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GLOBAL MARKETS UNDER THE MICROSCOPE

The most recent dynamic linkages across global commodities, equity and currency markets and their implications for portfolio risk management.

August 24, 2016

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Abstract

This study takes a global perspective in examining the most recent relationships between the world prices of three key commodities - oil, industrial and precious metals, the global stock market and the broad US dollar exchange rate. Second, it assesses the cross-asset correlation and volatility properties of these asset classes to provide practical implication for global equity portfolio managers and policy makers with respect to optimal asset allocation and hedging strategies among these markets. The research utilizes daily frequency data and is covering two periods 1) June 1, 2012 – Oct 1, 2014 and 2) Oct 1, 2014 – May 20, 2016.

In terms of long-run dynamics, the empirical results from the ARDL models show that there is no long-run relationship between the five markets. However, the impulse response functions reveal short-run positive two-way interactions between the prices of oil, industrial metals, precious metals and world equity markets, and significant negative two-way interactions between these four markets and the global exchange rate represented by the broad US dollar trade weighted index. Furthermore, variance decomposition provides evidence that during the second period, world equity markets, industrial metals and the global exchange rate became more heavily driven by movements in oil prices. In terms of investment decisions, the DCC-GARCH portfolio optimization results indicate that a pure global equity investor could reap strong diversification benefits being invested in the broad US dollar index. Furthermore, shorting precious metals is the most effective strategy that an equity investor could use in order to minimize the risk associated with global equity price fluctuations. Lastly, the investor should currently stay out of the oil markets because buying derivatives based on a broad oil index would only increase the riskiness of the portfolio without bringing any extra returns.

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1. Introduction

The objective of the paper is twofold. First, it quantitatively examines the dynamic cross-market linkages between global prices of commodities such as oil, industrial and precious metals, the world stock market and the global exchange rate. Second, it assesses the cross-asset correlation and volatility properties of these asset classes to provide practical implications for global equity portfolio managers and policy makers with respect to optimal asset allocation, portfolio risk management and diversification benefits among these markets.

Regarding the first objective of this study, recent developments in the global industrial commodity markets have revived the interest of policy makers in the dynamic relationships between commodities and more traditional asset classes such as equity and currencies. Some of those recent developments include the end-of-2014 OPEC breakdown or China's ongoing rebalancing away from commodity-heavy industries. These have caused large swings in oil and metals price which can severely affect the performance of equity markets, currencies, regions and sectors. For instance, for commodity producing nations, falling prices mean lost export earnings, lost jobs and currency crises (The Economist, 2015). Therefore to ensure financial stability policy makers should respond in a timely manner to such shocks, while similarly, investors need to be aware of this indirect exposure to manage their overall portfolio risk and return.

Regarding the second objective of this study, global investors in many financial institutions often look into commodity markets searching for new ways to diversify their portfolio investments. These markets are viewed as a profitable alternative destination since historically they have exhibited low correlation with traditional asset classes such as equity and bonds and positive co-movement with inflation. The low correlation implies that including commodities in a traditional stock only portfolio can reduce the overall risk and improve the risk-adjusted performance of the total portfolio. Considering the aforementioned benefits, capital allocations to both commodity and financial assets have become increasingly popular and now stock investors also often choose commodities such as precious metals as a refuge during periods of stress in traditional asset markets (Silvennoinen & Thorp, 2013). On the other hand, if commodity securities and conventional financial assets are concurrently held by more investors, the set of common state variables driving stochastic discount factors grows. In a nutshell this means that the recent bad developments in commodity markets may cause liquidation across several markets and this is exactly the reason why global investors are worried about the systemic risk from the commodity price rout via industrial companies and the banking system.

As noted earlier, one of those peculiar commodity market developments is the steady downward trend in industrial and precious metals prices since 2011. In particular, Bloomberg industrial metals index, which tracks the performance of a broad range of industrial metals, fell by 53% between 2011 and 2016, while the Bloomberg precious metals index decreased by 51% during the same period. China consumes around half of the global production of metals and the ongoing rebalancing away from commodity-heavy sectors has significantly contributed to the decrease in prices. Extraction costs have also fallen due to low energy prices and this, together with lower demand from China, further contributed to this long-term decrease in metal prices (The Riksbank, 2016). More recently, crude oil prices fell by 60% between June 2014 and June 2016, from $115 to $50 a barrel respectively, making it one of the quickest and largest declines in oil history. This near 60% plunge can be attributed to a number of factors: several years of upward surprises in the production of unconventional shale oil, geopolitical risks, sluggish world demand which is also reflected in the decline of metals prices, an appreciation of the US dollar and most importantly to OPEC itself, which kept producing more oil than what the markets had expected. Retrospectively, the sudden 2014 drop in the price of oil that was caused mostly by OPEC was succeeded by the expansion of oil supply from non-OPEC countries and in particular, an increase in US shale production. In response to that, in November 2014, OPEC decided to maintain its' output level of 30 million barrels a day which in turn signalled a shift in the cartel's strategy from "stabilization of prices in international oil markets", i.e. price targeting, to maintaining market share hoping that would squeeze US shale operators and drive out the highest-cost producers - further dampening the price of oil (Financial Times, 2016).

