, raw commodity returns are used without considering that commodities are often used as inputs in industrial production. Therefore, our analysis considers that there is a specific supply and demand for commodities by using a regression of the raw commodity returns, on factors identified in the existing literature. Then time varying correlations are estimated by implementing two methods: rolling window correlations and dynamic conditional correlations. Changes of these correlations are analyzed through time without an a priori specification of any crisis period. Subsequently, OLS regressions are used in order to identify flight-to-quality in a posteriori specified crisis periods. A panel regression is also used in order to treat commodities as a homogeneous asset class. Monthly S&P500 index returns and 19 commodities are analyzed. Our findings vary depending on the methodology used. Our main conclusions are that flight-to-quality from stocks to most commodities is found during crises not a priori specified and to all commodities during crises specified a posteriori. Thus, in periods of economic turmoil and increased risk-aversion, commodities become an alternative investment.

Keywords: flight-to-quality, dynamic conditional correlations, rolling window, OLS, panel, commodities, equities

Table of Contents

1. Introduction

The aim of this thesis is to investigate correlations from stocks to commodities by testing for the presence of flight-to-quality. According to Baur and Lucey, (2009) flight-to-quality from an asset class “a” to an asset class “b” is defined as a decrease in the correlation coefficient during falling “a” market returns.

The literature has investigated the existence of flight-to-quality from stocks to bonds (Baur and Lucey, 2009; Beber, Brandt and Kavajecz, 2009; Durand, Junker and Szimayer, 2010; Billio and Caporin, 2010; Dajcman, 2012), flight-to-quality in both spot equity indices and index futures (Inci, Li and McCarthy, 2011), flight-to-quality in government bonds and high-yielded corporate bonds (Brière, Chapelle and Szafarz, 2012).

Over the last decade there has been a remarkable change within commodity markets. Specifically, there have been a large number of speculators and hedgers who consider commodities as financial assets. Also, there has been a considerable increase of demand for commodity funds. So far there is little evidence of flights or contagion between commodities and other assets.

Most of the existing literature on commodities has focused on co-movements and common factors between commodities (e.g. Byrne, Fazio and Fiess, 2013) or only on common factors between commodity prices or commodity returns (e.g. Creti, Joëts and Mignon, 2013; Vansteenkiste, 2009). To our knowledge, there is only one study in the literature that tests for flight-to-quality from stocks to commodities. This study of Chan, Treepongkaruna, Brooks and Gray (2011) uses a Markov regime-switching model to examine the relationships between the returns of stocks, bonds, oil, gold and real estate assets. In our study we try to expand the analysis for flight-to-quality by including additional categories of commodities.

The study of Chan, Treepongkaruna, Brooks and Gray (2011) along with studies that simply test for co-movements between stocks and commodities (e.g. Byrne, Fazio and Fiess, 2013 and Creti, Joëts and Mignon, 2013) use raw commodity returns and do not take into consideration that commodities are not common assets, such as stocks and bonds, but they are most often used as inputs in the production of other goods or services. Therefore, any analysis with respect to commodity returns should take into account that there is a specific supply and demand for these products. To deal with this problem in our study we filter demand parametrically using a simple regression of the raw commodity returns, on factors that have been identified in the existing literature.

This thesis contributes to the literature by investigating for flight-to-quality from equities to different categories of individual commodities. This is rather important for diversification, asset allocation and hedging strategies.

2. Literature Review

The aim of this study is to examine whether flight-to-quality exists between equity and commodity returns. To do so, we mainly base on the test for flight-to-quality of Baur and Lucey (2006). To the best of our knowledge, there is only one study on flight-to-quality between stocks and commodities, namely the study of Chan, Treepongkaruna, Brooks and Gray (2011). The rest of the literature simply examines co-movements between stocks and commodities. Indeed, many papers have been written concerning the relationship between commodities and equities. However, there is no consensus about whether stocks and commodities move in the same direction, indicating market integration, or exhibit a negative relationship, possibly meaning that commodities can be generally used as a hedge. Some of the studies indicating a positive or negative relationship between stocks and commodities are presented to the following paragraphs.

Equity-commodity co-movements

Lately, commodities and equities are considered to be substitutes. Also, commodity traders take into consideration both the commodity and equity market movements in order to specify the direction of equity indices as well as commodity prices. So, according to Choi and Hammoudeh (2010) it is of great interest to know how the volatility of equities and commodities changes when it shifts from a high to a low state. They also state that this information helps options traders in pricing financial derivatives, commodity portfolio managers in deciding their hedging strategies, commodity exporting countries in determining the volatility impact of commodities on their economies and monetary authorities in deciding whether or not to react to commodity or equity volatility changes depending on the volatility durations.

In general, there are two contradicting theories for the correlation between commodity and equity prices. The first theory, which is now not widely accepted, considers equity prices as the discounted value of future dividends, therefore if commodity prices increase it means that production costs for a firm also increase and consequently profits decrease and less dividend is available to be distributed to stockholders. According to the second theory, commodity prices increase when there is a rise in demand during an economic boom. As a result, both equity and commodity prices could increase (decrease) when there is positive (negative) news about the global macroeconomic outlook. Lombardi and Ravazzolo (2013) refer to these theories and converge with the second one when they examine the correlation between equity and commodity prices in the recent years.

The fact that new ways of diversification of investors' portfolios have appeared since the increased financial integration between countries and the financialization of commodities which has increased the number of participants and the liquidity in the commodity markets, is also stated by Sadorsky (2014). He states that benefits from these investment opportunities result from studying the correlations between stocks and commodities. He also suggests that good estimates of correlation and volatility are useful for risk management, portfolio optimization, derivative pricing, and hedging.

The market integration view is also supported by Delatte and Lopez (2013). They state that since 2000 there has been a significant increase in commodity prices along with a simultaneous arrival of investors who want to diversify their portfolios. These developments also highlight the raised debate in the literature about the cross-market linkages between commodities and other assets such as stocks and bonds. According to Delatte and Lopez (2013) the lack of consensus is possibly due to the different methodologies that are implemented in each study.

Similarly, Ohashi and Okimoto (2016) mention that since the 2000s commodities are considered an asset class similar to stocks and bonds. Several studies found that commodities and stocks are negatively correlated thus diversification opportunities have emerged. They argue however, that this increase in investment has attracted new participants in commodity markets such as institutional investors and hedge funds. Consequently, this influx of funds into commodity markets, namely the "financialization" of commodities has made these markets more integrated into stock and bond markets as well as among themselves. In the same spirit, Buyuksahin, Haigh and Robe (2007) state that in the past decade, exposure to commodity prices is increasingly observed by purchasing commodities and taking positions in commodity futures, exchange-traded funds or commodity index funds. So, in their study, dynamic correlation and cointegration techniques are used to examine whether the degree of co-movement between benchmark commodity and stock investment returns has changed in the last fifteen years.

Also based on the statement that as more investors such as hedge funds and ETFs (exchange traded funds) trade in both commodity and stock markets for speculative purposes, correlations between commodities and stocks are affected, Silvennoinen and Thorp (2013) question the view that during periods of economic turmoil, in particular when commodity and equity prices are negatively correlated, commodities work as a hedge to investors' portfolios. Thus they investigate closer integration between traditional assets and commodity futures returns under the hypothesis that financialization has not affected the traditional asset-commodity relationship.

In addition, the financialization phenomenon is supported by the study of Creti, Joëts and Mignon (2013). Although, in this study, it is evident that correlations between commodity and stock markets vary across time and demonstrate high volatility, results from the 2007-2008 financial crisis highlight the links between equity and commodity returns indicating the financialization phenomenon. However, in the short run, these links are loosened in the sense that correlations during times of financial stress are decreased, implying the existence flight-to-quality phenomenon. Moreover, between 2007 and 2011, they observe an increase for almost all correlations between equities and commodities.

Generally, the impact of the increasing participants in the commodity markets after the financialization of commodities has been the center of debates in the literature. Bicchetti and Maystre (2013) refer to the fact that after the dot-com bubble, many investors used commodities futures to diversify their portfolios because their returns were uncorrelated with stock returns. The financialization of commodities has been considered to provide liquidity and transfer risk to those who are willing to bear it although, others believe that it leads to price distortions. The latter argument is enhanced by the fact that growing correlations between commodity and equity indices seem to constitute a form of these price distortions. However, at high frequencies increased correlations between commodity and stock returns could relate to shocks from those markets rather than relate to the financialization of commodities.

Moreover, co-movements between equities bonds and commodity futures are investigated by Gorton and Rouwenhorst (2004). Commodity futures are derivative securities; they have short maturity claims on real assets and seasonality in price levels and volatilities. Unlike corporate securities such as bonds and equities that represent the discounted value of future cash flows, commodities offer insurance for the future value of the firm’s inputs or outputs. A connection between commodity spot prices and the expected future spot prices is a result of inventory decisions that link current and future scarcity of commodities. In a sense, we can say that futures prices can be considered as bets on the expected future spot price. At origination, the value of futures contracts is zero while no amount of cash is required in order to enter either a short or a long position.

Finally, based on the fact that the decision to include commodity futures in a portfolio depends not only on the risk-return characteristics of the contracts included in it but also to the way that commodity futures correlate with the rest of the portfolio in periods of increased volatility and over time, Chong and Miffre (2009) similar to Gorton and Rouwenhorst (2004) focus on commodity futures and investigate the conditional return correlation between commodity futures and other asset classes such as global equities and fixed income securities.

The above studies use various models in order to test for equity-commodity co-movements. The most usual method is the Dynamic Conditional Correlation (DCC) of Engle (2002) or modified versions of the DCC estimator. However the variables considered in each study vary.

In particular, Creti, Joëts and Mignon (2013) examine whether correlations between stocks and commodities evolve over time and depend on the situation (bearish or bullish) on the stock market using a dynamic conditional correlation (DCC) GARCH model. The sample consists of daily spot prices for 25 commodities covering various sectors, such as energy, precious metals, non-ferrous metals, agricultural, oleaginous, food, exotic and livestock. The period covered is January 3, 2001 to November 28, 2011. All prices are quoted in US dollars. An aggregate commodity price index, the Commodity Research Bureau (CRB) index and the main US stock market index, namely the S&P500 index are also considered. The databases used are Datastream and Thomson Financial.

The use of DCC is also encountered in Buyuksahin, Haigh and Robe (2007). The data used are daily, weekly and monthly returns of the S&P500 index as a proxy for the rates of return on investments in U.S. equities and the S&P GSCI (Standard and Poor’s Goldman Sachs Commodity Index) total return data, which includes twenty-four commodity futures contracts, as a proxy for the rates of return on investments in commodities. The data span the period January 15, 1991 to July 2, 2007 and the databases used are Bloomberg and Bridge-CRB. The sample period is then separated into three sub-periods. Then correlations are computed as simple cross-correlations across these three sub-periods and then the findings are confirmed using the dynamic conditional correlation methodology of Engle (2002). In addition, cointegration techniques are used in order to investigate whether long-term common trends exist between commodities and equities despite the fact that these prices may deviate from each other in the short term.

After finding two volatility regimes for five commodities (copper, gold, silver, WTI crude oil and Brent oil) and the S&P500 index, Choi and Hammoudeh (2010) study the correlations for those commodities and the S&P500 index also using the DCC model. The commodities examined in this paper are traded extensively and are also affected by macro-financial variables. Markov regime-switching models are used in the analysis because they are able to detect changes in the volatility states and duration in each state and they also help measure the correlations of movements among markets in each state. Markov regime-switching model's variance changes in different states of the economy. That is why, in this study, Markov regime-switching models are preferred in order to examine changes in volatility between two regimes for five commodities and US equity markets and the volatility's duration. Also, this paper investigates the dynamic correlations between equity markets and commodities and their implications for risk management in those markets using the dynamic conditional correlation (DCC) multivariate GARCH model. Finally, the sensitivity of commodities and the S&P500 to financial and geopolitical events is also examined. The data used in the study of Choi and Hammoudeh (2010) comprises of weekly spot prices for WTI oil, Brent oil, copper, silver, gold and the S&P500 index covering a period from January 2, 1990 to May 1, 2006.

In addition, volatility and correlations between oil, copper, wheat and equity prices of emerging markets are modeled by Sadorsky (2014) also using the DCC-AGARCH model of Engle (2002) to model conditional correlations between the assets under consideration and the VARMA-AGARCH model to model the volatility dynamics between these assets. Furthermore, the dynamic conditional correlation model is used to construct optimum portfolio weights as well as hedge ratios. It is worth noting that assets of emerging markets are particularly chosen in this analysis because they are considered important to the global economy. Specifically, in 2010 emerging economies accounted for almost half of global GDP. In addition, oil is globally used, with the biggest increases in its consumption are anticipated from emerging countries, copper is used to predict economic activity and wheat is considered a major food. Specifically, the data used are daily data on the MSCI Emerging Markets Index which consists of 21 emerging market country indices. Furthermore, data consist of the International Grains Council wheat price index, the continuous contract on the WTI crude oil futures contract and the continuous futures contract on the COMEX copper contract. All prices are in U.S. dollars and the data span the period January 3, 2000 to June 29, 2012. The data are taken from Data Stream International.

Dynamic conditional correlations between commodity futures and equities are also used by Chong and Miffre (2009) and Bicchetti and Maystre (2013). In particular, Chong and Miffre (2009) use the Dynamic Conditional Correlation model (DCC) of Engle (2002) to examine correlations between commodity futures and S&P500 returns. The data consist of 25 commodities and 13 traditional asset classes. In particular the data consist of closing prices on the nearby or second nearby contracts of 11 agricultural futures namely, cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar and wheat, of 5 energy futures namely, crude oil, heating oil, lumber, natural gas and unleaded gas, 4 livestock futures namely, feeder cattle, frozen pork bellies, lean hogs and live cattle and 5 metal futures namely, copper, gold, palladium, platinum and silver. The data also comprise of 7 equity asset classes namely, the S&P500 composite index, the Russell 2000 Index, the Russell 1000 Value Index, the Russell 1000 Growth Index, the MSCI Europe Index, the MSCI Asia Pacific Index and the MSCI Latin America Index. Furthermore, this paper investigates 6 bond indices from JP Morgan: US Cash with 6-month maturity, US Cash with 12-month maturity, United States Government Securities, Global Asia, Global Africa and Global Europe. The data are weekly and obtained from Datastream International. The dataset spans the period January 1, 1981 to December 27, 2006 for most series.

Similarly, Bicchetti and Maystre (2013) examine dynamic conditional correlations between several commodity futures and US equity market using the DCC model of Engle (2002). To do so, they use prices at high frequencies of the E-mini S&P500 futures and futures contracts of light WTI crude oil, wheat, sugar, corn, live cattle, and soybeans. Their sample spans the period January 1998 to December 2011 and the database used is the Thomson Reuters Tick History (TRTH).

Commodity futures but without the use of the DCC are also examined in the study of Gorton and Rouwenhorst (2004). In their paper, the long-term return to commodity futures is investigated using an equally-weighted index of commodity futures. By analyzing the returns of this equally-weighted index of commodity futures the average commodity future's behavior can be investigated during the average time period. The equally-weighted index of commodity futures is then compared to an equally-weighted portfolio of spot commodities for the period 1959 to 2004. Also, the correlation of commodities with other asset classes such as stocks and bonds is examined over various investment horizons. The dataset consists of daily prices for individual futures contracts since 1959 and the data source used is the Commodities Research Bureau (CRB).

Moreover, a time varying Bayesian Dynamic Conditional Correlation model is used by Lombardi and Ravazzolo (2013). If the correlation has increased it means that investment in commodity-related products for diversification purposes has been the wrong strategy. The data collected to implement the above methodology are weekly data of the MSCI (Morgan Stanley Capital International global equity index) and the SPGSCI (Standard & Poor's Goldman Sachs commodity index) indices. The dataset spans the period January 1980 to December 2012. In addition, weekly point and density forecasts for commodity and equity returns are produced over a sample from 2005W1 to 2012W52 with 24 steps ahead forecast using a bivariate Bayesian Vector Autoregressive model and a bivariate Bayesian Dynamic Conditional Correlation model.

An alteration of the DCC, namely the Double Smooth Transition Conditional Correlation (DSTCC-GARCH) is used by Silvennoinen and Thorp (2013). The data used consist of futures contracts on 24 commodities such as grains and oilseeds, meat and livestock, food and fibre, metals and petroleum. The Wednesday-Wednesday log returns of futures contracts span the period May 1990 to July 2009. Also, equity and bond weekly log changes in total returns stock price indices are used, in particular, S&P500 for the US, FTSE100 for the UK, DAX for Germany, CAC for France and TOPX for Japan in local currencies. Furthermore, a total returns fixed interest index for US Treasuries is taken into account in the dataset.

Excess commodity co-movements changes are examined by Ohashi and Okimoto (2016) also using a smooth-transition dynamic conditional correlation (STDCC) model. The term "excess co-movements" is used to describe the correlation in the returns of commodities which are filtered out from common factors that affect them. With the STDCC model changes of excess co-movements can be examined both in the long-term and the short-term contemporaneously. However, before proceeding to the STDCC model a simple OLS regression is implemented in order to filter commodity returns from macroeconomic common factors. The factors taken into consideration are the CPI, exchange rate, industrial production, money stock, stock price index, and interest rate. The data used are monthly for a period from January 1983 to July 2011. The agricultural raw material, metal, and beverage indices are used for commodity prices. Also, oil prices are proxied with the average prices of WTI, U.K. Brent and Dubai. In addition, as far as the common factors are concerned, data are obtained from the Federal Reserve Economic Data (FRED) and include the seasonally adjusted CPI, the 3-month T-bill rate, the seasonally adjusted industrial production, the S&P500 index, the seasonally adjusted money supply, M1, and the trade-weighted exchange rate index.

Finally, a different methodology from the DCC is used by Delatte and Lopez (2013) to examine equity-commodity co-movements. In their study, the correlation coefficient, as a measure of the dependence structure between two returns, is challenged while the dependence structure, that exists between stock and commodity futures returns over the past 20 years, is estimated via copula. Specifically, six copula models, three constant and three time-varying, are estimated for each pair of returns and the best model is chosen. The copula approach is different from the DCC models, often used in the literature, in the sense that the dependence structure does not rely on the marginal distributions of returns. The data they consider in this analysis are the Dow-Jones UBS Commodity Index (DJ-UBS), the Goldman Sachs Commodity Index (SP-GSCI) and four major equity indices namely the S&P500, FTSE100, DAX30, and CAC40 index. In addition, 21 spot and futures commodity prices on agricultural, energy and industrial metals markets are included in the sample examined so that the heterogeneity among commodities is taken into account. The data span the period January 1990 to February 2012 and the database used is Bloomberg.

Results from the above studies on co-movements between commodities and equities are separated in studies finding positive correlations and thus supporting the market integration view and studies finding negative correlations and thus implying that commodities can be generally used as a hedge.

In particular, results from the study of Lombardi and Ravazzolo (2013) indicate that correlations have increased significantly since 2008, while they have been around zero a decade ago. Also, it is found that absolute predictability for commodity returns is significantly lower than absolute predictability for equity returns. In addition, equities seem to contain information to forecast commodities, while the opposite is not supported. Consequently, one benefits from following a dynamic asset allocation strategy but this does not come without cost because including commodities in a portfolio increases its volatility compared to a commodity free portfolio. This contradicts the perception that commodities can work as a hedge. Finally, an active short-term investment exercise indicated that gains are generated, notably at times of large price variability, when a time-varying joint model for commodities and equities is used instead of passive strategies.

A positive commodity-equity relationship is also found in Silvennoinen and Thorp (2013). Their results show that the benefits of diversification when investors of equity markets use commodities have declined. This is because correlations between S&P500 and most of the commodity futures returns examined in this paper have increased not only during the current economic crisis but also from an earlier date. In addition correlations between S&P500 and many commodities tend to rise when the VIX index rises, meaning that correlations are affected by financial shocks. Finally, results for German, French, UK and Japanese equity returns indicate that commodity futures and equity markets are integrated not only in the US but also in other developed economies.

In the same spirit, Sadorky's (2014) results suggest that dynamic conditional correlations between equity prices from emerging markets and oil and equity prices from emerging markets and wheat have increased since 2002. Correlations between copper and equity prices from emerging markets have also slightly increased since 2002. The fact that correlations have increased can be explained by the financial market integration and the financialization of commodity markets. Also, correlations increased in the crises period between 2008 and 2009 and as it is stated in this paper, it is reasonable to expect asset correlations to rise during financial crises. In addition, there is evidence of long-term volatility spillovers from wheat to equity prices from emerging markets, from oil to wheat, from oil to equity prices from emerging markets, from equity prices from emerging markets to oil and from equity prices from emerging markets to wheat. These volatility spillovers may be a result of herding behavior in financial markets or of common fundamental factors affecting commodities and emerging stock markets. These findings suggest that diversification benefits between emerging market stocks, copper, wheat, and oil are reduced after 2008. Also, hedge ratios and portfolio weights vary over the sample period which means that they should be updated frequently in order to provide optimal values. Finally, it is found that on average oil is the cheapest hedge for emerging market stock prices while copper is the most expensive. However, since the hedging positions must be regularly adjusted, this information should not be seriously taken into consideration.

Another study with evidence of positive equity-commodity correlations is the one of Bicchetti and Maystre (2013). Their study shows that between 2006 and early 2008 positive dynamic conditional correlations exist between the commodities under consideration and the S&P500. Yet, a structural break appears in 2008 that impacts not only the energy sector but various other commodities as well. Then, the DCCs sharply shift to positive values in October 2008. Afterward, the positive correlations persist except for the period February to April 2011 which is the period of a major supply shock in crude oil possibly related to the uprising in Libya. These findings are important for diversification and portfolio allocation in commodities and they show that after the financialization of commodities, it is more likely that commodity prices react to events in global financial markets.

In addition, Delatte and Lopez's (2013) results suggest that co-movements between the assets considered are best described by a time-varying relation and that these co-movements are most of the time in the same, either positive or negative, direction. It is important to take into consideration that the level of dependence varies during the period considered, otherwise there is false evidence of tail dependence between stock and commodity returns. In their study, integration of stock indices with certain commodities is found to have strengthened which means that there are no diversification benefits of commodity futures.

Moreover, while the impact of the 2007–2008 financial crisis is remarkable, some commodities are characterized by speculation according to Creti, Joëts and Mignon (2013). Such commodities are especially oil, coffee and cocoa for which correlations with the S&P500 returns grow in times of increasing stock prices and diminish in times of bearish financial markets. Furthermore, gold is found to be a safe-haven because its correlations with stock returns are mostly negative and diminish in times of declining stock prices. Also, despite the fact that commodities have some common features, they cannot be considered as a homogeneous asset class. Their results suggest that coffee, cocoa, and gold can be used for diversification purposes in times of decreasing stock prices.

Finally, a positive relationship is found in the literature we examine not only for "simple" co-movements but also for "excess co-movements" in Ohashi and Okimoto (2016). Their results indicate increasing excess co-movements trends in the long-run that are not just the result of the financial crisis of 2008 or the impact of the common factors but also of the "financialization" of commodities that started in 2000. Also, fluctuations in the excess co-movements in the short-run are evident.

Contrary to the previously found positive equity-commodity co-movements, results from Buyuksahin, Haigh and Robe (2007) suggest that stock-commodity simple cross-correlations are very low or negative. Low or negative correlations are also evident after the use of the DCC model. Specifically, correlations between equities and commodities fluctuate over the sample period and are often close to zero or even negative. These results suggest that commodities should be used for portfolio diversification purposes. In addition, except for a period in the late 1990's, little statistical evidence of cointegration is evident, even in the last five years. This means that stocks and commodities are not correlated over long horizons and, consequently, benefits can result from portfolio diversification across the two asset classes. Finally, joint commodity-equity return behaviors for the whole sample as well as for three successive sub-periods are examined in order to identify cross-asset extreme linkages in the case of commodities. Contrary to the view that extreme linkages between commodities and equities exist, little evidence of an increase in co-movements between equities and commodities is found during periods of extreme returns.

There is also evidence in the study of Choi and Hammoudeh (2010) that since 2003 commodities have increasing correlations among each other which limit their use as a hedge while, decreasing correlations are evident between commodities and the S&P500 index. However, the high negative correlation between equities and oil during 2006 is considered a short run phenomenon. In general, the negative correlation between the S&P500 and WTI oil suggests that since oil is an input in production when its price increases inflationary pressures are caused and consequently corporate earnings are negatively affected. In addition, they find that WTI and Brent oil have the highest volatility among the five commodities, with Brent indicating more volatility persistence than WTI oil, while gold has the lowest. Also, the S&P500 index has a slightly higher volatility than gold and the highest return among the commodities under consideration. Thus, stocks are considered a more profitable investment than those five commodities on a risk-return basis. Furthermore, their study finds that there are two regimes in equity and commodity markets, thus when those markets shift from a low to high volatility regime risk-averse investors request higher compensations. The lowest (highest) the sensitivity to regime shifts, the lowest (highest) the compensation demanded by investors. As far as duration is concerned gold is found to have the longest duration in the high volatility state while the S&P500 index shows greater duration of volatility than the commodities over the two regimes.

In the same spirit, Chong and Miffre (2009) suggest that correlations between commodity futures and S&P500 returns fell over time and consequently adding commodity futures to a portfolio has increased risk reduction since the 1980s. Also, correlations between 11 commodity futures and the S&P500 returns tend to fall in periods of economic turmoil such as in a hurricane, a war or a sudden rise in inflation. These results of decreased return correlations between some commodities and equities or Treasury-bills could indicate a flight-to-quality or could be related to the fact that commodities are used as inputs in production. The latter explanation suggests that when commodity prices increase, production costs and uncertainty for the firm also increase, therefore long investors in commodity futures are benefited while stockholders are not. In addition, it is found that in periods of increased price volatility adding commodity futures to a long-term fixed income global portfolio will not reduce risk any further. Finally, results are not the same for all commodities because each commodity has its own characteristics and behavior.

Finally, the returns of investments in commodity futures are found to exceed those in spot commodities in Gorton and Rouwenhorst (2004). Furthermore, they suggest that the futures index and the spot index series are highly correlated and that, as compared to equities, diversified investments in commodity futures have a slightly lower risk. As far as correlations are concerned they find that commodity futures can provide effectively diversifications of bond and stock portfolios because over most horizons correlations between equities, bonds and commodities are negative. This negative correlation can be explained either by the outperformance of commodities compared to bonds and stocks in periods of unexpected inflation or by the fact that commodity futures returns vary with the stage of the business cycle thus diversifying the systematic component of risk which is not supposed to be diversifiable. The aforementioned results of Gorton and Rouwenhorst’s (2004) study are important for investors because they suggest that commodities are an asset class useful for diversification purposes and for researchers in the sense that asset pricing theory is challenged because so far it has mainly focused on stocks.

Factors affecting commodities

The papers we mentioned earlier in this thesis are studies that simply test for co-movements between stocks and commodities. However, these studies use raw commodity returns and do not take into consideration that commodities are not common assets, such as stocks and bonds, but they are most often used as inputs in the production of other goods or services. Therefore, any analysis with respect to commodity returns should take into account that there is a specific supply and demand for these products. To deal with this problem in our study we filter demand parametrically using a simple regression of the raw commodity returns, on factors that have been identified in the existing literature. The error term of this regression indicates the fraction of the commodity returns that is not explained by demand and supply for industrial purposes. Hence, this non systematic part of the commodity returns reflects investors' expectations on future commodity prices and consequently is more suitable to be used in our analysis than raw returns.

The factors we found to be paid most attention by the literature are real interest rates (Frankel, 2008; Svensson, 2008; Vansteenkiste, 2009; Byrne, Fazio and Fiess, 2013; Ma, Vivian and Wohar, 2015; Ohashi and Okimoto, 2016), global demand (Vansteenkiste, 2009; Lombardi, Osbat and Schnatz, 2012; Byrne, Fazio and Fiess, 2013; Ohashi and Okimoto, 2016), aggregate supply (Vansteenkiste, 2009; Byrne, Fazio and Fiess, 2013), the dollar exchange rate (Sjaastad, 2008; Vansteenkiste, 2009; Sari, Hammoudeh and Soytas, 2010; Zhang and Wei, 2010; Lombardi, Osbat and Schnatz, 2012; Ma, Vivian and Wohar, 2015; Ohashi and Okimoto, 2016), inflation (Blose, 2010; Browne and Cronin, 2010; Worthington and Pahlavani, 2007; Zhang and Wei, 2010; Ohashi and Okimoto, 2016) and the impact of oil prices (Baffes, 2007; Krugman, 2008; Zhang and Wei, 2010; Sari, Hammoudeh and Soytas, 2010; Lombardi, Osbat and Schnatz, 2012; Byrne, Fazio and Fiess, 2013).

In particular, since the remarkable increase in commodity prices in the 2000s and the so-called financialization of commodities, interest has been raised about commodity common movements according to Ma, Vivian and Wohar (2015). They state that commodity co-movements have changed over the last decade since participants and especially speculators have increased in these markets. So, the source of these co-movements has been under investigation by the literature. Specifically, in the literature supply and to a lesser extent demand, of individual commodities is considered to determine their prices and returns. However, since the increase of speculators such as hedge funds and investment funds in these markets, supply and demand are not the only factors that affect commodities. Commodities, as found in the literature, are also affected by global demand, mainly from emerging markets, real interest rates, aggregate supply shifts, the dollar exchange rate, macroeconomic uncertainty, inflation and the impact of oil prices.

Similarly, Byrne, Fazio and Fiess (2013) agree that after the significant increase in commodity prices in the 2000s, many studies about the determinants of commodity prices co-movements have been conducted. It has been argued that real interest rates, global demand and supply and oil prices are among these determinants. Byrne, Fazio and Fiess (2013) also cite that commodity prices movements are of great interest for countries' authorities because they affect imports, exports, monetary and fiscal policies. Specifically, when commodity prices increase, countries that depend on commodity imports have to come up against inflation. In addition, when exports are concentrated in commodity producing countries as a result of substitution effects, the rest of the countries are unable to diversify their own shocks to their balance of trade and consequently to their current account.

In the same spirit, Vansteenkiste (2009) agrees that there is an increase in commodity prices in the recent years. Specifically, she states that in the last fifteen years, nominal commodity prices have been relatively low but more recently certain non-fuel commodity prices have increased and reached their unprecedented highest levels in 2007 and 2008. This commodity price prosperity has lasted longer than earlier ones with the price increases being also larger than those of earlier bursts. Moreover, this burst included at least four major commodity groups and all of the major ones in 2005. The above have raised interest in understanding commodity price evolution. So, according to Vansteenkiste (2009), the literature mentions several factors that might have caused the recent increase in commodity prices. Apart from commodity-specific factors such as geopolitical risks or weather conditions increased demand from countries especially from emerging ones such as China are considered. Oil prices are also considered another important factor since they affect other commodity prices in the sense that oil is used as an input in the production of other commodities. Furthermore, the depreciation of the US dollar against other currencies plays an important role as a commodity factor because most commodities are US dollar-denominated. Specifically, commodities prices rise when the US dollar depreciates against other currencies because commodities become cheaper for consumers of other currencies and therefore producers' profits are reduced. Another notable factor is US real interest rates because low interest rates lead to the expansion of money supply and consequently inflationary pressures and also to the decrease of demand for liquid assets by sovereigns such as China or Chile. Apart from those factors, certain studies claim that speculation might also have caused the commodity price increases but other argue that if speculation was behind the commodity price increases then excess supply should have been evident.

Another study, namely the one of Lombardi, Osbat and Schnatz (2012), strengthens the argument that increased commodity prices have raised the academic interest in identifying the determinants of commodity prices. In particular, they state that, prices of different commodities have increased between 2003 and 2008 causing global inflationary pressures. Such determinants are found to be global demand, especially from emerging economies, short-term interest rates, in the sense that lower interest rates increase the incentive to carry inventories and hence encourage investment in commodities and US dollar fluctuations, in the sense that in periods of US dollar weakness commodity exporters raise commodity prices which are usually denominated in US dollars. In addition, Lombardi, Osbat and Schnatz (2012) refer to situations where more complex linkages across commodities lead to commodity price co-movements. Such an example is oil and non-energy commodity prices who relate through transportation and fertilizer prices since the production of fertilizers is based mainly on energy. Increased fertilizer prices then lead to increased food prices. Another example is that since maize and sugarcane are used in making biofuels, incentives for their planting are increased. Consequently, the supply of wheat and soybeans, which are competitive crops, is limited in the absence of available arable land. As a result, agricultural commodity prices rise. However, there are factors also affecting commodity price co-movements that are more difficult to measure. Such factor is the financialization of commodities.

What is more, Browne and Cronin (2010) refer to the fact that the recent increases in commodity prices combined with a prolonged expansionary monetary policy of the US Federal Reserve and strong money growth have raised the interest in studying whether monetary policies affect commodity prices. Monetarist propositions suggest that, when money demand is stable, the percentage change of the total level of prices adjusts equally in exogenous changes in the money stock. They also suggest that in the long term, all prices, either consumer goods or commodities, are adjusted the same by the money stock. For instance, if the amount of cash is doubled then eventually, all other remaining equal, all prices of goods, either commodities or consumer ones, double as well.

Focusing on interest rates as a main determinant of commodity prices, Frankel (2008) states that, there is a rather widespread theory suggesting a negative relationship between the real interest rate and commodities, namely the overshooting theory. According to the overshooting theory when monetary policies are contracting, the real interest rate temporarily raises either due to a nominal interest rate increase or a fall in expected inflation, or both. Consequently, real commodity prices decrease until commodities become so "undervalued" that the expectation of future appreciation counterbalances the higher interest rate. Then firms do not take into consideration the cost of carry and are eager to hold inventories. In the long term, there is an adjustment of the general price level to the money supply change so that the real interest rate, the real money supply, and the real commodity price are finally restored. It is thought that the reason why the overshooting phenomenon exists is the quick adjustment of agricultural and mineral products compared to other slowly adjusting prices. This theory suggests that when the real interest rate is high money flows out of foreign currencies, emerging markets, commodities and other securities.

Contrary to other studies that refer to several commodity determinants, Sjaastad (2008) draws his attention only to exchange rates. He cites that ever since the Bretton woods international monetary system seized to exist, there is evidence of price instability in the world gold market. This is most probably a consequence of floating exchange rates of the major currencies. A change in any exchange rate will affect commodity prices in at least one currency or in both currencies when the countries issuing them are big. Also, several currencies of the world are related directly or indirectly to one of the three major currencies, namely the dollar, the euro and the yen. Consequently, shocks to the major currencies exchange rates are transmitted globally in the form of inflationary or deflationary shocks.

Another study focusing on exchange rates but also in oil prices as factors affecting commodities is the study of Sari, Hammoudeh and Soytas (2010). They refer to the growing interest in examining co-movements between oil, precious metals, and exchange rates not only due to their increasing prices but also due to their increased economic uses. As gold is being used as a hedge when risk is increased in financial markets, it seems that its price has affected other precious metals commodity prices as well. For instance, in high inflation periods, investors turn to precious metals, as a substitute for gold, in their hedging strategies. This substitution has also occurred due to the increased industrial use of precious metals. In addition, many consider gold as the leader of precious metals; however silver, having more industrial uses, has led gold sometimes. In addition, oil, as well as precious metals commodities, is denominated in US dollars, yet this is not their only connection. These assets are used as a hedge for other dollar-denominated assets such as equities. What is more, oil prices' increases can affect precious metals' production because of power shortages. As far as the dollar exchange rate is concerned, it may also co-move with oil and precious metals because these assets are dollar-denominated. For example, investors who expect inflation move from dollar-denominated assets such as stocks to dollar-denominated physical assets such as oil and precious metals. Also, the majority of oil's and precious metals' exports and imports emanate from the US and the euro area.

Likewise, Zhang and Wei (2010) state that from 2002 to 2008, a boom period for crude oil and gold prices took place as a result of US dollar depreciation, oil supply management by the OPEC and geopolitical events. However, by the end of the 2008 crisis, crude oil and gold prices dropped remarkably until the commodity market demand started to recover since 2009.

A study focusing only on oil prices as a determinant of commodities is the one of Baffes (2007). He states that oil prices have been considered fairly low by the authorities and consumers in oil-importing countries in the past twenty years. The World Bank and IMF forecast that oil prices will be in a range of 55$ to 65$ in the next five to ten years due to the strong demand, especially by emerging economies, and the capacity constraints that characterize the supply side. Moreover, crude oil prices have an impact on other commodities on the supply side because oil is used as inputs in the production of most primary commodities. Also, other commodities such as maize and sugar are substitutes for oil in the sense that they are used in biofuel production. As far as demand is concerned, some commodities are competitive to synthetic products made of crude oil while others such as gas and coal are substitutes for oil. What is more, the demand for precious metals is expected to rise because investors consider them as a hedge against crude oil price spikes which are often linked to inflation. Furthermore, oil price increases lead to the rise of the oil exporting counties' disposable income and consequently the demand for several commodities. However, for the oil importing countries oil price increases lead to the reduction of disposable income and hence to a slower industrial production. Consequently, lower industrial production leads to lower demand for raw materials and metals and increased production and transportation costs, thus lowering their prices, but on the contrary lower industrial production does not have a negative effect on food commodities due to their small income elasticity.

In the same spirit, Krugman (2008) suggests that the increase in oil prices is responsible for the increase in food prices. Also, oil price increase creates an incentive for biofuel production.

As far as inflation is concerned, Blose (2010) cites that most studies in the literature examine the relationship between gold prices and inflation ex-post and they find a significant relationship between them. Conversely, the relationship between gold prices and expected inflation is unclear. Also, Worthington and Pahlavani (2007) cite that investors are interested in including gold to their portfolios in order to diversify against inflation, currency or political crisis.

Finally, it is worth noting that Ohashi and Okimoto's (2016) study is the only one, to the best of our knowledge, which filters commodity returns from macroeconomic common factors, as we intend to do in our own study. However, apart from the CPI, exchange rate, interest rate and industrial production, which we will also use in our filtering of commodity returns, they consider a stock price index, namely the S&P500 and money stock as two more factors that affect commodities.

The aforementioned papers focusing on factors that affect commodities use various models in order to empirically identify commodity determinants. Many of those papers use OLS regressions. Such a study is the one of Frankel (2008). In this paper, in order to test whether real commodity prices are related to real interest rates, an OLS regression is applied to the real commodity price, computed by subtracting the logarithm of the commodity price index from the logarithm of the CPI, against the real interest rate, computed as the difference of the one-year interest rate from the one-year interest rate. The commodity price indices under consideration are the Dow Jones, the Commodity Resources Board and the Moody's. Results suggest that commodity prices are significantly negatively correlated to interest rates for the period 1950 to 1979. Yet, since 1980 this relationship has not been stable.

In addition an OLS regression of the commodity prices on crude oil prices, also considering inflation and technological change, is used by Baffes (2007) to examine the relationship between crude oil and other commodities. Inflation is proxied by the Manufacture Unit Value. The data used are annual prices of 35 internationally traded commodities including metals, raw materials, and food and they span the period 1960 to 2005.

Moreover, the unexpected changes in the CPI are regressed against bond yields and then against gold prices in Blose's (2010) study. As far as the relationship between unexpected CPI changes and gold prices is concerned there are two hypotheses examined. The first hypothesis, namely the carrying cost hypothesis, supports that unexpected CPI changes will not have an impact on gold prices on the CPI announcement date because carrying costs counterbalance any speculation benefits. The second hypothesis, namely the expected inflation effect hypothesis, supports that either speculative or hedging purchase deriving from unexpected CPI changes affect gold prices on the CPI announcement date. The variables considered in this study are monthly CPI announcements, and particularly the unexpected changes in the CPI as a proxy for changes in future inflation expectations, as well as the London PM fixing as a proxy for gold price. The unexpected changes in the CPI are obtained when the expected changes in the CPI are subtracted from its actual changes. The data span the period March 1988 to February 2008.

After finding the existence of common factors with a dynamic factor model Vansteenkiste (2009) also uses an OLS estimation in order to determine those factors. In particular, she uses a dynamic factor model in order to identify whether there are common factors that affect non-fuel commodity prices without measuring or specifying these factors directly. Also, the importance of each factor is assessed over time. Then, it is examined whether the common factor identified by the dynamic factor model is affected by macroeconomic shocks or verifies the presence of excess co-movement supporting the speculation argument. In order to determine these common factor drivers, an OLS estimation by a means of a general-to-specific approach is used. In this analysis, 32 nominal non-fuel commodity prices are used split in three categories, namely agricultural raw material, metals, and food. Also, UK Brent spot prices are used as a proxy for oil prices, the US short-term interest rate deflated by the US CPI inflation is used as a proxy for the real interest rate, the US dollar effective exchange rate is used as a proxy for the dollar exchange rate, phosphate rock, and potash prices are used as a proxy for input costs, namely fertilizer prices, the Dow Jones stock market index is used as a proxy for financial variables and the industrial production in the OECD plus six major non-OECD countries, namely India, China, Russia, South Africa and Indonesia is used as a proxy for global demand. The data span the period January 1957 to May 2008 and are taken from the IMF IFS database and the Federal Reserve Board of Governors on a monthly basis but are then aggregated to the quarterly frequency in order to avoid strong monthly fluctuations.

The extent to which 43 commodity returns from six sectors, among which industrial metals, energy, raw metals and cereals, are driven by individual and common factors is examined by Ma, Vivian and Wohar (2015). Contrary to the aforementioned studies that used OLS regressions, they only use a dynamic factor model which dismantles the commodity returns into a common or market factor, a commodity-specific factor and a sectoral factor. This model examines how much of the variance of the overall return is attributable to each factor at each point in time. The data span the period January 1984 to December 2013 and the data sources are IMF and Thomson Datastream.

Other studies use cointegration tests in order to find whether commodities are driven by common factors and causality tests in order to determine those factors. Such studies are of Zhang and Wei (2010) who investigate the price changes of oil and gold along with their cointegrating relationship and causality. These two commodities are particularly chosen to be taken into consideration because they play an important role in the commodity markets due to their considerable trading volume and value. Especially gold is considered a store of value when there is political and economic uncertainty. The data used are daily oil prices using Brent spot price obtained from the US Energy Information Agency and daily gold prices based on the London PM fix. The data cover the period January, 4 2000 to March, 31 2008. Both prices are dollar-denominated which means that the US dollar volatility causes oil and gold prices to move in the same direction.

Likewise, Worthington and Pahlavani (2007) investigate the relationship between gold and US inflation in the long run. A novel unit root testing procedure is applied in order to estimate the timing of significant structural breaks so as not to consider them exogenous. Taking these breaks under consideration a cointegration test is employed between gold and inflation. The data used are monthly prices of gold and the US inflation rate taken from Global Financial Data. The analysis is conducted in two subsamples, namely from January 1945 to February 2006 and from January 1973 to February 2006.