Overall, given this fundamental commodity price uncertainty, and especially oil uncertainty caused by both supply and demand factors, CME group (2016) report that investors have recently shifted their focus away from the benefits of cheap commodities to the risk of growth-damaging deflation. According to the group, credit fears of defaulting energy and metals companies have prompted stocks to be much more heavily driven by movements in oil and metals prices than they normally are. The possibility of increased defaults has also led bank stocks to correlate much more tightly with fluctuations in the price of crude oil, while the deteriorating current account balances of oil and metals commodity net exporters cause their currencies to depreciate against the dollar (The Riksbank, 2016). All in all, this implies that in 2016 oil, metals, global equity and exchange rates are expected to co-move together and bad news is that one market can cause liquidation across the other markets as well, meaning that the diversification benefits of combining these assets in a multi-asset class portfolio are disappearing and hedging strategies become much more expensive. Therefore, before adjusting their asset allocations or formulating an optimal hedging strategy, global investors must carefully assess the risk transmission channels and time-varying market conditions in the current context of volatile stocks, plunging metals prices and increasing uncertainty in the crude oil market. Also, as already mentioned, a good understanding of commodity prices' behaviour and their interdependences as well as their relation to the equity and currency markets is also important for producers, consumers, and policymakers.

In the light of these complex relations between the markets and their implications on investment strategies, the paper firstly examines dynamic cross-linkages between global oil, industrial and precious metals, exchange rates (U.S. dollar against a basket of 26 other currencies) and equity prices and then builds on to provide two practical examples of portfolio diversification and hedging from the perspective of a global equity investor. More specifically, the following questions will be answered:

I. To what extent are oil, industrial metals, precious metals, world equity and global currency markets interdependent? Are there any long and short term relationships between these assets classes?

II. Do these relationships differ before and after OPEC's change of strategy in 2014?

III. Can a global equity investor lower his portfolio risk (while keeping returns the same) by including any of the other asset classes into the portfolio?

IV. Can a global equity investor protect himself from unfavourable stock price movements by using cross-asset hedging strategies? The inclusion of which asset would bring the most benefits?

A considerable amount of research has been conducted on the linkages between oil, equity, currency, industrial and precious metals prices (Chakraborty & Bordoloi, 2012; Kawamoto, Kimura, Morishita, & Higashi, 2011; Fratzscher, Schneider, & Robays, 2014; Soytas, Sari, Hammoudeh, & Hacihasanoglu, 2009; Sari, Hammoudeh, & Soytas, 2010; Hammoudeh & Alesia, 2004; Ciner, 2013; Wang, Abhankyar, & Xu, 2013; Lizardo & Mollick, 2010; Kilian & Park, 2009). However, to the best of my knowledge, this is the first paper to compare and analyse the direction and magnitude of the dynamic relationships between these asset classes before and after the 2014 oil crash. In particular, the data used in this research captures the period from June 1 – 2012 until May 20 -2016, and in order to investigate the long and short term relationships before and after the OPEC's breakdown at the end of 2014, the analysis is conducted separately for two periods. The pre-breakdown period is from June 1 – 2012 until October 1-2014 and the post-breakdown one is from October 1 – 2014 until May 20 – 2016. Importantly, the paper gives a unique insight into the long and short term relationships from a global perspective by considering major global-only data such as international commodity price indices, the world stock markets and a broad exchange rate (U.S. dollar against a basket of 26 other currencies). By taking a global perspective, the analysis avoids country specific effects that may be inherent to domestic industrial specialization, foreign exchange regimes, financial developments and market sizes. The paper then builds on by assessing the cross-asset correlation and volatility properties in order to determine the best hedging strategy and optimal allocation weights for commodity-equity and currency-equity portfolio holdings. Such analysis is not present in any other research paper so far. All in all, shedding light on the short and long run dynamics between different asset classes as well as the insights given on portfolio optimisation make the empirical results crucial not only for various policy makers around the world but also for global portfolio managers and financial investors.

The main outcome for both periods is that there are significant interactions between global oil, currency, metals, and equity prices in the short run, but not in the long-run. In particular on a global level, there are significant positive two-way interactions between the prices of oil, industrial metals, precious metals and world equity markets, and significant negative two-way negative price interactions between these four markets and the global exchange rate. Interestingly, shocks in oil and industrial metals have the highest influence on the price variance of the other asset classes during both periods. It was further found that after the 2014 OPEC breakdown, world equity markets, industrial metals and the global exchange rate are more heavily driven by movements in oil prices. On that note, impulse response analysis revealed that during the second period these markets have become much more responsive to innovations in oil price, while variance decomposition concluded that oil price shocks have started to explain bigger portion of the price variance of these markets.

Furthermore, from the portfolio optimization exercise it becomes evident that for a pure global equity investor the most optimal portfolio construction in terms of risk and return is to invest 20% of his capital in the world equity index and the remaining 80% in the global currency market. In this way, while keeping his portfolio returns the same, the investor will be able to reduce his portfolio risk by around 80%. On the other hand, considering an investor holding a one dollar long position in global equity, the most effective strategy that he can use to minimize the risk associated with global equity price fluctuations is to short 3 dollar cents of precious metals. Finally, the equity investor should currently stay out of the oil markets as buying derivatives based on a broad oil index would only increase the riskiness of the portfolio without bringing any extra returns.

The rest of the paper is structured as follows. Chapter 2 provides an extensive literature review by discussing the causal bilateral relationships between the global markets under investigation. Then, Chapter 3 further continues by presenting the empirical findings of related papers. Chapter 4 outlines this study's research questions and hypotheses. Chapter 5 describes the methodology used and the reasoning behind the choice of models such as ARDL, VAR/VECM and DCC-GARCH which are used to investigate the complex system of interactions among the global markets. Chapter 6 describes the data. Chapter 7 is devoted to discussing the empirical results of the long and short-term cross-asset linkages and Chapter 8 is devoted to the equity portfolio optimization exercise. Finally, Chapter 9 draws the main conclusions reached in the study.

2. Theoretical review

This chapter outlines the theoretical predictions and empirical findings of other studies in order to formulate the transmission channels between the analysed markets and then design the research hypotheses.

2.1. Stylized background of the analysed global markets

Firstly, the study will closely examine the oil markets, since oil is the most traded raw material and the leading energy commodity futures contract in the world by volume. Oil was initially traded for its primary purposes such as industrial use and transportation, but over the course of time it achieved a crucial position in the investment portfolios of retail and institutional investors (Tiwari & Sahadudheen, 2015). Due to its economic and investment value oil price is often quite volatile. The swings in oil prices are usually caused by various factors such as OPEC output, supply and spare capacities, economic growth, geopolitical developments, US crude production and inventories data, speculation, hedging, extreme weather conditions, dollar fluctuations and developments in equity markets (Focus Economics, 2016).

Secondly, the paper also focuses on examining the price movements of industrial metals being an interesting subject for investors, consumers and manufacturers. They affect the decision of investors for portfolio allocation, as well as the industrial production of manufacturers and therefore the economic growth pattern of world nations (Behmiri & Manera, 2015). Furthermore, industrial metals are seen as a proxy for global business cycle developments since historically rising metal prices have indicated strong demand and global economic strength, while lower prices - a weaker economy (IMF, 2015). All in all, there are numerous factors influencing the price of industrial metals such as expectations of economic growth, supply expectations based on existing stocks, transportation costs, energy costs related to extraction from the mine, the strength of the US dollar, substitution effect with other metals, geopolitical pressure in respective metal producing countries and supply of recycled metals (Focus Economics, 2016).

Thirdly, the price movements of precious metals are also considered in the paper, since these metals are not only industrial inputs but also investment assets which are commonly known as a “safe havens” to avoid the increasing risk in the financial markets (Ghazali, Lean, & Bahari, 2015; Baur & Lucey, 2010; Baur & McDermott, 2010). Using precious metals is, among others, one of the risk management tools in hedging and diversifying equity and commodity portfolios (Hood & Malik, 2013). Precious metals are mainly influenced by confidence in paper money, inflation pressures and interest rate movements, health of electronics industry, consumer choices in jewellery industry, gold price dynamics, global economic growth, commodity-specific events like mine or plant closures and also currency movements (Focus Economics, 2016). All in all, different precious metals serve different industrial purposes, while at an investment level they can be substituted one for the other.

Forth, the global interlinkage between commodity and equity markets is of crucial importance and therefore the world equity market is considered in the study. In theory, stock prices are equal to the sum of discounted values of expected future cash flows. The discounted corporate cash-flows of an individual stock reflect both idiosyncratic company prospects and also overall economic conditions (interest rates, inflation, production costs, exchange rates, economic growth etc.). Market participants therefore identify factors influencing the future cash flows in order to formulate their investment decisions. Investors are also particularly interested in wider equity market indices as they convey strong messages on the status and stability of the overall economy (Barunik, Kocenda, & Vacha, 2013). Furthermore, economic conditions may be influenced by shocks in industrial commodities resulting from their important use in the production and consumption processes in companies. This in turn implies that equity markets can react significantly to oil and metals markets fluctuations.

Lastly, the foreign exchange market, which is used as a snapshot of global trade and economic activity, is the world's biggest financial market with average daily turnover of around $6 trillion in 2015 (Reuters, 2016). At individual country level, currency markets play a vital role in a country's level of trade, which is critical to most every free market economy in the world. For this reason, exchange rates are among the most watched, analyzed and governmentally manipulated economic measures. As a general rule, currency markets are ultimately driven by inflation and interest rate differentials against other countries and economic factors that, in turn, are indicators of a country’s economic strength. The value of the US dollar against other currencies is very important for commodity and equity market participants since commodities and stocks that are traded on the world markets are priced in U.S. dollars (Sari, Hammoudeh, & Soytas, 2010). Therefore, to analyze the dynamic linkages between commodities and equities, this study also considers the role of the US dollar.

The interplay between these global markets is further explained in the following sections and serves as a theoretical prediction helping to design the research hypotheses.

2.2. What are the major transmission channels between the oil and the two metal groups?

In theory, industrial metals should exhibit strong positive relationship with petroleum prices through the cost-push channel. In particular, base metals extraction, smelting, refining and transportation are very energy intensive and thus positive changes in oil can increase the price of base metals (Behmiri & Manera, 2015). On the other hand, negative oil price shocks could actually be good news for the economy as they may increase the financial and the physical demands for industrial metals which could also lead to increases in their prices and volatility if inventory levels are low. Also, a relationship in the other way could be present (base metals to oil). As already mentioned, it is known that industrial metals mirror manufacturing and growth and thus investors see them as proxy for future economic activity (Behmiri & Manera, 2015). Therefore price increase in industrial metals may signal rebound in economic growth in turn increasing the price of energy as more oil is needed to meet higher expected production demand.