Vector autoregressive (VAR) models and factor-augmented VAR (FAVAR) models are also used by various studies in the literature that examines commodity factors. These particular models are used in order to provide empirical evidence on the response of the variables considered to various exogenous impulses. Indeed, Sari, Hammoudeh and Soytas (2010) examine the directional relationships between the major precious metals and oil prices and the euro-US dollar exchange rate as well as who drives who in the long term. To do so, they implement a vector autoregressive model (VAR) and then they estimate the generalized-forecast error variance decompositions and generalized impulse response functions. Before implementing the VAR model, cointegration is tested. Since no cointegration is found the first differences of the data are used in the VAR model. The variables considered are daily spot prices of gold, silver, palladium, platinum, WTI crude oil and the US dollar/euro exchange rate. Dummy variables for the New York City attack of September 11, the Iraq war in 2003 and the OPEC's establishment of the oil price band in 2000 are also used. The data span the period January 1999 to October 2007.

In addition, a cointegrating VAR approach is used by Browne and Cronin (2010) in order to examine whether the commodity prices affect consumer prices due to their overshooting caused by money supply. In the analysis commodity prices are considered to be flexible because commodities are exchanged in auction markets that are characterized as fast-moving and participants of these markets are more equally informed and have more resources than participants of consumer goods markets. On the contrary, consumer prices are characterized as "sticky" because of frictions slowing down their adjustment in labor and goods markets. The data used in this analysis are quarterly and they span the period 1959Q1 to 2009Q4. The “sticky” goods prices are proxied by the CPI while for commodities three indices are used, namely the Commodity Research Bureau Spot Index consisting of 22, sensitive to changes in economic conditions, basic commodities, the Commodity Research Bureau Raw Industrials index and the Conference Board’s Sensitive Materials Index (SENSI) comprising of raw materials and metals but excluding food and energy.

A factor-augmented VAR (FAVAR) approach is also used by Lombardi, Osbat and Schnatz (2012) in order to examine linkages across fifteen non-energy commodity prices, several macroeconomic variables and the real price of WTI crude oil. It is worth noting that a FAVECM model is also used in this study in order to test for cointegration. Finding no cointegration, the analysis is conducted using a FAVAR model. After the implementation of the FAVAR approach, an impulse response analysis is also implemented. The data used in this paper are quarterly and span the period 1975Q1 to 2008Q3 while the database used is the IMF IFS. The commodities under consideration are cotton, seven metals, namely aluminium, copper, iron ore, lead, nickel, tin and zinc and seven commodities in the food and tropical beverages category, namely cocoa, coffee, maize, rice, soybeans, sugar, and wheat. The macroeconomic factors examined are global industrial production, proxied by the industrial production index of the OECD countries plus six major non-OECD countries, the US interest rate, proxied by 1-year US Treasury notes and bond yield deflated by the US CPI and the US dollar effective exchange rate.

A different approach, however still including a FAVAR model, is implemented by Byrne, Fazio and Fiess (2013). In this study, commodity price co-movements are first identified using a methodology proposed by Ng (2006) and then a Panel Analysis of Nonstationary and Idiosyncratic Components (PANIC) is applied in order to find common factors in the prices of commodities. Subsequently, the common factor found is related to the commodity prices’ microeconomic fundamentals by implementing a Factor Augmented Vector Auto Regression (FAVAR) model. The single trade-weighted index of Grilli and Yang (1988), consisted of 24 prices of internationally traded non-fuel commodities for the period 1900 to 1986, is taken into consideration in this paper since it is widely used for empirical research. These yearly data have been recently updated by Pfaffenzeller et al. (2007). They have also been revised by the authors of this paper up to 2008.

Finally, contrary to all the aforementioned approaches encountered in the commodity factors literature, Sjaastad (2008) uses an international pricing model in order to examine the impact of exchange rates on the international price of a homogeneous commodity traded in well-organized markets. This commodity's prices can be at either minor or major currencies. Gold is considered an appropriate commodity to be taken into consideration in this study, in the sense that it is highly homogeneous and is traded in well-organized futures and spot markets. Furthermore, since the annual production of gold is rather small compared to the global stock, the countries producing gold are not able to dominate the world gold market. It is worth noting that the gold-producing countries' currencies are not all traded in organized markets. The data used in the analysis comprise of daily gold spot prices in US dollars and gold forward prices that refer to 164 90-day contracts also in US dollars. These data span the period January 1991 to June 2004 and are provided by Bill Cowan of Anglo Gold Ashanti Australia Limited. In addition, for the same period, spot and 90-day forward exchange rates between the US dollar, the UK pound sterling, and the Japanese yen, are used. These exchange rates are taken from the IMF Data Bank. Also, for a period covering January 1991 to December 1998, data for the DM exchange rates are obtained from the Bundesbank and data for the remaining exchange rates and for the euro are acquired from the IMF.

Results from various studies examining commodity factors identify the existence of a common factor through a factor model and then relate it to several commodity determinants such as real interest rates, exchange rates, global demand, and oil prices. Such a study is of Vansteenkiste (2009) in which the dynamic factor analysis indicates the existence of one common factor which affects significantly, with a few exceptions, non-fuel commodity prices. In the second step of her analysis, it is found that movements in the common factor can be explained by macroeconomic fundamentals, namely the US real interest rates, input costs, the US dollar effective exchange rate and lately by global demand. These results suggest that the idea of excess co-movement among non-fuel commodity prices because of speculative buying is contradicted because this co-movement is found to be explained by macroeconomic fundamentals.

Similarly, a common factor is identified by Byrne, Fazio and Fiess (2013) and they suggest that there is indeed co-movement in commodity prices. Specifically, the common factor explains at least 50% of the variation in the prices of sugar, silver, rice, wheat, maize, rubber, tin, copper, and palm oil. Then, this common factor is found to be related to the real interest rate, risk, as captured by a measure of stock market uncertainty, global demand, as proxied by the growth rate of US real GDP and supply, as proxied by crude oil prices. Notably, the FAVAR approach indicates a negative relationship between real commodity prices and real interest rates. In addition, there is evidence of a negative correlation between risk and commodity prices and of a positive correlation between commodity prices and global demand and supply. However, it must be noted that the impact of the initial period of global demand and supply factors is found to be smaller than the real interest rate and risk factors. The above findings are important for monetary policy decisions. For instance, monetary easing may result in higher commodity prices, since the real interest rate is found to be related to commodity prices.

A common factor and a local factor are able to explain movements in commodity returns according to the findings of Ma, Vivian and Wohar (2015). Especially, after 2000, the importance of the common factor for driving commodity returns rises significantly. Specifically, the common factor contributes positively and statistically significantly to the variance of commodity returns for more than 30 out of the 43 commodities under consideration. This contribution of common components in commodity markets along with market integration suggests a greater impact in these markets from economic shocks. It also suggests that commodities become a less efficient tool for diversification. Finally, it is worth mentioning that the change in the exchange rate is found to be the most important determinant of the common factor among other candidates examined in this study. However, for the period 1994 to 2003 a bivariate regression indicates that market economic uncertainty as proxied by the VIX index, the real T-bill, and the lagged common factor are significant.

Other studies, without first identifying the existence of a common factor, also highlight oil prices, industrial production, exchange rates, real interest rates and inflation as common commodity factors. Specifically, Lombardi, Osbat and Schnatz's (2012) results indicate that common factors drive commodity prices. Specifically, non-energy commodities are found to gather in two groups. The first group is labeled "metals factor" and the second "food factor". Both common factors, after using a simple analysis and multivariate OLS estimates, are found to be positively correlated to oil prices and industrial production and negatively correlated to the real exchange rate. After the implementation of the FAVAR approach, an impulse response analysis suggests that non-energy commodity prices demonstrate a positive response to a rise in global industrial production in 13 out of 15 cases. Also, it is found that exchange rates have a strong impact on non-energy commodity prices. Contrary to the previous results, no robust spillovers from oil to non-oil commodity prices are found. Only for iron ore and sugar a significant and positive response to oil price shocks is identified. Finally, interest rate shocks have no systematic impact on non-energy commodity prices.

Contrary to the previous studies that find several common factors, Frankel (2008) focuses only on interest rates. He finds that when regressing oil inventories against interest rates the coefficient on the real interest rate is mostly negative. However, the coefficient on the real interest rate is negative when three factors concerning the demand for oil inventories are also taken into consideration in a regression of inventories against interest rates. These factors are industrial production, as a proxy for changes in demand, obtained from the IMF IFS, composite risk rating obtained from the Political Risk Services Group, as a proxy of supply disruptions, and the spot-futures price spread. The coefficient, however, is significant only for composite risk and the spot-futures price spread. Moreover, when other counties are included in the analysis the results also show a significant negative coefficient on the real US interest rate. It is noted that this paper also investigates the results for agricultural inventories but the author suggests that the results might be spurious and thus cannot be considered serious. This is because risk and other important variables were not possible to be taken into consideration.

Supporting Frankel's (2008) empirical findings that real interest rates affect commodity prices, Svensson (2008) suggests that these finding also make sense theoretically. The theoretical sense is based on the fact that commodity prices can be considered as asset prices, thus they are discounted present values of expected future returns. So, when real interest rates increase this means that the discount factors and consequently the present value of the expected future returns falls. This means that this negative effect should prevail given that real interest rate increases are not systematically correlated with expected returns increases or risk premium decreases.

Another study finding exchange rates and inflation as common commodity factors is the one of Sjaastad (2008). The findings of this paper are based on the analysis of the world gold market, without being able to generalize these results for other commodities. Specifically, it is found that, during the period under consideration, the market efficiency hypothesis holds for this market. Furthermore, the major gold producers such as Australia, Russia, and South Africa seem to have no remarkable influence over the gold's world price. What is more, ‘‘world" inflation has a negative but statistically significant effect on gold prices. "World" inflation is defined as the natural logarithm of a weighted average of the European, US, and Japanese CPI price levels with the European price level being the weighted average of UK, German, French and Italian GDP deflators. Finally, although during the 1980s half of this market power was possessed by the European currency bloc, in the 1990s the dollar area along with Japan seems to have become dominant. Thus, appreciations or depreciations of the euro and the yen against the US dollar can affect significantly the price of gold in all other currencies.

Similarly, Sari, Hammoudeh and Soytas (2010) find that oil is a common determinant for commodities, but they also highlight exchange rates as a common factor. In particular, their results of the generalized forecast error variance decompositions suggest that, compared to the four precious metals, there is a rather strong relationship between oil and silver price returns. This is possible because silver is used in the auto industry like oil and is just as highly volatile. It is also found that oil price returns and gold have a very weak relationship probably due to the fact that gold is the least volatile of precious metals and oil is characterized by great volatility. In addition, oil price changes may be caused by crises, inflation or changes in exchange rate while gold is used as a hedge against inflation. Weak relationships are also found between oil price returns and each of platinum and palladium price returns. Moreover, there is a strong relationship between gold and other precious metals price returns as well as between gold price returns and changes in exchange rates. This overall weak relationship between oil and the four precious metals is mostly explained by the speculation attacks, due to seasonality and weather conditions, to oil prices and by their frequent management by OPEC. The results of the generalized variance decomposition further disclose that, neither in the short nor in the long run, there are remarkable linkages between changes in exchange rate and oil price return. Consequently, since there is a generally weak relationship between precious metals and oil spot prices on the one hand and exchange rate changes, on the other, investors may benefit, in the long term, from diversification into the precious metals. The same stands for precious metals exporters; when they export one of these four commodities they can substitute with one of the rest in order to diversify when prices fluctuate in the long term. The impulse response function results suggest that spot precious metals' prices and exchange rates may be closely related after shocks take place in the short term. Shocks in the precious metals and oil are common but affect on a small positive level each other. These results support the efficient market hypothesis in the sense that they indicate that traders can use a rise in silver, which is the same volatile as oil, as a sign for oil price increases. However, such opportunities eliminate within a few days. Another important finding, that concerns monetary authorities, is that gold and to a lesser extent silver can give valuable information for the dollar/euro exchange rate behavior. Contrary to gold and silver, oil gives no such information for the exchange rate changes and neither the opposite is evident. Finally, as far as precious metals traders are concerned, platinum price increases can be used to predict palladium price increases in the short term due to their close relationship.

In addition, Baffes (2007) focuses on oil as a commodity determinant. His results indicate that non-energy, precious metals, and food commodity prices, as well as the fertilizer index, are strongly affected by crude oil prices. Yet, beverages, metals, and raw materials indicate mixing results. These results suggest that, provided that crude oil prices remain high, the latest commodity price burst will possibly last longer than earlier ones. This will especially hold for fertilizers, food commodities, and precious metals which are found to be strongly related to oil prices.

A high positive correlation between gold and oil prices is also indicated by the results of Zhang and Wei (2010). In addition, oil’s price coefficient of variance is double from that of gold but their volatilities have both doubled in the period 2004 to 2008. Also, there is evidence of a long-term or a significant cointegration relationship between gold and oil prices that is attributed to the fact that they are driven by similar or common factors. These factors are found to be the US dollar because in the analysis it is found that the US dollar index may Granger causes both crude oil and gold prices. Another common factor mentioned in their study is inflation. Specifically, high crude oil prices seem to deteriorate inflation, because oil is used as a raw material in industrial production, while gold resists it and becomes a hedging tool so that its demand and thus its price increases. Also, increases in gold prices have been observed after oil-exporting countries use their oil proceedings in order to invest in gold so as to dissipate market risk and preserve commodity value. Moreover, geopolitical events seem to influence both oil and gold prices contemporaneously. As for the interaction between gold and oil prices, it is found that the crude oil price change on the gold price, although much smaller than the opposite relationship, can last for one day contrary to the opposite relationship that lasts only on the same day. Granger causality results show that the crude oil price return change Granger causes the gold price returns change which means that the two prices share similar trends. Yet, change in gold price return does not significantly Granger causes changes in crude oil price returns. Finally, since cointegration is found between oil and gold prices, the analysis proceeds by applying a vector error correction model. Based on that model, it is evident that crude oil affects the entire commodity market more than gold. This is important because is suggests that oil price developments should be given more attention. It must be noted that all the paper's results are static and not time-varying.

Inflation is also found to be a common commodity determinant in Browne and Cronin (2010). Specifically, cointegration of commodity prices with the money stock as well as cointegration of consumer prices with the money stock is found. Also, commodity prices are found to react rather quickly and overshoot the values of their new equilibrium, after a money shock. Contrary to commodity prices, consumer prices converge slowly to equilibrium. The results suggest that commodity price increases drive consumer price inflation due to the different speed of both commodity and consumer price adjustment to monetary policies. The above findings are important for monetary authorities when shocks of asset prices correction and uncertainty provoked by them occur. Central banks who are forced to ease monetary policy, without being able to absorb the money stock increase when uncertainty is eventually eliminated, are likely to start a new asset price cycle.

In the same spirit, Worthington and Pahlavani's (2007) results suggest that a strong cointegrating relationship is evident between gold and US inflation. As a result, gold is considered a hedge against inflation. However, it is worth noting that although various studies we already mentioned suggest inflation as a common commodity determinant, Blose (2010) cannot empirically prove that the same holds for expected inflation. His results from the regression models of unexpected CPI changes against bond yields indicate that bond yields are positively affected by unexpected CPI changes. The results from the regression models of unexpected CPI changes against gold prices suggest that gold prices do not react in expected inflation, thus the carrying cost hypothesis holds. Therefore, market inflation expectations cannot be defined using spot gold prices. Investors who intend to use speculation against market inflation expectations should thus turn to bond markets.

Flight-to-quality

Different assets' portfolios are held by investors in order to reduce their risk, according to Baur and Lucey (2009). They cite that, if during crises periods diversification is less effective than normal periods, this might indicate cross market contagion. However, if several assets' prices increase during periods of financial crises, investors' losses are partly reduced. Such an example is a flight-to-quality event during which investors "fly" from equities to bonds. So, if in periods of crises the equity-bond relationship becomes negative, losses for investors holding both equities and bonds will be limited as a result of the positive bond returns. This insinuates that flights increase the financial system's stability.

Many financial and currency crises have occurred in the past twenty years according to Billio and Caporin (2010). Some of these crises had regional or global aftereffects but most of them hit emerging economies due to their vulnerable underdeveloped financial markets as well as their large public deficits. Such crises were the Wall Street crash of 1987, the European monetary system breakdown of 1992, the Mexican pesos crisis of 1994, the "Asian Flu" of 1997, the "Russian Cold" of 1998, the Brazilian devaluation of 1999, the Internet bubble burst of 2000, and the July default crisis in Argentina of 2001.

In the present thesis we investigate for the presence of flight-to-quality effects from equities to commodities. To the best of our knowledge there is only one paper, the study of Chan, Treepongkaruna, Brooks and Gray (2011), that examines flight-to-quality from equities to commodities. According to this study, some linkages exist between commodity, financial and real estate markets. Specifically, strong linkages among various assets were evident in the latest global financial crisis during which housing prices dropped significantly in the US, leading to the bankruptcy of many banks and financial institutions. Consequently, global equity markets and commodity prices dropped sharply. In addition, during that period, oil prices have been the most volatile in their history while gold prices reached their highest, until that time, level. Moreover, corporate bond spreads increased remarkably. Understanding the linkages between commodity, financial and real estate assets is important not only for asset allocation and portfolio diversification but also for policy makers who wish to know how to deal with the largely interconnected assets during periods of economic turmoil. That is why in this study flight-to-quality is investigated.

However, flight-to-quality from equities to commodities has not been investigated any further in the literature. Most studies focus on flight-to-quality from equities to bonds. The theory behind flight-to-quality from stocks to bonds is stated by Durand, Junker and Szimayer (2010). In particular, the discounting theory suggests that the values of equities are the net present value of shareholders' future cash flows. Higher discount rates reduce the present value of the expected cash flows. Consequently, during periods of economic turmoil, higher interest rates lead to a decrease of expected cash flows. The above suggest that equity and bond returns should be positively correlated. Conversely, the flight-to-quality theory suggests that investors "fly" from risky assets such as equities to less risky assets, namely bonds. Thus, lower stock returns are linked to higher bond returns. These two theories might either be competing or complementary. In particular, the two theories could be considered complementary if the discounting theory holds in normal economic periods while the flight-to-quality theory holds in periods of economic crises.

The discount rate effect is also mentioned in Dajcman (2012). In particular, it is stated that equity and bond prices should have a positive correlation, which means that equity returns and the changes of sovereign bond yields should be negatively correlated, due to a common discount rate effect. However, there have been periods that equity market returns and the changes of sovereign bond yields are positively correlated. This might be the case because of variations in expected inflation since inflation increases affect bonds negatively, but not equities. Also, in periods of economic turmoil, the flight-to-quality phenomenon might appear.

Other studies test directly for contagion and test indirectly for flight-to-quality through testing for contagion. Contagion might be the result of the fact that during financial crises a market-specific shock could be transmitted globally to different markets in size and structure according to Billio and Caporin (2010). This global transmission could be easily achieved since, according to Choudhry and Jayasekera (2014) linkages between equity markets around the world have increased since domestic markets are no longer isolated and consequently have become more sensitive to shocks and news from markets of all over the world.

In addition, also focusing on contagion, Brière, Chapelle and Szafarz (2012) state that contagion, as well as globalization, tend to increase correlations among assets, thus they can be confused with each other. This is because, some support that economic globalization together with the increased market integration are responsible for the upward trend in correlations among international equity markets. Others support that market contagion in crises periods is associated with these correlation movements. Globalization which is the general rise of correlations among asset classes and across geographical areas is established for both stocks and government bonds. However, contagion results from crises spread to markets different from those they originally came from.

Finally, periods of economic turmoil are associated with flight-to-quality when investors turn to less risky assets and flight-to-liquidity when investors turn to more liquid assets. In general, according to Beber, Brandt and Kavajecz (2009), it is difficult to understand whether an increase in the prices of a fixed-income security such as bonds is affected by credit quality or liquidity because these two phenomena are mostly positively correlated. However, it is of great interest to know if there is flight-to-quality or flight-to-liquidity in crises periods in order to be able to best interpret investors' behavior during such times.

As far as the methodologies for testing for flight-to-quality are concerned, there have been a few different approaches in the literature. The present thesis' methodology mainly bases on the test for flight-to-quality of Baur and Lucey (2006, 2009). Baur and Lucey (2006, 2009) after providing definitions of flight-to-quality, flight-from-quality and contagion, proceed in detecting a priori flight-to-quality events by using a cumulative correlation change measure contrary to most studies that only consider a posteriori crisis events. Subsequently, independently of the cumulative correlation change measure's results, a linear regression including Dummy variables of a posteriori defined crisis events is used to detect flight-to-quality. Testable restrictions are derived in terms of this linear regression model. Another advantage of the OLS approach is that it allows for the inclusion of additional factors that affect flight-to-quality events such as volatilities. Moreover, Baur and Lucey's (2006, 2009) definitions are used in the literature and particularly in the only paper, to our knowledge, that tests for flight-to-quality from stocks to commodities, namely the study of Chan, Treepongkaruna, Brooks and Gray (2011).

Another study, adopting the definitions of Baur and Lucey (2006, 2009) is the study of Choudhry and Jayasekera (2014).

Specifically, in their study, Baur and Lucey (2006) try to explain the level and the changes of correlations between stocks and bonds. Contagion is defined according to the literature as a rise of the correlation coefficient compared to a benchmark period during a period of economic turmoil. Flight-to-quality from equities to bonds is defined as a decrease in the correlation coefficient and concurrent falling equity markets and flight-from-quality from bonds to equities is defined as a decrease in the correlation coefficient and concurrent increasing equity markets. Contagion and flight-to-quality are mutually exclusive phenomena regarding correlations between equities and bonds. This paper also focuses on negative contagion which is defined as an increase in correlations caused by negative shocks because it is considered more important for investors.

The methodology of Baur and Lucey (2006) is analyzed in three steps. In the first step, time-varying correlations are obtained either by using the Dynamic Conditional Correlation (DCC) estimator of Engle (2002) or by estimating rolling window correlations. The second step involves testing for the presence of flights or contagion by using the time-varying correlations obtained from the first step. In particular, first, flights or contagion are detected by estimating a cumulative measure of correlation change, which is not based on a priori defined periods of economic crises and is defined as time series of Y day cumulative correlation change (Y-CCC). Secondly, the presence of flights or contagion is tested in terms of a regression where the dependent variable is the time-varying correlations while the control variables are lagged cross-product of assets' returns, positive and negative returns, conditional volatilities, and dummy variables representing financial, economic or political events. Finally the existence of two regimes is investigated. The data used are daily continuously compounded MSCI equity and bond index returns of the US and of European countries, namely UK, which is a non-euro country, Finland, Belgium, Germany, Spain, France, Italy, and Ireland. The MSCI bond indices are sovereign total return indices with maturities longer than 10 years. All indices are in local currency and the data span the period November, 30 1995 to November 30, 2005.

Similarly, the existence of flights and whether they affect diversification strategies as well as the stability of the financial system are investigated by Baur and Lucey (2009). In particular, it is examined whether contagion between equities and bonds exists in certain periods and whether flight-to-quality from equities to bonds and equity market contagion or flight-from-quality and bond market contagion are related to one another. Their study is of significant contribution to the literature because it estimates time-varying conditional equity–bond correlations and finds a significant fluctuation of these correlations within rather short time periods. Also, their study suggests a new econometric framework for testing the existence of flights between equities and bonds not only within a country but across countries as well. What is more, definitions of flight-to-quality, flight-from-quality and contagion are derived.

The econometric framework of Baur and Lucey (2009) consists of three steps. In the first step, using the dynamic conditional correlation (DCC) estimator of Engle (2002), time-varying equity–bond correlations are estimated in order to assess the evolution of correlations between equities and bonds through time. Knowing if the correlations are stable, show a trend, or fluctuate in a random way is useful for the determination of a benchmark that will be used in the flights and cross-asset contagion analysis. In the second step, the correlations between equities and bonds are examined focusing on periods of financial crises. If a negative correlation between equities and bonds, affecting mostly stock markets, is found during a crisis period, it suggests that bond prices increase which is consistent with a flight-to-quality from equities to bonds. If the level is positive, it means that equity and bond prices fall together which is consistent with cross-asset contagion or a flight to alternative assets, namely gold or cash. This step involves a regression of bond returns on stock returns, dummy variables of crisis events and an additional crisis dummy including a pre-crisis sub-sample. This additional dummy is necessary for a time-varying benchmark to be employed. In the third step of the analysis, an effort to link flights to cross-country contagion is made by testing whether flight-to-quality or flight-from-quality are country-specific phenomena only or constitute a common feature across countries. Finding such evidence that the common feature of flight-to-quality exists across countries might imply that there is cross-country equity market contagion. Respectively, for flight-from-quality such evidence might imply cross-country bond contagion. In this step a panel model is used with dependent variable bond returns across countries and control variables stock returns across countries, dummy variables of crisis events across countries and an additional crisis dummy across countries including a pre-crisis sub-sample.

The data used in the analysis of Baur and Lucey (2009), are daily continuously compounded MSCI equity and bond index returns of Germany, Italy, France, the US, the UK, Australia, Japan, and Canada. The MSCI bond indices are sovereign total return indices with maturities longer than 10 years. Furthermore, all indices are in local currencies and the data span the period January 1994 to September 2006. It is worth noting that correlation changes are taken into consideration in the analysis because the level of correlations does not reveal the behavior of investors. In addition, the major political and financial events considered are the 1997 Thailand turmoil, the 1997 Asian crisis, the 1998 Russian crisis, the September 11, 2001 terrorist attacks, the 2001 Enron crisis, and the 2002 WorldCom crisis.

An approach similar to the cumulative measure of Baur and Lucey (2006) is also found in Dajcman (2012). His paper examines the co-movement between equity market returns and the changes of sovereign bond yields for the Eurozone countries that had the biggest impact of the sovereign debt crisis and for the core Eurozone country, namely Germany whose sovereign bonds are considered as “safe havens”. The periods of financial market turmoil analyzed in this paper are the 11 September 2001 attack, the 2002 Internet bubble burst, the 2006 Middle East financial market crash, the 2007–2008 global financial crisis and the 2011 sovereign debt crisis in the Eurozone. The data used for index prices obtained from Yahoo! Finance, are PSI 20 for Portugal, ISEQ for Ireland, IBEX35 for Spain, FTSE MIB for Italy, and DAX for Germany. The yields of central government bonds with 10-year maturity dates were also considered and obtained from the Denmark’s Central Bank. This analysis is implemented using the DCC-GARCH model. After computing the dynamic conditional correlation for a particular country the flight-to-quality indicator for this country’s financial market is calculated. This flight-to-quality indicator is calculated as a moving window indicator of flight-to-quality around a day *x* based on 20 trading days around day *x*. The values of a window take the value 1 if a negative sovereign bond yield change and a negative equity market return are evident on the same day or 0 if a negative sovereign bond yield change and a negative stock market return were not evident for a particular day. Consequently, the flight-to-quality indicator takes values within the interval [0, 1]. The closer this value is to 1, the more durable the flight-to-quality phenomena are around day *x*. When this value is equal to 0 this means that for none of the 20 trading days a flight-to-quality phenomenon was evident. When this value is equal to 1 this means that for all 20 trading days around day *x* a flight-to-quality phenomenon was observed.

Moreover, the study, which is the only one to our knowledge, examining flight-to-quality between equity and commodity returns, is of Chan, Treepongkaruna, Brooks and Gray (2011). In this study, they examine linkages across US stocks, Treasury bonds, oil, gold and US housing using a univariate and a multivariate Markov regime-switching model and particularly the Markov Switching Intercept Autoregressive Heteroscedasticity (MSIAH) model. The univariate Markov regime-switching model characterizes the marginal return distribution of the assets taken into consideration while the multivariate Markov regime-switching model characterizes the joint distribution of returns of the assets taken into consideration and allows for variation in these returns across regimes. The data used are monthly returns of S&P500 index, Fama-Bliss 1-year Treasury bond prices, West Texas Instrument (WTI) Cushing crude oil spot prices, gold spot prices quoted in US Dollars per troy ounce and the S&P Case-Shiller Composite-10 home price index. Bloomberg is the basic database from which the data are gathered, while the Center for Research in Security Prices (CRSP) is also used for the Treasury bond prices. The data cover the period January 1987 to December 2008.

It is worth noting that the methodology implemented in the study of Chan, Treepongkaruna, Brooks and Gray (2011), namely the Markov regime-switching model is not considered the most appropriate for testing flight-to-quality events according to Durand, Junker and Szimayer (2010). Flight-to-quality events in regime-switching models are evident in the regime of negative correlations between the assets considered. Thus, since flight-to-quality events are rare, the regime of negative correlations between the assets considered has considerably fewer observations than the regime of positive correlations. Consequently, the conditional distributions of such rare events cannot be estimated accurately.

Another approach on testing for flight-to-quality is based on copulas. For multivariate time series, the copula function is a very useful tool because it allows to model the dependence between the variables separately from their marginal distributions. In practice, we usually know the dynamics of the marginal distribution of the data, while we have limited knowledge of the joint dependence of the data. Therefore, copulas result in a two step estimation procedure, which can be advantageous. For instance, in the first step either unconditional marginal distributions or conditional distributions are modeled via a GARCH model. Then, in the second step we model the cross dependence of the estimated marginal distributions. However, this statistical methodology is mostly parametric or non parametric. The choice of parameters affects the estimation results to a large extent. Consequently, misspecification errors are highly possible when parameters are not chosen correctly. As far as non parametric copulas such as the Bernstein copula are concerned, the estimated cross dependence of the data is not stable.

A copula methodology to test for flight-to-quality is found in Durand, Junker and Szimayer (2010). In their paper, a dependence function, or copula, combining the features of the Frank and the Gumbel copulas, is estimated in order to examine the relationship between stock and long-term bond returns. The features of the Frank copula allow for the examination of any homogeneous relationship between the two assets considered while the Gumbel copula allows for the analysis of any dependence structure at the tails of the distribution of the assets' examined returns. The combined copula can capture "normal" and "rare" states in the stock-bond relationship while the separate statistical treatment of the dependence and marginal behavior of data is possible. In the analysis, the CRSP value-weighted index of US stocks and the CRSP 30 year bond index are used in a quarterly frequency for the period 1952 to 2003.

In the literature another approach for testing for flight-to-quality is also the local correlation approach. This approach examines correlation in certain quantiles of the time series. The problem with such methodologies is that they yield inefficient estimates of the correlations of the specific parts of the distributions of the data, because the quantiles of the data exhibit time-variability, and the proposed method does not account for this type of nonstationarity.

A local correlation methodology to test for flight-to-quality is found in Bradley and Taqqu (2004, 2005). Bradley and Taqqu (2004) propose a definition for contagion and implement a test for it using a local correlation approach. According to that definition, contagion from market A to market B is evident if the dependence between the two markets is bigger when A's performance seems to be significantly below its typical one than when A performs is its usual way.

In addition, in Bradley and Taqqu (2005) the local correlation approach of their study in 2004 is also implemented. The data used are taken from Datastream and consist of daily stock price indices from developed markets, namely the US, Germany, Canada, Australia, United Kingdom, Hong Kong, Japan, Switzerland, Netherlands, France, Italy, and Belgium markets. The data span the period January 1980 to May 2002. From the price indices, daily, weekly and monthly return indices are constructed. Also, the returns of a Merrill Lynch US Government Bond index representing one to ten-year maturity bonds are used in the analysis for the period November 1986 to May 2002.

A local correlation methodology to test for flight-to-quality based on the previous study of Bradley and Taqqu (2004, 2005) is also found in Inci, Li, and McCarthy (2011). They define flight-to-quality as an explicit and rapid increase in risk aversion which is measured by a non-linear local correlation approach. By this approach, both normally and non-normally distributed time series can be taken into account. The methodology implemented is based on the papers of Bradley and Taqqu (2004, 2005) who define flight-to-quality from market A to market B. According to Bradley and Taqqu (2004, 2005), flight-to-quality from market A to market B is evident if the dependence between the two markets falls when the performance of market A is significantly below its typical one. In addition, using the local correlation approach, the reaction in one market with respect to the change in the financial returns in other markets is specified. The advantages of local correlation are that there is no need for defining a crisis and a non-crisis period or correcting for heteroscedasticity.

The spot data used in the analysis of Inci, Li, and McCarthy (2011) are daily returns of the DAX30, Nikkei225, S&P500, Hang Seng Index, FTSE100, and ten-year US Treasury bond index returns. These data are gathered from the FactSet database. Also, futures data obtained by Price-Data are DAX30, Nikkei225, S&P500, FTSE100, Hang Seng, ten-year T-Bond, three-month T-bill and one-year to ten-year composite bond futures. As far as the spot data are concerned, the sample period is January 3, 1985 to November 8, 2008. An exception is the German spot data which start from January 7, 1994. As for the futures data, the entire sample ends on July 11, 2008 but starts in different periods. Specifically, their corresponding starting dates are May 3, 1984 for FTSE 100 and the US data, September 25, 1990 for Nikkei 225, October 22, 1997 for Hang Seng and November 7, 1997 for DAX 30.

Another study on concentrating on measures of dependence relevant to specific parts of the underlying probability distribution, as Bradley and Taqqu (2004, 2005), is the study of Hartmann, Straetmans and de Vries (2004). In this study, the authors state that it is of great interest to study whether markets crash jointly or not because the more markets crash contemporaneously; the more at risk are large banks holding diversified portfolios. Also, they propose a nonparametric measure, not predisposed toward the normal distribution, to characterize asset return linkages during periods of turmoil. In particular, the expected number of market crashes conditional on the event that at least one market crashes is directly measured. Moreover, they support that correlation analysis is predisposed toward multivariate normal distribution which based on this paper's analysis dramatically underestimates the frequency of extreme market spillovers. That is why they use the aforementioned alternative approach. Furthermore, the data used in their analysis are taken from Datastream and consist of weekly observations for the stock indices of Germany, France, the United States, the United Kingdom and Japan. Also, prices for the indices of 10-year government bonds are obtained. The data span the period February 27, 1987 to November 18, 1999.

In the literature different approaches to test directly for flight-to-quality exist, as mentioned above. However, there are also other studies focusing on testing for contagion that also test indirectly for flight-to-quality. Such a study testing for globalization and contagion, and indirectly for flight-to-quality based on a GLR test and is of Brière, Chapelle and Szafarz (2012). However, this methodology does not take into account time-varying correlations and as stated in Brière, Chapelle and Szafarz (2012) the GLR test may suffer from distortions due to violations of the assumption of return independence.

In particular, globalization and contagion phenomena are tested separately for all financial crises from 1978 to 2010 in Brière, Chapelle and Szafarz (2012). In order to implement tests for globalization and contagion they use the GLR approach. The GLR test is applied in order to test the equality of correlation matrices. The dataset used in the above analysis consists of weekly returns of stock indices, corporate bonds, and government bonds. For government bonds the 10-year benchmark indices of Datastream are used while for corporate bonds data are obtained from Merrill Lynch investment grade bonds and high yield bonds are taken into account. As far as stock indices are concerned, the geographical areas taken into consideration are the Eurozone, US, UK and Japan and the database used is Datastream. The data span the period August 1978 to December 2010 for equities, January 1980 to December 2010, for government bonds, except for Japan for which the series starts in January 1984, and finally July 1998 to December 2010 for corporate bonds.

In the context of studies that primarily focus on testing for contagion, the study of Choudhry and Jayasekera (2014) focuses on volatility spillovers and also provides evidence for flight-to-quality using a multivariate GARCH-GJR approach. It is worth noting that multivariate GARCH models, compared to DCC models we use in the present thesis, have the problem of over-parametrization which means that more parameters lead to less reliable estimation results.

In particular, Choudhry and Jayasekera (2014) investigate volatility, return, and leverage spillover effects between the banking industries of Germany, US, and the UK, who are considered major economies, and other European Union countries who are considered smaller and more stressed, namely Ireland, Greece, Italy, Portugal and Spain. Their analysis covers the period January 1, 2002 to January 1, 2014 which includes the global financial crisis period 2007 to 2014. The multivariate GARCH-GJR approach is implemented using daily banking industry equity indices from the database Datastream and the analysis is conducted in two sub-periods, namely a pre-crisis period January 1, 2002 to June 30, 2007 and a crisis period July 1, 2007 to November 1, 2014, in order to examine changes in spillovers from the first to the second sub-period. A spillover effect in returns insinuates that an exploitable trading strategy exists, thus making a profit from this strategy provided that these profits are bigger than transaction costs means that market efficiency is violated. Spillover effects are also important are useful for hedging strategies.

What is more, the analysis of Choudhry and Jayasekera (2014) apart from the investigation of spillover effects also focuses on the leverage effect which is present when positive or negative shocks cause an asymmetric change in volatility. In particular, negative shocks, namely bad news, cause higher volatility. In addition, this study investigates the existence of flight-to-quality or flight-from-quality from the banking sector of the smaller and more stressed EU economies to the major economies and contagion between them. The paper uses the definitions of Baur and Lucey (2009) according to which contagion is defined as an increase of the correlation coefficient during crisis periods compared to a benchmark period, flight-to-quality from banking sectors of small and more stressed EU economies to major economies is defined as a decrease in the correlation coefficient and contemporaneously decreasing stock markets and flight-from-quality from banking sectors of major economies to small and more stressed EU economies is defined as a decrease in the correlation coefficient and contemporaneously increasing stock markets. Moreover, contagion is classified in positive contagion which is a rise of correlation due to positive shocks and negative contagion which is a rise in correlation resulted from negative shocks.

Another paper that belongs to the literature that mainly focuses on contagion and secondarily on flight-to-quality events is the one of Billio and Caporin (2010). In their study they state that, in the broad sense, contagion is the spreading of positive or negative shocks across countries either in crisis or tranquil periods. A more restrictive definition is that contagion is the spreading of shocks that exceeds what should be anticipated by fundamentals. According to this definition any co-movements are provoked by common shocks. Finally the most restrictive definition of contagion suggests that contagion is the change in the transmission mechanism that occurs in periods of economic turmoil. Such changes can be the remarkable increase in cross-market correlations. This study focuses on the third definition.

Moreover, in the paper of Billio and Caporin (2010), contagion events are identified and differentiated from flight-to-quality events. The concurrent relationships among American and Asian equity markets are investigated using a specific multivariate GARCH model representation. In particular, analyzing the correlation matrix over rolling windows in the estimated residuals allows for a graphical analysis as well as for the development of a statistical test of correlation movements. The movements identified in the unconditional or long-run correlation matrix might be linked to permanent changes. The data used in this study are daily stock market indices for six countries, namely USA, Brazil, Mexico, Japan, Singapore, and Hong Kong along with their exchange rates regarding to the U.S. dollar. The dataset spans the period June 20, 1995 to November 16, 2005.

Finally, papers that discuss on flight-to-quality phenomena suggest that investors in times of increased uncertainty and volatility become more risk-averse and turn to safer assets. Thus, when investors demand a higher risk premium in times of turmoil this suggests a flight-to-quality phenomenon. However we must bear in mind that such flights may be flights-to-liquidity when liquidity rather than risk premia broaden.

Flight-to-liquidity is discussed in Vayanos (2004) who proposes a model that generates time-varying liquidity premia that rise with volatility. Thus, flight-to-liquidity is linked to times of high volatility. Asset-pricing implications of the time-varying liquidity premia theory are also explored. Flight-to-liquidity events happen when liquidity premia broaden dramatically during extreme market episodes and so investors, suddenly, strongly prefer holding liquid assets. A significant factor that drives liquidity premia variation is the degree of market uncertainty.

The relationship between order flow, namely flights, credit quality and liquidity of fixed-income securities is also examined in everyday markets as well as in periods of economic turmoil by Beber, Brandt and Kavajecz (2009). Knowing these relationships in everyday markets and how they are altered in periods of economic turmoil improves the understanding of financial markets and notably fixed-income markets. The data used in their study are MTS data for order flow and yield spreads of Finland, Belgium, Austria, Greece, Italy, Portugal, Germany, Spain, France, and the Netherlands are taken into account. In addition to the MTS data, data from the sovereign credit default swap market are acquired from Lombard Risk of Fitch Rating Inc in order to estimate the credit quality exogenously for each of the countries considered. The time period taken into consideration is April 2003 to December 2004 and it includes news events that are directly linked to flight-to-quality, namely the 2003 US war with Iraq invasion, the 2004 Madrid bombings, the 2004 Tsunami and the 2004 Saudi Arabia bombings. Flights are classified by identifying periods of large positive or large negative total bond market order flow and then matching them with significant news events. It is worth noting that the Euro-area bonds are characterized by a unique negative relationship between liquidity and credit quality contrary to the strong positive relationship found in the US debt markets. For instance, Italy’s sovereign debt is very risky but simultaneously very liquid.

As far as the results of all the studies we mentioned above that test for flight-to-quality are concerned, there is wide evidence of flight-to-quality from stocks to bonds irrespectively of the methodology implemented in each study. In particular, results from the study of Baur and Lucey (2006) indicate extreme negative changes of the correlation in falling equity markets in October and the first two weeks of November 1997, in June 1998, in October 2000, in January 2001 and before the September 11 attacks of the same year. Also, such large drops were evident in September 2003, in August 2004 and in April 2005. On the other hand, increases were found in March and August 2005 and after the attacks of September 11, 2001. Furthermore, extreme correlations for the UK bond and equity market are remarkably lower and less frequent than for the US market. Also, extreme correlation changes are rather rare for Germany. This means that the most distinct flight-to-quality events are in the 1997 Asian and 1998 Russian crisis while contagion is found after September 11, 2001. Results from the regression analysis indicate the existence of flight-to-quality, flight-from-quality and contagion and that the equity and bond market volatility explains up to 30 percent of the correlations between equities and bonds. Also, the coefficient estimates are the highest for the US, lower for the UK and the lowest for Germany. Moreover, there is weak evidence for contagion for Germany. Finally, when considering for positive and negative correlation regimes, the rate of explanation of the equity-bond correlations increases to almost 80 percent and shows that higher equity market volatility decreases correlations, contributing to flight-to-quality, and higher bond market volatility increases correlations, contributing to contagion. Also, when the regime of the correlations is taken into consideration in the analysis, the volatility of bond market is found to be more important than the volatility of equity market.

Flight-to-quality is also evident in Baur and Lucey (2009). Results from this study indicate the existence of flights and their frequent occurrence during financial crises periods. Specifically, flight-to-quality from equities to bonds for almost all countries aside from Australia and Canada is evident during the Russian crisis. Also, flight-from-quality from bonds to equities for all countries except for Japan is evident during the Enron crisis. The largest number of flights, namely the flights during the Asian, Russian, 11 September and Enron crises, are found for the US, Australia, Canada and Italy have the second largest number of flights, Germany, UK and France exhibit two flight events and finally Japan exhibits only one flight episode during the Russian crisis. Also, cross-country contagion is implied by the fact that flights are found to occur simultaneously in many countries. In particular, contemporaneous flight-to-quality events from equities to bonds are found during the Asian crisis, joint cross-asset contagion or a flight to alternative assets is evident after the 11 September crisis and a common flight-from-quality from bonds to equities is found during the Enron crisis. Consequently, an indirect testing of cross-country contagion could be performed by testing for flight-to-quality or flight-from-quality across countries. The above results are very important for investors in the sense that the occurrence of flights in periods of economic turmoil means that investors can use diversification strategies. This ability to diversify in times that it is most needed improves the stability and resiliency of the financial system. Finally, it is found that financial markets in which flights exist in periods of economic crises have smaller losses than markets in which no flights are evident.