Next, when we turn to oil and precious metals linkage it is important to note that rising oil price generates higher inflation which increases the demand for precious metals and hence pushes up the their prices (Zhang & Wei, 2010; Thai & Chang, 2011; Wang, Abhankyar, & Xu, 2013). In other words, for economies which a large portion of their oil consumption, increase in oil prices can lead to inflation, which can subsequently push investors to hedge their portfolios with precious metals. Furthermore, common uses of oil and precious metals in industries such as automobiles and petrochemicals also forces co-movements in the prices of these commodities (Jain & Ghosh, 2013). On the same note, oil is also a significant cost input into the gold mining and production processes. Therefore lower oil prices could help the bottom lines of mining companies which could then lead to reduction in the price of gold as costs decrease (Behmiri & Manera, 2015). Concerning the other precious metals, silver prices are uniquely affected by both cost-push and an inflation channel effect due to silver’s many industrial uses as well as its role as a store of value, along with gold, for investors. Price transmissions in the other direction could also be present. Melvin and Sultan (1990) observe that oil exporting countries keep gold in their international reserves and it has a significant share in their asset portfolios. If oil exporters anticipate that the oil price will go down, they tend to buy precious metals to preserve value. Therefore, price developments in gold might affect price changes and volatility in oil markets. To sum up, the theoretical linkages between oil and metal commodities hint towards overall positive price relationship between the two asset classes.

2.3. What are the major transmission channels between the industrial and precious metals?

The theory suggests that the relationship between base and precious metals is caused by two major influencing factors - industrial production and inflation (Farrow, 2009; Jaiswal & Uchil, 2015). Regarding the former channel, during the bull phase of the business cycle when industrial production is increasing both industrial and precious metals are demanded due to their industrial application. In case of low inventory levels, their prices may increase due to this supply-demand disequilibrium. Strong relationship might be also present in bear markets as slowdown in industrial production would translate into lower expectations of future production and thus lower precious and industrial metals prices. However, this relationship would most likely be weaker in bear markets as certain precious metals such as gold would be bought as a vehicle for wealth conservation resulting in upward pressure on their prices. Similarly, the prices of these two types of metals could be connected through the inflation channel (Ghazali, Lean, & Bahari, 2015, Worthington & Pahlavani, 2006). As mentioned, precious metals have acted as a hedge against inflation, while industrial metals are seen as a proxy for inflation. Increasing industrial metals prices could translate into higher expected inflation which would be a signal for investors "fly to safety" to protect their wealth by buying safer assets such as precious metals or currencies of commodity producing countries against the USD. To sum up, the theoretical linkages between precious and industrial metals suggest positive price relationship between the two metal groups.

2.4. What are the major transmission channels between commodities and equity markets?

The relationship between global equity and commodity markets is multi-faceted and complex. Jones and Kaul (1996) suggest two kinds of effects – a direct and an indirect one. The direct effect occurs when changes in the costs of commodities affect a firm's profitability. The indirect impact of commodity price rises takes place through their effects on the inflation rate via the costs of goods, and the resulting fall in consumers' purchasing power will then adversely affect their demand for end products and services. Eventually, this will feed through to firms' cash flows (Jones & Kaul, 1996). Thus, through their impacts on the real economy via effects on firms' cost bases and consumers' purchasing powers, commodity price shocks should have pervasive effects on the prices of the vast majority of stocks and not just on those of heavy users such as airlines or those of producers such as oil and gas extractors (Brooks, 2014; IMF, 2015). However, due to the different commodity production and consumption needs, the linkages between oil, metals and stock markets vary drastically across countries.

On the other hand, oil and industrial metals prices can also react to stock price movements. For instance, continuously rising, equity markets indicate optimism about the status of the economy. This gives incentive for companies to boost production to meet expected customer demand. Increase in production also means increases in demand (and price) for oil, since oil is a direct input for companies' production and transportation processes. Furthermore, a permanent positive equity-price shock can reflect improvement in world economic outlook and increase investors' risk appetite, which can in turn lead to a rise in global commodity prices by facilitating an increase in commodity futures investment by hedge funds and institutional investors (Kawamoto, Kimura, Morishita, & Higashi, 2011). Similarly, when fundamental factors of oil and metals markets cannot provide sufficient explanation of their price movements, investors' expectation on future changes can be heavily disturbed by exterior information spillovers from other markets such as equity (as they convey information of future economic conditions). In this situation commodity investors become more sensitive to external information and change their trading strategies when they perceive risk changes in the other markets especially in equity (Liu, Qiang, & Fan, 2013).

The connection between precious metals and stock price movements are mainly due to the hedge and safe haven properties of precious metals. According to Coudert and Raymond (2011) and Tuysuz (2013), during periods of equity market distress, the price of risky financial assets falls almost simultaneously as the losses in the equity market cause contagion in other markets, and there is 'flight to quality' resulting in increase in prices of safer assets (particularly gold compared to other assets).

Considering the various transmission channels and given the fact that commodity production and consumption needs vary drastically across countries, it is thus hard to predict what would be the price relationship between commodities and equity market at the global level. Given that these markets partly reflect the expectation of global economic growth, overall positive price relationship is expected between commodities and the world equity market.

2.5. What are the major transmission channels between the currency markets and the rest of the markets?

Conventional theories suggest that price spillovers from commodities to currency are mostly a result of the effect of commodity price changes on inflation expectations or of the wealth transfer between commodity producers and consumers when the commodity prices move. In particular, sustained decline in oil and base metals prices, as experienced in the last couple of years, is a threat to net exporters decreasing their export revenues and current account balances which in turn causes their currencies to depreciate. The effect is the opposite for net importers such as the US (Grisse, 2010; Kawamoto, Kimura, Morishita, & Higashi, 2011).