Similarly, results from Dajcman's (2012) study indicate that co-movement between equities and bond yields changes is time varying. Specifically, for Germany co-movement between equities and bond yields changes is mainly positive during the period examined while for the countries with the biggest effects of the sovereign debt crisis the correlation becomes negative more frequently and for a longer period, especially after the onset of the Eurozone's sovereign debt crisis. In addition, Greece's sovereign debt crisis resulted in decreased correlations in the countries that faced the greatest debt problems, namely Italy, Portugal, Ireland, and Spain. However, normally, financial crises lead to higher correlation. Similar results are evident for Italy's and Portugal's debt crises. Finally, it is found that before 2010, when the Eurozone's debt crisis begun, financial turmoil resulted in flight-to-quality phenomena for all countries taken into consideration in this study, especially during the global financial crisis. Yet, after 2010, the flight-to-quality phenomenon is only evident in Germany.

Flight-to-quality is evident only from stocks to bonds in Chan, Treepongkaruna, Brooks and Gray's (2011) study. No flight-to-quality events are found from stocks to commodities but only flight-from-quality and contagion. In particular, results from the univariate analysis suggest that there are two regimes for each of the assets examined. When regime switches can be predicted, in the first regime, a switch between oil, equities and real estate is proposed, while, in the second regime, a switch between bonds and gold is proposed. However, in order to deal with the commonality between regimes in the univariate analysis, a multivariate analysis is implemented. In the multivariate analysis correlations between the returns of the assets and how they vary across regimes are taken into consideration. Results from the multivariate analysis suggest that there are two regimes, namely a "tranquil" regime and a "crisis" regime, in the joint distribution of the assets examined. In particular, during the "tranquil" regime equities, real estate and oil returns seem to be positive while gold and bond prices seem to decline. Conversely, during the "crisis" regime, equities, real estate assets and oil are found to demonstrate negative mean returns while gold and bonds show positive mean returns. This variation in returns on the different assets examined across regimes seems to generate gains from switching assets depending on the identified regime. For instance, switching from equities, real estate and oil to gold and bonds is suggested when there is a shift to the "crisis" regime. The results from this paper also suggest that in a "tranquil" regime with low volatility and considerably positive stock returns there is evidence of flight-from-quality from gold to stocks, while in a "crisis" period with high volatility and significantly negative stock returns there is evidence of contagion between stocks, oil and real estate and of a flight-to-quality from stocks to Treasury bonds. These results are important for diversification and asset allocation strategies. In particular, dynamic allocation strategies can be implemented in order to rebalance portfolios, provided that regime shifts can be predicted or identified shortly after their occurrence. However, even if regime switches cannot be predicted, investors who wish to hedge the risk of financial crises should hold Treasury bonds in their investment portfolios because, as the aforementioned analysis suggests, contagion between stocks and other assets is evident in such periods.

In the same spirit, results from the study of Durand, Junker and Szimayer (2010) indicate a positive relationship between the returns of equities and bonds, supporting the discounting theory, during normal periods, and a flight-to-quality from equities to bonds during periods of extreme events. Also, Bradley and Taqqu's (2004) findings suggest that there is contagion from the US stock markets to stock markets of various developed countries and flight-to-quality from the US stock market to the US bond market. It is worth noting that lower return frequencies show different amounts of contagion between markets. Specifically, a single occurrence of contagion is evident when weekly returns are used while two incidents of contagion are evident when monthly returns are taken into consideration.

Moreover, there is evidence of flight-to-quality from domestic and foreign spot equity markets to US Treasury bonds as well as of flight-to-quality from domestic and foreign index futures to US bond futures when market risk rises according to the findings of Inci, Li, and McCarthy (2011). It is rather surprising, though, that when the market risk becomes extremely high flight-to-quality is eliminated. The above findings suggest that optimal portfolio composition should be revised dynamically and regularly whereas changes of the interplay among financial markets occur, due to market conditions.

Furthermore, small but significant cross-asset linkages in times of economic turmoil are found in Hartmann, Straetmans and de Vries (2004) while the strongest extreme linkages are between different national stock markets. In addition, it is found that contemporaneous crashes between bond markets are much less likely than between equity markets. Also, equity-bond contagion is nearly as common as flight-to-quality from equities to bonds.

Another study finding flight-to-quality events is the one of Choudhry and Jayasekera (2014). Specifically, their results from the GARCH-GJR suggest that returns, as well as volatility, rise substantially from pre-crisis to crisis periods. Specifically, in the pre-crisis period spillover from the major economies to the smaller EU economies is found but the opposite is not evident. This means that the return and volatility transmission mechanisms are asymmetric between the UK, US, and Germany that are considered as major economies and smaller EU economies. In addition, in the crisis period, spillover effects from the major economies increase. However, contrary to the pre-crisis period results, spillover from smaller EU economies to major economies, notably Germany and the UK, is explicitly evident. The differences in the crisis periods, as far as spillover effects are concerned, are possibly due to the increased information asymmetries between firms and investors that result from uncertainty in funding and liquidity as well as macroeconomic uncertainty. This uncertainty causes investors to liquidate risky assets and turn to safer ones. Finally, this study finds evidence of contagion between the major economies and the larger of the smaller EU economies, namely Italy, Spain, and Portugal, through the shift from pre-crisis to crisis periods. Also, flight-to-quality is apparent from Greece and Ireland to major economies. The above findings insinuate that the banking industry of Portugal, Spain and Italy may be more closely linked to major economies due to trade and investment connections or increasing financial integration with these economies.

Moreover, flight-to-quality events are found in Billio and Caporin (2010). In more detail, their results indicate relevant concurrent relationships between Asian and South American markets. Also, among the American markets, a relevant effect from the U.S. to Brazil and Mexico is found. Moreover, Hong Kong plays a significant role, affecting not only most markets among the Asian markets but the U.S. market as well. When the local currencies are considered the impact of the U.S. returns on most countries is apparent. Conversely, when the exchange rates effects are taken into account, Japan appears as a relevant market driver. Yet, Hong Kong seems to be a relevant source and receiver of information. In addition, results suggest that there is a relevant correlation movement during and after the Asian crisis, around 1997.

However, the correlation movements evidenced in this period were not common to stock and exchange rate markets. The analysis also found additional periods of economic turmoil and made it possible to distinguish whether these periods were connected with relevant movements in the equity markets, in the exchange rate markets, or in both, just like in the Asian crisis. Two other turmoil periods were also found, namely the period June 2001 to mid-August 2001 associated with movements in the exchange rate market and the period in June 2003 to September 2003 also linked to movements in the exchange rate markets that possibly resulted from the Iraq war. As far as the flight-to-quality events are concerned, only a short period from September to December 2004 is noted. This period is once more associated only with the exchange rates market. This flight-to-quality event could be linked to long-term effects of the Iraq war and the Argentina default, the start of oil prices increases, the beginning of China's and India's economic booms, or simultaneous stagnation of South American economies.

An interesting finding about increased risk premia during crisis periods that are accompanied with flight-to-quality phenomena is stated in Brière, Chapelle and Szafarz (2012). In more detail, their study suggests, based on the results of the GLR test for globalization, that globalization has an effect on market interdependence because the differences in correlation between the two sub-periods of the sample are significant for all assets considered. Subsequently, the GLR is used to test for contagion. The test compares correlation along all markets separating crisis periods from other periods assuming that all crises have at least some common attributes as far as the correlation matrices are concerned. That is, the correlation matrix of the crisis regime is compared to the correlation matrix of the non-crisis regime. Results indicate that contagion is evident neither globally nor in the world markets' bond segments. It is noted that the authors' definition of "crisis" includes currencies, corporate bankruptcies or loss of confidence such as in the case of Enron and WorldCom, events arising from a bond or stock crash, sovereign debt, and other types of crises, such as terrorist attacks. Also, the start and end dates of the crisis are obtained from previous papers.

What is more, globalization coincides with the closer synchronization of economic cycles, thus in order to make sure that the globalization effect is neutralized Brière, Chapelle and Szafarz (2012) adjust the time periods so that crises are not systematically apparent at the samples' beginning or end. After this adjustment, it is ensured that contagion is not evident. Furthermore, as for the identification of the link between stocks and bonds, the GLR was implemented by taking into account correlation between assets of different classes. These pairs of assets could be associated with flight-to-quality effects and exclude the effects associated with contagion since these two phenomena are mutually exclusive. Flight-to-quality is generally present when investors turn to safer assets. The results of the study suggest that flight-to-quality is evident during crisis periods, increases risk premia and reduces correlations between assets. In particular, significant differences for correlations are found between government bonds and investment grade bonds and between government bonds and equities.

It is worth mentioning that the analysis of Brière, Chapelle and Szafarz (2012) is of great interest because it suggests that diversification strategies can help investors prepare for crises. The flight-to-quality effect is present during crises periods, when correlations between stocks and bond fall remarkably, offsetting the increased volatility of stocks. Consequently, if investors are able to detect flight-to-quality they can hedge their risk during crises. Finally, flight-to-quality according to the rationality assumption is considered as a market anomaly, so it is not expected to last for long when identified. Yet, if the behavioral finance literature is taken into consideration, some market anomalies can turn out to be self-fulfilling and persevere for much longer. In other words, flight-to-quality will last for a long time if it is a result of irrational fears and not of smart hedging strategies in crises periods.

The previous analysis of Brière, Chapelle and Szafarz (2012) found increased risk premia during crises periods. As mentioned before in our literature review, when investors demand a higher risk premium in times of turmoil this suggests a flight-to-quality phenomenon. However such flights may be flights-to-liquidity when liquidity rather than risk premia broaden. Increased liquidity premia are evident in Vayanos (2004). In his study it is assumed that investors are fund managers who face withdrawals when fund performance deteriorates. This leads to a preference for liquidity which is not only time-varying but also increases with volatility. It is evident that, in volatile times when assets and volatility become more negatively correlated, investors become more risk averse and correlations of pair wise assets, betas of illiquid assets and assets' liquidity premia rise. In particular, investors' risk aversion rises during volatile times, so that the risk premium investors demand per unit of volatility rises as well. This is called a flight-to-quality phenomenon. In this study, it is also shown that assets become more negatively correlated with volatility and more correlated with one another. Also, illiquid assets' risk rises, because their market betas rise.

Finally, the findings of Beber, Brandt and Kavajecz (2009) are important for academics for the better understanding of cross-market dynamics and the risk premia sources, for practitioners for better firm-level decisions and trading strategies and for policy makers who wish to know ways to manage problems caused by flights. Specifically, their results suggest that investors are interested in both liquidity and credit quality depending on times and reasons. Most sovereign yield spreads are explained by credit quality differences with liquidity being also important especially for countries with low credit risk and during times of market uncertainty. Yet, large flows into and out of bond markets are mostly linked to liquidity. Results from a conditional yield spread decomposition implemented in the analysis show that liquidity has an increased importance during periods of market uncertainty. This can be explained by the fact that short-term liquidity and transaction costs are considered more important than credit risk in long horizons.

Dynamic Conditional Correlation

We close our literature review with the papers focusing on the Dynamic Conditional Correlation (DCC) of Engle (2002) methodology which we are going to implement in the present thesis. The DCC model has been criticized in the literature, however even its critics admit that it is the most popular estimator used in examining dynamic correlations. Indeed, in the very literature we examined in the previous sections of our literature review the DCC model is used by various papers such as the papers of Baur and Lucey (2006, 2009), Dajcman (2012), Cho, Choi, T.Kim and W. Kim (2016), Lombardi and Ravazzolo (2013), Sadorsky (2014), Bicchetti and Maystre (2013), Creti, Joëts and Mignon (2013), Chong and Miffre (2009) and of Choi and Hammoudeh (2010). Also, modified versions of the DCC model are used in Billio and Caporin (2010) and Ohashi and Okimoto (2016).

In Engle's (2002) paper it is cited that a reliable estimate for correlations between financial variables has been investigated in a wide range of academic studies. Methods such as rolling correlations which is rather simple and multivariate GARCH methods which are more complicated have been investigated in the literature. A remarkable problem of many multivariate GARCH models is that they involve a large number of parameters to be estimated so that optimization is not easy. In his paper Engle presents the dynamic conditional correlation (DCC) estimators whose main computational advantage over multivariate GARCH models is that the number of parameters that must be estimated during the correlation process is independent of number of series to be correlated so, very large correlation matrices can be estimated easily. A comparison of DCC with simple multivariate GARCH and various other estimators reveals that the DCC is often the most accurate. This holds after considering the mean absolute error criterion, diagnostic tests or tests based on value at risk calculations. Moreover, DCC models are not only competitive with the multivariate GARCH specifications but are also superior to moving average methods.

However, Bauwens, Laurent and Rombouts (2006) state that a drawback of the DCC models is that in defining the conditional correlations they involve scalars so that all the conditional correlations obey the same dynamics.

Finally, according to Caporin and McAleer (2013) there is a growing interest in the Dynamic Conditional Correlation (DCC) of Engle (2002) because it is the most popular representation of dynamic conditional correlations. However, there are several issues that should be taken into consideration by potential DCC users. Such issues are the fact that DCC does not yield dynamic conditional correlations because it represents the dynamic conditional covariances of the standardized innovations; DCC is stated rather than derived because the deriving of conditional correlations applies to a conditional matrix rather than the full conditional covariance; DCC has no moments which is due to the fact that the properties stated by Engle (2002) are not derived ones; DCC does not have testable regularity conditions; DCC yields inconsistent two step estimators because the conditional matrix is not the expectation of the standardized residuals cross-products; DCC has no asymptotic properties; DCC is not dynamic empirically as the effect of news is typically extremely small; DCC cannot be distinguished empirically from diagonal BEKK in small systems; and finally that DCC may be a useful filter or a diagnostic check, but it is not a model.

3. Data

In the present thesis we consider monthly prices of the S&P500 index as a proxy for equity prices obtained from Datastream. As far as the factors that affect commodities are concerned, we consider monthly prices of the 1-month T-Bill return from Ibbotson and Associates obtained from the official website of E.F. Fama and K.R. French, monthly prices of the industrial production of OECD countries plus six major, and specifically, we use the monthly prices of the OECD industrial production index obtained from the OECD database as well as the monthly prices for industrial production indices for Russia, Brazil, Indonesia, South Africa, China and India also obtained from the OECD database. Moreover, we use monthly prices of the Japanese Yen to one U.S. Dollar exchange rate, as a proxy for the dollar exchange rate, obtained from the FRED (Federal Reserve Bank of St. Louis) database and monthly prices of the US CPI obtained from Datastream. All prices are quoted in US dollars and the data span the period April 1994 to September 2016.

As far as the commodities used in the present thesis are concerned, we use monthly spot prices for 19 commodities from four different sectors. In particular, we use monthly spot prices for two energy commodities, namely natural gas and crude oil, monthly spot prices for four precious metals, namely gold, silver, platinum and palladium, monthly spot prices for seven industrial metals, namely aluminium alloy, aluminium 99,7%, copper, zinc, tin, lead and nickel and monthly spot prices for six agricultural commodities, namely corn, wheat, soyabeans, cocoa, cotton and pulp. In is worth noting that corn, wheat and soyabeans belong to the “grains” subcategory of agricultural commodities while cocoa and cotton belong to the “softs” subcategory of agricultural commodities. All 19 monthly spot prices are obtained from Datastream and are quoted in US dollars. The data span the period April 1994 to September 2016.

4. Methodology

In the present thesis we implement a four-step methodology in order to test for flight-to-quality from stocks to commodities. The empirical analysis is based mainly on Baur and Lucey (2006) and Baur and Lucey (2009). This methodology is preferred, because it is the only study where we can investigate for the presence of flights through explicit testable conditions. Other studies use these conditions to test for flight to quality. Notably, Chan, Treepongkaruna, Brooks and Gray (2011) use a Markov regime-switching model to examine the relationships between the returns of stocks, bonds, oil, gold and real estate assets and they define flights and contagion based on the conditions of Baur and Lucey (2009). Similarly, Choudhry and Jayasekera, (2014) analyze the existence of flight to quality or flight from quality from the banking sector of smaller to major EU economies and contagion between them, also based on the conditions of Baur and Lucey (2009).

The study of Chan, Treepongkaruna, Brooks and Gray (2011) along with studies that simply test for co-movements between stocks and commodities (e.g. Byrne, Fazio and Fiess, 2013 and Creti, Joëts and Mignon, 2013) use raw commodity returns and do not take into consideration that commodities are not common assets, such as stocks and bonds, but they are most often used as inputs in the production of other goods or services. Therefore, any analysis with respect to commodity returns should take into account that there is a specific supply and demand for these products.

To deal with this problem in the first step of our methodology we filter demand parametrically using a simple OLS regression of the raw commodity returns, on factors that have been identified in the existing literature. The error term of this regression indicates the fraction of the commodity returns that is not explained by demand and supply for industrial purposes. Hence, this non systematic part of the commodity returns reflects investors' expectations on future commodity prices and consequently is more suitable to be used in our analysis than raw returns.

The factors we found to be paid most attention by the literature are real interest rates (Frankel, 2008; Svensson, 2008; Vansteenkiste, 2009; Byrne, Fazio and Fiess, 2013; Ma, Vivian and Wohar, 2015; Ohashi and Okimoto, 2016), global demand (Vansteenkiste, 2009; Lombardi, Osbat and Schnatz, 2012; Byrne, Fazio and Fiess, 2013; Ohashi and Okimoto, 2016), aggregate supply (Vansteenkiste, 2009; Byrne, Fazio and Fiess, 2013), the dollar exchange rate (Sjaastad, 2008;

Vansteenkiste, 2009; Sari, Hammoudeh and Soytas, 2010; Zhang and Wei, 2010; Lombardi, Osbat and Schnatz, 2012; Ma, Vivian and Wohar, 2015; Ohashi and Okimoto, 2016), inflation (Blose, 2010; Browne and Cronin, 2010; Worthington and Pahlavani, 2007; Zhang and Wei, 2010; Ohashi and Okimoto, 2016) and the impact of oil prices (Baffes, 2007; Krugman, 2008; Zhang and Wei, 2010; Sari, Hammoudeh and Soytas, 2010; Lombardi, Osbat and Schnatz, 2012; Byrne, Fazio and Fiess, 2013).

Specifically, in order to implement the first step of our methodology we run the following regression using the Ordinary Least Squares method:

$$r_{ct} = a_i + b_1 F_{1t} + b_2 F_{2t} + b_3 F_{3t} + b_4 F_{4t} + b_5 F_{5t} + b_6 F_{6t} + b_7 F_{7t} + b_8 F_{8t} + b_9 F_{9t} + b_{10} F_{10t} + b_{11} F_{11t} + u_{ct} \quad (1)$$

where,

- r_{cit} denotes the commodity returns of each commodity considered in this thesis
- a denotes the constant
- F_{1t} denotes real interest rates proxied by the 1-month T-Bill return from Ibbotson and Associates, obtained from the official website of E.F. Fama and K.R. French
- F_{jt} (j=2, …, 8) denotes global demand proxied by the industrial production of OECD countries plus six major. Specifically, we use the OECD industrial production index obtained from the OECD database as well as the industrial production indices for Russia, Brazil, Indonesia, South Africa, China and India also obtained from the OECD database
- F_{9t} denotes the first differences of the dollar exchange rate proxied by the Japanese Yen to one U.S. Dollar exchange rate obtained from the FRED (Federal Reserve Bank of St. Louis) database
- F_{10t} denotes the inflation rate proxied by the first differences of the US CPI rate of return obtained from Datastream
- F_{11t} denotes the oil returns proxied by the WTI crude oil returns obtained from Datastream
- u_{ct} are the residuals of each commodity considered

We must note that as far as crude oil is concerned we omit the F_{11t} variable from equation (1).

In order to examine correlations between stocks and the commodity residuals, we take into consideration that these correlations evolve over time. The fact that correlations are time-varying is obvious if we simply split our sample in two equal parts, calculate their simple correlations and then compare them. Since correlations change in time, we must take this time variability into account in the second step of our methodology. Therefore, we firstly use rolling window correlations and then we implement the Dynamic Conditional Correlation of Engle (2002).

Specifically, we calculate rolling window correlations between equity returns proxied by the S&P500 index and the commodity residuals obtained from the previous step, using a window of 24 observations. The formula for calculating rolling window correlations is the following:

$$\rho_n = \frac{\sum_{k=t-n+1}^{t}(r_{sk}-\bar{r}_{sk})(u_{ck}-\bar{u}_{ck})}{\sqrt{\sum_{k=t-n+1}^{t}(r_{sk}-\bar{r}_{sk})^2 \cdot \sum_{k=t-n+1}^{t}(u_{ck}-\bar{u}_{ck})^2}} \qquad (2)$$

where,

- ρ_n is the rolling window correlation between equity and commodity returns
- $\bar{r}_{sk} = \frac{1}{n}\sum_{k=t-n+1}^{t} r_{sk}$ (3)
- $\bar{u}_{ck} = \frac{1}{n}\sum_{k=t-n+1}^{t} u_{ck}$ (4)
- r_s stands for the equity returns proxied by the S&P500 index
- u_c stands for the residuals of each commodity obtained from equation (1)
- *n* stands for the length of the rolling window

Rolling window correlations method provides information on the evolution of correlations between equity and commodity returns. However, when estimating rolling window correlations between assets' returns we obtain short term correlation estimations. The fact that the rolling window technique assigns an equal weight to all observations in the estimation window and zero weight to older observations raises an issue because when we examine assets' returns we are interested in more recent window observations or in the observations of the last window. Thus, we would rather prefer a technique that assigns less weight in old observations and more weight to the recent ones.

Another issue of the rolling window technique is the determination of the proper window length. If we choose a rather narrow window we face the risk of overlooking observations that are relevant to our analysis because we give zero weight to these observations. On the other hand, if we choose a rather wide window, we risk giving weight to older observations that might not be important to our analysis.

The aforementioned issues can be solved by using the Dynamic Conditional Correlation (DCC) of Engle (2002) instead of rolling window correlations. DCC assigns less weight to older observations and more weight to the recent ones. Also there is no use of a window which eliminates the second problem of rolling correlations technique. What is more, DCC takes into account changes in volatility.

Subsequently, we implement and the Dynamic Conditional Correlation of Engle (2002) in order to estimate the stock-commodity conditional correlations. In this process we are going to use the commodity residuals, u_{it}, from the OLS regression (1). The DCC model is based on a two-step approach. In the first step, we estimate time varying variances using a GARCH model. In the second step, we estimate a time varying correlation matrix using the standardized innovations from the first step estimation.

Specifically, consider a $n \times 1$ vector of normally-distributed with mean zero and covariance matrix H_t returns series r_t of n assets assumed to have the following structure:

$$r_t \sim N(0, H_t) \tag{5}$$

$$H_t = D_t R_t D_t \tag{6}$$

where,

- H_t is the conditional covariance matrix
- R_t is the time varying correlation matrix
- D_t is a diagonal matrix of time-varying standard deviations given by $D_t = diag\sqrt{E_{t-1}(r_{i,t}^2)} = diag\sqrt{h_{i,t}}$ (7), where $h_{i,t}$ can be thought of as univariate GARCH models, so the standardized disturbance can be expressed as $\varepsilon_{i,t} = \frac{r_{i,t}}{\sqrt{h_{i,t}}} = D_t^{-1} r_{i,t}$ (8), where $\varepsilon_{i,t} \sim N(0, R_t)$ (9)

Consider the following conditional correlations:

$\rho_{ij,t} = \frac{E_{t-1}[r_{i,t}r_{j,t}]}{\sqrt{E_{t-1}[r_{i,t}^2 r_{j,t}^2]}}$ (10). Re-writing these conditional correlations by substituting equation (8) to equation (10) yields $\rho_{ij,t} = E_{t-1}\varepsilon_{i,t}\varepsilon_{j,t}$ (11). In other words, we expressed equation (10) in terms of standardized innovations from GARCH estimates.

What is more, it holds that $Cov_{t-1}(\varepsilon_{i,t}\varepsilon_{j,t}) = E_{t-1}\varepsilon_{i,t}\varepsilon_{j,t} - E_{t-1}\varepsilon_{i,t} \cdot E_{t-1}\varepsilon_{j,t}$ (12). Since (9) holds this means that $Cov_{t-1}(\varepsilon_{i,t}\varepsilon_{j,t}) = E_{t-1}\varepsilon_{i,t}\varepsilon_{j,t}$ (13). Equation (13) suggests the equivalence of conditional correlation of returns and conditional covariance between the standardized disturbances. Therefore, the matrix R represents the time-varying conditional correlation matrix of returns as well as the conditional covariance matrix of the standardized residuals (Engle, 2002).

The DCC model of Engle (2002) suggests the following dynamics of the correlation matrix:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{14}$$

$$Q_t = (1 - a - \beta)\bar{Q} + a(\varepsilon_{i,t-1}\varepsilon_{j,t-1}) + \beta Q_{t-1} \tag{15}$$

where,

- $\bar{Q}$ is the unconditional correlation matrix of standardized residuals
- Q_t^* is a diagonal matrix composed of square root of the diagonal elements of Q_t, namely $q_{ij,t}$

The correlation estimator is given by the typical element of R_t in the following form:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{16}$$

This specification ensures the mean reversion as long as $\alpha + \beta < 1$ (17). The resulting estimator is called DCC by log-likelihood with mean reverting model. The log-likelihood of the DCC model outlined above is given by:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + 2log(|D_t|) + log(|R_t|) + \varepsilon' R_T^{-1}\varepsilon) \tag{18}$$

The log-likelihood function has two components: the volatility part, which contains terms in D_t ; and the correlation part, which contains terms in R_t. In the first stage of the estimation, n univariate GARCH(1,1) estimates are obtained, which produces consistent estimates of time-varying variances (D_t). In the second stage, the correlation part of the log-likelihood function is maximized, conditional on the estimated D_t from the first stage.

Having estimated rolling window correlations and the dynamic conditional correlations among equity returns and commodity residuals from equation (1), we base on the formal definition of flight-to-quality stated in the paper of Baur and Lucey (2006, 2009) in order to identify flight-to-quality events. According to this definition flight-to-quality from equities to commodities is defined as a decrease in the correlation coefficient and concurrent falling equity markets.

Therefore, in order to identify flight-to-quality using rolling window correlation estimates, we multiply two dummy variables:

$$Y_{3,t} = Y_{1,t} Y_{2,t} \qquad (19)$$

where,

- $Y_{1,t}$ is a dummy variable which takes the value 1 when the rolling window correlations between the residuals of commodity returns from equation (1) and stock returns turn from positive to negative from one month to the following one, and 0 otherwise. It has to be noted that our time series of commodity residuals is monthly, so since flight-to-quality phenomena are short-run ones it means that 30 days are sufficient to capture the event
- $Y_{2,t}$ is a dummy variable which takes the value 1 when stock returns are negative and 0 otherwise

Similarly, in order to identify flight-to-quality using dynamic conditional correlation estimates, we multiply two dummy variables:

$$Y^*_{3,t} = Y^*_{1,t} Y^*_{2,t} \qquad (20)$$

where,

- $Y^*_{1,t}$ is a dummy variable which takes the value 1 when the dynamic conditional correlations between the residuals of commodity returns from equation (1) and stock returns turn from positive to negative from one month to the following one, and 0 otherwise. It has to be noted that our time series of commodity residuals is monthly, so since flight-to-quality phenomena are short-run ones it means that 30 days are sufficient to capture the event

- $Y_{2,t}^{*}$ is a dummy variable which takes the value 1 when stock returns are negative and 0 otherwise

The product of $Y_{3,t}$ and rolling window correlations is presented in graphs for each commodity taken into consideration in the present thesis. Thus, we are able to see the date of the flight-to-quality event as well as the value of the rolling window correlation in that particular date. Similarly, the product of $Y_{3,t}^{*}$ and dynamic conditional correlations is presented in graphs for each commodity taken into consideration in the present thesis. Therefore, we can see the date of the flight-to-quality event as well as the value of the dynamic conditional correlation in that particular date.

The aforementioned methodology presents graphically flight-to-quality events but suffers from one disadvantage. We do not obtain statistically significant results for the dates of flight-to-quality events. However, the main advantage of this process is that flight-to-quality events are not determined a posteriori but dates of flight-to-quality events are identified instead.

In order to perform a more formal flight-to-quality test we follow the methodology of Baur and Lucey (2009). Baur and Lucey (2009) define flight-to-quality from stocks to bonds as a decrease in the correlation coefficient during falling stock markets compared to a benchmark period resulting in a negative correlation level. If the pre-crisis stock–bond correlations are positive and become negative in the crisis period, there is flight-to-quality. In our thesis we use the same definition but instead of bonds we examine flight-to-quality from stocks to commodities. The following regression tests for flight-to-quality:

$$u_{c,t} = a + \beta r_{s,t} + \gamma_1 r_{s,t} Z_{1,t} + \gamma_2 r_{s,t} Z_{2,t} + \gamma_3 r_{s,t} Z_{3,t} + \gamma_4 r_{s,t} Z_{4,t} + \gamma_5 r_{s,t} Z_{5,t} + \gamma_6 r_{s,t} Z_{6,t} + \gamma_7 r_{s,t} Z_{7,t} + \gamma_8 r_{s,t} Z_{8,t} + \gamma_9 r_{s,t} Z_{9,t} + \gamma_{10} r_{s,t} Z_{10,t} + \gamma_1^{*} r_{s,t} Z_{1,t}^{*} + \gamma_2^{*} r_{s,t} Z_{2,t}^{*} + \gamma_3^{*} r_{s,t} Z_{3,t}^{*} + \gamma_4^{*} r_{s,t} Z_{4,t}^{*} + \gamma_5^{*} r_{s,t} Z_{5,t}^{*} + \gamma_6^{*} r_{s,t} Z_{6,t}^{*} + \gamma_7^{*} r_{s,t} Z_{7,t}^{*} + \gamma_8^{*} r_{s,t} Z_{8,t}^{*} + \gamma_9^{*} r_{s,t} Z_{9,t}^{*} + \gamma_{10}^{*} r_{s,t} Z_{10,t}^{*} + v_{c,t} \quad (21)$$

where,

- $u_{c,t}$ are the residuals of each commodity obtained from equation (1)
- $r_{s,t}$ are the equity returns proxied by the S&P500 index
- $Z_{1,t}$ is a dummy variable which is 1 if t is in the currency crisis period of Asia 1997 and 0 otherwise, $Z_{2,t}$ is a dummy variable which is 1 if t is in the sovereign debt crisis of Russia 1998 and 0 otherwise, $Z_{3,t}$ is a dummy variable which is 1 if t is in the crisis related to the 1998 collapse of the Long Term Capital Management (LCTM) hedge fund and 0 otherwise, $Z_{4,t}$ is a dummy variable which is 1 if t is in the currency crisis of Brazil 1999 and 0 otherwise, $Z_{5,t}$ is a dummy variable which is 1 if t is in the 2000 E-crash and 0 otherwise, $Z_{6,t}$ is a dummy variable which is 1 if t is in the sovereign debt crisis of Argentina 2001 and 0 otherwise, $Z_{7,t}$ is a dummy variable which is 1 if t is in the September 11th crisis and 0 otherwise, $Z_{8,t}$ is a dummy variable which is 1 if t is in the crisis related to the bankruptcy of WorldCom 2002 and 0 otherwise, $Z_{9,t}$ is a dummy variable which is 1 if t is in the Subprime crisis of 2007 and 0 otherwise, and $Z_{10,t}$ is a dummy variable which is 1 if t is in the Subprime crisis of 2008 – 2009 and 0 otherwise
- $Z^*_{q,t}$ $(q = 1,2,\dots,10)$ is a dummy variable comprised of a sub-sample period. The dummy variable takes the value 1 for the month preceding the start of each of the aforementioned ten crises, and 0 otherwise
- $v_{c,t}$ is the error term

We must note that, knowing that correlations are not stable from the previous steps dictates the determination of a time-varying benchmark. Therefore, the additional dummy Z^* is necessary for a time-varying benchmark to be employed.

Furthermore, the level of stock–commodity correlation in a crisis period is given by the sum of the parameters β and γ_i $(i = 1,2,\dots,10)$. If the sum of β, γ_i and γ^*_q $(q = 1,2,\dots,10)$ is significantly negative, there is flight-to-quality from stocks to commodities if the crisis period is characterized by falling stock markets.

Our final step comprises of a pooled panel regression with time-varying benchmarks. Thus, we treat commodities as a homogeneous asset class in order to identify a common flight-to-quality event for all commodities considered in this thesis. The panel model is the following:

$$u_{c,m,t} = a_m + \beta r_{s,m,t} + \gamma_1 r_{s,m,t} Z_{1,m,t} + \gamma_2 r_{s,m,t} Z_{2,m,t} + \gamma_3 r_{s,m,t} Z_{3,m,t} + \gamma_4 r_{s,m,t} Z_{4,m,t} + \gamma_5 r_{s,m,t} Z_{5,m,t} + \gamma_6 r_{s,m,t} Z_{6,m,t} + \gamma_7 r_{s,m,t} Z_{7,m,t} + \gamma_8 r_{s,m,t} Z_{8,m,t} + \gamma_9 r_{s,m,t} Z_{9,m,t} + \gamma_{10} r_{s,m,t} Z_{10,m,t} + \gamma_1^* r_{s,m,t} Z_{1,m,t}^* + \gamma_2^* r_{s,m,t} Z_{2,m,t}^* + \gamma_3^* r_{s,m,t} Z_{3,m,t}^* + \gamma_4^* r_{s,m,t} Z_{4,m,t}^* + \gamma_5^* r_{s,m,t} Z_{5,m,t}^* + \gamma_6^* r_{s,m,t} Z_{6,m,t}^* + \gamma_7^* r_{s,m,t} Z_{7,m,t}^* + \gamma_8^* r_{s,m,t} Z_{8,m,t}^* + \gamma_9^* r_{s,m,t} Z_{9,m,t}^* + \gamma_{10}^* r_{s,m,t} Z_{10,m,t}^* + v_{c,m,t} \quad (22)$$

where,

- $u_{c,m,t}$ are the residuals of all the commodities obtained from equation (1)
- $r_{s,m,t}$ are the equity returns proxied by the S&P500 index
- $Z_{1,m,t}$ is a dummy variable which is 1 if *t* is in the currency crisis period of Asia 1997 and 0 otherwise, $Z_{2,m,t}$ is a dummy variable which is 1 if *t* is in the sovereign debt crisis of Russia 1998 and 0 otherwise, $Z_{3,m,t}$ is a dummy variable which is 1 if *t* is in the crisis related to the 1998 collapse of the Long Term Capital Management (LCTM) hedge fund and 0 otherwise, $Z_{4,m,t}$ is a dummy variable which is 1 if *t* is in the currency crisis of Brazil 1999 and 0 otherwise, $Z_{5,m,t}$ is a dummy variable which is 1 if *t* is in the 2000 E-crash and 0 otherwise, $Z_{6,m,t}$ is a dummy variable which is 1 if *t* is in the sovereign debt crisis of Argentina 2001 and 0 otherwise, $Z_{7,m,t}$ is a dummy variable which is 1 if *t* is in the September 11th crisis and 0 otherwise, $Z_{8,m,t}$ is a dummy variable which is 1 if *t* is in the crisis related to the bankruptcy of WorldCom 2002 and 0 otherwise, $Z_{9,m,t}$ is a dummy variable which is 1 if *t* is in the Subprime crisis of 2007 and 0 otherwise, and $Z_{10,m,t}$ is a dummy variable which is 1 if *t* is in the Subprime crisis of 2008 – 2009 and 0 otherwise
- $Z_{q,m,t}^*$ $(q = 1,2, \dots ,10)$ is a dummy variable comprised of a sub-sample period. The dummy variable takes the value 1 for the month preceding the start of each of the aforementioned ten crises, and 0 otherwise
- $v_{c,m,t}$ is the error term

5. Empirical Results

Before interpreting any results it should be helpful to highlight some of each commodity's different attributes. Specifically, as for the energy commodities considered in this thesis, namely natural gas and oil, according to the World Economic Outlook of the International Monetary Fund (2016) oil is used primarily to fuel transportation with the transport sector accounting for roughly two-thirds of oil use in the world. According to the same World Economic Outlook, natural gas is used mainly as an input into the power sector, consisting of electricity and heat generation, which accounts for more than one-third of total primary energy consumption. Natural gas consumption has increased steadily since the 1970s, so now it accounts for nearly 25 percent of global primary energy consumption. Moreover, natural gas is the cleanest energy source so, considering its relative cleanliness and abundance, natural gas can play an important role as a bridge in the transition from coal to renewables. Finally, the industry, transport, and building construction sectors also consume electricity and heat that are generated by primary energy.

As far as the metals are concerned, according to the World Economic Outlook of the International Monetary Fund (2015), they come in a variety of forms, from base metals to precious metals. Base metals are those that corrode relatively easily. Within base metals, a distinction is made between ferrous and nonferrous metals. Ferrous metals tend to be heavy and rather abundant while nonferrous metals do not contain iron in significant amounts. Nonferrous metals are generally more expensive than ferrous metals and have several desirable properties. For example, alluminium has low weight, copper has higher conductivity, zinc and nickel have nonmagnetic properties, or resistance to corrosion. The term “base metals” is commonly used in contrast with “noble metals,” which unlike most base metals are resistant to corrosion or oxidation. Noble metals tend to be precious metals, often because of their perceived scarcity. Examples of precious metals are gold, platinum, silver and palladium. Chemically, precious metals are less reactive than most elements and have high luster and high electrical conductivity.

Regarding agricultural commodities and particularly food commodities, according to the World Economic Outlook of the International Monetary Fund (2016), food categories, which include cereals such as wheat and corn, beverages such as cocoa or oilseeds such as soyabeans, differ in a variety of ways in terms of nutritional value, perishability, and storability. Food access is primarily seen as an issue that has to do with poor countries; however developments in food markets are indicative of structural developments at the global level. The rapid growth in emerging markets, the demographic transition, and technological developments have and will continue to affect food markets. Moreover, trade-policy instruments, such as export and import tariffs, subsidies, and quotas, have serious distributional consequences for consumers. Markets that are specially distorted include those for soyabeans which are a key animal feed. Other influences are local agricultural and weather conditions because about 85 percent of food is produced in the country where it is consumed. Finally, land and technology availability are key drivers of food production.

The last two commodities considered, namely cotton and pulp are both agricultural commodities. Cotton is a basic crop that is a major input for the textile, agriculture, and food industries. 64 percent of cotton is used for apparel, 28 percent for home furnishings, and 8 percent for industrial products. Pulp is the main feedstock used in the manufacture of paper and paperboard.

Having analyzed in short each commodity's attributes we proceed with the interpreting of our findings. Observing Table 6 which demonstrates the Augmented Dickey Fuller test results for all the time series of equity prices, commodity prices and prices of the factors affecting commodities, we conclude that, either with constant or with constant and trend, the Augmented Dickey Fuller test results suggest that the prices time series are not stationary. Thus, we use the returns time series of the aforementioned variables instead. Returns are calculated as the logarithmic differences of prices. Table 7 confirms that time series of equity, commodity and factors returns are stationary.

According to Table 8 which describes the summary statistics of the equity and commodity returns, the standard deviation of the S&P500 index returns, which is used as a proxy for equity returns, is almost the smallest among all commodities considered. The same results for standard deviation hold for the residuals of commodity returns that are calculated with regression (1). The results are shown in Table 9.

However, the measures of risk mentioned in Tables 8 and 9 are not time-varying. If we split the whole sample in two equal samples, as in Tables 10 and 11, we observe that for all the returns of S&P500 and all the residuals of commodities considered the standard deviation varies. This is an indication that the variance is time-varying. Therefore, we use GARCH(1,1) models for each series of equity returns and commodity residuals returns in order to find out whether either the GARCH (written as beta(1) term in Tables 12 to 31) or ARCH terms (written as alpha(1) in Tables 12 to 31) of the GARCH model are statistically significant. Specifically, for the equity returns the GARCH(1,1) model is specified as follows:

$$r_{s,t} = c + e_{s,t} \tag{23}$$

$$E\left[e_{s,t}^2\right] = \sigma_{s,t}^2 = h_{s,t} \tag{24}$$

$$h_{s,t} = a_0 + a_1 e_{s,t-1}^2 + b_1 h_{s,t-1}, a_0, a_1 \geq 0, b_1 \geq 0 \tag{25}$$

where:

· $r_{s,t}$ are the equity returns proxied by the S&P500 index

And for the returns of each commodity residuals the GARCH(1,1) model is specified as follows:

$$u_{c,t} = c + e_{c,t} \tag{26}$$

$$E\left[e_{c,t}^2\right] = \sigma_{c,t}^2 = h_{c,t} \tag{27}$$

$$h_{c,t} = a_0 + a_1 e_{c,t-1}^2 + b_1 h_{c,t-1}, a_0, a_1 \geq 0 , b_1 \geq 0 \tag{28}$$

where:

· $u_{c,t}$ are the residuals of each commodity obtained from equation (1)

Observing Tables 12 to 31, we notice that, except for alluminium 99.7% and corn, all the returns of commodity residuals have either a statistically significant GARCH term or an ARCH term or both. In other words they have ARCH effects or heteroskedasticity. This means that risk is time-varying. However, for alluminium 99.7% and corn Tables 10 and 11 indicate time-varying risk as well, since standard deviation does not remain constant over time. Plotting the conditional volatilities, $h_{s,t}$ and $h_{c,t}$ for each commodity, we observe how variance changes over time and also compare the risk of the S&P500 index return with the risk of the returns of each commodity residuals. The plots are shown to Graphs 1 to 19 and are explained in further detail later when we refer to flight-to-quality results.

Equity-commodity correlations

After examining the summary statistics and particularly the standard deviations of the variables considered in this thesis, our main purpose is to examine correlations between equities and commodity residuals and then observe the test results for flight-to-quality. In order to examine correlations between stocks and the commodity residuals, we take into consideration that these correlations evolve over time. As we already mentioned in the methodology section, the fact that correlations are time-varying is obvious if we simply split our sample in two equal parts, calculate their simple correlations and then compare them. In particular, Table 32 shows the simple correlations between the S&P500 index returns and each of the commodity returns taken into consideration in the present thesis. Tables 33 and 34 exhibit the simple equity-commodity returns correlations. We observe that Tables 33 and 34 demonstrate different results compared to Table 32 and also among one another. These results suggest that correlations between equity and commodity returns are time-varying. The same holds for Tables 35, 36 and 37 that show the simple correlations between the S&P500 index returns and the returns of the residuals of every commodity considered in the present thesis for three different sample periods. We observe that Tables 36 and 37 demonstrate different results compared to Table 35 and also among one another, suggesting that correlations are time-varying.

Since correlations change in time, we must take this time variability into account in the second step of our methodology. Therefore, we firstly use rolling window correlations and then we implement the Dynamic Conditional Correlation of Engle (2002). Results of the rolling window correlations and the Dynamic Conditional correlations between the S&P500 index and each commodity residuals returns are plotted in Graphs 58 to 95.

According to Graph 58, it is obvious that the dynamic conditional correlations between the S&P500 index and the defactorized natural gas returns are mostly negative which might suggest that natural gas can work as a hedge for equities.

However a different result is presented in Graph 59, which suggests that rolling window correlations vary over time around zero. In is worth noting that, the different results might be due to the fact that the DCC estimator is more efficient with high frequency data that exhibit strong conditional heteroscedasticity effects, rather than the monthly data. Monthly data include less noise than daily ones but in our analysis, since the defactorization of commodities included macroeconomic variables available only in monthly frequencies, the entire analysis had to be implemented with monthly data for all the variables taken into consideration.

Dynamic conditional correlations between defactorized oil returns and the S&P500 index returns are presented in Graph 94. It is obvious that DCCs are mostly positive which is in line with the study of Creti, Joëts and Mignon (2013) which suggests that oil is a commodity mostly related to the stock markets. Rolling window correlations in Graph 95 suggest the same mostly positive relationship. Therefore, the financialization view of the literature seems to hold for oil. Besides, according to Creti, Joëts and Mignon (2013) the Commodity Futures Trading Commission (CFTC) considers oil the most financialized commodity.

Dynamic conditional correlations and rolling window correlations between precious metals and the S&P500 index are presented in Graphs 60 to 67 while DCCs and rolling window correlations between industrial or non-ferrous metals and the S&P500 are presented in Graphs 70 to 83. It is noted that, in our thesis we have taken into consideration two different types of alluminium namely, alluminium alloy and alluminium 99.7%. An aluminum alloy is a chemical composition where other elements are added to pure aluminum in order to enhance its properties, primarily to increase its strength. These other elements include iron, silicon, copper, magnesium, manganese and zinc at levels that combined may make up as much as 15 percent of the alloy by weight.

In particular, as far as DCCs are concerned, gold is different than the rest of precious metals. Gold exhibits mostly negative DCCs in Graph 60 which is in line with the literature that supports that commodities serve as a hedge. Similar results hold for rolling window correlations in Graph 61. Contrary to gold, the other three precious metals, namely silver, platinum and palladium, in Graphs 62, 64 and 66, mostly exhibit positive DCCs. This means that they verify the financialization theory. Similarly, in Graphs 65 and 67 rolling window correlations suggest the same results for platinum and palladium. However, Graph 63 demonstrates a slightly different result. Correlations start as mostly negative and after 2004 they become mostly positive. The difference might be a result of the different econometric approach. Similar conclusions are evident in Creti, Joëts and Mignon (2013).

As far as non-ferrous metals are concerned, we observe that Graphs 70 to 83 exhibit positive dynamic conditional correlations between the S&P500 index and all non-ferrous metals considered, namely alluminium alloy, alluminium 99.7%, copper, zinc, tin, lead and nickel. Also, the rolling window correlations also exhibit mostly positive correlations but also demonstrate negative ones in a few periods. As a result, we can conclude that the financialization theory holds for all non-ferrous metals.

Dynamic conditional correlations and rolling window correlations between the S&P500 index returns and defactorized food commodity returns are presented in Graphs 84 to 91. In particular, corn exhibits only positive DCCs suggesting the financialization theory. The same holds for soyabeans' DCCs except for a short period in 2003 that exhibits negative DCCs with the S&P500. Similarly, cocoa has mostly positive DCCs expect for short periods in 1999 and 2003. Therefore, we can conclude that for corn, soyabeans and cocoa the financialization theory applies. However, the DCCs between the S&P500 and wheat are time-varying and this might be explained by wheat's own market fundamentals. It is noticeable that the rolling window correlations of all food commodities are time-varying but most periods are periods of positive rolling window correlations.

The dynamic conditional correlations between cotton and the S&P500 are presented in Graph 68 and are positive for the whole period examined suggesting the financialization theory. However, in Graph 69, where rolling window correlations are plotted, correlations are time-varying but after the crisis of 2008 they are positive supporting the literature's view of financialization. As far as pulp is concerned, Graphs 92 and 93 demonstrate the DCCs and rolling window correlations between the S&P500 and pulp suggesting that correlations are time-varying around zero and are either positive or negative.

Flight-to-quality

In the literature there are no studies on flight-to-quality between equities and commodities. The study of Chan, Treepongkaruna, Brooks and Gray (2011) who use a Markov regime-switching model to examine the relationships between the returns of stocks, bonds, oil, gold and real estate assets, define flights and contagion based on the conditions of Baur and Lucey (2009). However, they do not find flight-to-quality from the equity markets to any commodity market.

Having applied the methodology described in a previous section, which is based on the study of Baur and Lucey (2006), in equations (19) and (20) we present the product of $Y_{3,t}$ and rolling window correlations in Graphs 39 to 57. Thus, we are able to detect the date of the flight-to-quality event as well as the value of the rolling window correlation in that particular date. Similarly, the product of $Y_{3,t}^{*}$ and dynamic conditional correlations is presented in Graphs 20 to 38. Therefore, we can detect the date of the flight-to-quality event as well as the value of the dynamic conditional correlation in that particular date.

In particular, the aforementioned methodology using the DCC of Engle (2002) and equation (20) suggests that there is not flight-to-quality from the S&P500 index to gold, cotton, corn, alluminium alloy, alluminium 99.7%, copper, zinc, tin, lead and nickel. However, there is flight-to-quality from the S&P500 index to natural gas in December 2001 that coincides with the Argentina crisis and March 2004, to crude oil in January 2005, to silver in May 2000 and February 2001, to platinum in December 1999, April 2000 that coincides with the E-crash, February 2001, January 2015 and January 2016, to palladium in April 2000 that coincides with the E-crash, February 2001, December 2001 and January 2016, to wheat in June 1996, September 1998 that coincides with the Russian crisis, September 1999, September 2000, December 2000, May 2004, October 2007, July 2008, May 2016 and September 2016, to soyabeans in March 2001 that coincides with a US recession according to NBER and September 2002, to cocoa in September 2002 and to pulp in September 1994 that coincides with the bonds crisis, April 1997, December 1999, April 2000 that coincides with the E-crash, November 2000, June 2001 that coincides with a US recession according to NBER , May 2002, July 2002 which coincides with the WorldCom crisis, November 2003, July 2002, November 2003, July 2004, January 2005, May 2006, January 2008, July 2010, November 2012, August 2013 and January 2015.

Moreover, using equation (19) with the rolling window methodology, we find that flight-to-quality events occur for all commodities except crude oil. Specifically, there is flight-to-quality from the S&P500 index to natural gas in July 1997 that coincides with the Asian crisis, June 2002 that coincides with the WorldCom crisis, January 2005, February 2009 that coincides with the Subprime crisis of 2008-2009 and February 2010, to gold in July 1996, January 2009 that coincides with the subprime crisis of 2008-2009, November 2012, to silver in April 1996, March 1997, March 2011, August 2011 and November 2012, to platinum in October 2000, to palladium in September 1998 that coincides with the Russian crisis, to cotton in September 1994 that coincides with the bonds crisis, in December 2001 that coincides with the Argentina crisis, in December 2002, and in February 2003, to alluminium alloy in September 1998 that coincides with the Russian crisis, in May 2012 and November 2012, to alluminium 99.7% in December 1997 that coincides with the Asian crisis, May 2012 and October 2012, to copper in December 1997 that coincides with the Asian crisis, to zinc in September 2000 and October 2012, to tin in September 2000 and March 2001 that coincides with a US recession according to NBER , to lead in November 1994 that coincides with the bonds crisis and December 1997 that coincides with the Asian crisis, to nickel in November 2001 that coincides with the Argentina crisis, to corn in September 1998 that coincides with the Russian crisis and April 2013, to wheat in October 2000, to soyabeans in November 1994 that coincides with the bonds crisis and September 1998 that coincides with the Russian crisis, to cocoa in February 2009 that coincides with the Subprime crisis of 2008-2009, in March 2011 and in August 2013, and to pulp in August 2000, December 2001 that coincides with the Argentina crisis, September 2002, January 2009 that coincides with the Subprime crisis of 2008-2009, June 2013 and August 2013.

We observe that most of the found flight-to-quality dates coincide with known crises periods. Therefore, we conclude commodities are indeed an alternative to investors who become more risk averse in crises periods and seek for quality assets. However, the analysis we described before has certain disadvantages. First, rolling window correlations depend on the chosen window length. Moreover, our thesis uses monthly data due to the restrictions of the first step of the commodity defactorization. Most commodity factors are macroeconomic variables that are issued only in a monthly basis. The problem is that the DCC estimator is more efficient with high frequency data that exhibit strong conditional heteroscedasticity effects, rather than the monthly data. Thus, equation (20) identifies a lot less flight-to-quality events than equation (19) which is based on rolling window correlations. Until now, we implemented the procedures in order to detect for the presence of possible flight-to-quality events. We test for the presence of flight-to-quality in the next part of this analysis.

In order to account for the aforementioned problems we base on the methodology of Baur and Lucey (2009). Our methodology is presented in equation (21) and the regression's results for each individual commodity are presented in Tables 38 to 56. In Tables 38 to 56 the control variables are the product of $r_{s,t}$ and the dummy variable $Z_{i,t}$ $(i = 1,2, \dots ,10)$ of equation (21). So, for $i = 1$ the control variable for the product of $r_{s,t}$ and the dummy variable $Z_{i,t}$ is written as resxD_ASIA_1997, for $i = 2$ the control variable is written as resxD_RUSSIA_1998, for $i = 3$ the control variable is written as resxD_LTCM_1998, for $i = 4$ the control variable is written as resxD_BRAZIL_1999, for $i = 5$ the control variable is written as resxD_2000_E_CRASH, for $i = 6$ the control variable is written as resxD_ARGENTINA_2001, for $i = 7$ the control variable is written as resxD_SEPTEMBER_11_2001, for $i = 8$ the control variable is written as resxD_WORLD_COM_2002, for $i = 9$ the control variable is written as resxD_SUBPRIME_2007 and for $i = 10$ the control variable is written as resxD_SUBPRIME_2008_2009.

Also, the control variables of the product of $r_{s,t}$ and the dummy variables $Z^*_{q,t}$ $(q = 1,2, \dots ,10)$ are written as follows. For $q = 1$ the control variable for the product of $r_{s,t}$ and the dummy variable $Z^*_{q,t}$ is written as resxD_SUB_ASIA_1997, for $q = 2$ the control variable is written as resxD_SUB_RUSSIA_1998, for $q = 3$ the control variable is written as resxD_SUB_LTCM_1998, for $q = 4$ the control variable is written as resxD_SUB_BRAZIL_1999, for $q = 5$ the control variable is written as resxD_SUB_2000_E_CRASH, for $q = 6$ the control variable is written as resxD_SUB_ARGENTINA_2001, for $q = 7$ the control variable is written as resxD_SUB_SEPTEMBER_11_2001, for $q = 8$ the control variable is written as resxD_SUB_WORLD_COM_2002, for $q = 9$ the control variable is written as resxD_SUB_SUBPRIME_2007 and for $q = 10$ the control variable is written as resxD_SUB_SUBPRIME_2008_2009.

The level of stock–commodity correlation in a crisis period is given by the sum of the parameters β and γ_i $(i = 1,2, \dots ,10)$. If the sum of β, γ_i and γ^*_q $(q = 1,2, \dots ,10)$ is significantly negative, there is flight-to-quality from stocks to commodities if the crisis period is characterized by falling stock markets. Taking into consideration the aforementioned conditions applied to the results of Tables 38 to 56 we find flight-to-quality events from the S&P500 index to natural gas during the Russian crisis of 1998 and the Subprime crisis of 2008-2009, to gold during the LTCM crisis of 1998, the September 11^{th} 2001 crisis, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009, to silver during the LTCM crisis of 1998, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009, to platinum during the LTCM crisis of 1998 and the Subprime crisis of 2008-2009, to palladium during the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009, to cotton during the LTCM crisis of 1998, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009, to alluminium alloy during the Subprime crisis of 2007 and the Subprime crisis of 2008-2009, to alluminium 99.7% during the Subprime crisis of 2008-2009, to copper during the Russian crisis of 1998, the Subprime crisis of 2007 and the Subprime crisis of 2008-2009, to zinc during the LTCM crisis of 2008, the Subprime crisis of 2007 and the Subprime crisis of 2008-2009, to tin during the LTCM crisis of 2008, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009, to lead during the LTCM crisis of 1998, the September 11^{th} crisis of 2001 and the Subprime crisis of 2008-2009, to nickel during the LTCM crisis of 1998, to corn during the Russian crisis of 1998, the September 11^{th} crisis of 2001, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009, to wheat during the Russian crisis of 1998 and the Subprime crisis of 2007, to soyabeans during the Russian crisis of 1998, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009, to cocoa during the LTCM crisis of 1998, the September 11^{th} crisis of 2001, the WorldCom crisis of 2002, the Subprime crisis of 2007 and the Subprime crisis of 2008-2009, to pulp during the LTCM crisis of 1998 and the WorldCom crisis of 2002 and to crude oil during the LTCM crisis of 1998, the September 11^{th} crisis of 2001, the WorldCom crisis of 2002, the Subprime crisis of 2007 and the Subprime crisis of 2008-2009.

Why do flights-to-quality occur from S&P500 returns to commodities? We elaborate on this question on this section. Flights-to-quality occur by definition from a risky asset to a non risky asset. However, commodities are considered to be risky assets, sometimes riskier than the stocks. Consequently why do we find statistical significant flights from stock returns to commodities during crises? We find that approximately all commodity returns have higher volatility than the S&P500 returns, however, based on Graphs 1 to 19, during various crises periods, S&P500 returns exhibit higher volatility than the commodities. Thus, commodities can be considered less risky assets than the S&P 500 returns because their second moments present less variability in time when compared with the second moments of the stock markets returns. Specifically, we observe that throughout the sample the level of conditional volatilities of the commodities is higher than the conditional volatilities of the stock returns. However during various crises periods, the conditional volatilities of the commodities do not change significantly. On the other hand, the volatility of the stock returns increases substantially; in most cases the stock return volatility is much higher than the commodity return volatility. Therefore, it makes sense that commodities are chosen as alternative assets during flight-to-quality events because in times of crises investors become more risk averse and choose assets with less risk. Having defactorized commodity returns we can see why investors turn to commodities as an investment and not for industrial purposes.

In particular, we are going to compare commodity and equity volatilities, as shown in Graphs 1 to 19, on average and during the flight-to-quality periods detected by equation (21). So, as far as energy commodities are concerned, we observe that natural gas is on average more volatile than the S&P500, however during the Subprime crisis of 2008-2009 the risk of the S&P500 index is much higher. Crude oil is on average riskier than the S&P500 and remains so during the LTCM crisis of 1998, and the Subprime crisis of 2007. However, during the September 11th crisis of 2001, the WorldCom crisis of 2002, and the Subprime crisis of 2008-2009, crude oil's risk is smaller than the S&P500's risk.

As far as precious metals are concerned, gold is on average less risky than the S&P500 but during the LTCM crisis of 1998, the September 11th 2001 crisis, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009 the risk of the S&P500 is much higher. Also, during the Subprime crisis risk is almost four times bigger for the S&P500 compared to gold's risk. Silver is on average riskier than the S&P500 even during the LTCM crisis of 1998, however during the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009 the S&P500 becomes much riskier. In fact during the Subprime crisis of 2008-2009 S&P500 becomes four times riskier than silver. Platinum is also riskier on average than the S&P500 but during the LTCM crisis of 1998 and more remarkably during the Subprime crisis of 2008-2009 its risk becomes smaller. For palladium, which is on average more volatile than the S&P500, a month after the WorldCom crisis of 2002 and during the Subprime crisis of 2008-2009 its risk is higher than the S&P500's.

As far as industrial metals are concerned, alluminium alloy has on average almost the same risk as the S&P500. However, during the Subprime crisis of 2007 S&P500's risk is higher and also during the Subprime crisis of 2008-2009 S&P500's risk is almost four times higher than alluminium alloy's. Alluminium 99.7% is much more volatile than the S&P500 on average but also in this case we observe that S&P500's risk becomes four times bigger than alluminium's 99.7%. Copper is on average a riskier asset than the S&P500. Once more we observe that during crises copper's risk lowers but this is not the case for the Subprime crisis of 2007. However, during the Russian crisis of 1998 copper's risk is also smaller than S&P500's risk and once again the S&P500's risk during the Subprime crisis of 2008-2009 becomes more than four times bigger than copper's risk. Zinc's risk is also bigger than the S&P500's on average, however during the Subprime crisis of 2008-2009 zinc's risk is two times less than the S&P500's risk. Contrary to most commodities, zinc's risk remains bigger than the S&P500's during the LTCM crisis of 2008 and the Subprime crisis of 2007. Tin is also riskier on average than the S&P500 index, however S&P500's risk is bigger during the LTCM crisis of 2008, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009. Specifically, for the Subprime crisis of 2008-2009 S&P500's risk is twice as big as tin's risk. In the same spirit, lead is riskier on average than the S&P500 index, however S&P500's risk is bigger during the LTCM crisis of 1998, the September 11th crisis of 2001 and the Subprime crisis of 2008-2009. Also, nickel's risk is smaller than the S&P500's during the LTCM crisis of 1998 although on average its risk is bigger.

As far as agricultural commodities are concerned, corn returns throughout the sample have higher conditional volatility than the S&P500 returns but this is not the case during the crisis of September 11th, 2001, the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009 during which S&P500's risk is more than four times bigger than corn's. However, during the Russian crisis of 1998 corn's risk remains bigger than the S&P500's risk. Soyabeans also have bigger risk on average compared to the S&P500. Also, during the Russian crisis of 1998 soyabeans' risk remains bigger. However, during the WorldCom crisis of 2002 and the Subprime crisis of 2008-2009 soyabeans compared to the S&P500 are a safer asset to invest in. Cocoa is also riskier than the S&P500 on average and with the exception of the Subprime crisis of 2007 during all the other identified flight-to-quality events its risk is lower than the S&P500's. In particular, these flight-to-quality events during which cocoa is safer than the S&P500 are the LTCM crisis of 1998, the September 11th crisis of 2001, the WorldCom crisis of 2002, and the Subprime crisis of 2008-2009. Pulp, on the other hand, is a commodity with an average risk lower than the S&P500 index. During the LTCM crisis of 1998 and the WorldCom crisis of 2002 the difference of risk is even bigger with pulp remaining the safer investment compared to the S&P500. Cotton is on average riskier than the S&P500 and although during the WorldCom crisis of 2002 becomes almost equally risky as the S&P500, during the LTCM crisis of 1998 and the Subprime crisis of 2008-2009 it is riskier. It is worth noting that during the Subprime of 2008-2009 S&P500's risk is twice the size of cotton's risk. Finally, contrary to most commodities, wheat's risk is also on average bigger than S&P500's risk and remains so during the identified flight-to-quality events of the Russian crisis of 1998 and the Subprime crisis of 2007 which means that investors turned to wheat not because of its reduced risk but because they considered that investing in a food commodity that can be stored is a better choice than stock returns.

In general, we observe that the results of equation (21) combined with the conditional volatility analysis of the S&P500 and each commodity residuals suggests that almost all commodities are safe havens during crises events. This is also justified by the fact that during crises investors become more risk averse and hence they seek for safer and more quality investments. Commodity returns, having been defactorized, represent commodities as an asset class and not only as an input for industrial purposes. Investors in times of crises prefer to invest in commodities because they can be stored and not lose their value while stocks can be completely devaluated once a company bankrupts.

Considering commodities as a homogeneous asset class, we run a pooled OLS panel regression as presented in equation (22). The pooled OLS results are presented in Table 57. We must note that in Table 57 variable D1 refers to the product of $r_{s,m,t}$ and $Z_{1,m,t}$ which is a dummy variable which is 1 if *t* is in the currency crisis period of Asia 1997 and 0, D2 refers to the product of $r_{s,m,t}$ and $Z_{2,m,t}$ which is a dummy variable which is 1 if *t* is in the sovereign debt crisis of Russia 1998 and 0 otherwise, D3 refers to the product of $r_{s,m,t}$ and $Z_{3,m,t}$ which is a dummy variable which is 1 if *t* is in the crisis related to the 1998 collapse of the Long Term Capital Management (LCTM) hedge fund and 0 otherwise, D4 refers to the product of $r_{s,m,t}$ and $Z_{4,m,t}$ which is a dummy variable which is 1 if *t* is in the currency crisis of Brazil 1999 and 0 otherwise, D5 refers to the product of $r_{s,m,t}$ and $Z_{5,m,t}$ which is a dummy variable which is 1 if *t* is in the 2000 E-crash and 0 otherwise, D6 refers to the product of $r_{s,m,t}$ and $Z_{6,m,t}$ which is a dummy variable which is 1 if *t* is in the sovereign debt crisis of Argentina 2001 and 0 otherwise, D8 refers to the product of $r_{s,m,t}$ and $Z_{7,m,t}$ which is a dummy variable which is 1 if *t* is in the September 11th crisis and 0 otherwise, D9 refers to the product of $r_{s,m,t}$ and $Z_{8,m,t}$ which is a dummy variable which is 1 if *t* is in the crisis related to the bankruptcy of WorldCom 2002 and 0 otherwise, D10 refers to $Z_{9,m,t}$ which is a dummy variable which is 1 if *t* is in the Subprime crisis of 2007 and 0 otherwise, and D11 refers to the product of $r_{s,m,t}$ and $Z_{10,m,t}$ which is a dummy variable which is 1 if *t* is in the Subprime crisis of 2008 – 2009 and 0 otherwise. Also, D_SUB_i (i=1, 2, 3, 4, 5, 6, 8, 9, 10, 11) refer to the product of $r_{s,m,t}$ and $Z^{*}_{q,m,t}$ $(q = 1,2,\ldots,10)$ which is a dummy variable comprised of a sub-sample period. The dummy variable takes the value 1 for the month preceding the start of each of the aforementioned ten crises, and 0 otherwise.

Our findings, using the same conditions for interpreting results as in regression (21), suggest that there is flight-to-quality from the S&P500 to commodities as a homogeneous asset class during the Subprime crisis of 2008-2009. This makes sense if we consider the results for the conditional volatilities of every commodity. Even for commodities for which the Subprime crisis period of 2008-2009 was not found as a period that a flight-to-quality occurred, their conditional volatility was smaller than the S&P500's conditional volatility during the Subprime crisis of 2008-2009. Also, for all individual commodities except for nickel, wheat and pulp a flight-to-quality event was identified by equation (21) during the Subprime crisis of 2008-2009.

6. Conclusions

This thesis investigated for the presence of flight-to-quality from S&P500 returns to a wide range of commodities. In our analysis instead of using raw commodity returns we used the residuals of the regression of raw commodity returns on five factors. By using a simple regression of the raw commodity returns, on inflation, oil price returns, exchange rates, interest rates and industrial production we took into account that commodities, unlike ordinary assets such as stocks, have a specific demand and supply because they are often used in the industrial production.

Then we used two different approaches in order to identify flight-to-quality events without having specified crises periods a priori. Specifically, dynamic conditional correlations and rolling window correlations were estimated and changes of these correlations were analyzed across time. We found that most of the events identified as flights-to-quality from the S&P500 to commodities coincided with crises periods. However, the two different methods mostly identified different dates as flights-to-quality. In our analysis we used monthly data which in general include less noise than daily ones. The use of monthly data was chosen in the present thesis because the defactorization of commodities in our first step included macroeconomic variables only available in monthly frequencies. This meant that the entire analysis had to be implemented with monthly data for all the variables taken into consideration.

Subsequently, we followed the approach of Baur and Lucey (2009) by using OLS regressions in order to identify flight-to-quality in a posteriori specified crises periods. The crises events which were taken into consideration were the Asian crisis of 1997, the Russian crisis of 1998, the LTCM crisis of 1998, the Brazilian crisis of 1999, the 2000 E-Crash, the Argentina crisis of 2001, the September 11th crisis of 2001, the WorldCom crisis of 2002, the Subprime crisis of 2007 and the Subprime crisis of 2008-2009. We find evidence of the presence of flights-to-quality from stock returns to all commodities. We also find that although commodities are risky assets, their conditional volatility does not increase as much as the volatility of stock returns during crises periods, and as a consequence, they are considered as less risky assets than the stocks. Therefore, the presence of flight-to-quality from stock returns to commodities during crises events is justified. Another reason why investors prefer to invest in commodities in times of crises is because commodities can be stored and not lose their value during crises while stocks can be completely devaluated once a company bankrupts.

Finally, results from a panel regression, that was also used in order to treat commodities as a homogeneous asset class, suggest that there is flight-to-quality from the S&P500 to commodities during the Subprime crisis of 2008-2009. These results are also justified if we consider our conditional volatilities analysis for every commodity.

Our thesis empirically finds flight-to-quality from equities to commodities suggesting that in periods of economic turmoil and increased risk-aversion, commodities become an alternative investment to stocks. This thesis contributes to the literature because to our knowledge there has been no empirical evidence of flight-to-quality from stocks to commodities. Another contribution of our thesis is that it treats commodities as an asset class and not as inputs in industrial production by filtering demand and supply parametrically. These results are important for asset allocation and hedging strategies in times when they are needed most.

References

Baffes J., (2007), "Oil spills on other commodities", *Resources Policy,* 32: 126–134.

Baur, D. and Lucey, B.M., (2006), "Flight-to-quality or Contagion? An Empirical Analysis of Stock-bond correlations", Working Paper.

Baur, D.G., Lucey, B.M., (2009). Flights and contagion. An empirical analysis of stock-bond correlations. *Journal of Financial Stability,* 5: 339–352.

Bauwens L., Laurent S., Rombouts J.V.K., (2006), "Multivariate GARCH models: a survey", *Journal of Applied Econometrics,* 21:79-109.

Beber, A., Brandt, M.W. and Kavajecz, K.A., (2009), "Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market", *The Review of Financial Studies* v 22 n 3.

Bicchetti D., Maystre N., (2013), "The synchronized and long-lasting structural change on commodity markets: Evidence from high frequency data", *Algorithmic Finance,* 2:233–239.

Billio, M. and Caporin, M. (2010), "Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion", *Computational Statistics and Data Analysis*, 54: 2443-2458.

Blose, L.E. (2010), "Gold prices, cost of carry, and expected inflation," *Journal of Economics and Business,* 62: 35-47.

Bradley B.O., Taqqu M.S., (2004), "Framework for Analyzing Spatial Contagion between Financial Markets", *Finance Letters,* 2 (6): 8-15.

Bradley B.O., Taqqu M.S., (2005), "Empirical Evidence on Spatial Contagion Between Financial Markets, *Finance Letters,* 3 (1): 77-86.

Brière, M., Chapelle, A. and Szafarz, A. (2012), "No contagion, only globalization and flight to quality", *Journal of International Money and Finance,* 31:1729-1744.

Browne F., Cronin D., (2010), "Commodity prices, money and inflation", *Journal of Economics and Business,* 62: 331-345.

Buyuksahin B., Haigh M.S., Robe M.A., (2007), “Commodities and Equities: A “Market of One”?”, Working Paper.

Byrne, J.P., Fazio, G. and Fiess, N., (2013), “Primary commodity prices: Co-movements, common factors and fundamentals”, *Journal of Development Economics,* 101: 16-26.

Caporin M., McAleer M., (2013), “Ten Things You Should Know About the Dynamic Conditional Correlation Representation”, Working Paper.

Chan, K.F., Treepongkaruna, S., Brooks, R. and Gray, S., (2011), “Asset market linkages: Evidence from financial, commodity and real estate assets”, *Journal of Banking &* Finance*,* 35: 1415-1426.

Choi K., Hammoudeh S., (2010), “Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment”, *Energy Policy,* 38: 4388-4399.

Chong J., Miffre J., (2009), “Conditional Correlation and Volatility in Commodity Futures and Traditional Asset Markets”, Working Paper. (The article was presented at the University of Essex, EDHEC Business School, the Academy of Financial Services 2005 conference, the Financial Management Association 2005 conference and the 2007 EDHEC Alternative Investment Days).

Choudhry, T., Jayasekera, R., (2014), “Returns and volatility spillover in the European banking industry during global financial crisis: Flight to perceived quality or contagion?”,*International Review of Financial Analysis,* 36: 36-45.

Creti, A., Joëts, M. and Mignon, V., (2013), “On the links between stock and commodity markets' volatility”, *Energy Economics,* 37: 16-28.

Dajcman, S., (2012), “Comovement between stock and bond markets and the ‘flight-toquality’ during financial market turmoil – a case of the Eurozone countries most affected by the sovereign debt crisis of 2010–2011”, *Applied Economics Letters,* 19: 1655-1662.

Delatte A.L., Lopez C., (2013), “Commodity and equity markets: Some stylized facts from a copula approach”, *Journal of Banking & Finance,* 37: 5346–5356.

Durand, R.B., Junker, M. and Szimayer, A., (2010), "The flight-to-quality effect: a copula-based analysis", Accounting and Finance, 50: 281-299.

Engle, R.F., 2002. "Dynamic conditional correlation: A new simple class of multivariate GARCH models." *Journal of Business and Economic Statistics*, 20: 339-350.

Frankel, J.A. (2008), "The effect of monetary policy on real commodity prices." In: Campbell, J.Y. (Ed.), Asset Prices and Monetary Policy. NBER, University of Chicago, Chicago: 291-333.

Gorton G., Rouwenhorst K.G., (2004), "Facts and Fantasies about commodity futures", Yale ICF Working Paper No. 04-20.

Grilli, E., Yang, M.C., (1988), "Primary commodity prices, manufactured goods prices, and the terms of trade of developing countries: what the long run shows", *The World Bank Economic Review*, 2: 1–47.

Hartmann P., Straetmans S., de Vries C.G., (2004), "Asset Market Linkages in Crisis Periods", *The Review of Economics and Statistics*, 86(1): 313–326.

Inci, A.C., Li, H.C. and McCarthy, J. (2011), "Measuring flight to quality: a local correlation analysis", *Review of Accounting and Finance*, Vol. 10, No.1: 69-87.

International Monetary Fund (IMF), (April 2016), "World Economic Outlook – Commodity Special Feature".

International Monetary Fund (IMF), (October 2015), "World Economic Outlook – Adjusting to Lower Commodity Prices".

International Monetary Fund (IMF), (October 2016), "World Economic Outlook – Commodity Special Feature".

Krugman, P. (2008), "Running Out of Planet to Exploit," New York Times Op-Ed Column, April 21, 2008.

Lombardi M.J., Osbat C., Schnatz B., (2012), "Global commodity cycles and linkages: a FAVAR approach", *Empirical Economics*, 43:651–670.

Lombardi M.J., Ravazzolo F. (2013), "On the correlation between commodity and equity returns: implications for portfolio allocation", Bank for International Settlements, Working Papers, No 420.

Ma, J., Vivian, A. and Wohar, M (2015), "What Drives Commodity Returns? Market, Sector or Idiosyncratic Factors?", Working Paper.

Ng, S., (2006), "Testing cross-section correlation in panel data using spacings", *Journal of Business and Economics Statistics*, 24: 12–23.

Ohashi K., Okimoto T., (2016), "Increasing trends in the excess comovement of commodity prices", *Journal of Commodity Markets*, 1:48–64**.**

Pfaffenzeller, S., Newbold, P., Rayner, A., (2007), "A short note on updating the Grilli and Yang Commodity Price Index", *The World Bank Economic Review*, 21: 151–163.

Sadorsky P., (2014), "Modeling volatility and correlations between emerging market stock prices and prices of copper, oil and wheat", *Energy Economics*, 43: 72-81.

Sari, R., Hammoudeh, S., and Soytas, U. (2010), "Dynamics of oil price, precious metal prices, and exchange rate," *Energy Economics*, 32: 351-362.

Silvennoinen A., Thorp S., (2013), "Financialization, crisis and commodity correlation dynamics", *Journal of International Financial Markets, Institutions & Money*, 24: 42-65.

Sjaastad, L.A. (2008), "The price of gold and the exchange rates: Once again," *Resources Policy*, 33: 118-124.

Svensson, L. (2008). "The effect of monetary policy on real commodity prices: comment." In: Campbell, J.Y. (Ed.), Asset Prices and Monetary Policy. NBER, University of Chicago, Chicago.

Vansteenkiste, I. (2009), "How important are common factors in driving non-fuel commodity prices? A dynamic factor analysis," European Central Bank Working Papers, No. 1072.

Vayanos D., (2004), “Flight to quality, Flight to liquidity and the pricing of risk”, NBER Working Paper Series 10327.

Worthington A.C.Pahlavani M., (2007), “Gold investment as an inflationary hedge: cointegration evidence with allowance for endogenous structural breaks”, *Applied Financial Economics Letters,* 3: 259-262.

Zhang Y.J., Wei Y.M., (2010), “The crude oil market and the gold market: Evidence for cointegration, causality and price discovery”, *Resources Policy,* 35: 168-177.

TABLES

Table 1 - Positive commodity-equity co-movements

PAPERS	MODEL	VARIABLES	RESULTS
Lombardi and Ravazzolo, 2013	• Time varying Bayesian Dynamic Conditional Correlation model • Bivariate Vector Autoregressive model	• MSCI (Morgan Stanley Capital International global equity index) • SPGSCI (Standard & Poor's Goldman Sachs commodity index)	• Correlations have increased significantly since 2008, while they have been around zero a decade ago
Sadorsky, 2014	• DCC-GARCH model • VARMA-GARCH model	• MSCI Emerging Markets Index which consists of 21 emerging market country indices • International Grains Council wheat price index • The continuous contract on the WTI crude oil futures contract • The continuous futures contract on the COMEX copper contract	• Long-term volatility spillovers from wheat to equity prices from emerging markets, from oil to wheat, from oil to equity prices from emerging markets, from equity prices from emerging markets to oil and from equity prices from emerging markets to wheat • Dynamic conditional correlations between equity prices from emerging markets and oil and equity prices from emerging markets and wheat have increased since 2002 • Also, correlations increased in the crises period between 2008 and 2009
Bicchetti and Maystre, 2013	• DCC model	• E-mini S&P500 futures • Futures contracts of light WTI crude oil, wheat, sugar, corn, live cattle and soybeans	• Between 2006 and early 2008 positive dynamic conditional correlations exist between the commodities under consideration and the S&P500 • The DCCs sharply shift to positive values in October 2008 • After 2008, the positive correlations persist except for the period February to April 2011
Delatte and Lopez, 2013	• Three constant copula models • Three time-varying copula models	• Dow-Jones UBS Commodity Index (DJ-UBS) • Goldman Sachs Commodity Index (SP-GSCI) • S&P500 • FTSE100 • DAX30 • CAC40 index • 21 spot and futures commodity prices on agricultural, energy and industrial metals	• Co-movements are most of the time in the same direction • Integration of stock indices with certain commodities is found to have strengthened
Creti, Joëts and Mignon, 2013	• DCC GARCH model	• 25 commodities covering energy, precious metals, non-ferrous metals, agricultural, oleaginous, food, exotic and livestock sectors • Commodity Research Bureau (CRB) index • S&P500	• The 2007-2008 financial crisis has highlighted the links between equity and commodity returns indicating the financialization phenomenon • In the short run, these links are loosened in the sense that correlations during times of financial stress are decreased, implying the existence flight-to-quality phenomenon • Between 2007 and 2011, for almost all correlations between equities and commodities, an increase is observed • Oil, coffee and cocoa are characterized by speculation

			• Gold is found to be a safe-haven
Ohashi and Okimoto, 2016	• OLS to filter commodity returns from macroeconomic common factors • Smooth-transition dynamic conditional correlation (STDCC) model	• Agricultural raw material index • Metal index • Beverage index • Oil prices proxied by WTI, UK Brent and Dubai • CPI • 3-month T-bill rate • Money supply, M1 • Trade-weighted exchange rate index	• Increasing excess co-movements trends in the long-run • Fluctuations in the excess co-movements in the short-run
Silvennoinen and Thorp, 2013	• Double Smooth Transition Conditional Correlation (DSTCC-GARCH) model	• Futures contracts of 24 commodities such as grains, oilseeds, meat, livestock, food, fibre, metals and petroleum • S&P500 • FTSE100 • DAX • CAC • TOPX • Total returns fixed interest index for US Treasuries	• Correlations between S&P500 and most of the commodity futures returns examined in this paper have increased not only during the current economic crisis but also from an earlier date • Correlations between S&P500 and many commodities tend to rise when the VIX index rises, meaning that correlations are affected by financial shocks • Results for German, French, UK and Japanese equity returns indicate that commodity futures and equity markets are integrated not only in the US but also in other developed economies

Table 2 - Negative equity-commodity co-movements

PAPERS	MODEL	VARIABLES	RESULTS
Chong and Miffre, 2009	• DCC model	• Futures prices for cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar, wheat, crude oil, heating oil, lumber, natural gas, unleaded gas, feeder cattle, frozen pork bellies, lean hogs, live cattle, copper, gold, palladium, platinum and silver • S&P500 composite index • Russell 2000 Index • Russell 1000 Value Index • Russell 1000 Growth Index • MSCI Europe Index • MSCI Asia Pacific Index • MSCI Latin America Index • 6 bond indices from JP Morgan: US Cash with 6-month maturity, US Cash with 12-month maturity, United States Government Securities, Global Asia, Global Africa and Global Europe	• Correlations between commodity futures and S&P500 returns fell over time • Correlations between 11 commodity futures and the S&P500 returns tend to fall in periods of economic turmoil possibly indicating a flight-to-quality or the fact that commodities are used as inputs in production
Choi and Hammoudeh, 2010	• Markov regime-switching models • DCC-GARCH	• Spot prices for WTI oil, Brent oil, copper, silver and gold • S&P500 index	• Since 2003 commodities have increasing correlations among each other • Since 2003 decreasing correlations are evident between commodities and the S&P500 index

Buyuksahin and Robe, 2007	• Dynamic correlation techniques • Cointegration techniques	• S&P500 index • S&P GSCI (Standard and Poor's Goldman Sachs Commodity Index	• Stock-commodity simple cross-correlations are very low or negative • Low or negative correlations are also evident after the use of the DCC • Little statistical evidence of cointegration meaning that stocks and commodities are not correlated over long horizons • Little evidence of an increase in co-movements between equities and commodities is found during periods of extreme returns
Gorton and Rouwenhorst, 2004	• Analyzing the returns of an equally-weighted index of commodity futures • Simple correlations of commodities and other asset classes	• Individual futures contracts	• Over most horizons correlations between equities, bonds and commodities are negative

Table 3 - Factors affecting commodities

PAPERS	MODEL	VARIABLES	FACTORS EXAMINED AND FOUND EMPIRICALLY
Ma, Vivian and Wohar, 2015	• Dynamic Factor model	• 43 commodity returns from six sectors among which industrial metals, energy, raw metals and cereals	**Referred as examined by the literature:** • Global Demand • Real Interest Rates • Aggregate Supply • Dollar Exchange Rate • Macroeconomic Uncertainty • Inflation • Oil Prices **Found important:** • Dollar Exchange Rate • Economic Uncertainty (VIX) • Real T-bill
Byrne, Fazio and Fiess, 2013	• Methodology of Ng (2006) • Panel Analysis of Nonstationary and Idiosyncratic Components (PANIC) • Factor Augmented Vector Auto Regression (FAVAR) model	• Trade-weighted index of Grilli and Yang (1988), consisted of 24 prices of internationally traded non-fuel commodities	**Referred as examined by the literature:** • Real Interest Rates • Global Demand • Global Supply • Oil Prices **Found important:** • Real Interest Rates • Global Demand proxied by the growth rate of US real GDP • Global Supply proxied by crude oil prices
Krugman, 2008			**Refers to:** • Oil prices
Lombardi, Osbat and Schnatz, 2012	• FAVAR model • FAVECM model • Impulse response analysis	• Cotton spot prices • Aluminium spot prices • Copper spot prices	**Referred as examined by the literature:** • Global Demand • Interest Rates

		• Iron spot prices • Ore spot prices • Lead spot prices • Nickel spot prices • Tin spot prices • Zinc spot prices • Cocoa spot prices • Coffee spot prices • Maize spot prices • Rice spot prices • Soybeans spot prices • Sugar spot prices • Wheat spot prices • Industrial production of the OECD countries plus six major non-OECD • US interest rate proxied by 1-year US Treasury notes • Bond yield deflated by the US CPI • US dollar effective exchange rate	• Real Exchange Rate • Oil Prices • Fertilizer Prices • Financialization of commodities **Found important:** • Oil Prices • Industrial Production • Real Exchange Rate • Interest rate shocks have no systematic impact on non-energy commodity prices
Sjaastad, 2008	• International pricing model	• Gold spot prices • Gold forward prices • Spot and 90-dat forward exchange rates between the US dollar, the UK pound sterling and the Japanese yen	**Referred as examined by the literature:** • Exchange Rates **Found important:** • Inflation • US Exchange Rate
Sari, Hammoudeh and Soytas, 2010	• Vector Autoregressive (VAR) model	• Gold spot prices • Silver spot prices • Palladium spot prices • Platinum spot prices • WTI crude oil spot prices • US dollar/euro exchange rate • Dummy variables for the New York City attack of September 11, the Iraq war in 2003 and the OPEC's establishment of the oil price band in 2000	**Found important:** • US Exchange Rate • Oil Prices
Vansteenkiste, 2009	• Dynamic Factor model • OLS by means of general-to-specific approach	• 32 nominal non-fuel commodity prices split in 3 categories (agricultural raw material, metals and food) • UK Brent spot prices as a proxy for oil prices • US short-term interest rate deflated by the US CPI inflation as a proxy for real interest rate • US dollar effective exchange rate • Phosphate rock and potash prices as a proxy for input costs • Dow Jones index • Industrial Production in the OECD plus six major non-OECD countries as a proxy for global demand	**Referred as examined by the literature:** • Geopolitical Risks • Weather conditions • Demand from emerging countries • Oil Prices • US Exchange Rate • US Real Interest Rates • Speculation **Found important:** • US Real Interest Rates • Input costs proxied by Fertilizer Prices • US Exchange Rate • Global Demand
Blose, 2010	• Regression of the	• CPI announcements as a proxy	**Referred as examined by the literature:**

	unexpected changes in the CPI against bond yields and then against gold prices	for future inflation expectations • London PM as a proxy for gold prices	• Inflation **Found important:** • Gold does not react to unexpected inflation
Browne and Cronin, 2010	• VAR model	• CPI • Commodity Research Bureau Spot Index consisting of 22 basic commodities • Commodity Research Bureau Raw Industrials index • Conference Board's Sensitive Materials Index (SENSI) comprising of raw materials and metals but excluding food and energy	**Referred as examined by the literature:** • Money supply **Found important:** • Inflation (through money supply)
Worthington and Pahlavani, 2007	• Unit root testing procedure to estimate the timing of significant structural breaks • Cointegration test	• US inflation • Gold spot prices	**Found important:** • US Inflation
Frankel, 2008 Svensson, 2008	• OLS regression to the real commodity price index against interest rate • OLS regression of oil inventories against interest rates • OLS regression of oil inventories against interest rates, industrial production as a proxy of changes in demand, composite risk rating as a proxy for supply distortions and the spot-futures price spread	• Commodity Research Bureau Raw Industrials index • Conference Board's Sensitive Materials Index (SENSI) comprising of raw materials and metals but excluding food and energy • Industrial production as a proxy for changes in global demand • Composite risk rating as a proxy for supply distortions • Spot-futures price spread • CPI • US interest rate	**Referred as examined by the literature:** • Real Interest Rates **Found important:** • Real Interest Rates
Baffes, 2007	• OLS regression of the commodity prices on crude oil prices, also considering inflation and technological change	• Inflation proxied by the Manufacture Unit Value • 35 internationally traded commodities including metals, raw materials and food	**Found important:** • Oil Prices
Zhang and Wei, 2010	• Cointegration test • Causality test	• Brent spot price as a proxy for oil prices • Gold prices based on the London PM fix	**Found important:** • Oil Prices • US dollar Exchange Rate • Inflation
Analyzed in co-movement papers: Ohashi and Okimoto, 2016	• OLS to filter commodity returns from macroeconomic common factors • Smooth-transition dynamic conditional correlation (STDCC) model	• Agricultural raw material index • Metal index • Beverage index • Oil prices proxied by WTI, UK Brent and Dubai • CPI • 3-month T-bill rate • Money supply, M1 • Trade-weighted exchange rate index	**Factors used for filtering commodity returns:** • CPI • Exchange Rates • Industrial Production • Money stock • Stock price index • Interest Rate