Generally, equity market can impact exchange rates in different ways (Agrawal, Srivastav, & Srivastava, 2010). For instance, if South Africa's equity market registers impressive gains, it is likely to observe a large influx of foreign investment into the country, as international investors rush in to take advantage of the momentum. This influx of money would appreciate the South African rand, because in order to participate in the equity market rising, foreign investors need to convert their own domestic currency into rand. The opposite also holds true: a market downturn would lead to depreciation of the rand as foreign investors sell their equity holdings and convert the rand into their domestic currencies.

Finally, there are theoretical suggestions that the global strength of the US dollar can influence fluctuations of equity and commodity prices in the long term. When the dollar rises in value against other currencies, it makes dollar-denominated assets (such as oil, precious and industrial metals) more expensive for consumers who operate using these other currencies, which then weighs on demand. On the flip side, if the value of the dollar drops, the value of their local currency increases. So these countries can and tend to buy more of those commodities, which then translate into higher global commodity prices (Sari, Hammoudeh, & Soytas, 2010; Grisse, 2010).

To sum up, the theoretical linkages suggest overall negative price relationship between the global exchange rate (US dollar against other currencies) and the rest of the asset classes.

3. Empirical review

There are numerous studies related to the interactions between individual commodities and the financial and currency markets of different countries around the world. The results on these relationships are mixed in so far as most of the research papers have been conducted using individual commodities, individual country stock markets and currency exchange rates. This chapter provides a comprehensive review of the most important empirical findings regarding the dynamic linkages between these markets.

Some past studies of commodities price interlinkages have examined price volatility modelling and risk transmission for a broad set of precious metals, industrial commodities and the US dollar against other currencies. Employing OLS regressions with annual data over the period 1960 – 2005, Baffes (2007) finds evidence of strong responses of precious metal prices to crude oil prices. In particular, the elasticity for the aggregate metals index to crude oil price changes was discovered to be 0.11, implying that a 10 percent increase in the price of crude oil will induce a 1.1 percent increase in the aggregate metals index in the long run. When considering an individual country case (Turkey), Soytas, Sari, Hammoudeh & Hacihasanoglu (2009) use augmented LA-VAR model and do not find any long-run relationship between international oil prices, the Turkish lira/US dollar exchange rate and Turkish gold and silver prices. Concerning the short run, they document unidirectional causality from Turkish Lira/US dollar exchange rate to gold spot prices, thus confirming the hedging role of gold against exchange rate during crises. In a related study using daily data from 1999 until 2007, Sari, Hammoudeh, & Soytas (2010) employ ARDL bounds testing procedure and VAR modelling to examine the long and short-term dynamic price linkages among EUR/USD, crude oil and four precious metals. Initially, they do not find any sufficient evidence of the existence of long-run relationships between the set of variables. However, in the short-run they find positive bilateral price feedbacks between precious metals and oil, and strong negative feedbacks between the USD and precious metals. In particular, they found that unexpected dollar appreciation has a negative impact on precious metals prices and this effect dies out quickly by the second day. The impulse response analysis further revealed that the US dollar responds negatively to innovations in each of the commodities. Similarly, the variance decomposition analysis revealed that spot metal prices are strongly related to the exchange rate where exchange rate explains a minimum of 2% and a maximum of 9.3% of the variance depending on the metal, but only weakly driven by oil price movements. On the same note, Fratzscher, Schneider, and Robays (2014) employ SVAR modelling to discover that a 10% increase in the oil price leads to a depreciation of the US dollar effective exchange rate by 0.28% on impact, whilst a weakening of the US dollar by 1% causes oil prices to rise by 0.73%.

Furthermore, Bremond, Hache and Joets (2014) also do not find any long-term relationship between oil and other commodities such as industrial and precious metals. Using granger causality test in a panel VAR framework, however, they observe that the WTI crude oil price Granger-causes metals prices, while a reverse causality is not validated. They also observe fast co-movements in the short run for these groups of commodities due to the hedging behaviour of market participants and the influence of exchange traded funds. Based on a multivariate VARMA-GARCH model, Hammoudeh, Yuan, McAleer, and Thompson (2010) document strong sensitivity of metal volatility to exchange rate variability. They further point out the role of gold as a hedge against exchange rate risk when optimal weights and hedge ratios are computed.

On the individual commodities front, a long-run relationship between oil price and gold price was examined by Zhang and Wei (2010). Using a VECM model with daily data spanning from 2000 until 2008, they find a long run relationship between oil and gold prices, where changes in the oil price cause changes in the gold prices. Behmiri and Manera (2015) employ GARCH and GJR models to find that oil price shocks significantly influence the daily spot price volatility of aluminum, copper, lead, nickel, tin, zinc, gold, silver, palladium and platinum. Lizardo and Mollick (2010) discover that oil prices significantly explain movements in the value of the U.S. dollar against major currencies from the 1970s to 2008. Interestingly, it was found that increases in the real oil prices lead to US dollar depreciation against oil exporter currencies and to US dollar appreciation against net oil importer currencies.

Regarding the relationship between commodities and stock markets on a more global level, most of the studies reach conflicting results considering for cointegration between oil price and stock prices (Ciner, 2013; Hammoudeh & Alesia, 2004), linear or nonlinear relationship (Balcilar & Ozdemir, 2013; Wang, Abhankyar, & Xu, 2013), and the response of stock prices to oil price shocks (Wang, Abhankyar, & Xu, 2013; Creti, Ftiti, & Guesmi, 2014; Cunado & Garcia, 2014). In particular, Wang, Abhankyar, & Xu, 2013, Creti, Ftiti, and Guesmi (2014) and Cunado and Garcia (2014) studied the existence of dynamic interlinkages between oil price and stock markets for oil-importing and oil-exporting countries. The former conduct a broader and more sophisticated analysis compared to the latter two dividing oil price shocks into demand and supply shocks, which was also done by Cunado and Garcia (2014). Using a structural VAR proposed by Kilian and Park (2009) find that oil supply shock had a positive effect on equity markets in UK, US and Italy and insignificant negative effect on other oil-importing countries and all oil-exporting countries. Their findings partly align with the results of Creti, Ftiti, and Guesmi (2014) who find a long-run relationship between oil prices and all oil importing countries whereas from oil-exporting countries only Kuwait and Venezuela were cointegrated with the oil price. Cunado and Garcia (2014) study the impact of oil price shocks on the stock markets of 12 oil importers discovering that demand shocks have negative impact on majority of oil-importers such as Italy, Luxembourg, UK and Portugal. Moreover, Papiez and Smiech (2012) analysis based on Hong (2001) and Cheung and Ng (1996) tests indicated that contemporaneous causality was observed between the volatility of the crude oil price, the volatility of metals prices, and the volatility of S&P 500. Regarding stock markets effects on oil prices, Fratzscher, Schneider, and Robays (2014) identify that a 1% positive US equity market shock increases oil prices by 0.7% and on average around 16% of the variability in oil prices is explained by equity price shocks. Wang, Wang and Huang (2010) who investigate the relationship between prices of oil and gold, exchange rate and equity markets of Taiwan, China, Japan, United State (US) and Germany found that there exists a long-run cointegration among all variables in each country except for US.

Next on a more global level, using VAR modelling with monthly data spanning from 2000 until 2011, Kawamoto, Kimura, Morishita, & Higashi (2011) find that world commodity prices respond positively to innovations in the global stock price index (MSCI AC World Index). They explain this result by the fact that a rise in world equity markets can contribute to an economic recovery through wealth effects and consequently to an increase in world industrial production leading to a rise in global commodity prices by increasing the industrial demand. Similarly, Chakraborty and Bordoloi (2012) employ SVAR modelling to discover that from 1994-2012 around 7% of global commodity prices variation is explained by the MSCI World equity index. Looking at the reverse relationship, Guentner (2011) reports that from 1974-2011, oil supply and demand shocks account for almost 28% of the forecast error variance in global stock market returns. In a recent study, Partalidou, Kiohos, Giannarakis and Sariannidis (2016) find a positive effect of an aggregate metal index on the Dow Jones Industrial Average (DJIA) index returns – a 1 % increase in metal prices leads to a 0.3% boost in DJIA index. With the exception of Partalidou, Kiohos, Giannarakis and Sariannidis (2016), all the above mentioned papers use aggregated indices that track the movement of all commodity types and it is evident that more research is needed on the relationship between different individual commodity groups and the global stock market.

Lastly, regarding the relationship between global stock markets and the effective US dollar exchange rate, Fratzscher, Schneider, and Robays (2014) examine the relationship between oil prices, the US dollar and equity prices. They find that both oil prices and the effective US dollar exchange rate are significantly affected by changes in US equity market returns. Specifically, an increase in risk and risk aversion (as proxied by the VIX) leads to an appreciation of the US dollar, in line with the often-mentioned flight-to-safety phenomenon which entails a US dollar appreciation in periods of uncertainty and crises. On the other hand, on average around 5.9% of the variability of stock returns is explained by the US dollar. Also, Azar (2015) finds that a 1% appreciation of the US dollar trade-weighted index leads to a 1% fall in US equity returns.

All in all, there are numerous studies related to the interactions between individual commodities and the financial and currency markets of different countries around the world. The results on these relationships are mixed in so far as most of the research papers have been conducted using individual commodities and individual country stock markets and currency exchange rates. There is a substantial lack of literature concerning the interactions of these five asset classes on an aggregated global level, which in turn calls for further research.

4. Hypothesis development

As seen from above, the relationship between commodity, currency and equity markets can be complicated depending on the risk appetite of investors and the overall state of the global economy. The study's objective is to empirically investigate the most recent relationships and thus given the newest global commodity price developments one major transmission channel stands out amongst others. This transmission channel, together with the theoretical and empirical review, serves as benchmark for designing the research hypotheses. It goes as follows - an initial negative oil price shock puts a downward pressure on industrial and precious metal prices through the input cost and hedging channels. The corresponding decline in metals should theoretically lead investors to reassess growth prospects of the world economy as base metals are often used as a proxy for global growth. This low growth signal can depress the stock prices of different companies and financial institutions due to expectations of declining future cash flows. On the flip side, lower commodity prices can lead to positive effect in commodity importing countries. It is logical to assume that rational traders and investors would move their capital away from commodity exporting into commodity importing countries which would then negatively hit commodity-linked currencies such as the Russian rouble and also the Australian and Canadian dollars.