Analyzed in co-movement papers: Silvennoinen and Thorp, 2013	• Double Smooth Transition Conditional Correlation (DSTCC-GARCH) model	• Futures contracts of 24 commodities such as grains, oilseeds, meat, livestock, food, fibre, metals and petroleum • S&P500 • FTSE100 • DAX • CAC • TOPX • Total returns fixed interest index for US Treasuries	**Found important:** • Uncertainty proxied by VIX

Table 4 - Flight-to-quality

PAPERS	MODEL	VARIABLES	RESULTS
Baur and Lucey, 2006	• DCC and rolling window correlations • Y-CCC cumulative correlation change • Regression with dependent variable the time-varying correlations and control variables the lagged cross-product of assets' returns, positive and negative returns, conditional volatilities, and dummy variables representing financial, economic or political events. • The existence of two regimes is investigated	• MSCI equity and bond indices for US, UK, Finland, Belgium, Germany, Spain, France, Italy and Ireland • Dummy variables for crises events	• Extreme negative and positive changes of the correlation in falling equity markets • The most distinct flight-to-quality events are in the 1997 Asian and 1998 Russian crisis while contagion is found after September 11, 2001. • Regression results show that the coefficient estimates point to the existence of flight-to-quality, flight-from-quality or a correction of FTQ and contagion
Baur and Lucey, 2009	• DCC • Regression of bond returns on stock returns, dummy variables of crisis events and an additional crisis dummy including a pre-crisis sub-sample • Panel model is used with dependent variable bond returns across countries and control variables stock returns across countries, dummy variables of crisis events across countries and an additional crisis dummy across countries including a pre-crisis sub-sample	• MSCI equity and bond index returns of Germany, Italy, France, the US, the UK, Australia, Japan, and Canada • Dummy variables for crises events	• Flight-to-quality from equities to bonds for almost all countries aside from Australia and Canada is evident during the Russian crisis. Also, flight-from-quality from bonds to equities for all countries except for Japan is evident during the Enron crisis • Cross-country contagion is implied by the fact that flights are found to occur simultaneously in many countries. In particular, contemporaneous flight-to-quality events from equities to bonds are found during the Asian crisis, joint cross-asset contagion or a flight to alternative assets is evident after the 11 September crisis and a common flight-from-quality from bonds to equities is found during the Enron crisis
Chan, Treepongkaruna, Brooks and Gray, 2011	• Markov-regime switching model	• S&P500 index • Fama-Bliss 1-year Treasury bond prices • WTI crude oil spot prices • Gold spot prices • S&P Case-Shiller	• In the “tranquil” regime with low volatility and considerably positive stock returns there is evidence of flight-from-quality from gold to stocks • In a “crisis” period with high volatility and significantly negative stock returns

		Composite-10 home price index	there is evidence of contagion between stocks, oil and real estate and of a flight-to-quality from stocks to Treasury bonds
Durand, Junker and Szimayer, 2010	• A dependence function or copula, combining the features of the Frank and the Gumbel copulas	• CRSP value-weighted index of US stocks • CRSP 30 year bond index	• A positive relationship between the returns of equities and bonds, during normal periods • A flight-to-quality from equities to bonds during periods of extreme events
Bradley and Taqqu, 2004, 2005	• Local Correlation approach	• Stock price indices for US, Germany, Canada, Australia, United Kingdom, Hong Kong, Japan, Switzerland, Netherlands, France, Italy, and Belgium • Merrill Lynch US Government Bond index representing one to ten-year maturity bonds	• Contagion from the US stock markets to stock markets of various developed countries • Flight-to-quality from the US stock market to the US bond market
Inci, Li and McCarthy, 2011	• Local Correlation approach	• DAX30 • Nikkei225 • S&P500 • Hang Seng Index • FTSE100 • Ten-year US Treasury bond index • Three-month T-bill • One-year to ten-year composite bond futures	• Flight-to-quality from domestic and foreign spot equity markets to US Treasury bonds when market risk rises • Flight-to-quality from domestic and foreign index futures to US bond futures when market risk rises
Hartmann, Straemans and de Vries, 2004	• Non parametric measure of dependence	• Stock indices of Germany, France, the United States, the United Kingdom and Japan • Indices of 10-year government bonds	• Equity-bond contagion as common as • Flight-to-quality from equities to bonds
Dajcman, 2012	• DCC-GARCH model • Moving window indicator of flight-to-quality around a day *x* based on 20 trading days around day *x*	• PSI 20 for Portugal • ISEQ for Ireland • IBEX35 for Spain • FTSE MIB for Italy • DAX for Germany • The yields of central government bonds with 10-year maturity from the Denmark's Central Bank	• Before 2010, when the Eurozone's debt crisis begun, financial turmoil resulted in flight-to-quality phenomena for all countries taken into consideration especially during the global financial crisis • After 2010, the flight-to-quality phenomenon is only evident in Germany
Brière, Chapelle and Szafarz, 2012	• GLR test for globalization and contagion	• Merrill Lynch investment grade bonds and high yield bonds • Stock indices for the Eurozone, US, UK and Japan	• Contagion is not evident • Flight-to-quality is evident during crisis periods
Choudhry and Jayasekera, 2014	• Multivariate GARCH-GJR	• Banking industry equity indices	• Spillover from the major economies to the smaller EU economies in the pre-crisis period • Spillover from smaller EU economies

			to major economies, notably Germany and the UK, is explicitly evident in the pre-crisis period • Contagion between the major economies and the larger of the smaller EU economies, namely Italy, Spain, and Portugal • Flight-to-quality is apparent from Greece and Ireland to major economies
Billio and Caporin, 2010	• Multivariate GARCH • DCC with breaks	• Stock market indices for USA, Brazil, Mexico, Japan, Singapore and Hong Kong • Exchange rates of Brazil, Mexico, Japan, Singapore and Hong Kong regarding to the US dollar	• Concurrent relationships between Asian and South American markets • A relevant effect from the US to Brazil and Mexico • Hong Kong most markets including the US market • When local currencies considered the US affects most countries • When exchange rates are considered Japan is an important market driver • Flight-to-quality events are evident from September to December 2004
Vayanos, 2004	• Model generating time-varying liquidity premia that rise with volatility		In volatile times: • Assets and volatility become more negatively correlated • Investors become more risk averse • Correlations of pair wise assets increase • Betas of illiquid assets and assets' liquidity premia rise • Assets become more negatively correlated with volatility • Assets become more correlated with one another • Illiquid assets' risk rises because their market betas rise
Beber, Brandt and Kavajecz, 2009	• Flights are classified by identifying periods of large positive or large negative total bond market order flow and then matching them with significant news events	• MTS data for order flow and yield spreads of Finland, Belgium, Austria, Greece, Italy, Portugal, Germany, Spain, France, and the Netherlands • Data from the sovereign credit default swap market from Lombard Risk of Fitch Rating Inc	• Investors are interested in both liquidity and credit quality depending on times and reasons • Most sovereign yield spreads are explained by credit quality differences • Liquidity is important especially for countries with low credit risk and during times of market uncertainty • Liquidity has an increased importance during periods of market uncertainty

Table 5 - Dynamic Conditional Correlation (DCC)

PAPERS	FINDINGS
Engle, 2002	• DCC estimators are presented • Comparison of DCC with simple multivariate GARCH and various other estimators reveals that the DCC is often the most accurate • DCC models are not only competitive with the multivariate GARCH specifications but also superior to moving average methods
Bauwens, Laurent and Rombouts, 2006	• A drawback of the DCC models is that in defining the conditional correlations they involve scalars so that all the conditional correlations obey the same dynamics
Caporin and McAleer,	• DCC does not yield dynamic conditional correlations

2013	• DCC is stated rather than derived • DCC has no moments • DCC does not have testable regularity conditions • DCC yields inconsistent two step estimators • DCC has no asymptotic properties; • DCC is not dynamic empirically as the effect of news is typically extremely small • DCC cannot be distinguished empirically from diagonal BEKK in small systems • DCC may be a useful filter or a diagnostic check, but it is not a model.

Table 6 – Augmented Dickey Fuller Test for equity commodity and factors prices

VARIABLES	ADF_Constant_PVALUE	ADF_Constant and Trend_PVALUE
S&P 500 COMPOSITE - PRICE INDEX	0.7889	0.587798352
NATURAL_GAS	0.05408	0.203692711
GOLD	0.9205	0.745897058
SILVER	0.6593	0.649876542
PLATINUM	0.5636	0.66660792
PALLADIUM	0.3508	0.172574911
COTTON	0.05526	0.171439444
ALUMINIUM_ALLOY	0.05015	0.066145318
ALUMINIUM_99.7%	0.3337	0.623502454
COPPER	0.6656	0.848871091
ZINC	0.1039	0.044910485
TIN	0.5177	0.138908801
LEAD	0.4962	0.022092961
NICKEL	0.2183	0.499907311
CORN	0.2198	0.31972133
WHEAT	0.1841	0.314649222
SOYABEANS	0.4593	0.445117151
COCOA	0.511	0.202810794
PULP	0.6943	0.010905208
CRUDE_OIL	0.4083	0.15569639
US CPI SADJ	0.8435	0.889915006
Rf	0.2005	0.035469247
YEN/USD	0.08587	0.02881
INDIA_IND_PROD	0.917	0.72748508
CHINA_IND_PROD	0.5533	0.793527365
BRAZIL_IND_PROD	0.3596	0.918392074
RUSSIA_IND_PROD	0.8689	0.520355787
S.AFRICA_IND_PROD	0.2205	0.198119494
INDONESIA_IND_PROD	0.9974	0.867892375
OECD_IND_PROD	0.2371	0.060631546

Table 7 – Augmented Dickey Fuller Test for equity, commodity and factors returns

VARIABLES	ADF_Constant_PVALUE	ADF_Constant and Trend_PVALUE

S&P 500 COMPOSITE - PRICE INDEX	2.73E-29	4.01E-31
NATURAL_GAS	5.53E-30	1.45E-32
GOLD	6.73E-30	2.73E-32
SILVER	1.08E-29	8.43E-32
PLATINUM	1.54E-12	5.18E-12
PALLADIUM	1.07E-27	8.51E-29
COTTON	7.45E-11	5.40E-10
ALUMINIUM_ALLOY	1.34E-15	2.40E-15
ALUMINIUM_99.7%	6.20E-11	4.97E-10
COPPER	8.87E-25	4.06E-25
ZINC	7.40E-09	7.18E-08
TIN	1.14E-16	1.27E-16
LEAD	1.63E-22	5.90E-24
NICKEL	2.89E-20	3.53E-21
CORN	7.24E-19	2.65E-19
WHEAT	4.62E-28	2.72E-29
SOYABEANS	3.88E-05	0.0003416
COCOA	5.05E-07	5.12E-06
PULP	1.38E-08	7.33E-08
CRUDE_OIL	6.71E-20	1.12E-20
US CPI SADJ	1.94E-06	2.94E-06
Rf	0.2005	0.035469247
YEN/USD	0.0001423	0.001067
INDIA_IND_PROD	0.0003242	0.0008395
CHINA_IND_PROD	2.74E-09	2.23E-08
BRAZIL_IND_PROD	7.76E-30	3.25E-32
RUSSIA_IND_PROD	2.11E-12	1.10E-11
S.AFRICA_IND_PROD	3.58E-18	1.22E-18
INDONESIA_IND_PROD	0.0002603	0.0007839
OECD_IND_PROD	2.31E-05	0.0001516

Table 8 - Summary Statistics of equity and commodity returns – Sample: 1994:05 - 2016:09

Variable	Mean	Median	Minimum	Maximum
SP500	0.00586331	0.0118105	-0.269726	0.165515
NATURAL_GAS	0.00144151	-0.00281294	-0.529402	0.641684
GOLD	0.00469692	0.00246373	-0.176717	0.187593
SILVER	0.00485135	0.00191022	-0.334935	0.256273
PLATINUM	0.00362444	0.00601686	-0.303491	0.284311
PALLADIUM	0.00608387	0.0123841	-0.433759	0.409203
COTTON	-0.000496399	0.000000	-0.247152	0.268667
ALUMINIUM_ALLOY	0.000521292	0.00149993	-0.292874	0.134305
ALUMINIUM_997	0.000787564	0.00239689	-0.182241	0.167653
COPPER	0.00347552	-0.000162324	-0.399625	0.229527
ZINC	0.00343851	0.00806900	-0.415291	0.223548

TIN	0.00483957	0.00467879	-0.314245	0.178990
LEAD	0.00568226	0.00655740	-0.324731	0.332444
NICKEL	0.00247791	0.00462652	-0.484525	0.292148
CORN	0.000800143	0.00272109	-0.346126	0.273001
WHEAT	0.000812971	-0.00508260	-0.326315	0.310952
SOYABEANS	0.00146956	0.00392928	-0.226969	0.216878
COCOA	0.00323982	-0.00117078	-0.210551	0.290113
PULP	0.00275813	0.000000	-0.422677	0.144831
CRUDE_OIL	0.00359987	0.00916139	-0.416591	0.293503
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
SP500	0.0495800	8.45598	-1.59247	6.38984
NATURAL_GAS	0.168169	116.662	0.209011	1.11246
GOLD	0.0452199	9.62756	0.212353	2.35528
SILVER	0.0811723	16.7319	-0.281708	2.13576
PLATINUM	0.0651796	17.9833	-0.576443	3.62697
PALLADIUM	0.104302	17.1440	-0.649483	2.68242
COTTON	0.0771496	155.418	0.190556	1.14614
ALUMINIUM_ALLOY	0.0538815	103.361	-0.875405	4.32298
ALUMINIUM_997	0.0574812	72.9861	-0.230076	0.567900
COPPER	0.0776939	22.3546	-0.623661	3.40392
ZINC	0.0753823	21.9229	-0.970090	4.27812
TIN	0.0706904	14.6067	-0.348891	1.53438
LEAD	0.0920276	16.1956	-0.265136	2.18624
NICKEL	0.100496	40.5567	-0.549633	2.48863
CORN	0.0879626	109.934	-0.550392	2.05031
WHEAT	0.0925061	113.788	0.132458	1.39701
SOYABEANS	0.0695824	47.3490	-0.227303	0.854424
COCOA	0.0698779	21.5685	0.337278	1.46356
PULP	0.0469293	17.0149	-2.57091	25.0382
CRUDE_OIL	0.109491	30.4152	-0.523667	1.37627
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
SP500	-0.0750646	0.0710227	0.0512038	0
NATURAL_GAS	-0.276449	0.315810	0.188434	0
GOLD	-0.0616615	0.0738341	0.0498813	0
SILVER	-0.111699	0.138555	0.0903023	0
PLATINUM	-0.114641	0.100591	0.0708210	0
PALLADIUM	-0.195322	0.171661	0.0994659	0
COTTON	-0.115793	0.132434	0.0879156	0
ALUMINIUM_ALLOY	-0.0807980	0.0889464	0.0550237	0
ALUMINIUM_997	-0.0926198	0.0918616	0.0781731	0
COPPER	-0.121283	0.130092	0.0816890	0
ZINC	-0.119172	0.112805	0.0857215	0
TIN	-0.107249	0.130381	0.0794391	0
LEAD	-0.165446	0.145271	0.0998838	0
NICKEL	-0.147038	0.163062	0.122501	0
CORN	-0.164085	0.132999	0.0892421	0
WHEAT	-0.156775	0.176609	0.106652	0
SOYABEANS	-0.123745	0.112764	0.0787222	0

COCOA	-0.0978745	0.120393	0.0797446	0
PULP	-0.0638163	0.0751544	0.0239593	0
CRUDE_OIL	-0.174562	0.167483	0.143413	0

Table 9 - Summary Statistics for equity returns and residuals of commodity returns – Sample: 1994:05 - 2016:09

Variable	Mean	Median	Minimum	Maximum
SP500	0.00586331	0.0118105	-0.269726	0.165515
res_NATURAL_GAS	-1.34135e-018	-0.00587385	-0.490771	0.628044
res_GOLD	-1.44453e-018	-0.000986788	-0.165454	0.189622
res_SILVER	-8.33183e-018	-0.00363431	-0.311522	0.233899
res_PLATINUM	-2.78588e-018	0.000942056	-0.276180	0.254943
res_PALLADIUM	-1.57350e-018	0.00606550	-0.387238	0.348979
res_COTTON	5.67493e-019	0.00329603	-0.263047	0.252428
res_ALLUMINIUM_ALLOY	-7.89976e-018	-0.00274598	-0.185250	0.153090
res_ALLUMINIUM_997	-2.16679e-018	-0.00416610	-0.157348	0.180832
res_COPPER	-8.34473e-018	-0.00312424	-0.256934	0.198392
res_ZINC	-3.00513e-018	0.00114169	-0.358755	0.211122
res_TIN	-5.00426e-018	-0.00181972	-0.239445	0.176716
res_LEAD	-3.76609e-018	-0.000938437	-0.295882	0.310674
res_NICKEL	-3.68871e-018	-0.00178530	-0.400436	0.289218
res_CORN	4.93332e-018	0.00244519	-0.343513	0.252770
res_WHEAT	6.95179e-018	-0.00620305	-0.327628	0.279123
res_SOYABEANS	-1.80566e-018	3.12508e-005	-0.201980	0.199872
res_COCOA	-2.06361e-018	-0.00311520	-0.187383	0.242327
res_PULP	-4.12722e-019	-0.00242516	-0.423106	0.141878
res_CRUDE_OIL	7.58377e-018	0.00692733	-0.323728	0.317855
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
SP500	0.0495800	8.45598	-1.59247	6.38984
res_NATURAL_GAS	0.162935	undefined	0.224948	1.23013
res_GOLD	0.0423348	undefined	0.360492	2.73986
res_SILVER	0.0772042	undefined	-0.189260	1.62309
res_PLATINUM	0.0599958	undefined	-0.233447	2.72243
res_PALLADIUM	0.0980495	undefined	-0.261428	1.54705
res_COTTON	0.0746558	undefined	0.284704	1.13714
res_ALLUMINIUM_ALLOY	0.0469975	undefined	-0.0787679	1.74831
res_ALLUMINIUM_997	0.0513002	undefined	0.229397	0.598642
res_COPPER	0.0675130	undefined	-0.0367611	0.932503
res_ZINC	0.0715493	undefined	-0.802579	3.44435
res_TIN	0.0673460	undefined	-0.180386	0.928245
res_LEAD	0.0859072	undefined	-0.0717086	1.42793
res_NICKEL	0.0963555	undefined	-0.400977	1.93966
res_CORN	0.0856222	undefined	-0.547448	1.92083
res_WHEAT	0.0903310	undefined	0.0396670	1.13101
res_SOYABEANS	0.0674751	undefined	-0.361123	0.594703
res_COCOA	0.0674663	undefined	0.295922	0.883046
res_PULP	0.0458086	undefined	-2.69461	26.9459
res_CRUDE_OIL	0.0963551	undefined	0.180066	0.750245

Variable	5% Perc.	95% Perc.	IQ range	Missing obs.
SP500	-0.0750646	0.0710227	0.0512038	0
res_NATURAL_GAS	-0.287372	0.292673	0.174848	0
res_GOLD	-0.0662151	0.0746346	0.0513867	0
res_SILVER	-0.112880	0.129307	0.0926525	0
res_PLATINUM	-0.105003	0.0987802	0.0672501	0
res_PALLADIUM	-0.172321	0.160324	0.103245	0
res_COTTON	-0.117642	0.125532	0.0883499	0
res_ALLUMINIUM_ALLOY	-0.0701402	0.0838847	0.0471564	0
res_ALLUMINIUM_997	-0.0773113	0.0880623	0.0719732	0
res_COPPER	-0.110903	0.120687	0.0812069	0
res_ZINC	-0.121968	0.104494	0.0756740	0
res_TIN	-0.109218	0.124372	0.0708747	0
res_LEAD	-0.153117	0.142924	0.0903349	0
res_NICKEL	-0.140154	0.161904	0.121006	0
res_CORN	-0.157426	0.129436	0.0940992	0
res_WHEAT	-0.139877	0.169444	0.112345	0
res_SOYABEANS	-0.126530	0.104648	0.0853897	0
res_COCOA	-0.110129	0.114463	0.0814849	0
res_PULP	-0.0583575	0.0713031	0.0313501	0
res_CRUDE_OIL	-0.155920	0.158509	0.131375	0

Table 10 - Summary Statistics for equity returns and residuals of commodity returns – Sample: 1994:05 - 2005:05

Variable	Mean	Median	Minimum	Maximum
SP500	0.00744274	0.00967350	-0.173789	0.100545
res_NATURAL_GAS	0.00108934	-0.00137884	-0.490771	0.514451
res_GOLD	-0.00226608	-0.00302611	-0.0909503	0.189622
res_SILVER	-0.00110602	-0.00922298	-0.158914	0.169343
res_PLATINUM	0.00123457	0.00254824	-0.150155	0.145369
res_PALLADIUM	-0.00693882	-0.00335829	-0.387238	0.348979
res_COTTON	-0.00188632	0.00331518	-0.183156	0.235296
res_ALLUMINIUM_ALLOY	0.000346215	0.000340320	-0.124438	0.108831
res_ALLUMINIUM_997	0.000477614	-0.00274785	-0.139150	0.137075
res_COPPER	-0.000153112	-0.00516261	-0.169329	0.198392
res_ZINC	-0.000373718	-0.000358112	-0.282670	0.116924
res_TIN	-0.00140522	-0.00232593	-0.180321	0.151293
res_LEAD	-0.000293337	-0.00144814	-0.231901	0.189891
res_NICKEL	0.00479890	-0.00157137	-0.290622	0.289218
res_CORN	-0.00540530	0.00244519	-0.343513	0.175986
res_WHEAT	-0.00317570	-0.0100139	-0.202795	0.190206
res_SOYABEANS	-0.00263961	-0.000927492	-0.201980	0.144783
res_COCOA	-0.00124625	-0.0100660	-0.187383	0.242327
res_PULP	-0.000184415	-0.00304619	-0.423106	0.141878
res_CRUDE_OIL	0.00210464	0.0177825	-0.323728	0.289399
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
SP500	0.0462355	6.21217	-0.969641	2.46978

res_NATURAL_GAS	0.166118	152.494	0.130058	0.880708
res_GOLD	0.0326294	14.3991	1.66807	8.50956
res_SILVER	0.0585965	52.9798	0.286577	0.484399
res_PLATINUM	0.0461277	37.3633	-0.147685	1.16612
res_PALLADIUM	0.104920	15.1207	-0.202208	1.64252
res_COTTON	0.0700985	37.1615	0.262176	0.488013
res_ALLUMINIUM_ALLOY	0.0438209	126.572	-0.0300779	0.395575
res_ALLUMINIUM_997	0.0478086	100.099	0.257454	0.613046
res_COPPER	0.0613473	400.670	0.349626	0.556555
res_ZINC	0.0553144	148.011	-0.995604	4.12624
res_TIN	0.0533642	37.9755	-0.121986	1.64983
res_LEAD	0.0681155	232.209	-0.0433150	0.728023
res_NICKEL	0.0807871	16.8345	0.0783879	1.43098
res_CORN	0.0760998	14.0788	-1.04179	2.81090
res_WHEAT	0.0724919	22.8271	0.222276	0.292884
res_SOYABEANS	0.0630159	23.8732	-0.673987	0.939059
res_COCOA	0.0730251	58.5961	0.486400	0.842658
res_PULP	0.0598107	324.326	-2.43976	17.8444
res_CRUDE_OIL	0.0921483	43.7835	-0.211969	0.678928
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
SP500	-0.0765005	0.0808054	0.0539627	0
res_NATURAL_GAS	-0.300404	0.292308	0.184028	0
res_GOLD	-0.0470965	0.0431920	0.0379138	0
res_SILVER	-0.0970358	0.111925	0.0788258	0
res_PLATINUM	-0.0769754	0.0776042	0.0570689	0
res_PALLADIUM	-0.195194	0.163565	0.0931405	0
res_COTTON	-0.105478	0.124935	0.0907536	0
res_ALLUMINIUM_ALLOY	-0.0727826	0.0731535	0.0530529	0
res_ALLUMINIUM_997	-0.0669529	0.0930631	0.0613621	0
res_COPPER	-0.0778049	0.114748	0.0786612	0
res_ZINC	-0.0887294	0.0896189	0.0679120	0
res_TIN	-0.0871134	0.0939662	0.0595568	0
res_LEAD	-0.106574	0.124701	0.0790210	0
res_NICKEL	-0.117930	0.144870	0.0889937	0
res_CORN	-0.154761	0.100321	0.0874976	0
res_WHEAT	-0.109542	0.134354	0.101196	0
res_SOYABEANS	-0.119243	0.0800825	0.0757572	0
res_COCOA	-0.122768	0.125833	0.0808445	0
res_PULP	-0.0951163	0.0990615	0.0380449	0
res_CRUDE_OIL	-0.135668	0.150618	0.132136	0

Table 11 - Summary Statistics for equity returns and residuals of commodity returns 2005:06 - 2016:09

Variable	Mean	Median	Minimum	Maximum
SP500	0.00431872	0.0129039	-0.269726	0.165515
res_NATURAL_GAS	-0.00106531	-0.0124685	-0.479899	0.628044
res_GOLD	0.00221609	0.00235200	-0.165454	0.151221

res_SILVER	0.00108162	0.00421113	-0.311522	0.233899
res_PLATINUM	-0.00120734	0.000552169	-0.276180	0.254943
res_PALLADIUM	0.00678576	0.0133760	-0.326983	0.248048
res_COTTON	0.00184471	0.00128425	-0.263047	0.252428
res_ALLUMINIUM_ALLOY	-0.000338578	-0.00402855	-0.185250	0.153090
res_ALLUMINIUM_997	-0.000467079	-0.00630384	-0.157348	0.180832
res_COPPER	0.000149734	0.00344432	-0.256934	0.177398
res_ZINC	0.000365474	0.00518006	-0.358755	0.211122
res_TIN	0.00137423	-0.000341398	-0.239445	0.176716
res_LEAD	0.000286866	-0.000825101	-0.295882	0.310674
res_NICKEL	-0.00469305	-0.00230325	-0.400436	0.247213
res_CORN	0.00528606	0.00155719	-0.296862	0.252770
res_WHEAT	0.00310565	-0.00307498	-0.327628	0.279123
res_SOYABEANS	0.00258139	0.000402967	-0.191400	0.199872
res_COCOA	0.00121875	0.00315502	-0.178646	0.219599
res_PULP	0.000180347	-0.000615960	-0.0761709	0.0667476
res_CRUDE_OIL	-0.00205821	-0.00246521	-0.253805	0.317855
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
SP500	0.0527717	12.2193	-1.96845	8.26213
res_NATURAL_GAS	0.160369	150.537	0.326418	1.61741
res_GOLD	0.0500689	22.5934	-0.0946667	0.897663
res_SILVER	0.0920491	85.1030	-0.315408	1.01614
res_PLATINUM	0.0711492	58.9306	-0.209409	2.03106
res_PALLADIUM	0.0907058	13.3671	-0.274649	1.15317
res_COTTON	0.0790751	42.8659	0.282878	1.42800
res_ALLUMINIUM_ALLOY	0.0500696	147.882	-0.105071	2.39349
res_ALLUMINIUM_997	0.0546728	117.053	0.214647	0.493377
res_COPPER	0.0732706	489.338	-0.259669	0.943011
res_ZINC	0.0846806	231.701	-0.698974	2.28293
res_TIN	0.0788383	57.3692	-0.215080	0.223072
res_LEAD	0.100568	350.576	-0.0803852	0.931176
res_NICKEL	0.109567	23.3466	-0.514247	1.49538
res_CORN	0.0939910	17.7809	-0.340817	1.23094
res_WHEAT	0.105074	33.8332	-0.0678825	0.775383
res_SOYABEANS	0.0717076	27.7787	-0.175877	0.263813
res_COCOA	0.0617964	50.7045	0.00463967	0.723501
res_PULP	0.0258435	143.298	-0.185096	0.537329
res_CRUDE_OIL	0.100597	48.8761	0.483904	0.805548
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
SP500	-0.0788912	0.0666346	0.0500670	0
res_NATURAL_GAS	-0.279398	0.300158	0.166923	0
res_GOLD	-0.0811673	0.0920002	0.0629456	0
res_SILVER	-0.143026	0.165073	0.113185	0
res_PLATINUM	-0.123261	0.115262	0.0763987	0
res_PALLADIUM	-0.151264	0.163163	0.107195	0
res_COTTON	-0.123496	0.131994	0.0881422	0
res_ALLUMINIUM_ALLOY	-0.0688532	0.0860500	0.0453992	0
res_ALLUMINIUM_997	-0.0828963	0.0881225	0.0759024	0

res_COPPER	-0.118966	0.126249	0.0899898	0
res_ZINC	-0.139936	0.133643	0.0941983	0
res_TIN	-0.125541	0.139516	0.104634	0
res_LEAD	-0.191757	0.188809	0.102956	0
res_NICKEL	-0.154870	0.179323	0.139655	0
res_CORN	-0.174962	0.147245	0.106980	0
res_WHEAT	-0.167624	0.195809	0.120159	0
res_SOYABEANS	-0.133556	0.110690	0.0884082	0
res_COCOA	-0.0975750	0.0990558	0.0814773	0
res_PULP	-0.0549559	0.0450591	0.0275452	0
res_CRUDE_OIL	-0.164325	0.163735	0.121860	0

Table 12: GARCH, using observations 1994:05-2016:09 (T = 269) – Dependent variable: SP500

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.0108405	0.00238209	4.5508	<0.0001	***
alpha(0)	0.000280882	0.000158515	1.7720	0.0764	*
alpha(1)	0.314727	0.120105	2.6204	0.0088	***
beta(1)	0.62179	0.121259	5.1278	<0.0001	***

Table 13: GARCH, using observations 1994:05-2016:09 (T = 269) – Dependent variable: res_NATURAL_GAS

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.00236003	0.00877962	0.2688	0.7881	
alpha(0)	0.00992738	0.00425452	2.3334	0.0196	**
alpha(1)	0.298006	0.0922811	3.2293	0.0012	***
beta(1)	0.334255	0.191196	1.7482	0.0804	*

Table 14: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_SILVER

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.00146444	0.00420678	−0.3481	0.7278	
alpha(0)	0.000138527	0.000115539	1.1990	0.2305	
alpha(1)	0.0586457	0.0255588	2.2945	0.0218	**
beta(1)	0.919295	0.0371948	24.7157	<0.0001	***

Table 15: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_GOLD

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.000104447	0.00194505	0.0537	0.9572	
alpha(0)	9.62861e-05	9.71513e-05	0.9911	0.3216	
alpha(1)	0.277687	0.0976343	2.8442	0.0045	***

beta(1)	0.722313	0.0898019	8.0434	<0.0001	***

Table 16: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_PLATINUM

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.000583395	0.00325233	0.1794	0.8576	
alpha(0)	0.00026806	0.000206741	1.2966	0.1948	
alpha(1)	0.116696	0.0430646	2.7098	0.0067	***
beta(1)	0.812865	0.0841516	9.6595	<0.0001	***

Table 17: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_PALLADIUM

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.000774515	0.00534163	−0.1450	0.8847	
alpha(0)	0.000283682	0.000219593	1.2919	0.1964	
alpha(1)	0.101586	0.0373219	2.7219	0.0065	***
beta(1)	0.880086	0.0369154	23.8406	<0.0001	***

Table 18: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_COTTON

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.00067903	0.00397745	0.1707	0.8644	
alpha(0)	0.00053482	0.000286177	1.8688	0.0616	*
alpha(1)	0.159282	0.0563764	2.8253	0.0047	***
beta(1)	0.745698	0.0857247	8.6987	<0.0001	***

Table 19: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_ALLUMINIUM_ALLOY

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.00105729	0.00233519	−0.4528	0.6507	
alpha(0)	0.000622906	0.000258925	2.4057	0.0161	**
alpha(1)	0.416549	0.125474	3.3198	0.0009	***
beta(1)	0.372571	0.148835	2.5032	0.0123	**

Table 20: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_ALLUMINIUM_997

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.00017607	0.00304259	0.0579	0.9539	
alpha(0)	0.00205096	0.00171026	1.1992	0.2304	

alpha(1)	0.0939449	0.0993874	0.9452	0.3445	
beta(1)	0.126717	0.671179	0.1888	0.8503	

Table 21: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_COPPER

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.000566967	0.00388898	−0.1458	0.8841	
alpha(0)	0.000194648	0.000169665	1.1472	0.2513	
alpha(1)	0.0525625	0.028889	1.8195	0.0688	*
beta(1)	0.903882	0.054506	16.5832	<0.0001	***

Table 22: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_ZINC

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.00206195	0.00387298	−0.5324	0.5945	
alpha(0)	0.000133337	8.66898e-05	1.5381	0.1240	
alpha(1)	0.0755513	0.0336378	2.2460	0.0247	**
beta(1)	0.903527	0.0327705	27.5713	<0.0001	***

Table 23: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_TIN

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.00192348	0.00360551	−0.5335	0.5937	
alpha(0)	0.000476302	0.000294108	1.6195	0.1053	
alpha(1)	0.213678	0.0873467	2.4463	0.0144	**
beta(1)	0.697727	0.113922	6.1246	<0.0001	***

Table 24: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_LEAD

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.0023589	0.00432755	−0.5451	0.5857	
alpha(0)	0.00014625	0.000112066	1.3050	0.1919	
alpha(1)	0.0800449	0.0258199	3.1001	0.0019	***
beta(1)	0.89854	0.0308139	29.1602	<0.0001	***

Table 25: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_NICKEL

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.00309972	0.00508613	−0.6094	0.5422	

alpha(0)	0.000339747	0.000232183	1.4633	0.1434	
alpha(1)	0.118713	0.0551799	2.1514	0.0314	**
beta(1)	0.84844	0.0609077	13.9299	<0.0001	***

Table 26: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_CORN

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.000227698	0.00523783	0.0435	0.9653	
alpha(0)	0.00438757	0.00476211	0.9214	0.3569	
alpha(1)	0.0413788	0.0630647	0.6561	0.5117	
beta(1)	0.358905	0.649728	0.5524	0.5807	

Table 27: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_WHEAT

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.000645717	0.0050623	0.1276	0.8985	
alpha(0)	0.00255158	0.0010933	2.3338	0.0196	**
alpha(1)	0.207551	0.0951138	2.1821	0.0291	**
beta(1)	0.486785	0.172078	2.8289	0.0047	***

Table 28: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_SOYABEANS

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.000517504	0.00408372	0.1267	0.8992	
alpha(0)	0.000803875	0.000677957	1.1857	0.2357	
alpha(1)	0.0839814	0.0534572	1.5710	0.1162	
beta(1)	0.73598	0.18936	3.8867	0.0001	***

Table 29: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_COCOA

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.00113372	0.00393108	0.2884	0.7730	
alpha(0)	0.000249547	0.000239112	1.0436	0.2967	
alpha(1)	0.0587891	0.0358018	1.6421	0.1006	
beta(1)	0.885399	0.0776735	11.3990	<0.0001	***

Table 30: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_PULP

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.00207727	0.00178438	1.1641	0.2444	

alpha(0)	3.39391e-05	1.76127e-05	1.9270	0.0540	*
alpha(1)	0.245498	0.0510471	4.8092	<0.0001	***
beta(1)	0.754502	0.0431891	17.4697	<0.0001	***

Table 31: GARCH, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_CRUDE_OIL

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.000387663	0.0055605	−0.0697	0.9444	
alpha(0)	0.00264873	0.00239789	1.1046	0.2693	
alpha(1)	0.100034	0.0694814	1.4397	0.1499	
beta(1)	0.614685	0.295831	2.0778	0.0377	**

Table 32 – Correlations between equity and commodity returns – Whole Sample

WHOLE SAMPLE 1994M05 TO 2016M09	SP500
SP500	1
NATURAL_GAS	-0.00874
GOLD	-0.05386
SILVER	0.119634
PLATINUM	0.220933
PALLADIUM	0.239484
COTTON	0.214499
ALUMINIUM_ALLOY	0.249989
ALUMINIUM_997	0.27687
COPPER	0.33337
ZINC	0.318334
TIN	0.304846
LEAD	0.195546
NICKEL	0.3281
CORN	0.117042
WHEAT	0.078052
SOYABEANS	0.137936
COCOA	0.148184
PULP	0.033536
CRUDE_OIL	0.215935

Table 33 - Correlations between equity and commodity returns – First sub-sample

1994M05 TO 2005M05	SP500
SP500	1
NATURAL_GAS	-0.03231
GOLD	-0.21626
SILVER	-0.08017
PLATINUM	0.043272
PALLADIUM	0.08786
COTTON	-0.00653
ALUMINIUM_ALLOY	0.050905
ALUMINIUM_997	0.144962
COPPER	0.164829
ZINC	0.154688
TIN	0.043983
LEAD	0.087338
NICKEL	0.152543
CORN	0.027875
WHEAT	-0.08013
SOYABEANS	-0.04231
COCOA	-0.04609
PULP	-0.01692
CRUDE_OIL	0.025148

Table 34 – Correlations between equities and commodities – Second sub-sample

2005M06 TO 2016M09	SP500
SP500	1

NATURAL_GAS	0.009461
GOLD	0.037773
SILVER	0.231139
PLATINUM	0.318827
PALLADIUM	0.403401
COTTON	0.385265
ALUMINIUM_ALLOY	0.379841
ALUMINIUM_997	0.364872
COPPER	0.438305
ZINC	0.412911
TIN	0.454613
LEAD	0.255418
NICKEL	0.439623
CORN	0.178769
WHEAT	0.170902
SOYABEANS	0.267468
COCOA	0.351863
PULP	0.13499
CRUDE_OIL	0.346176

Table 35 – Correlations between equity and residuals of commodity returns – Whole Sample

WHOLE SAMPLE 1994M05 TO 2016M09	SP500
SP500	1
res_NATURAL_GAS	-0.021943856
res_GOLD	-0.058877224
res_SILVER	0.072544991
res_PLATINUM	0.171552688
res_PALLADIUM	0.20426883
res_COTTON	0.204192842
res_ALLUMINIUM_ALLOY	0.149688386
res_ALLUMINIUM_997	0.179884902
res_COPPER	0.255751667
res_ZINC	0.255252714
res_TIN	0.244075333
res_LEAD	0.134611797
res_NICKEL	0.272068956
res_CORN	0.090475991
res_WHEAT	0.064803328
res_SOYABEANS	0.094638516
res_COCOA	0.122149261
res_PULP	0.018567854
res_CRUDE_OIL	0.177087126

Table 36 - Correlations between equity and residuals of commodity returns – First sub-sample

1994M05 TO 2005M05	SP500
SP500	1
res_NATURAL_GAS	-0.013037794
res_GOLD	-0.2523681
res_SILVER	-0.122115408
res_PLATINUM	0.021774366
res_PALLADIUM	0.087066272
res_COTTON	0.010575394
res_ALLUMINIUM_ALLOY	0.024200894
res_ALLUMINIUM_997	0.110700276
res_COPPER	0.133364303
res_ZINC	0.110702983
res_TIN	0.029459117
res_LEAD	0.063055929
res_NICKEL	0.133258599
res_CORN	0.007304351
res_WHEAT	-0.083181616
res_SOYABEANS	-0.065316404
res_COCOA	-0.053738432
res_PULP	-0.028228048
res_CRUDE_OIL	0.03830786

Table 37 – Correlations between equities and residuals of commodities – Second sub-sample

2005M06 TO 2016M09	SP500
SP500	1
res_NATURAL_GAS	-0.030409474
res_GOLD	0.050682547
res_SILVER	0.18077925
res_PLATINUM	0.256702256
res_PALLADIUM	0.330016395
res_COTTON	0.35291924
res_ALLUMINIUM_ALLOY	0.243508126
res_ALLUMINIUM_997	0.231373068
res_COPPER	0.343987911
res_ZINC	0.340561143
res_TIN	0.37282752
res_LEAD	0.178048987
res_NICKEL	0.359528106
res_CORN	0.152011108
res_WHEAT	0.154832496
res_SOYABEANS	0.217412728
res_COCOA	0.30430343
res_PULP	0.117767477
res_CRUDE_OIL	0.2850788