All in all, considering the global significance of the recent commodity markets developments and their transmission to other markets, four important questions will be answered. These questions are broken down into several hypotheses that can be directly proven with the help of econometric modelling.

I. **To what extent are oil, industrial metals, precious metals, world equity and global currency markets interdependent? Are there any long and short term relationships between the assets classes?**

Hypotheses about the long-run relationships between the different asset classes:

- *H1: There is cointegration between oil and any of the two metal groups due to cost-push effects, involvement in inflation hedging strategies and industrial application in common sectors.*

- *H2: There is cointegration between the industrial and precious metals due to involvement in inflation hedging strategies, similar industrial application and also substitution effects in some common sectors.*

- *H3: There is cointegration between world equity markets and commodities as commodities are direct inputs for companies' production and transportation processes, but also since on a global level both asset classes can be considered as proxies for world economic outlook and get influenced by common macroeconomic and geopolitical factors.*

- *H4: There is cointegration between the global effective exchange rate (proxied by the US dollar against a basket of other major currencies) and the rest of the asset classes since commodities and stocks that are traded on the world markets are priced in U.S. dollars.*

Hypotheses about the short-term interactions between the different asset classes:

- *H5: A positive price innovation in any of the commodities leads to a significant and positive price responses of all asset classes with the exception of the global exchange rate which exhibits negative response.*

- *H6: A positive price innovation in world equity leads to a significant and positive price responses of all commodities and negative response of the global exchange rate.*

- *H7: A positive price innovation in the US dollar against other currencies leads to a significant and negative price responses in the rest of the markets.*

A summary of the hypothetical relationships is provided in the matrix table below:

	OIL	IM	PM	WE	GER
OIL		+	+	+	-
IM	+		+	+	-
PM	+	+		+	-
WE	+	+	+		-
GER	-	-	-	-	

Table 1. *Hypothetical relationships between the asset classes in a matrix representation. Notes: the table summarizes the bilateral hypothetical relationships between the different asset classes. OIL represents oil prices, IM indicates industrial metals prices, PM indicates precious metals prices, WE indicates a proxy for the global equity market, and GER represents the global exchange rate. The sign indicates price effects stemming from both asset classes. For example, row 2 column 1 means that IM prices positively influences OIL prices and also OIL prices has positive effect on IM prices.*

II. Do these relationships differ before and after the OPEC's change of strategy in 2014?

- *H8: After the 2014 OPEC breakdown, industrial metals, precious metals, world equity markets and the global exchange rate experience stronger price responses to innovations in oil prices.*

- *H9: After 2014 OPEC breakdown, oil price shocks explain bigger portion of the variance of the other asset classes.*

- *H10: After the 2014 OPEC breakdown, there is strengthening of the dynamic conditional correlations between oil and world equity as investors have recently started worrying about the risk of growth-damaging deflation stemming from historically low oil prices.*

The study then proceeds to answer two practical investment questions which have not been answered in the literature so far, namely:

III. **Can a global equity investor lower his portfolio risk (while keeping returns the same) by including any of the other asset classes into the portfolio? The inclusion of which asset would bring the most benefits?**

- *H11: Asset allocation strategy within precious metals gives the best diversification strategy in terms of reducing the equity portfolio risk while keeping returns at a given level (i.e. highest Variance Reduction Index), as it is expected that precious metals are the least correlated asset to world equity.*

IV. **Can a global equity investor protect himself from unfavourable stock price movements by using cross-asset hedging strategies?**

- *H12: The cheapest and most effective way (i.e. with the smallest beta ratio) for an equity investor to reduce the volatility of his unhedged portfolio is by holding a short position in precious metals.*

5. Empirical methodology

The following section describes the research design and gives justification of the chosen models in order to answer the research questions. The paper firstly assesses the length and magnitude of the dynamic cross-linkages between global oil, currency, metals and equity prices. The analysis is then extended to cover practical implications for portfolio optimization from the perspective of a global equity investor. Firstly, unit-root tests are implemented in order to scrutinize whether the time series data is stationary; these tests are premise for other techniques. Second, cointegration tests are carried out in order to measure the long-run relationship between the asset-classes, while impulse response and variance decomposition techniques are used to measure the short-run dynamics among the variables. The presence of cointegration means that there is a unique long-run relationship between the variables and in order to further measure the short-run relationships one has to use vector error correction (VECM) model. On the other hand, if no cointegration is found, then the short-run analysis is run on the first difference of variables by employing a vector autoregressive (VAR) model. In particular, variance decomposition and impulse response techniques examine the duration, speed of interactions and the contribution of returns innovation in one market to the variance of returns in another market. Finally, the paper makes use of DCC-GARCH models to determine the best hedging strategy and optimal allocation weights for commodity-equity and currency-equity portfolio holdings.

A graphical representation summarizing the full empirical procedure used in this study can be found in tables A1 and A2 in the appendix.

5.1. Unit root tests

To build the ARDL and VAR/VECM models, the time series variables need to be firstly tested for stationarity by looking at whether there is a unit root in the time series or not. Therefore, the data set used in this analysis was subjected to the standard Augmented Dickey-Fuller (ADF) and Philip Perron (PP) tests.