Table 38: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_NATURAL_GAS - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	***Std. Error***	***t-ratio***	***p-value***	
SP500	-0.427305	0.241452	−1.7697	0.078	*
resxD_ASIA_1997	1.55938	2.00218	0.7788	0.4368	
resxD_SUB_ASIA_1997	0.483626	0.241452	2.003	0.0463	**
resxD_RUSSIA_1998	-0.120841	0	−229484082922462.1900	<0.0001	***
resxD_SUB_RUSSIA_1998	-0.0710228	0.241452	−0.2941	0.7689	
resxD_LTCM_1998	-1.09857	0.241452	−4.5499	<0.0001	***
resxD_SUB_LTCM_1998	2.10389	0.241452	8.7135	<0.0001	***
resxD_BRAZIL_1999	-0.859843	0.241452	−3.5611	0.0004	***
resxD_SUB_BRAZIL_1999	1.15622	0.241452	4.7886	<0.0001	***
resxD_2000_E_CRASH	0.183445	0.378385	0.4848	0.6282	
resxD_SUB_2000_E_CRASH	1.27363	0.241452	5.2749	<0.0001	***
resxD_ARGENTINA_2001	2.6078	0.243057	10.7292	<0.0001	***
resxD_SUB_ARGENTINA_2001	2.06509	0.241452	8.5528	<0.0001	***
resxD_SEPTEMBER_11_2001	2.60199	0.241452	10.7765	<0.0001	***
resxD_SUB_SEPTEMBER_11_2001	-1.01343	0.241452	−4.1973	<0.0001	***

resxD_WORLD_COM_2002	0.971023	0.243877	3.9816	<0.0001	***
resxD_SUB_WORLD_COM_2002	0.688063	0.241452	2.8497	0.0047	***
resxD_SUBPRIME_2007	3.06141	0.37145	8.2418	<0.0001	***
resxD_SUB_SUBPRIME_2007	12.0213	0.241452	49.7876	<0.0001	***
resxD_SUBPRIME_2008_2009	0.469085	0.277936	1.6877	0.0927	*
resxD_SUB_SUBPRIME_2008_2009	-19.6544	0.241452	−81.4010	<0.0001	***

Table 39: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_GOLD - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	***Std. Error***	***t-ratio***	***p-value***	
const	0.00312987	0.00239882	1.3048	0.1932	
SP500	-0.152945	0.0889498	−1.7195	0.0868	*
resxD_ASIA_1997	-0.190544	0.235132	−0.8104	0.4185	
resxD_SUB_ASIA_1997	-0.405627	0.0787886	−5.1483	<0.0001	***
resxD_RUSSIA_1998	0.564643	0.0924127	6.11	<0.0001	***
resxD_SUB_RUSSIA_1998	-0.214913	0.0791163	−2.7164	0.0071	***
resxD_LTCM_1998	-0.217634	0.0801273	−2.7161	0.0071	***
resxD_SUB_LTCM_1998	-0.183019	0.0814723	−2.2464	0.0256	**
resxD_BRAZIL_1999	-0.740146	0.0786379	−9.4121	<0.0001	***
resxD_SUB_BRAZIL_1999	-0.964786	0.107719	−8.9565	<0.0001	***
resxD_2000_E_CRASH	-0.981282	0.0866676	−11.3224	<0.0001	***
resxD_SUB_2000_E_CRASH	-0.657251	0.108822	−6.0397	<0.0001	***
resxD_ARGENTINA_2001	-0.148971	0.0790662	−1.8841	0.0607	*
resxD_SUB_ARGENTINA_2001	0.011636	0.07984	0.1457	0.8842	
resxD_SEPTEMBER_11_2001	0.0130629	0.0961802	0.1358	0.8921	
resxD_SUB_SEPTEMBER_11_2001	-0.538727	0.138509	−3.8895	0.0001	***
resxD_WORLD_COM_2002	0.278562	0.111919	2.489	0.0135	**
resxD_SUB_WORLD_COM_2002	-0.413473	0.144689	−2.8577	0.0046	***
resxD_SUBPRIME_2007	0.929686	0.130948	7.0996	<0.0001	***
resxD_SUB_SUBPRIME_2007	5.94296	0.456363	13.0224	<0.0001	***
resxD_SUBPRIME_2008_2009	0.395597	0.0993012	3.9838	<0.0001	***
resxD_SUB_SUBPRIME_2008_2009	-15.2653	0.194412	−78.5200	<0.0001	***

Table 40: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_SILVER - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	***Std. Error***	***t-ratio***	***p-value***	

const	0.00202027	0.00399845	0.5053	0.6138	
SP500	0.0786231	0.12708	0.6187	0.5367	
resxD_ASIA_1997	-1.13435	0.940856	−1.2057	0.2291	
resxD_SUB_ASIA_1997	0.0526999	0.139253	0.3784	0.7054	
resxD_RUSSIA_1998	2.52764	0.154037	16.4093	<0.0001	***
resxD_SUB_RUSSIA_1998	-0.347149	0.136804	−2.5376	0.0118	**
resxD_LTCM_1998	-1.61144	0.156322	−10.3085	<0.0001	***
resxD_SUB_LTCM_1998	-2.22568	0.162265	−13.7164	<0.0001	***
resxD_BRAZIL_1999	0.00723633	0.143762	0.0503	0.9599	
resxD_SUB_BRAZIL_1999	-0.618624	0.227	−2.7252	0.0069	***
resxD_2000_E_CRASH	-0.955142	0.136475	−6.9986	<0.0001	***
resxD_SUB_2000_E_CRASH	-0.724451	0.140472	−5.1573	<0.0001	***
resxD_ARGENTINA_2001	-0.565263	0.145284	−3.8907	0.0001	***
resxD_SUB_ARGENTINA_2001	-0.150891	0.133887	−1.1270	0.2608	
resxD_SEPTEMBER_11_2001	-0.382282	0.12984	−2.9443	0.0035	***
resxD_SUB_SEPTEMBER_11_2001	0.595587	0.177967	3.3466	0.0009	***
resxD_WORLD_COM_2002	-0.178452	0.142176	−1.2552	0.2106	
resxD_SUB_WORLD_COM_2002	-0.705941	0.186853	−3.7781	0.0002	***
resxD_SUBPRIME_2007	1.58396	0.169522	9.3437	<0.0001	***
resxD_SUB_SUBPRIME_2007	10.4855	0.824564	12.7164	<0.0001	***
resxD_SUBPRIME_2008_2009	0.304349	0.177979	1.71	0.0885	*
resxD_SUB_SUBPRIME_2008_2009	-28.7544	0.383432	−74.9921	<0.0001	***

Table 41: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_PLATINUM - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−8.15067e-05	0.00343426	−0.0237	0.9811	
SP500	0.232858	0.117968	1.9739	0.0495	**
resxD_ASIA_1997	1.12977	1.03182	1.0949	0.2746	
resxD_SUB_ASIA_1997	0.663224	0.108546	6.11	<0.0001	***
resxD_RUSSIA_1998	2.06261	0.132302	15.5901	<0.0001	***
resxD_SUB_RUSSIA_1998	0.82505	0.108392	7.6118	<0.0001	***
resxD_LTCM_1998	-1.49674	0.113918	−13.1387	<0.0001	***
resxD_SUB_LTCM_1998	-1.64171	0.116801	−14.0555	<0.0001	***
resxD_BRAZIL_1999	-1.27215	0.109373	−11.6313	<0.0001	***
resxD_SUB_BRAZIL_1999	1.77419	0.160509	11.0535	<0.0001	***
resxD_2000_E_CRASH	-1.15735	0.109133	−10.6050	<0.0001	***
resxD_SUB_2000_E_CRASH	-1.6743	0.14395	−11.6311	<0.0001	***
resxD_ARGENTINA_2001	0.196331	0.112969	1.7379	0.0835	*
resxD_SUB_ARGENTINA_2001	-1.22758	0.108607	−11.3030	<0.0001	***

resxD_SEPTEMBER_11_2001	-0.896544	0.127071	−7.0555	<0.0001	***
resxD_SUB_SEPTEMBER_11_2001	4.2991	0.185282	23.203	<0.0001	***
resxD_WORLD_COM_2002	0.130748	0.171268	0.7634	0.4459	
resxD_SUB_WORLD_COM_2002	0.646291	0.194011	3.3312	0.001	***
resxD_SUBPRIME_2007	0.568644	0.189725	2.9972	0.003	***
resxD_SUB_SUBPRIME_2007	9.0189	0.665443	13.5532	<0.0001	***
resxD_SUBPRIME_2008_2009	0.0893746	0.165974	0.5385	0.5907	
resxD_SUB_SUBPRIME_2008_2009	-25.4841	0.288651	−88.2868	<0.0001	***

Table 42: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_PALLADIUM - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	***Std. Error***	***t-ratio***	***p-value***	
const	−0.00615531	0.00551058	−1.1170	0.2651	
SP500	0.676272	0.162717	4.1561	<0.0001	***
resxD_ASIA_1997	3.19247	2.72385	1.172	0.2423	
resxD_SUB_ASIA_1997	0.536674	0.177042	3.0313	0.0027	***
resxD_RUSSIA_1998	0.62907	0.212291	2.9632	0.0033	***
resxD_SUB_RUSSIA_1998	1.19544	0.173761	6.8798	<0.0001	***
resxD_LTCM_1998	-1.20689	0.200515	−6.0190	<0.0001	***
resxD_SUB_LTCM_1998	1.26073	0.208792	6.0382	<0.0001	***
resxD_BRAZIL_1999	-0.697648	0.18317	−3.8088	0.0002	***
resxD_SUB_BRAZIL_1999	2.91216	0.299353	9.7282	<0.0001	***
resxD_2000_E_CRASH	−0.112174	0.312975	−0.3584	0.7203	
resxD_SUB_2000_E_CRASH	−5.65714	0.185658	−30.4707	<0.0001	***
resxD_ARGENTINA_2001	0.116053	0.193635	0.5993	0.5495	
resxD_SUB_ARGENTINA_2001	−3.60514	0.169918	−21.2169	<0.0001	***
resxD_SEPTEMBER_11_2001	-1.05918	0.168257	−6.2950	<0.0001	***
resxD_SUB_SEPTEMBER_11_2001	2.84412	0.2419	11.7574	<0.0001	***
resxD_WORLD_COM_2002	-0.232349	0.188792	−1.2307	0.2196	
resxD_SUB_WORLD_COM_2002	-0.769404	0.254824	−3.0193	0.0028	***
resxD_SUBPRIME_2007	-1.88726	0.270423	−6.9789	<0.0001	***
resxD_SUB_SUBPRIME_2007	17.063	1.12689	15.1416	<0.0001	***
resxD_SUBPRIME_2008_2009	-0.581707	0.212643	−2.7356	0.0067	***
resxD_SUB_SUBPRIME_2008_2009	-30.0183	0.517021	−58.0601	<0.0001	***

Table 43: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_COTTON - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.000449362	0.00512733	−0.0876	0.9302	
SP500	0.23873	0.109441	2.1814	0.0301	**
resxD_ASIA_1997	−0.335908	0.24363	−1.3788	0.1692	
resxD_SUB_ASIA_1997	0.321385	0.137951	2.3297	0.0206	**
resxD_RUSSIA_1998	2.59123	0.197527	13.1184	<0.0001	***
resxD_SUB_RUSSIA_1998	−0.184625	0.133199	−1.3861	0.167	
resxD_LTCM_1998	-1.98969	0.168191	−11.8299	<0.0001	***
resxD_SUB_LTCM_1998	-2.89162	0.177989	−16.2460	<0.0001	***
resxD_BRAZIL_1999	-2.03746	0.146352	−13.9216	<0.0001	***
resxD_SUB_BRAZIL_1999	-0.66606	0.274916	−2.4228	0.0161	**
resxD_2000_E_CRASH	0.0479654	0.126849	0.3781	0.7057	
resxD_SUB_2000_E_CRASH	-0.40187	0.127613	−3.1491	0.0018	***
resxD_ARGENTINA_2001	2.36378	0.13829	17.0929	<0.0001	***
resxD_SUB_ARGENTINA_2001	-1.32217	0.127295	−10.3867	<0.0001	***
resxD_SEPTEMBER_11_2001	0.244275	0.111774	2.1854	0.0298	**
resxD_SUB_SEPTEMBER_11_2001	2.06731	0.18464	11.1964	<0.0001	***
resxD_WORLD_COM_2002	-0.947712	0.294639	−3.2165	0.0015	***
resxD_SUB_WORLD_COM_2002	-0.704642	0.197669	−3.5648	0.0004	***
resxD_SUBPRIME_2007	-1.40425	0.344736	−4.0734	<0.0001	***
resxD_SUB_SUBPRIME_2007	8.01667	1.0614	7.553	<0.0001	***
resxD_SUBPRIME_2008_2009	0.4899	0.127751	3.8348	0.0002	***
resxD_SUB_SUBPRIME_2008_2009	-2.41723	0.487346	−4.9600	<0.0001	***

Table 44: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_ALLUMINIUM_ALLOY - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0010026	0.0030273	0.3312	0.7408	
SP500	0.0755765	0.0935781	0.8076	0.4201	
resxD_ASIA_1997	0.0245224	0.245598	0.0998	0.9205	
resxD_SUB_ASIA_1997	−0.376288	0.0900679	−4.1778	<0.0001	***
resxD_RUSSIA_1998	0.33326	0.116623	2.8576	0.0046	***
resxD_SUB_RUSSIA_1998	0.816075	0.0893419	9.1343	<0.0001	***
resxD_LTCM_1998	-0.428976	0.0980139	−4.3767	<0.0001	***
resxD_SUB_LTCM_1998	1.13336	0.101427	11.1742	<0.0001	***

resxD_BRAZIL_1999	-1.06471	0.0917753	−11.6012	<0.0001	***
resxD_SUB_BRAZIL_1999	-1.09338	0.145445	−7.5175	<0.0001	***
resxD_2000_E_CRASH	-0.659198	0.172361	−3.8245	0.0002	***
resxD_SUB_2000_E_CRASH	0.950392	0.11451	8.2996	<0.0001	***
resxD_ARGENTINA_2001	0.632193	0.0901392	7.0135	<0.0001	***
resxD_SUB_ARGENTINA_2001	−0.0295702	0.0887545	−0.3332	0.7393	
resxD_SEPTEMBER_11_2001	0.0943816	0.100537	0.9388	0.3488	
resxD_SUB_SEPTEMBER_11_2001	0.0376234	0.15037	0.2502	0.8026	
resxD_WORLD_COM_2002	-0.214484	0.114518	−1.8729	0.0623	*
resxD_SUB_WORLD_COM_2002	1.12666	0.158044	7.1288	<0.0001	***
resxD_SUBPRIME_2007	-0.15929	0.27236	−0.5849	0.5592	
resxD_SUB_SUBPRIME_2007	-2.70841	0.596345	−4.5417	<0.0001	***
resxD_SUBPRIME_2008_2009	0.20838	0.151759	1.3731	0.171	
resxD_SUB_SUBPRIME_2008_2009	-2.25074	0.262227	−8.5832	<0.0001	***

Table 45: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_ALLUMINIUM_99.7 - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	***Std. Error***	***t-ratio***	***p-value***	
const	−0.000749925	0.00314	−0.2389	0.8114	
SP500	0.217569	0.08567	2.5396	0.0117	**
resxD_ASIA_1997	0.265609	0.47924	0.5542	0.5799	
resxD_SUB_ASIA_1997	-0.79534	0.07857	−10.1226	<0.0001	***
resxD_RUSSIA_1998	0.0420613	0.12093	0.3478	0.7283	
resxD_SUB_RUSSIA_1998	-0.12682	0.07799	−1.6262	0.1052	
resxD_LTCM_1998	-0.0277264	0.0867	−0.3198	0.7494	
resxD_SUB_LTCM_1998	-0.132556	0.0904	−1.4664	0.1438	
resxD_BRAZIL_1999	-1.10028	0.08017	−13.7238	<0.0001	***
resxD_SUB_BRAZIL_1999	-1.70517	0.1385	−12.3121	<0.0001	***
resxD_2000_E_CRASH	-0.417852	0.17972	−2.3250	0.0209	**
resxD_SUB_2000_E_CRASH	0.646543	0.11162	5.7926	<0.0001	***
resxD_ARGENTINA_2001	1.49603	0.07868	19.014	<0.0001	***
resxD_SUB_ARGENTINA_2001	-0.295904	0.07769	−3.8090	0.0002	***
resxD_SEPTEMBER_11_2001	-0.106761	0.09471	−1.1272	0.2607	
resxD_SUB_SEPTEMBER_11_2001	0.995678	0.15223	6.5407	<0.0001	***
resxD_WORLD_COM_2002	-0.160884	0.10767	−1.4942	0.1364	
resxD_SUB_WORLD_COM_2002	1.87676	0.16067	11.6809	<0.0001	***
resxD_SUBPRIME_2007	-0.6512	0.25551	−2.5487	0.0114	**

resxD_SUB_SUBPRIME_2007	9.05759	0.61154	14.8111	<0.0001	***
resxD_SUBPRIME_2008_2009	-0.0580089	0.10633	−0.5455	0.5859	
resxD_SUB_SUBPRIME_2008_2009	-4.99742	0.26273	−19.0210	<0.0001	***

Table 46: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_COPPER - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.000128448	0.00387303	−0.0332	0.9736	
SP500	0.343884	0.104422	3.2932	0.0011	***
resxD_ASIA_1997	-2.84431	1.46813	−1.9374	0.0538	*
resxD_SUB_ASIA_1997	0.289782	0.103642	2.796	0.0056	***
resxD_RUSSIA_1998	0.00815391	0.149206	0.0546	0.9565	
resxD_SUB_RUSSIA_1998	-0.42947	0.102161	−4.2039	<0.0001	***
resxD_LTCM_1998	-0.307822	0.116989	−2.6312	0.009	***
resxD_SUB_LTCM_1998	-0.159185	0.12225	−1.3021	0.1941	
resxD_BRAZIL_1999	-1.2053	0.106771	−11.2886	<0.0001	***
resxD_SUB_BRAZIL_1999	-3.23515	0.184414	−17.5429	<0.0001	***
resxD_2000_E_CRASH	-0.859865	0.151613	−5.6714	<0.0001	***
resxD_SUB_2000_E_CRASH	0.211417	0.131196	1.6115	0.1084	
resxD_ARGENTINA_2001	1.45124	0.104222	13.9245	<0.0001	***
resxD_SUB_ARGENTINA_2001	0.10381	0.100704	1.0308	0.3036	
resxD_SEPTEMBER_11_2001	−0.150572	0.11304	−1.3320	0.1841	
resxD_SUB_SEPTEMBER_11_2001	0.848256	0.178361	4.7558	<0.0001	***
resxD_WORLD_COM_2002	−0.0928185	0.147566	−0.6290	0.5299	
resxD_SUB_WORLD_COM_2002	0.425328	0.188429	2.2572	0.0249	**
resxD_SUBPRIME_2007	-3.79933	0.468025	−8.1178	<0.0001	***
resxD_SUB_SUBPRIME_2007	-22.1043	0.768545	−28.7612	<0.0001	***
resxD_SUBPRIME_2008_2009	0.161281	0.179515	0.8984	0.3698	
resxD_SUB_SUBPRIME_2008_2009	-3.26598	0.338347	−9.6527	<0.0001	***

Table 47: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_ZINC - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.00240469	0.0048424	−0.4966	0.6199	
SP500	0.427096	0.125516	3.4027	0.0008	***
resxD_ASIA_1997	1.43664	0.829968	1.731	0.0847	*
resxD_SUB_ASIA_1997	0.323714	0.120621	2.6837	0.0078	***
resxD_RUSSIA_1998	1.18571	0.18655	6.356	<0.0001	***
resxD_SUB_RUSSIA_1998	−0.071692	0.11904	−0.6023	0.5476	
resxD_LTCM_1998	-0.778012	0.136461	−5.7013	<0.0001	***

resxD_SUB_LTCM_1998	-1.47584	0.142952	−10.3240	<0.0001	***
resxD_BRAZIL_1999	-0.792787	0.124172	−6.3846	<0.0001	***
resxD_SUB_BRAZIL_1999	-2.21562	0.221079	−10.0218	<0.0001	***
resxD_2000_E_CRASH	−0.0720798	0.120945	−0.5960	0.5517	
resxD_SUB_2000_E_CRASH	0.593124	0.162759	3.6442	0.0003	***
resxD_ARGENTINA_2001	0.573692	0.120757	4.7508	<0.0001	***
resxD_SUB_ARGENTINA_2001	−0.403432	0.117648	−3.4292	0.0007	***
resxD_SEPTEMBER_11_2001	−0.0659631	0.137996	−0.4780	0.6331	
resxD_SUB_SEPTEMBER_11_2001	0.527191	0.224327	2.3501	0.0196	**
resxD_WORLD_COM_2002	-0.731583	0.140198	−5.2182	<0.0001	***
resxD_SUB_WORLD_COM_2002	2.70123	0.237252	11.3855	<0.0001	***
resxD_SUBPRIME_2007	-1.37478	0.848572	−1.6201	0.1065	
resxD_SUB_SUBPRIME_2007	-24.5511	0.953556	−25.7468	<0.0001	***
resxD_SUBPRIME_2008_2009	-0.0699936	0.269267	−0.2599	0.7951	
resxD_SUB_SUBPRIME_2008_2009	-2.08945	0.41468	−5.0387	<0.0001	***

Table 48: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_TIN - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	***Std. Error***	***t-ratio***	***p-value***	
const	−0.00180605	0.0044034	−0.4101	0.6821	
SP500	0.389933	0.147629	2.6413	0.0088	***
resxD_ASIA_1997	−0.591642	0.369988	−1.5991	0.1111	
resxD_SUB_ASIA_1997	−0.783888	0.137026	−5.7207	<0.0001	***
resxD_RUSSIA_1998	0.401652	0.169638	2.3677	0.0187	**
resxD_SUB_RUSSIA_1998	-0.504712	0.13664	−3.6937	0.0003	***
resxD_LTCM_1998	-0.255158	0.144964	−1.7601	0.0796	*
resxD_SUB_LTCM_1998	-0.621036	0.148955	−4.1693	<0.0001	***
resxD_BRAZIL_1999	-0.726321	0.138401	−5.2480	<0.0001	***
resxD_SUB_BRAZIL_1999	-2.79352	0.206918	−13.5006	<0.0001	***
resxD_2000_E_CRASH	-0.972245	0.138003	−7.0451	<0.0001	***
resxD_SUB_2000_E_CRASH	0.458214	0.180366	2.5405	0.0117	**
resxD_ARGENTINA_2001	1.24739	0.137069	9.1005	<0.0001	***
resxD_SUB_ARGENTINA_2001	0.514697	0.136672	3.7659	0.0002	***
resxD_SEPTEMBER_11_2001	0.0944864	0.158987	0.5943	0.5529	
resxD_SUB_SEPTEMBER_11_2001	1.88762	0.233202	8.0943	<0.0001	***
resxD_WORLD_COM_2002	-0.606373	0.192611	−3.1482	0.0018	***
resxD_SUB_WORLD_COM_2002	-0.632061	0.244391	−2.5863	0.0103	**
resxD_SUBPRIME_2007	0.909699	0.999626	0.91	0.3637	
resxD_SUB_SUBPRIME_2007	13.7495	0.856447	16.0541	<0.0001	***
resxD_SUBPRIME_2008_2009	-0.0870669	0.226259	−0.3848	0.7007	
resxD_SUB_SUBPRIME_2008_2009	-9.67866	0.372606	−25.9756	<0.0001	***

Table 49: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_LEAD - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.00175052	0.00509933	−0.3433	0.7317	
SP500	0.339857	0.144733	2.3482	0.0197	**
resxD_ASIA_1997	-1.13792	0.414462	−2.7455	0.0065	***
resxD_SUB_ASIA_1997	-0.335246	0.140086	−2.3931	0.0175	**
resxD_RUSSIA_1998	0.567359	0.196448	2.8881	0.0042	***
resxD_SUB_RUSSIA_1998	-0.307211	0.138574	−2.2170	0.0275	**
resxD_LTCM_1998	-0.436313	0.155394	−2.8078	0.0054	***
resxD_SUB_LTCM_1998	-0.966592	0.161742	−5.9762	<0.0001	***
resxD_BRAZIL_1999	-0.676881	0.143493	−4.7172	<0.0001	***
resxD_SUB_BRAZIL_1999	-1.158	0.240244	−4.8201	<0.0001	***
resxD_2000_E_CRASH	-0.648254	0.140741	−4.6060	<0.0001	***
resxD_SUB_2000_E_CRASH	0.193549	0.181222	1.068	0.2866	
resxD_ARGENTINA_2001	1.01809	0.140638	7.2391	<0.0001	***
resxD_SUB_ARGENTINA_2001	0.213926	0.137242	1.5587	0.1203	
resxD_SEPTEMBER_11_2001	−0.0390927	0.156811	−0.2493	0.8033	
resxD_SUB_SEPTEMBER_11_2001	-0.539373	0.243427	−2.2157	0.0276	**
resxD_WORLD_COM_2002	−0.256472	0.159244	−1.6106	0.1086	
resxD_SUB_WORLD_COM_2002	1.37554	0.256651	5.3596	<0.0001	***
resxD_SUBPRIME_2007	0.610026	0.935393	0.6522	0.5149	
resxD_SUB_SUBPRIME_2007	0.533569	1.00596	0.5304	0.5963	
resxD_SUBPRIME_2008_2009	−0.304522	0.286792	−1.0618	0.2894	
resxD_SUB_SUBPRIME_2008_2009	-8.04882	0.440732	−18.2624	<0.0001	***

Table 50: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_NICKEL - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.00460118	0.00603535	−0.7624	0.4466	
SP500	0.614738	0.167941	3.6604	0.0003	***
resxD_ASIA_1997	-1.82634	0.424964	−4.2976	<0.0001	***
resxD_SUB_ASIA_1997	-1.33586	0.156632	−8.5287	<0.0001	***
resxD_RUSSIA_1998	0.574255	0.232508	2.4698	0.0142	**
resxD_SUB_RUSSIA_1998	-0.986043	0.155337	−6.3478	<0.0001	***
resxD_LTCM_1998	-0.794238	0.172786	−4.5967	<0.0001	***
resxD_SUB_LTCM_1998	-0.405762	0.179948	−2.2549	0.025	**
resxD_BRAZIL_1999	1.82061	0.159941	11.383	<0.0001	***
resxD_SUB_BRAZIL_1999	-4.50479	0.27201	−16.5611	<0.0001	***
resxD_2000_E_CRASH	0.138319	0.209578	0.66	0.5099	

resxD_SUB_2000_E_CRASH	-2.72642	0.215722	−12.6385	<0.0001	***
resxD_ARGENTINA_2001	2.5018	0.163109	15.3382	<0.0001	***
resxD_SUB_ARGENTINA_2001	-0.610527	0.154492	−3.9518	0.0001	***
resxD_SEPTEMBER_11_2001	0.153955	0.184368	0.835	0.4045	
resxD_SUB_SEPTEMBER_11_2001	1.75354	0.292345	5.9982	<0.0001	***
resxD_WORLD_COM_2002	-0.849445	0.240227	−3.5360	0.0005	***
resxD_SUB_WORLD_COM_2002	2.01163	0.308379	6.5232	<0.0001	***
resxD_SUBPRIME_2007	-1.17773	1.04377	−1.1283	0.2603	
resxD_SUB_SUBPRIME_2007	33.7399	1.17985	28.5968	<0.0001	***
resxD_SUBPRIME_2008_2009	-0.0662716	0.290566	−0.2281	0.8198	
resxD_SUB_SUBPRIME_2008_2009	2.03628	0.509966	3.993	<0.0001	***

Table 51: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_CORN - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0007223	0.00585357	0.1234	0.9019	
SP500	0.0028151	0.12631	0.0223	0.9822	
resxD_ASIA_1997	0.870054	0.482203	1.8043	0.0724	*
resxD_SUB_ASIA_1997	−0.977795	0.16126	−6.0635	<0.0001	***
resxD_RUSSIA_1998	-2.49319	0.225505	−11.0561	<0.0001	***
resxD_SUB_RUSSIA_1998	-1.12679	0.155683	−7.2377	<0.0001	***
resxD_LTCM_1998	3.60032	0.196341	18.3371	<0.0001	***
resxD_SUB_LTCM_1998	4.22632	0.207627	20.3553	<0.0001	***
resxD_BRAZIL_1999	-0.924058	0.171062	−5.4019	<0.0001	***
resxD_SUB_BRAZIL_1999	-0.344246	0.31867	−1.0803	0.2811	
resxD_2000_E_CRASH	0.559861	0.152351	3.6748	0.0003	***
resxD_SUB_2000_E_CRASH	−0.776441	0.144151	−5.3863	<0.0001	***
resxD_ARGENTINA_2001	1.17359	0.162102	7.2398	<0.0001	***
resxD_SUB_ARGENTINA_2001	−0.615017	0.148706	−4.1358	<0.0001	***
resxD_SEPTEMBER_11_2001	0.167061	0.127684	1.3084	0.192	
resxD_SUB_SEPTEMBER_11_2001	-1.85998	0.207554	−8.9614	<0.0001	***
resxD_WORLD_COM_2002	-0.392894	0.133234	−2.9489	0.0035	***
resxD_SUB_WORLD_COM_2002	-1.55515	0.222253	−6.9972	<0.0001	***
resxD_SUBPRIME_2007	1.79364	0.132573	13.5294	<0.0001	***
resxD_SUB_SUBPRIME_2007	17.2016	1.21662	14.1389	<0.0001	***
resxD_SUBPRIME_2008_2009	0.577688	0.166482	3.47	0.0006	***
resxD_SUB_SUBPRIME_2008_2009	-5.20621	0.561284	−9.2755	<0.0001	***

Table 52: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_WHEAT - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0016755	0.00557	0.3006	0.764	
SP500	-0.074532	0.15742	−0.4735	0.6363	
resxD_ASIA_1997	0.387277	0.45942	0.843	0.4001	
resxD_SUB_ASIA_1997	-1.12326	0.1674	−6.7100	<0.0001	***
resxD_RUSSIA_1998	-0.142421	0.2147	−0.6633	0.5077	
resxD_SUB_RUSSIA_1998	-1.4873	0.16439	−9.0474	<0.0001	***
resxD_LTCM_1998	1.66623	0.19005	8.7674	<0.0001	***
resxD_SUB_LTCM_1998	0.939774	0.19825	4.7404	<0.0001	***
resxD_BRAZIL_1999	-1.2174	0.17317	−7.0300	<0.0001	***
resxD_SUB_BRAZIL_1999	3.77042	0.28964	13.0177	<0.0001	***
resxD_2000_E_CRASH	0.267593	0.18444	1.4508	0.1481	
resxD_SUB_2000_E_CRASH	−0.410634	0.18588	−2.2091	0.0281	**
resxD_ARGENTINA_2001	0.690792	0.16816	4.108	<0.0001	***
resxD_SUB_ARGENTINA_2001	1.61094	0.16098	10.007	<0.0001	***
resxD_SEPTEMBER_11_2001	0.119866	0.16526	0.7253	0.469	
resxD_SUB_SEPTEMBER_11_2001	2.57321	0.24696	10.4195	<0.0001	***
resxD_WORLD_COM_2002	-0.467513	0.17349	−2.6947	0.0075	***
resxD_SUB_WORLD_COM_2002	0.843851	0.26059	3.2382	0.0014	***
resxD_SUBPRIME_2007	0.800325	0.32131	2.4908	0.0134	**
resxD_SUB_SUBPRIME_2007	-11.9762	1.12839	−10.6135	<0.0001	***
resxD_SUBPRIME_2008_2009	0.685672	0.19113	3.5875	0.0004	***
resxD_SUB_SUBPRIME_2008_2009	9.72675	0.51059	19.05	<0.0001	***

Table 53: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_SOYABEANS - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00144815	0.00465979	0.3108	0.7562	
SP500	0.0813233	0.0902457	0.9011	0.3684	
resxD_ASIA_1997	-1.66698	1.07148	−1.5558	0.121	
resxD_SUB_ASIA_1997	-0.517925	0.103004	−5.0282	<0.0001	***
resxD_RUSSIA_1998	-0.0129801	0.179515	−0.0723	0.9424	
resxD_SUB_RUSSIA_1998	-0.595662	0.0994531	−5.9894	<0.0001	***
resxD_LTCM_1998	1.16805	0.127985	9.1265	<0.0001	***
resxD_SUB_LTCM_1998	1.89563	0.136523	13.8851	<0.0001	***
resxD_BRAZIL_1999	-1.77824	0.109623	−16.2214	<0.0001	***
resxD_SUB_BRAZIL_1999	-1.19478	0.223816	−5.3382	<0.0001	***
resxD_2000_E_CRASH	-0.155318	0.0952954	−1.6299	0.1044	
resxD_SUB_2000_E_CRASH	-0.692311	0.121624	−5.6922	<0.0001	***
resxD_ARGENTINA_2001	1.16881	0.103733	11.2675	<0.0001	***

resxD_SUB_ARGENTINA_2001	−1.135	0.0953298	−11.9061	<0.0001	***
resxD_SEPTEMBER_11_2001	0.231318	0.0991884	2.3321	0.0205	**
resxD_SUB_SEPTEMBER_11_2001	0.516524	0.181833	2.8406	0.0049	***
resxD_WORLD_COM_2002	-0.762412	0.126105	−6.0458	<0.0001	***
resxD_SUB_WORLD_COM_2002	-1.37615	0.194576	−7.0726	<0.0001	***
resxD_SUBPRIME_2007	1.33666	0.283008	4.7231	<0.0001	***
resxD_SUB_SUBPRIME_2007	21.1787	0.940009	22.5303	<0.0001	***
resxD_SUBPRIME_2008_2009	0.306534	0.139267	2.2011	0.0287	**
resxD_SUB_SUBPRIME_2008_2009	-10.0482	0.417453	−24.0703	<0.0001	***

Table 54: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_COCOA - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.000368678	0.00388199	0.095	0.9244	
SP500	-0.00703472	0.123418	−0.0570	0.9546	
resxD_ASIA_1997	-1.36758	0.579005	−2.3619	0.019	**
resxD_SUB_ASIA_1997	1.67323	0.131833	12.692	<0.0001	***
resxD_RUSSIA_1998	0.932871	0.149551	6.2378	<0.0001	***
resxD_SUB_RUSSIA_1998	-0.619563	0.129755	−4.7749	<0.0001	***
resxD_LTCM_1998	-0.447733	0.147068	−3.0444	0.0026	***
resxD_SUB_LTCM_1998	-0.675619	0.152535	−4.4293	<0.0001	***
resxD_BRAZIL_1999	-1.20387	0.135759	−8.8677	<0.0001	***
resxD_SUB_BRAZIL_1999	-2.46594	0.213828	−11.5324	<0.0001	***
resxD_2000_E_CRASH	1.26126	0.125208	10.0733	<0.0001	***
resxD_SUB_2000_E_CRASH	0.421959	0.139441	3.0261	0.0027	***
resxD_ARGENTINA_2001	3.48789	0.132932	26.2382	<0.0001	***
resxD_SUB_ARGENTINA_2001	0.966133	0.12735	7.5864	<0.0001	***
resxD_SEPTEMBER_11_2001	0.455964	0.127447	3.5777	0.0004	***
resxD_SUB_SEPTEMBER_11_2001	-3.03849	0.177935	−17.0764	<0.0001	***
resxD_WORLD_COM_2002	-0.631978	0.152649	−4.1401	<0.0001	***
resxD_SUB_WORLD_COM_2002	-1.28066	0.186819	−6.8551	<0.0001	***
resxD_SUBPRIME_2007	1.35988	0.513187	2.6499	0.0086	***
resxD_SUB_SUBPRIME_2007	-5.38255	0.792908	−6.7884	<0.0001	***
resxD_SUBPRIME_2008_2009	0.563276	0.179003	3.1467	0.0019	***
resxD_SUB_SUBPRIME_2008_2009	-7.09116	0.364893	−19.4335	<0.0001	***

Table 55: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_PULP - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.0006253	0.00392773	0.1592	0.8736	

SP500	-0.0696357	0.0595111	−1.1701	0.2431	
resxD_ASIA_1997	0.999201	0.983746	1.0157	0.3108	
resxD_SUB_ASIA_1997	0.58211	0.0899359	6.4725	<0.0001	***
resxD_RUSSIA_1998	1.78762	0.151313	11.814	<0.0001	***
resxD_SUB_RUSSIA_1998	0.493505	0.0853846	5.7798	<0.0001	***
resxD_LTCM_1998	-1.18859	0.117256	−10.1367	<0.0001	***
resxD_SUB_LTCM_1998	-1.34326	0.125719	−10.6846	<0.0001	***
resxD_BRAZIL_1999	-0.775173	0.0977689	−7.9286	<0.0001	***
resxD_SUB_BRAZIL_1999	-0.15429	0.205302	−0.7515	0.4531	
resxD_2000_E_CRASH	−0.0588296	0.0787271	−0.7473	0.4556	
resxD_SUB_2000_E_CRASH	−0.563481	0.0754598	−7.4673	<0.0001	***
resxD_ARGENTINA_2001	0.885098	0.0903444	9.7969	<0.0001	***
resxD_SUB_ARGENTINA_2001	0.135629	0.0795688	1.7046	0.0895	*
resxD_SEPTEMBER_11_2001	0.133214	0.0607494	2.1929	0.0293	**
resxD_SUB_SEPTEMBER_11_2001	1.85621	0.125343	14.809	<0.0001	***
resxD_WORLD_COM_2002	-0.176636	0.0631336	−2.7978	0.0056	***
resxD_SUB_WORLD_COM_2002	-0.662623	0.136202	−4.8650	<0.0001	***
resxD_SUBPRIME_2007	0.0620513	0.106783	0.5811	0.5617	
resxD_SUB_SUBPRIME_2007	1.1406	0.814293	1.4007	0.1626	
resxD_SUBPRIME_2008_2009	0.279336	0.0702469	3.9765	<0.0001	***
resxD_SUB_SUBPRIME_2008_2009	1.00876	0.37193	2.7122	0.0072	***

Table 56: OLS, using observations 1994:05-2016:09 (T = 269) - Dependent variable: res_CRUDE_OIL - HAC standard errors, bandwidth 4 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−0.00409937	0.00480387	−0.8533	0.3943	
SP500	0.702156	0.175123	4.0095	<0.0001	***
resxD_ASIA_1997	−1.59066	1.53775	−1.0344	0.302	
resxD_SUB_ASIA_1997	−2.82404	0.17874	−15.7997	<0.0001	***
resxD_RUSSIA_1998	0.131575	0.185066	0.711	0.4778	
resxD_SUB_RUSSIA_1998	0.925549	0.17698	5.2297	<0.0001	***
resxD_LTCM_1998	-3.00407	0.193216	−15.5477	<0.0001	***
resxD_SUB_LTCM_1998	-1.22074	0.198786	−6.1410	<0.0001	***
resxD_BRAZIL_1999	0.69627	0.182259	3.8202	0.0002	***
resxD_SUB_BRAZIL_1999	−4.13653	0.266515	−15.5208	<0.0001	***
resxD_2000_E_CRASH	-1.64758	0.174182	−9.4590	<0.0001	***
resxD_SUB_2000_E_CRASH	0.357792	0.197399	1.8125	0.0711	*
resxD_ARGENTINA_2001	-2.60835	0.179671	−14.5174	<0.0001	***
resxD_SUB_ARGENTINA_2001	-1.85083	0.175085	−10.5711	<0.0001	***
resxD_SEPTEMBER_11_2001	-0.533165	0.181588	−2.9361	0.0036	***
resxD_SUB_SEPTEMBER_11_2001	-3.01471	0.244553	−12.3274	<0.0001	***

resxD_WORLD_COM_2002	-0.892227	0.215224	−4.1456	<0.0001	***
resxD_SUB_WORLD_COM_2002	-3.35629	0.255297	−13.1466	<0.0001	***
resxD_SUBPRIME_2007	2.3867	0.23477	10.1661	<0.0001	***
resxD_SUB_SUBPRIME_2007	-38.1493	0.971146	−39.2828	<0.0001	***
resxD_SUBPRIME_2008_2009	-0.670272	0.266825	−2.5120	0.0126	**
resxD_SUB_SUBPRIME_2008_2009	-4.87558	0.446301	−10.9244	<0.0001	***

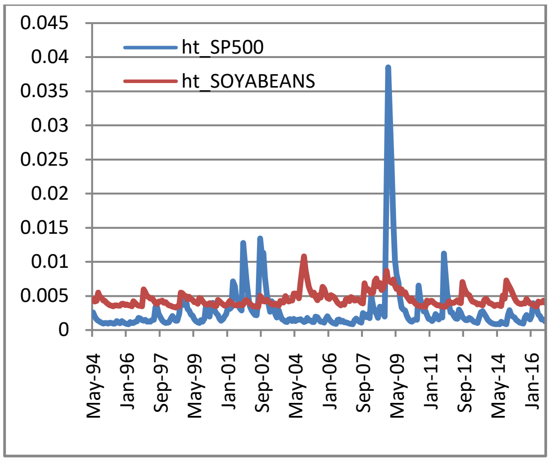
Table 57: Pooled OLS, using 5111 observations- Included 19 cross-sectional units - Time-series length = 269 - Dependent variable: rc - Robust (HAC) standard errors

	Coefficient	***Std. Error***	***t-ratio***	***p-value***	
const	−0.000247161	0.000666229	−0.3710	0.715	
SP500	0.192161	0.069034	2.7836	0.0123	**
D1	−0.15843	0.336629	−0.4706	0.6436	
D2	0.622217	0.262029	2.3746	0.0289	**
D3	−0.472182	0.329826	−1.4316	0.1694	
D4	-0.769774	0.19674	−3.9126	0.001	***
D5	-0.329694	0.159322	−2.0694	0.0532	*
D6	0.959283	0.30593	3.1356	0.0057	***
D8	0.0606606	0.170691	0.3554	0.7264	
D9	-0.322584	0.110622	−2.9161	0.0092	***
D10	0.265548	0.384747	0.6902	0.4989	
D11	0.144787	0.0880433	1.6445	0.1174	
D_SUB_1	−0.242611	0.224284	−1.0817	0.2937	
D_SUB_2	-0.150942	0.166183	−0.9083	0.3757	
D_SUB_3	−0.132393	0.391733	−0.3380	0.7393	
D_SUB_4	-0.942789	0.500056	−1.8854	0.0756	*
D_SUB_5	-0.476162	0.362927	−1.3120	0.206	
D_SUB_6	−0.297942	0.288188	−1.0338	0.3149	
D_SUB_8	0.580715	0.442597	1.3121	0.206	
D_SUB_9	0.0260811	0.342829	0.0761	0.9402	
D_SUB_10	2.78833	3.99327	0.6983	0.4939	
D_SUB_11	-8.78595	2.46145	−3.5694	0.0022	***

GRAPHS

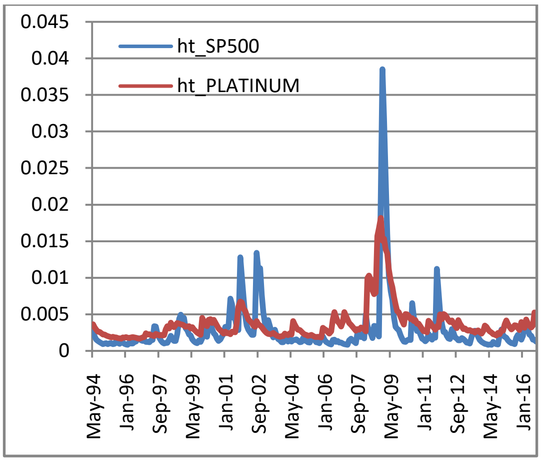
Graph 1

Conditional Volatilities (h_t) of S&P500 and Soyabeans



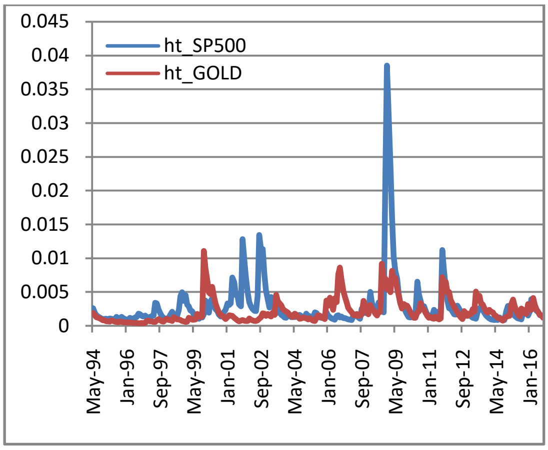
Graph 2

Conditional Volatilities (h_t) of S&P500 and Platinum



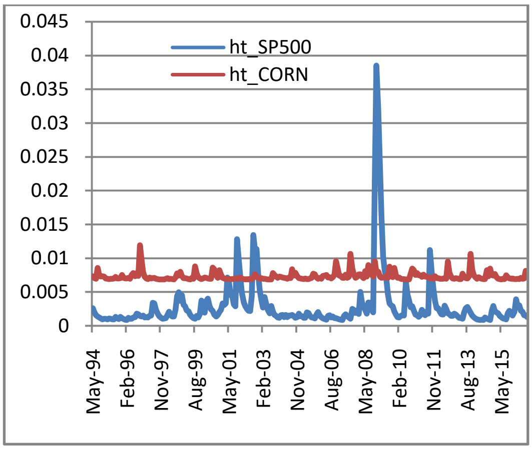
Graph 3

Conditional Volatilities (h_t) of S&P500 and Gold



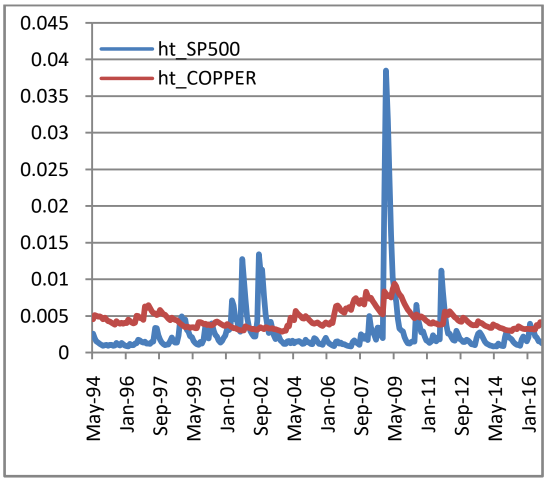
Graph 4

Conditional Volatilities (h_t) of S&P500 and Corn



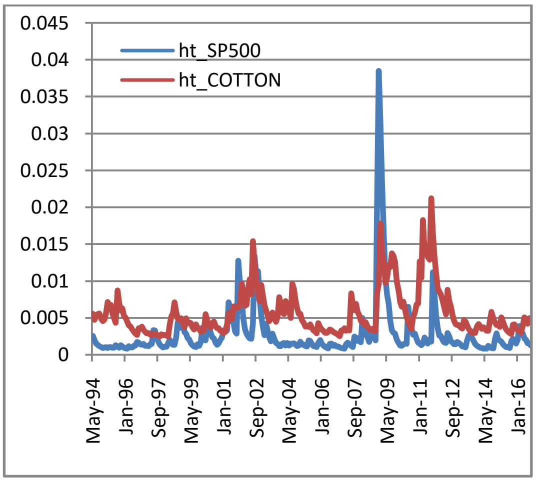
Graph 5

Conditional Volatilities (h_t) of S&P500 and Copper



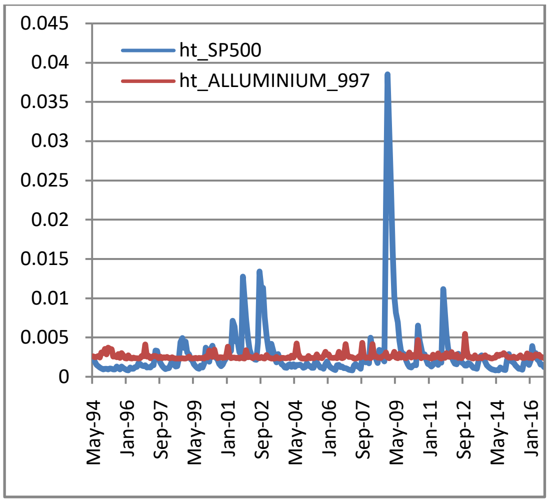
Graph 6

Conditional Volatilities (h_t) of S&P500 and Cotton



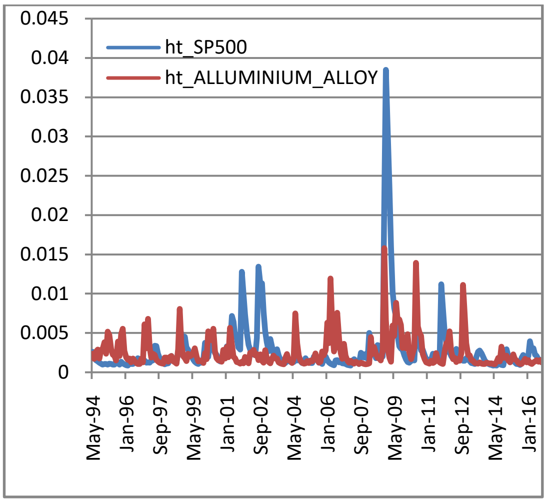
Graph 7

Conditional Volatilities (h_t) of S&P500 and Alluminium 99,7%



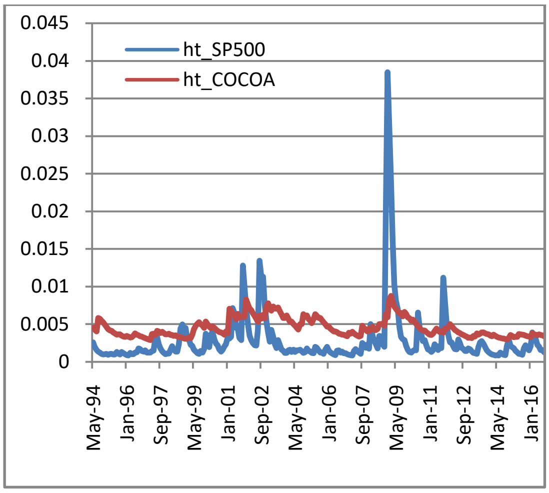
Graph 8

Conditional Volatilities (h_t) of S&P500 and Alluminium Alloy



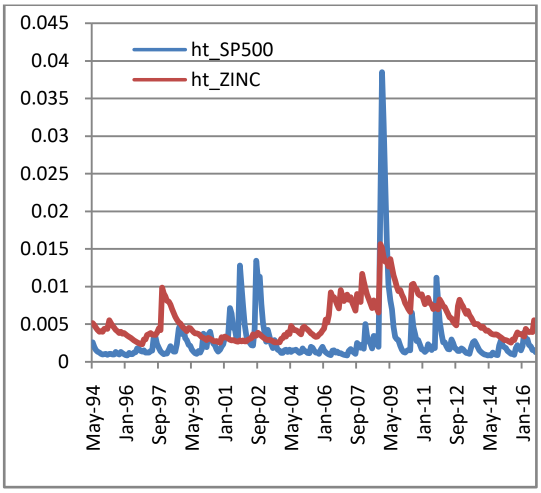
Graph 9

Conditional Volatilities (h_t) of S&P500 and Cocoa



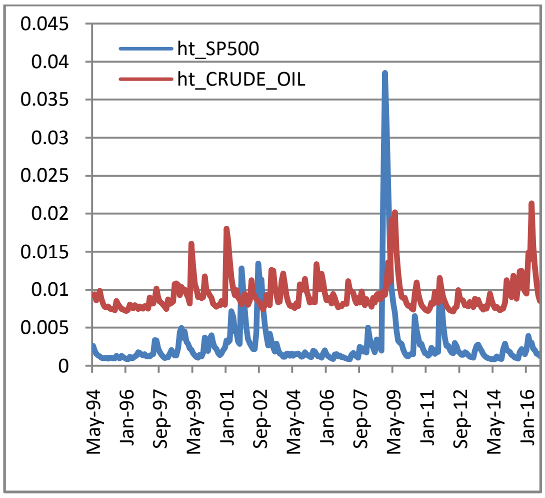
Graph 10

Conditional Volatilities (h_t) of S&P500 and Zinc



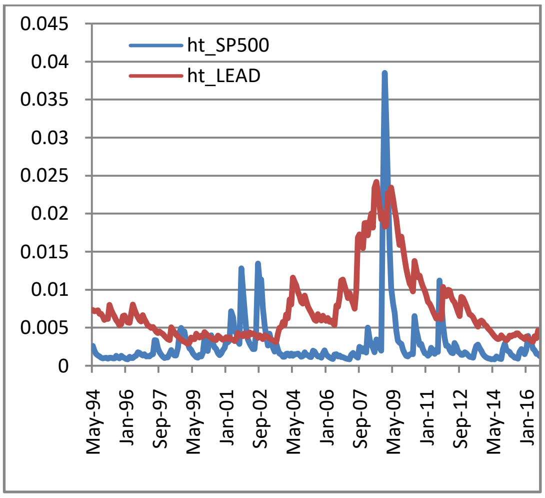
Graph 11

Conditional Volatilities (h_t) of S&P500 and Crude Oil



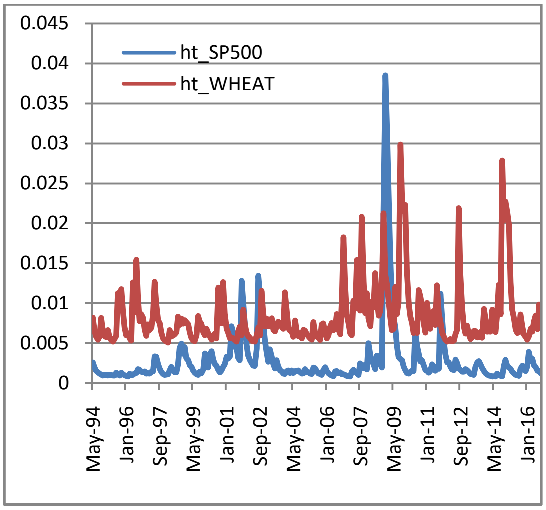
Graph 12

Conditional Volatilities (h_t) of S&P500 and Lead



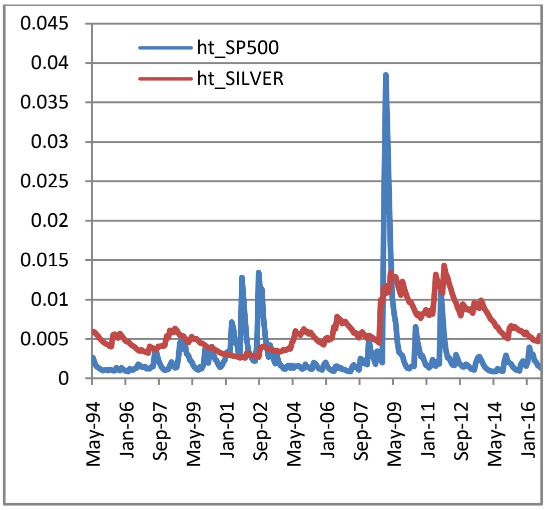
Graph 13

Conditional Volatilities (h_t) of S&P500 and Wheat



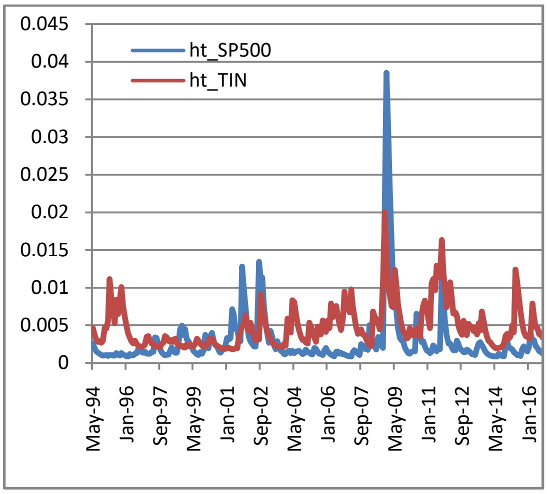
Graph 14

Conditional Volatilities (h_t) of S&P500 and Silver



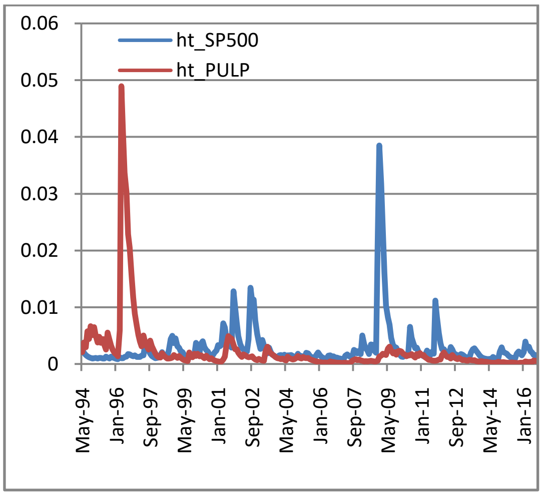
Graph 15

Conditional Volatilities (h_t) of S&P500 and Tin



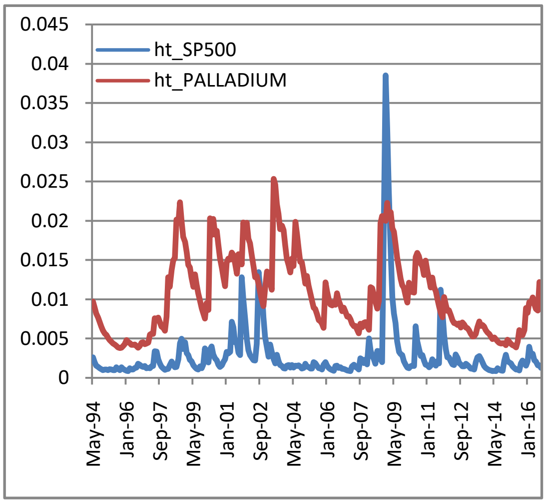
Graph 16

Conditional Volatilities (h_t) of S&P500 and Pulp



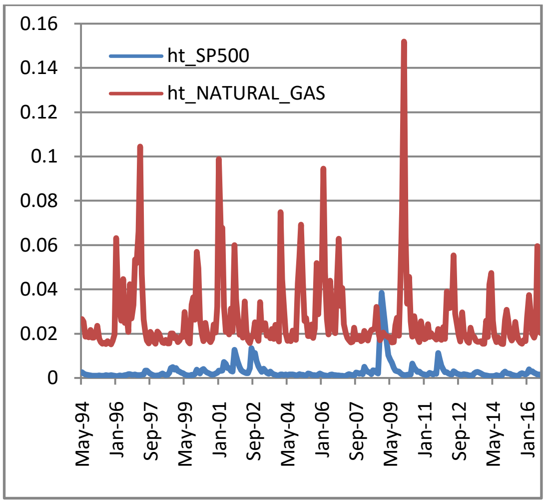
Graph 17

Conditional Volatilities (h_t) of S&P500 and Palladium



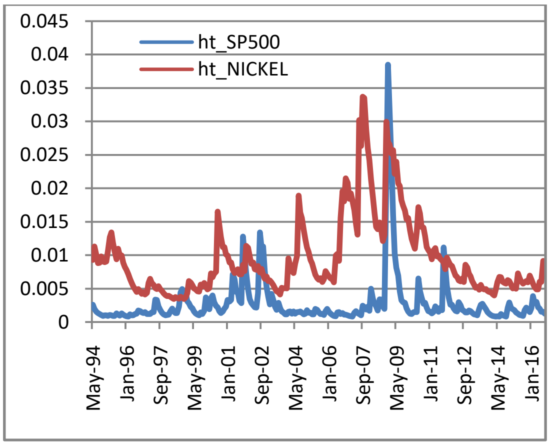
Graph 18

Conditional Volatilities (h_t) of S&P500 and Natural Gas



Graph 19

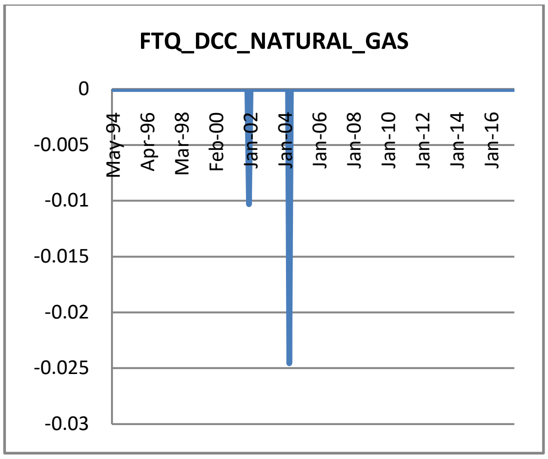
Conditional Volatilities (h_t) of S&P500 and Nickel



Graph 20

Dates of flight-to-quality (FTQ) from the S&P500 to Natural Gas

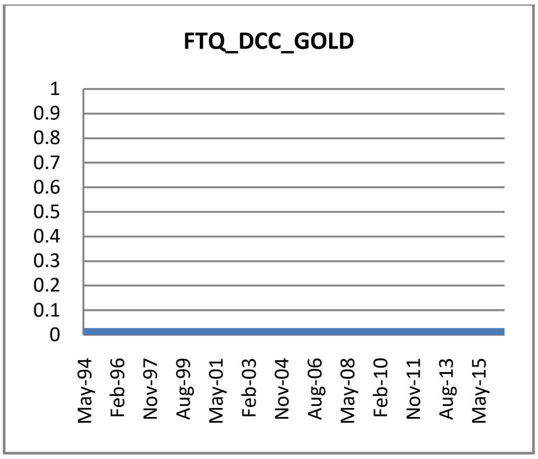
(DCC estimations used)



Graph 21

Dates of flight-to-quality (FTQ) from the S&P500 to Gold

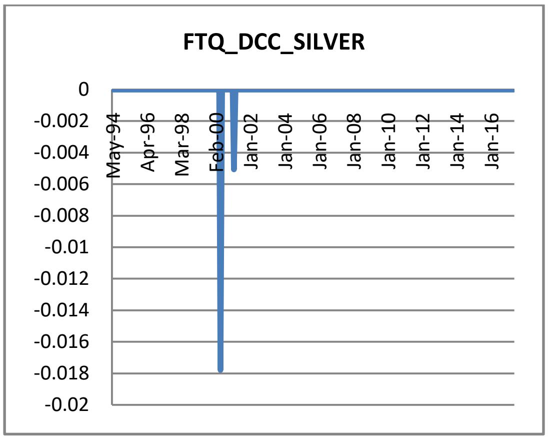
(DCC estimations used)



Graph 22

Dates of flight-to-quality (FTQ) from the S&P500 to Silver

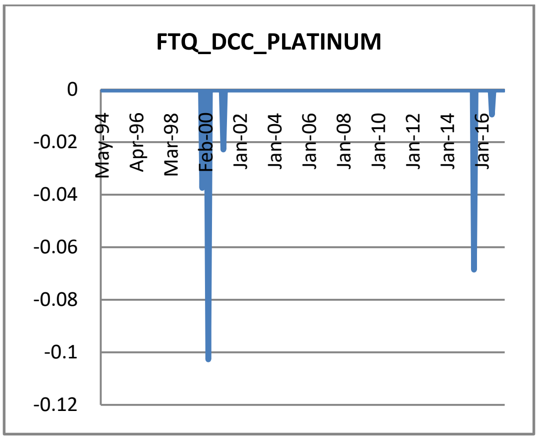
(DCC estimations used)



Graph 23

Dates of flight-to-quality (FTQ) from the S&P500 to Platinum

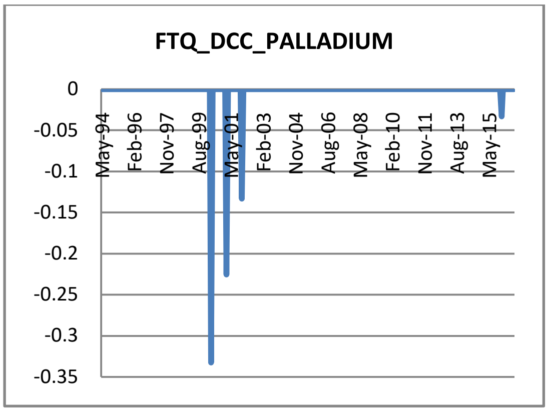
(DCC estimations used)



Graph 24

Dates of flight-to-quality (FTQ) from the S&P500 to Palladium

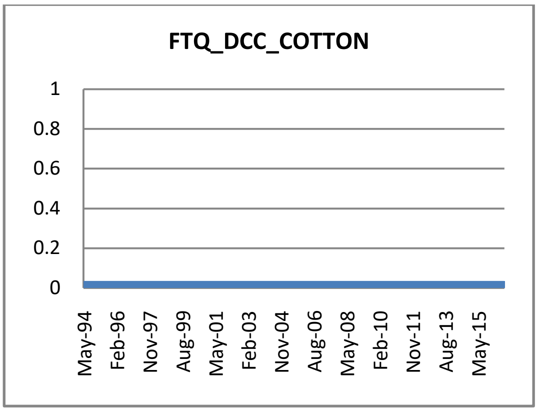
(DCC estimations used)



Graph 25

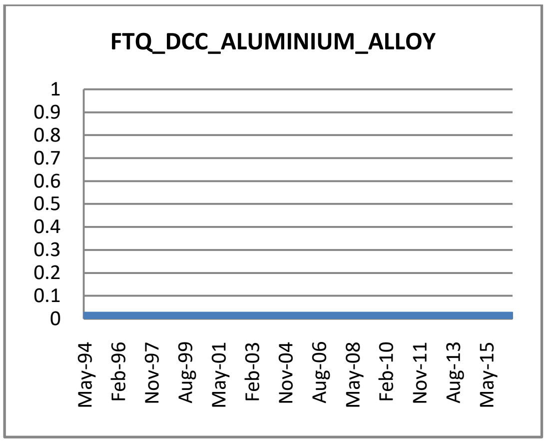
Dates of flight-to-quality (FTQ) from the S&P500 to Cotton

(DCC estimations used)



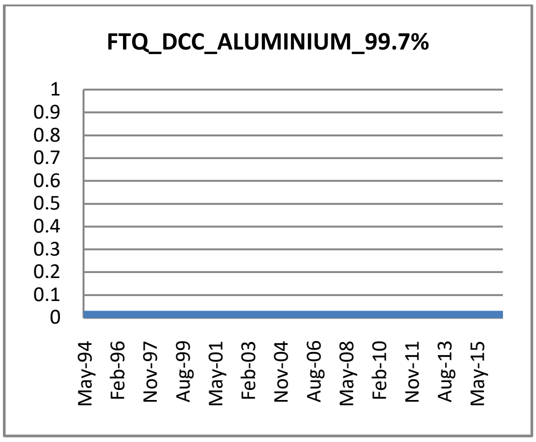
Graph 26

Dates of flight-to-quality (FTQ) from the S&P500 to Alluminium Alloy (DCC estimations used)



Graph 27

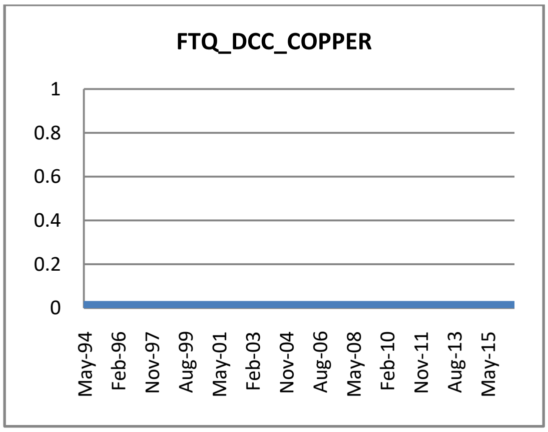
Dates of flight-to-quality (FTQ) from the S&P500 to Alluminium 99,7% (DCC estimations used)



Graph 28

Dates of flight-to-quality (FTQ) from the S&P500 to Copper

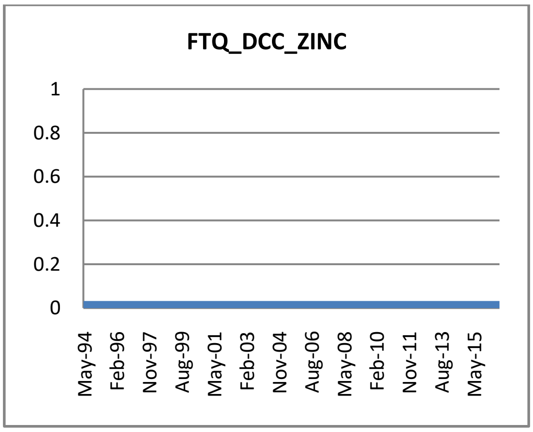
(DCC estimations used)



Graph 29

Dates of flight-to-quality (FTQ) from the S&P500 to Zinc

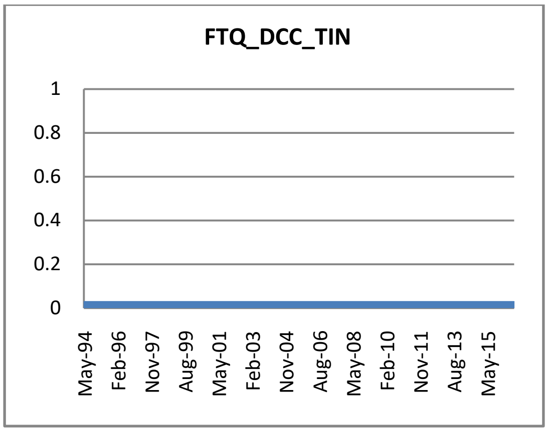
(DCC estimations used)



Graph 30

Dates of flight-to-quality (FTQ) from the S&P500 to Tin

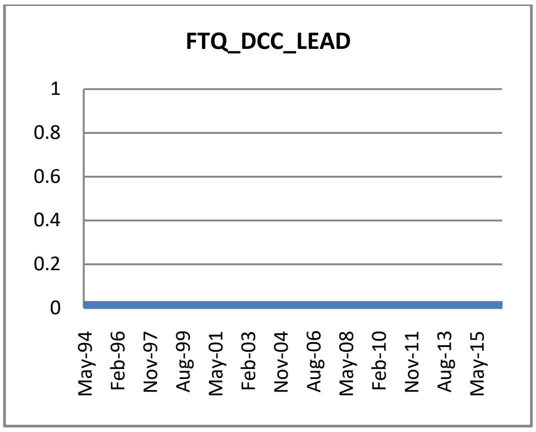
(DCC estimations used)



Graph 31

Dates of flight-to-quality (FTQ) from the S&P500 to Lead

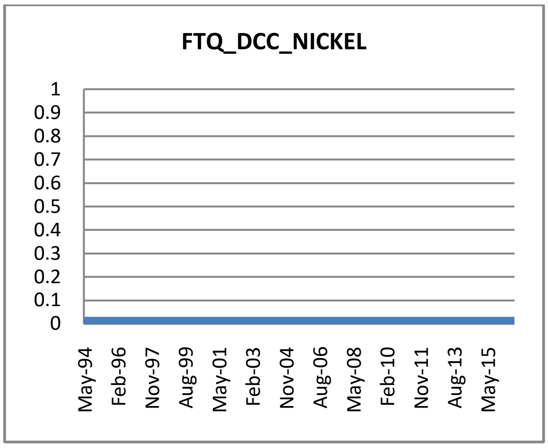
(DCC estimations used)



Graph 32

Dates of flight-to-quality (FTQ) from the S&P500 to Nickel

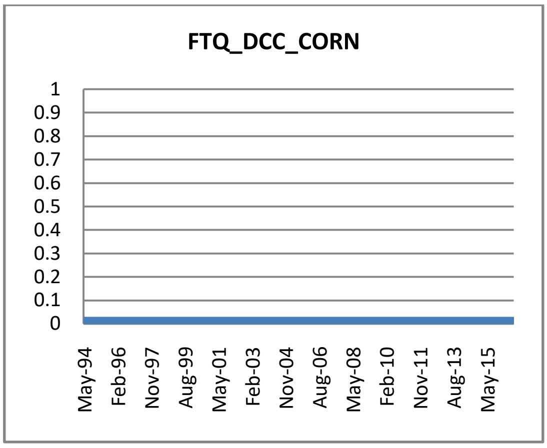
(DCC estimations used)



Graph 33

Dates of flight-to-quality (FTQ) from the S&P500 to Corn

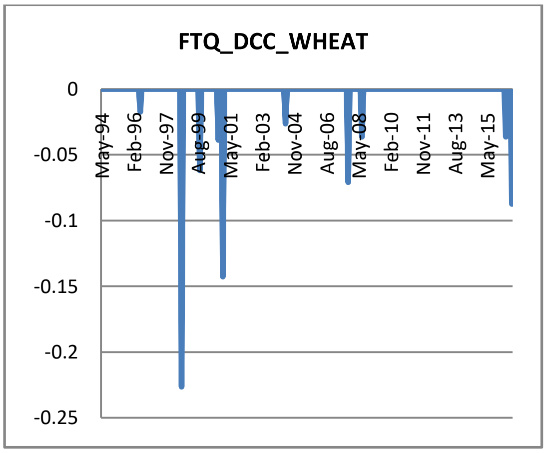
(DCC estimations used)



Graph 34

Dates of flight-to-quality (FTQ) from the S&P500 to Wheat

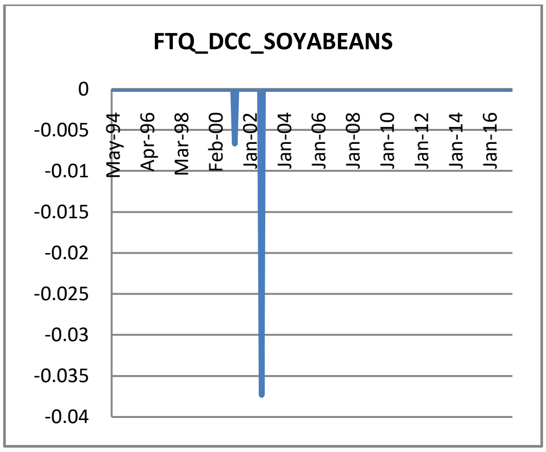
(DCC estimations used)



Graph 35

Dates of flight-to-quality (FTQ) from the S&P500 to Soyabeans

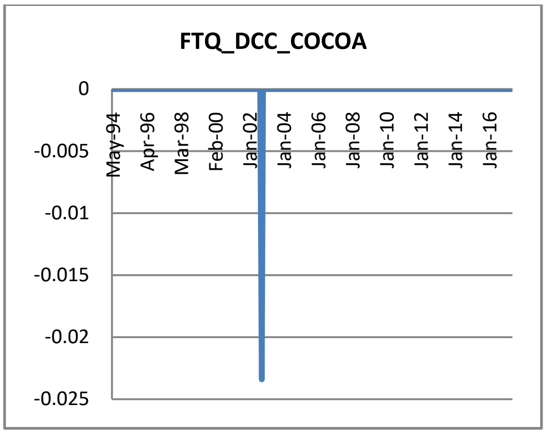
(DCC estimations used)



Graph 36

Dates of flight-to-quality (FTQ) from the S&P500 to Cocoa

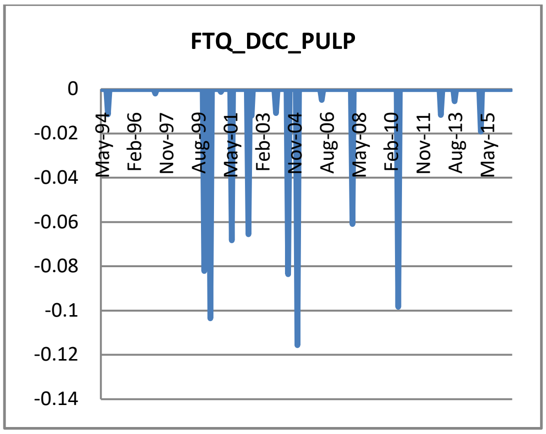
(DCC estimations used)



Graph 37

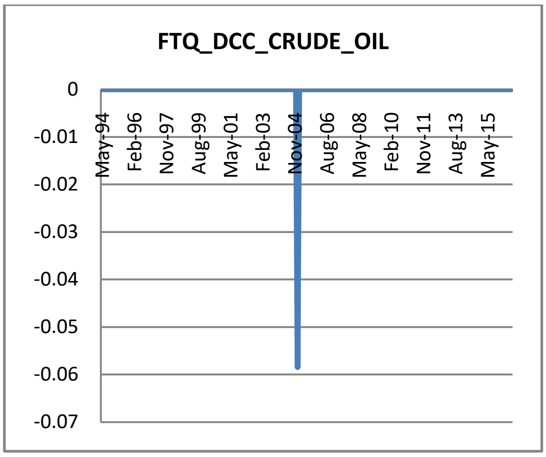
Dates of flight-to-quality (FTQ) from the S&P500 to Pulp

(DCC estimations used)



Graph 38

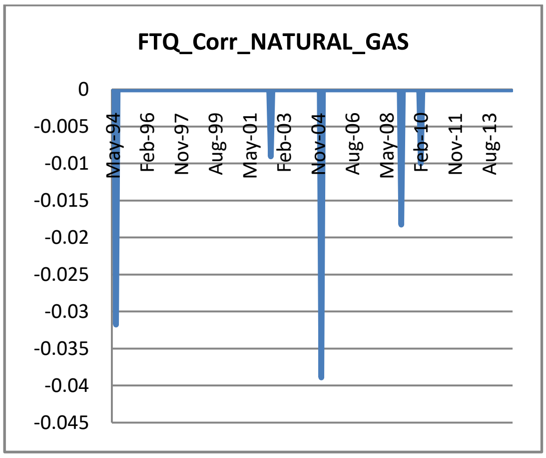
Dates of flight-to-quality (FTQ) from the S&P500 to Crude Oil (DCC estimations used)



Graph 39

Dates of flight-to-quality (FTQ) from the S&P500 to Natural Gas

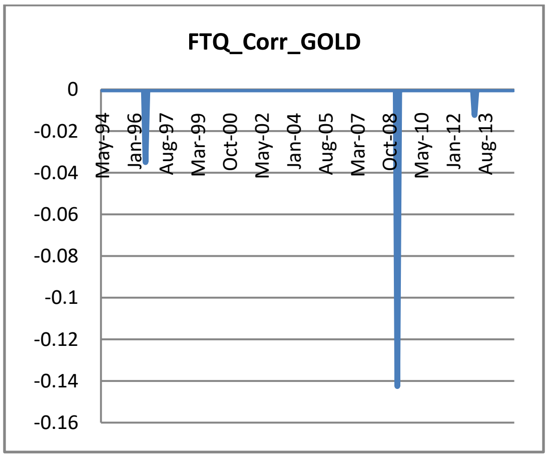
(Rolling window estimations used)



Graph 40

Dates of flight-to-quality (FTQ) from the S&P500 to Gold

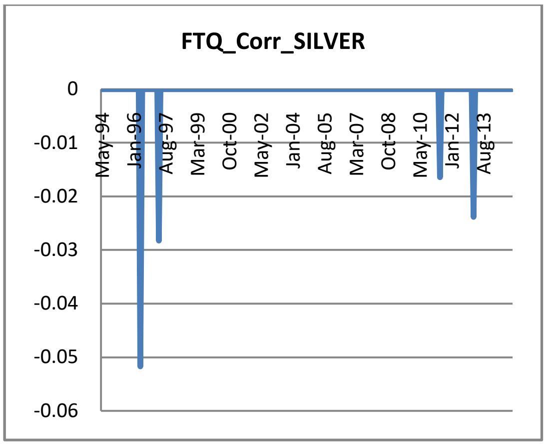
(Rolling window estimations used)



Graph 41

Dates of flight-to-quality (FTQ) from the S&P500 to Silver

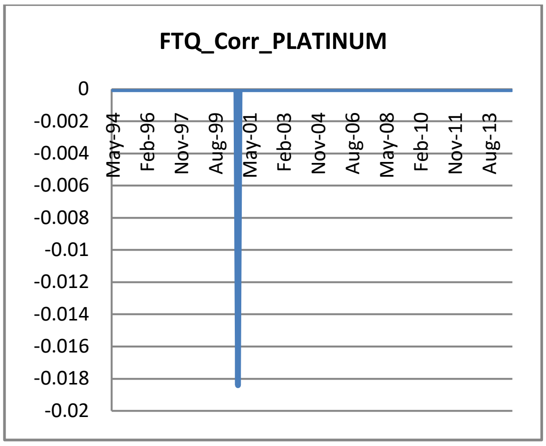
(Rolling window estimations used)



Graph 42

Dates of flight-to-quality (FTQ) from the S&P500 to Platinum

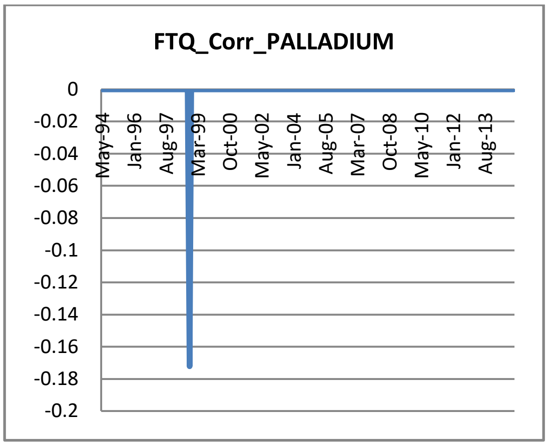
(Rolling window estimations used)



Graph 43

Dates of flight-to-quality (FTQ) from the S&P500 to Palladium

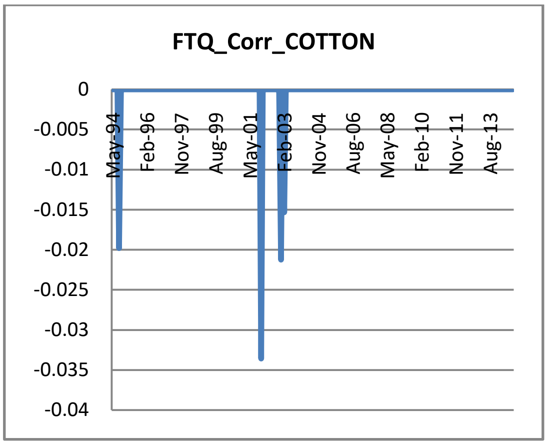
(Rolling window estimations used)



Graph 44

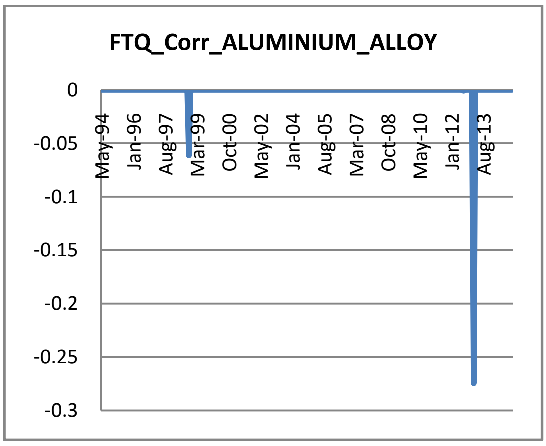
Dates of flight-to-quality (FTQ) from the S&P500 to Cotton

(Rolling window estimations used)



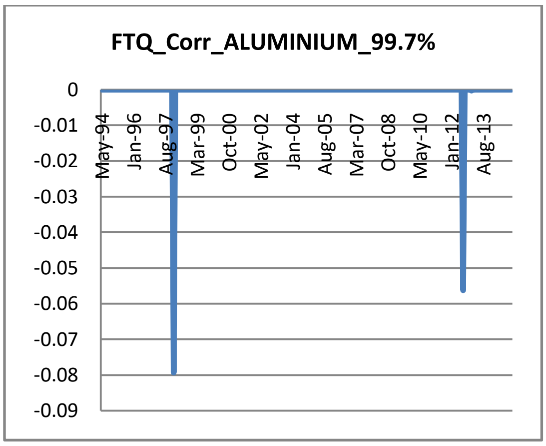
Graph 45

Dates of flight-to-quality (FTQ) from the S&P500 to Alluminium Alloy (Rolling window estimations used)



Graph 46

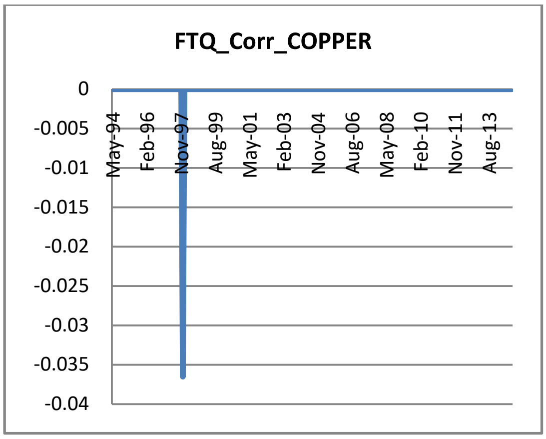
Dates of flight-to-quality (FTQ) from the S&P500 to Alluminium 99,7% (Rolling window estimations used)



Graph 47

Dates of flight-to-quality (FTQ) from the S&P500 to Copper

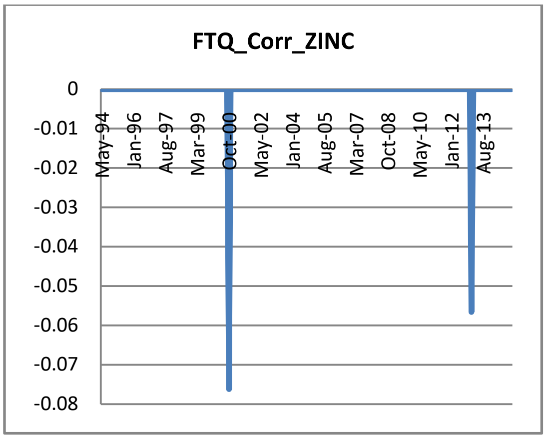
(Rolling window estimations used)



Graph 48

Dates of flight-to-quality (FTQ) from the S&P500 to Zinc

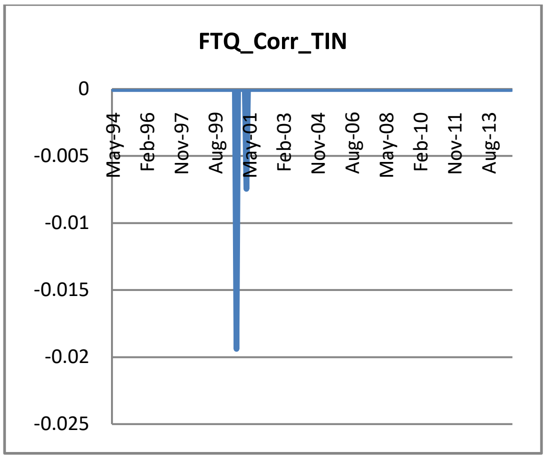
(Rolling window estimations used)



Graph 49

Dates of flight-to-quality (FTQ) from the S&P500 to Tin

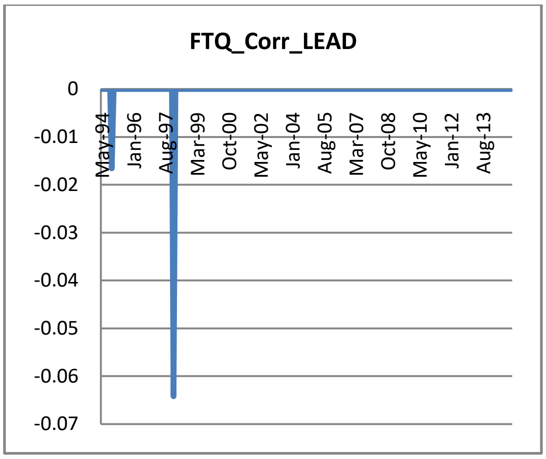
(Rolling window estimations used)



Graph 50

Dates of flight-to-quality (FTQ) from the S&P500 to Lead

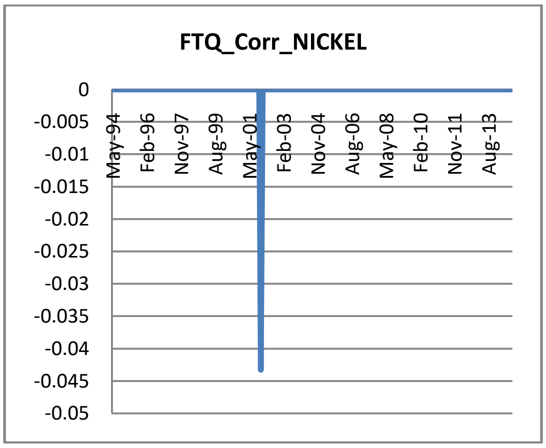
(Rolling window estimations used)



Graph 51

Dates of flight-to-quality (FTQ) from the S&P500 to Nickel

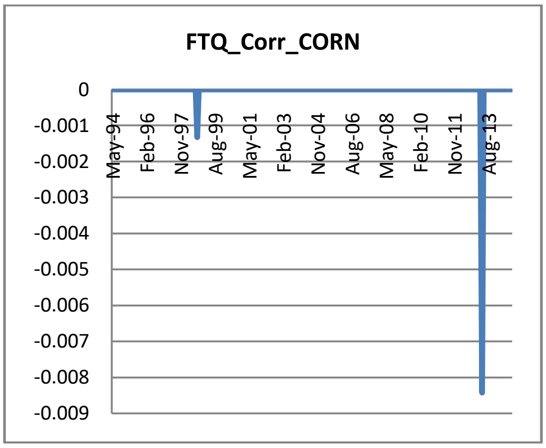
(Rolling window estimations used)



Graph 52

Dates of flight-to-quality (FTQ) from the S&P500 to Corn

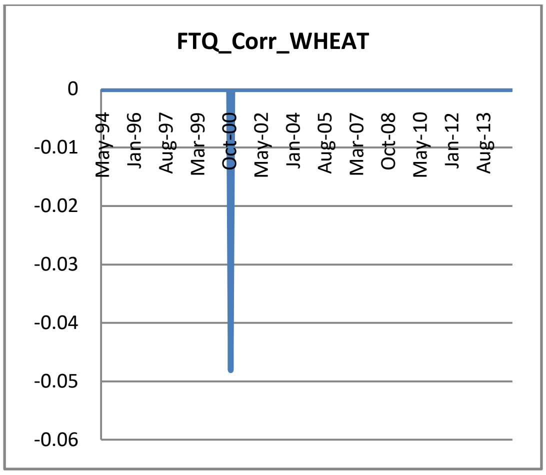
(Rolling window estimations used)



Graph 53

Dates of flight-to-quality (FTQ) from the S&P500 to Wheat

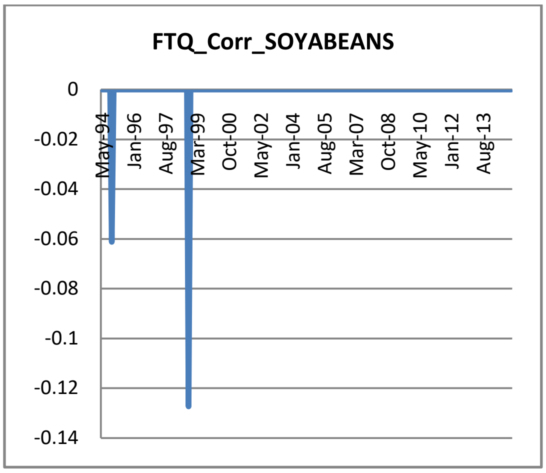
(Rolling window estimations used)



Graph 54

Dates of flight-to-quality (FTQ) from the S&P500 to Soyabeans

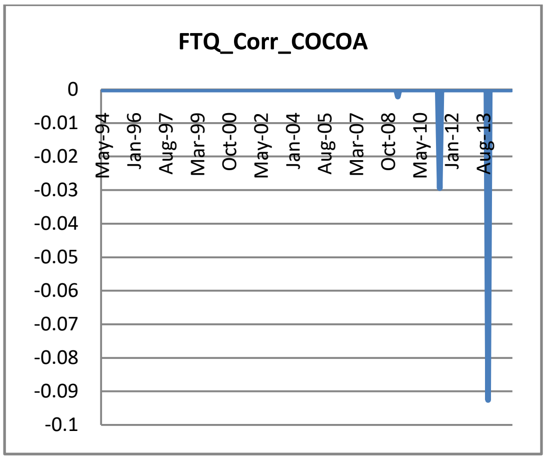
(Rolling window estimations used)



Graph 55

Dates of flight-to-quality (FTQ) from the S&P500 to Cocoa

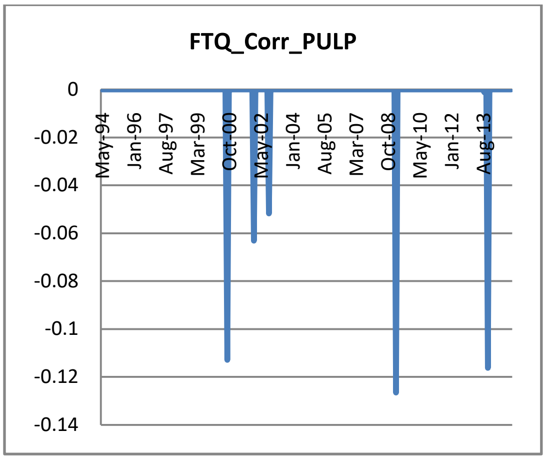
(Rolling window estimations used)



Graph 56

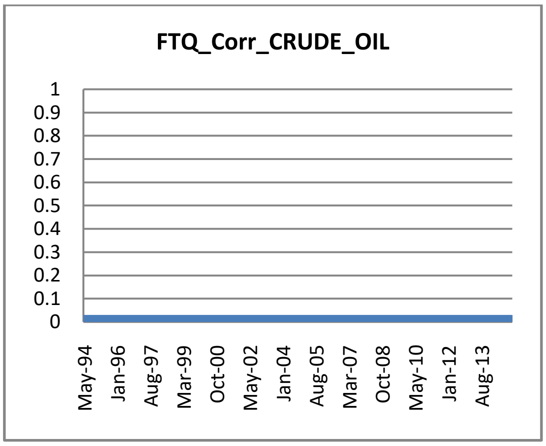
Dates of flight-to-quality (FTQ) from the S&P500 to Pulp

(Rolling window estimations used)



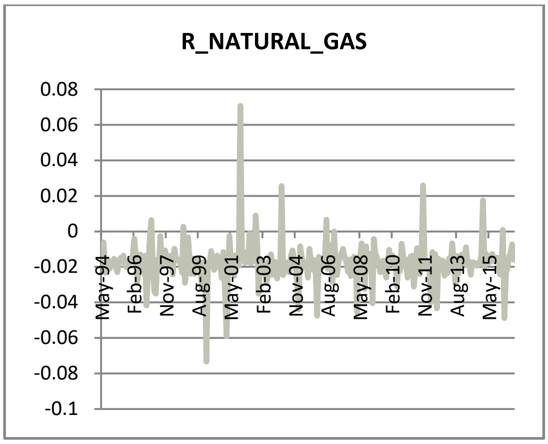
Graph 57

Dates of flight-to-quality (FTQ) from the S&P500 to Crude Oil (Rolling window estimations used)



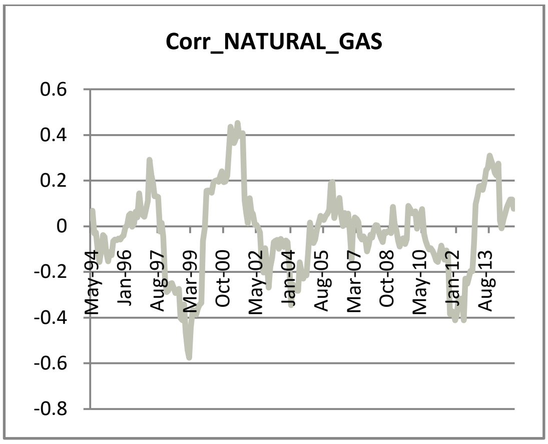
Graph 58

DCCs between S&P500 and Natural Gas



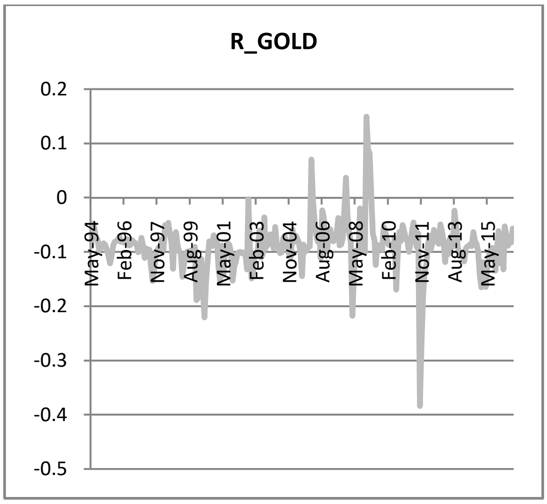
Graph 59

Rolling window correlations between S&P500 and Natural Gas



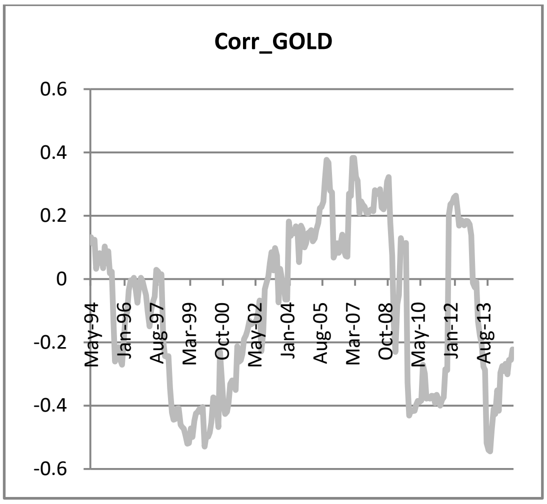
Graph 60

DCCs between S&P500 and Gold



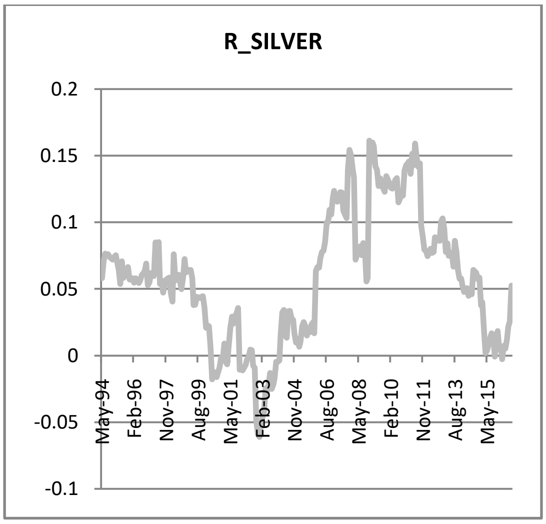
Graph 61

Rolling window correlations between S&P500 and Gold



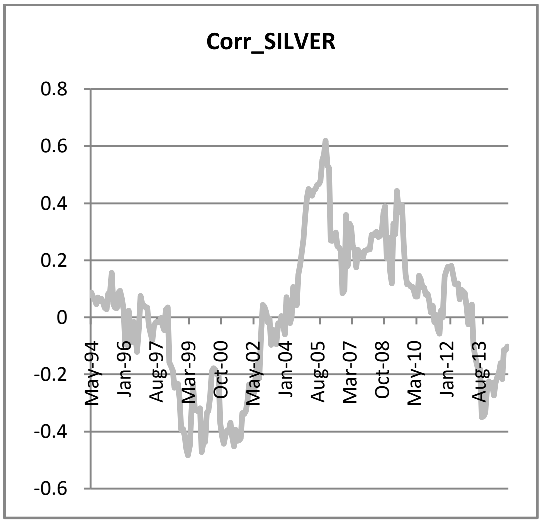
Graph 62

DCCs between S&P500 and Silver



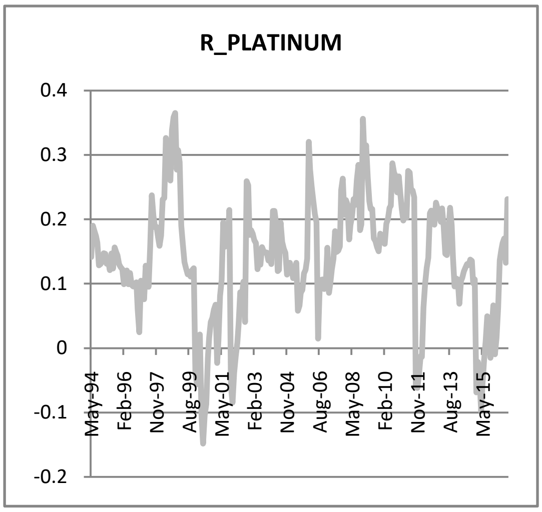
Graph 63

Rolling window correlations between S&P500 and Silver



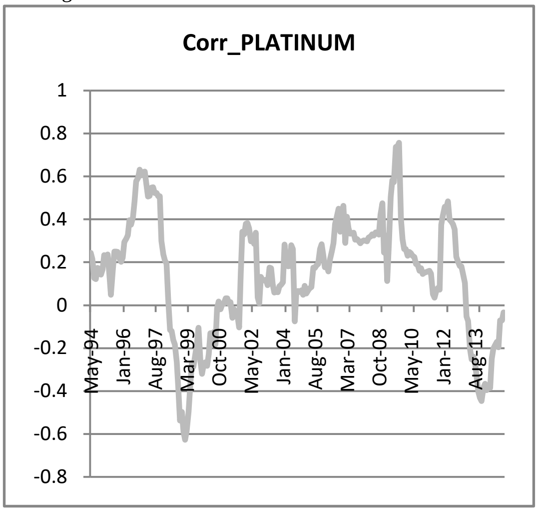
Graph 64

DCCs between S&P500 and Platinum



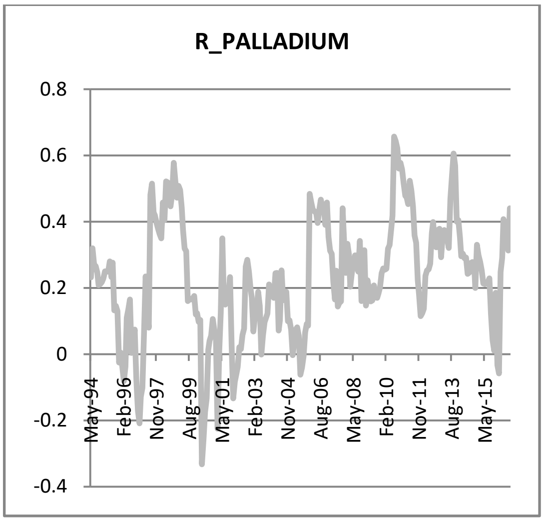
Graph 65

Rolling window correlations between S&P500 and Platinum



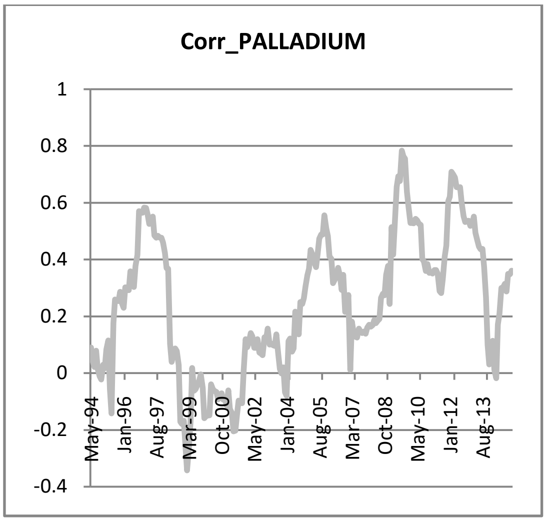
Graph 66

DCCs between S&P500 and Palladium



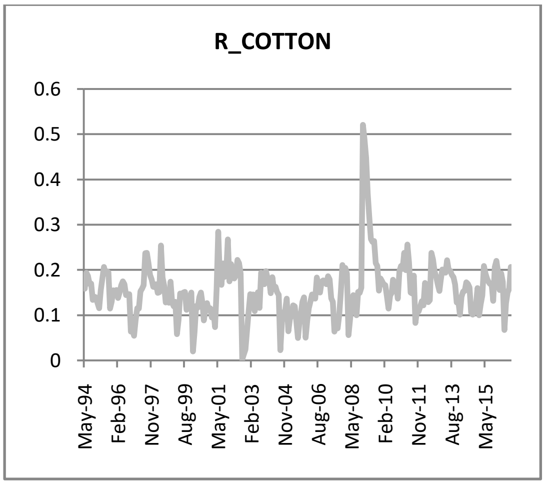
Graph 67

Rolling window correlations between S&P500 and Palladium



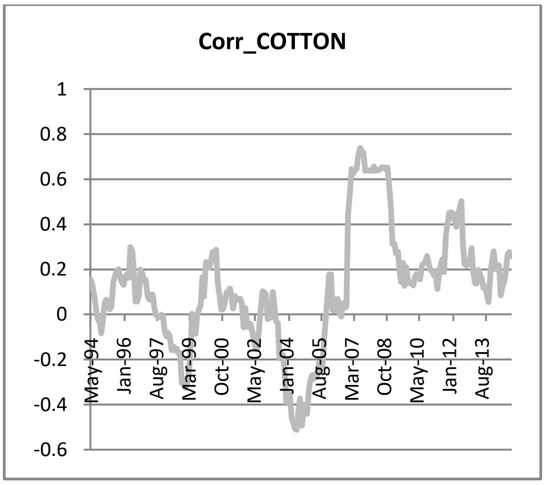
Graph 68

DCCs between S&P500 and Cotton



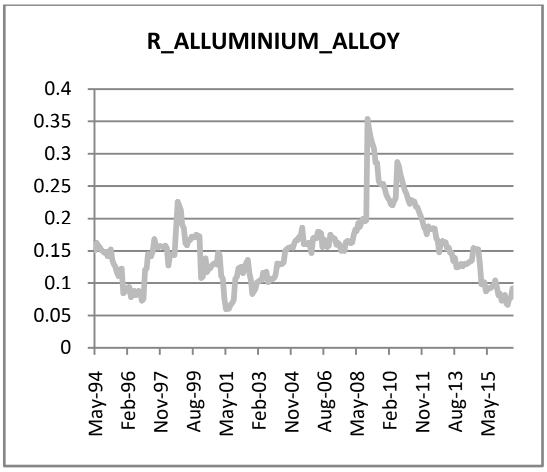
Graph 69

Rolling window correlations between S&P500 and Cotton



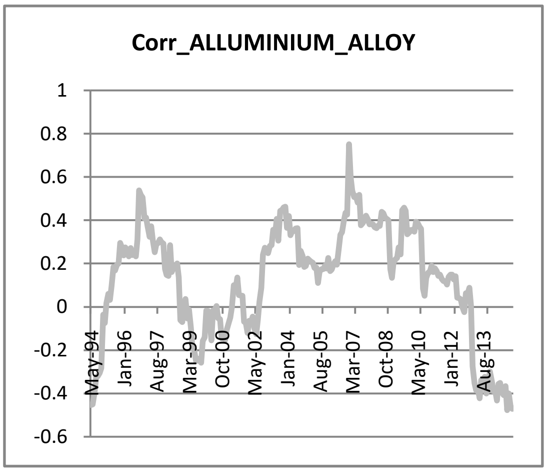
Graph 70

DCCs between S&P500 and Alluminium Alloy



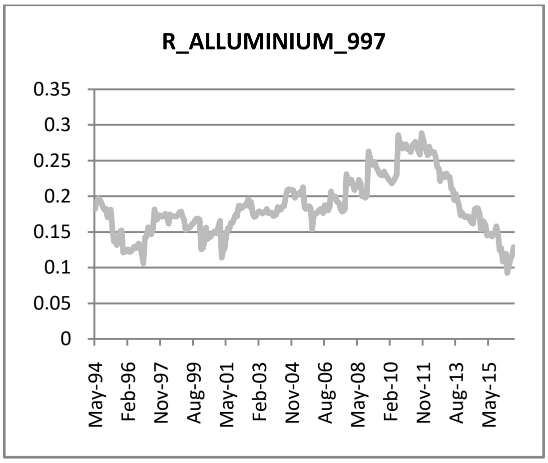
Graph 71

Rolling window correlations between S&P500 and Alluminium Alloy



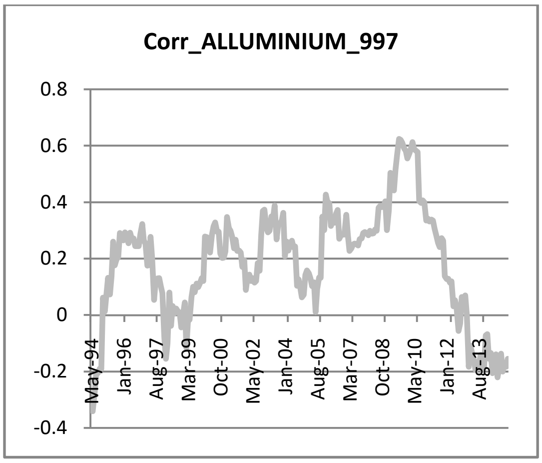
Graph 72

DCCs between S&P500 and Alluminium 99,7%



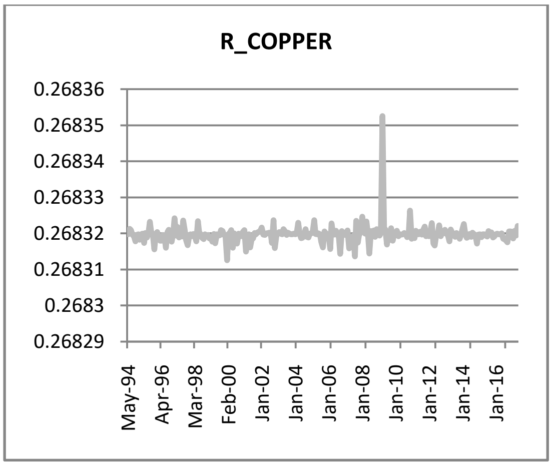
Graph 73

Rolling window correlations between S&P500 and Alluminium 99,7%



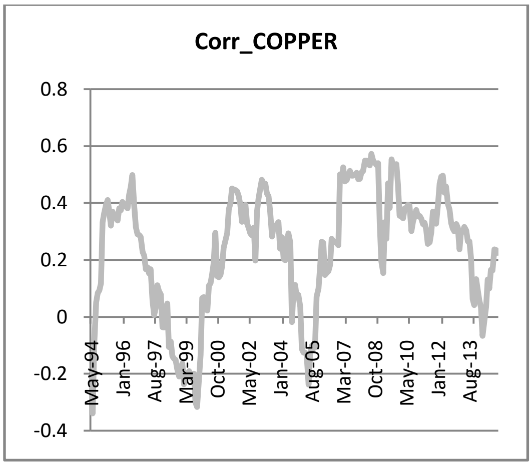
Graph 74

DCCs between S&P500 and Copper



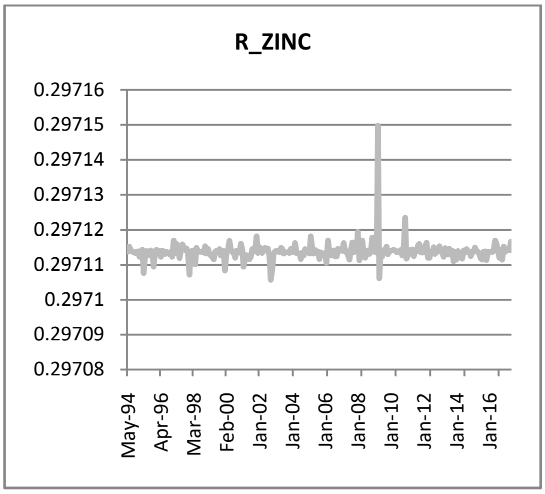
Graph 75

Rolling window correlations between S&P500 and Copper



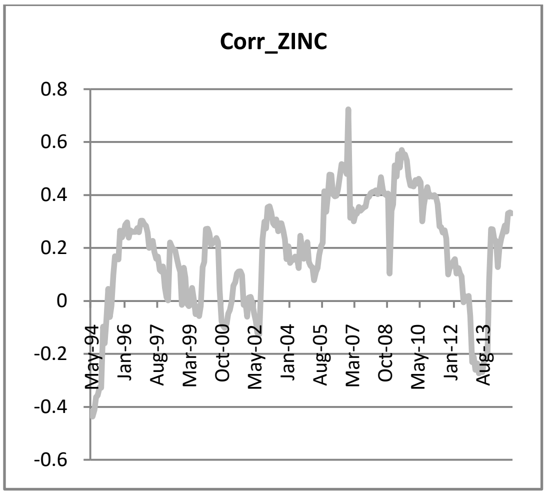
Graph 76

DCCs between S&P500 and Zinc



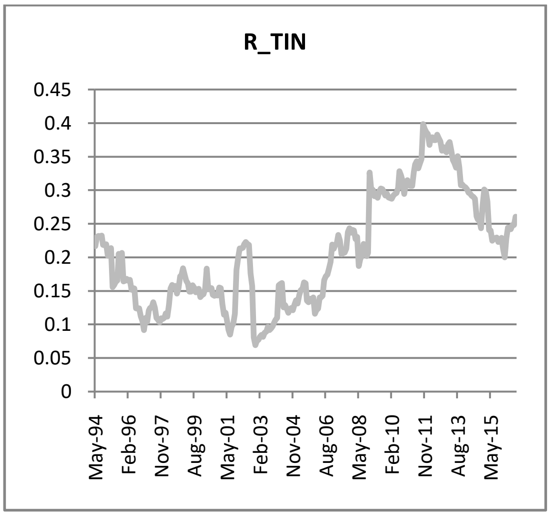
Graph 77

Rolling window correlations between S&P500 and Zinc



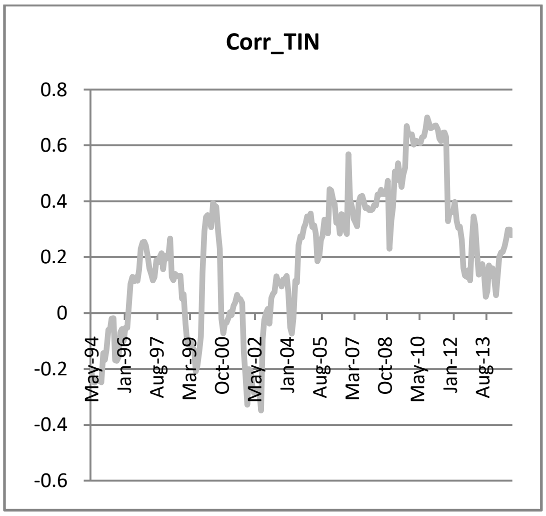
Graph 78

DCCs between S&P500 and Tin



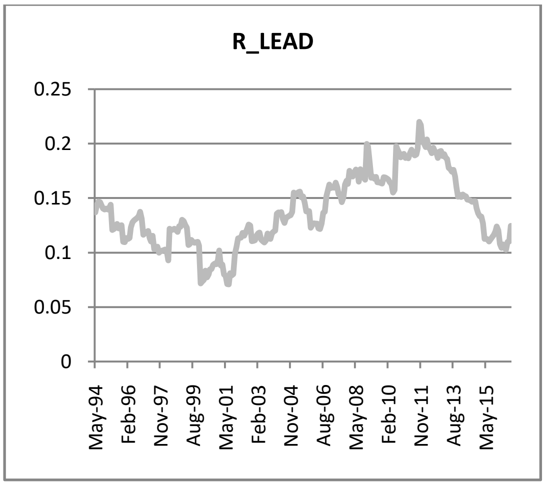
Graph 79

Rolling window correlations between S&P500 and Tin



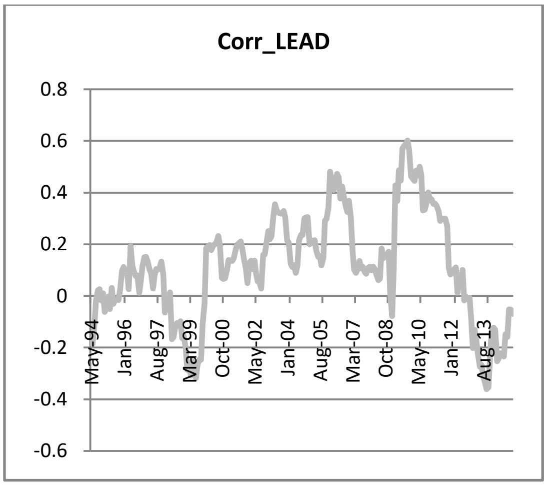
Graph 80

DCCs between S&P500 and Lead



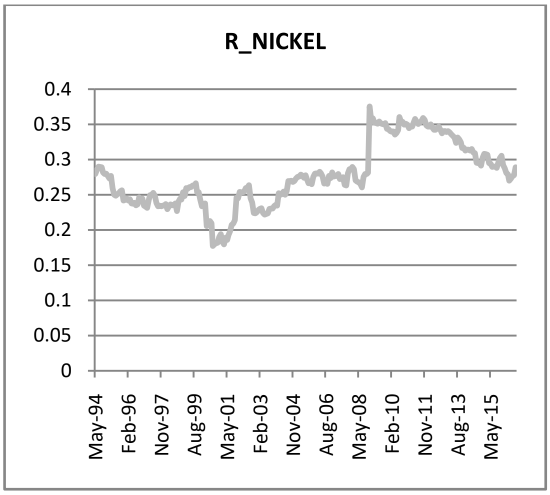
Graph 81

Rolling window correlations between S&P500 and Lead



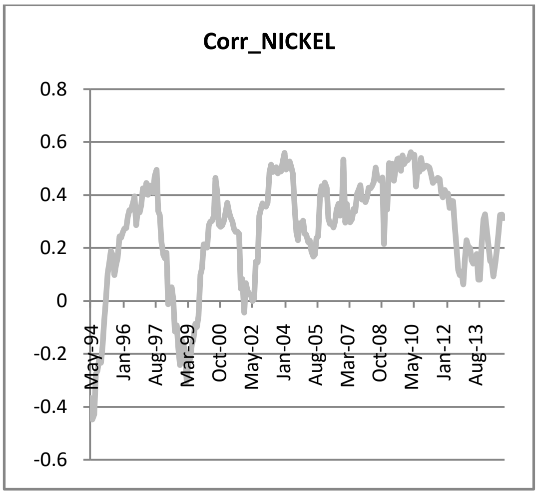
Graph 82

DCCs between S&P500 and Nickel



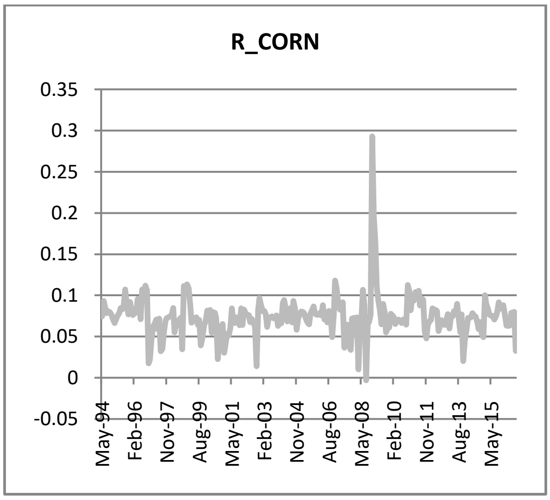
Graph 83

Rolling window correlations between S&P500 and Nickel



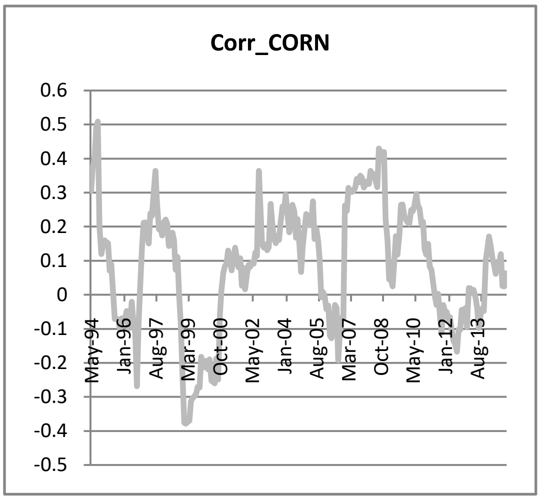
Graph 84

DCCs between S&P500 and Corn



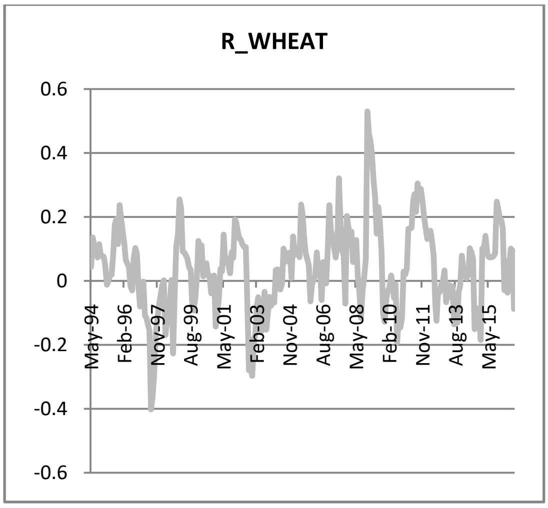
Graph 85

Rolling window correlations between S&P500 and Corn



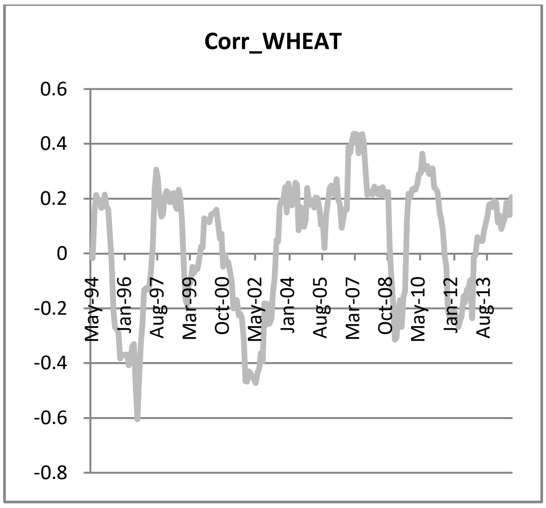
Graph 86

DCCs between S&P500 and Wheat



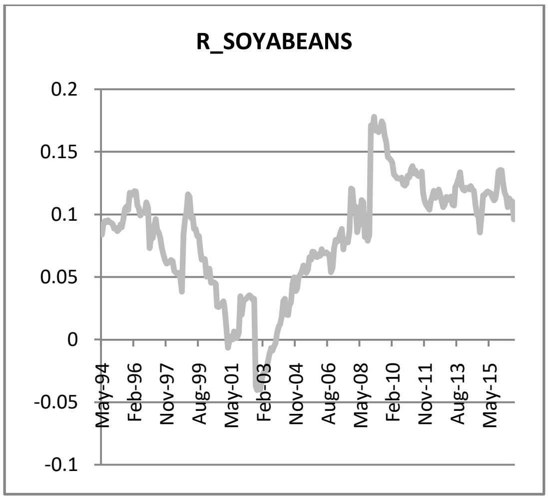
Graph 87

Rolling window correlations between S&P500 and Wheat



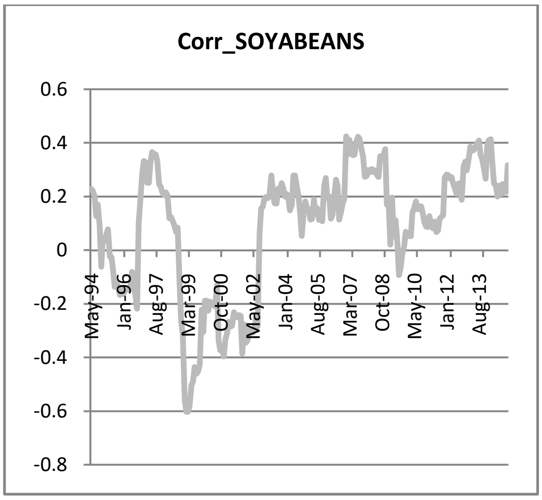
Graph 88

DCCs between S&P500 and Soyabeans



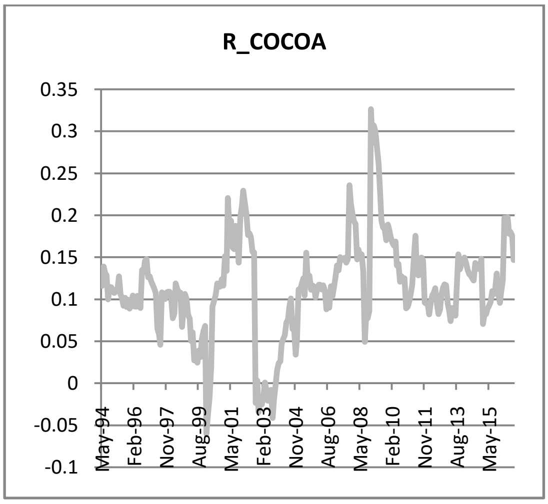
Graph 89

Rolling window correlations between S&P500 and Soyabeans



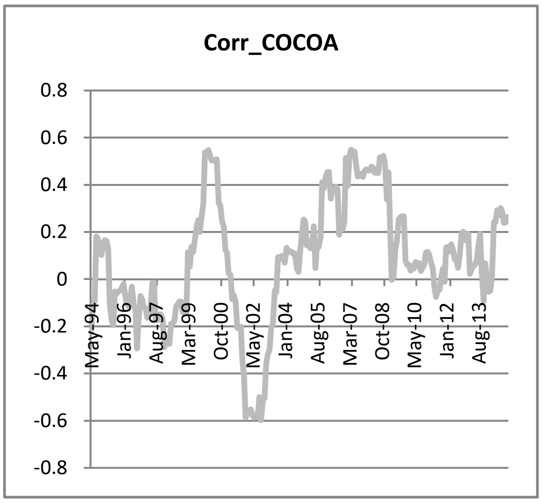
Graph 90

DCCs between S&P500 and Cocoa



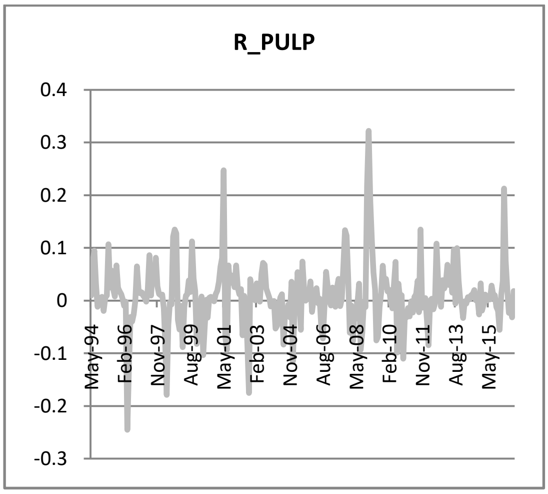
Graph 91

Rolling window correlations between S&P500 and Cocoa



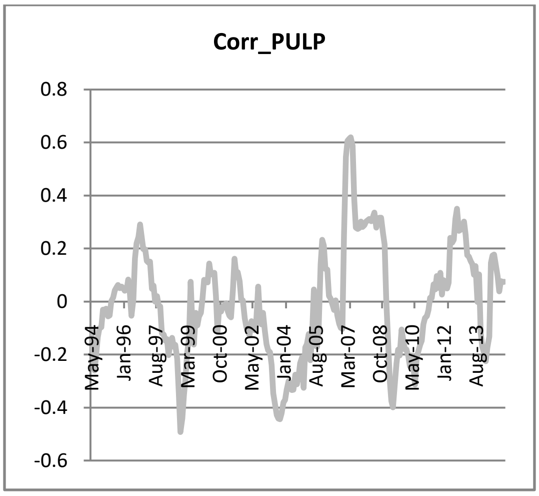
Graph 92

DCCs between S&P500 and Pulp



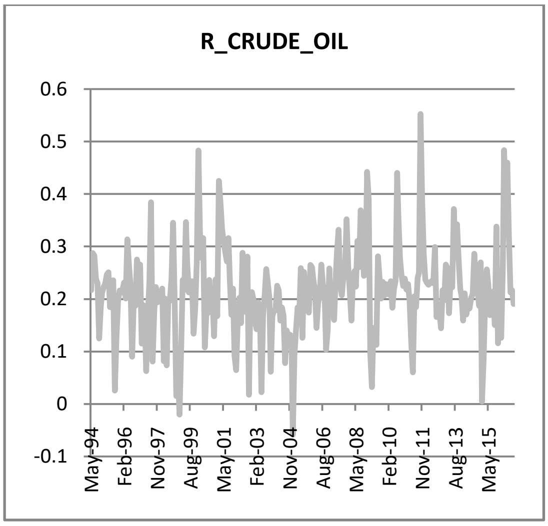
Graph 93

Rolling window correlations between S&P500 and Pulp



Graph 94

DCCs between S&P500 and Crude Oil



Graph 95

Rolling window correlations between S&P500 and Crude Oil