The study firstly uses ADF test (Dickey & Fuller, 1979). It is done by testing null hypothesis of the existence of unit root. The null hypothesis is rejected if the value of the ADF test statistic is more negative than the critical value. Rejection of the null hypothesis means that the data is stationary. The test consists of the following equation:

$$\Delta y_t = c + \delta t + \varphi y_{t-1} + \sum_{i=1}^{k-1} \beta_i y_{t-i} + u_t \qquad (1)$$

The ADF method tests the hypothesis:

H0: φ = 0, the time series has a unit root, i.e. it is non-stationary.

H1: φ < 0, the time series does not have a unit root, i.e. it is stationary.

Where Δ is the differentiating operator, *c* is the intercept, δt is a time trend, u_t is residual white noise, *k* is the optimal lag period which makes the residual white noises specified by the Schwartz Bayesian Information Criterion. If the specification with trend and intercept does not reject the hypothesis that the data is not-stationary, then the significance of the coefficient is checked. If the trend coefficient is not significant, a model without a trend term is estimated. This procedure is repeated until a stationary data is found.

To cross-check the ADF results, Phillips-Perron (PP) unit root test is also implemented in this study. In particular, their test is different from the ADF tests in terms of how it treats the serial correlation and heteroskedasticity in the errors[1]. The PP tests correct for any serial correlation and heteroskedasticity in the errors u_t non-parametrically by modifying the Dickey Fuller test statistics. The PP unit root test is specified as follows:

$$\Delta y_t = c + \delta t + \varphi y_{t-1} + u_t \qquad (2)$$

The null hypothesis that series y_t is non-stationary can be rejected if φ is statistically significant with a negative sign.

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[1] In particular, the ADF tests use a parametric autoregression to approximate the autoregressive moving average structure of the errors in the test regression, while the PP tests ignore any serial correlation in the test regression

As described in the next section, this study makes use of ARDL approach to cointegration and therefore it does not matter if the two tests contradict with each other as long as none of the variables is I(2).

5.2. Long-run relationships analysis: ARDL procedure

The most widely used methodologies for estimating the long-term relationships between a set of variables are ARDL bounds testing procedure developed by Perasan, Smith and Shin (1999, 2001) and Johansen cointegration procedure developed by Johansen (1988). The ARDL approach is chosen due to a number of advantages over conventional Johansen cointegration techniques. Firstly, the ARDL approach is applicable irrespective of whether the variables are purely I(0), purely I(1) or mutually cointegrated, while Johansen technique requires all variables to be I(1). Therefore, if a researcher is not sure of the unit root properties of the data, then applying the ARDL procedure is the appropriate model for empirical work[2]. Secondly, the unrestricted error correction version (ECM) of the ARDL models integrates the short run dynamics with long run equilibrium relationship. Finally, with the ARDL approach it is possible that different variables have different optimal numbers of lags, while in Johansen-type models this is not permitted.

The ARDL cointegration procedure involves two major steps. In the first step, one must investigate the existence of a long-run relationship predicted by theory among the variables in question using the ARDL bound test based on the Wald-test (F statistic). In case of cointegration between the variables, then the second step of the analysis would be to estimate the coefficients of the long-run relationship and determine their values, followed by the estimation of the short-run elasticity of the variables with the ECM representation of the ARDL model.

The first step in the ARDL bounds approach is to estimate the five equations by ordinary least squares (OLS). The theory suggests numerous economic channels through which the different markets can affect each other. This brings uncertainty about the direction of the long-term relationships between the variables. Therefore, the following five unrestricted regressions are estimated:

$$\Delta \boldsymbol{oil} = \alpha_0 + \alpha_1 oil_{t-1} + \alpha_2 equity_{t-1} + \alpha_3 pm_{t-1} + \alpha_4 im_{t-1} + \alpha_5 er_{t-1} + \sum_{i=1}^{a} \alpha_{6i} \Delta oil_{t-i} + \sum_{i=1}^{b} \alpha_{7i} \Delta equity_{t-i} + \sum_{i=1}^{c} \alpha_{8i} \Delta im_{t-i} + \sum_{i=1}^{d} \alpha_{9i} \Delta pm_{,t-i} + \sum_{i=1}^{e} \alpha_{10i} \Delta er_{,t-i} + \varepsilon_{1t} \quad (3)$$

$$\Delta \boldsymbol{equity} = \beta_0 + \beta_1 oil_{t-1} + \beta_2 equity_{t-1} + \beta_3 pm_{t-1} + \beta_4 im_{t-1} + \beta_5 er_{t-1} + \sum_{i=1}^{f} \beta_{6i} \Delta oil_{t-i} + \sum_{i=1}^{g} \beta_{7i} \Delta equity_{t-i} + \sum_{i=1}^{h} \beta_{8i} \Delta im_{t-i} + \sum_{i=1}^{i} \beta_{9i} \Delta pm_{,t-i} + \sum_{i=1}^{j} \beta_{10i} \Delta er_{,t-i} + \varepsilon_{2t} \quad (4)$$

$$\Delta \boldsymbol{im} = \gamma_0 + \gamma_1 oil_{t-1} + \gamma_2 equity_{t-1} + \gamma_3 pm_{t-1} + \gamma_4 im_{t-1} + \gamma_5 er_{t-1} + \sum_{i=1}^{k} \gamma_{6i} \Delta oil_{t-i} + \sum_{i=1}^{l} \gamma_{7i} \Delta equity_{t-i} + \sum_{i=1}^{m} \gamma_{8i} \Delta im_{t-i} + \sum_{i=1}^{n} \gamma_{9i} \Delta pm_{,t-i} + \sum_{i=1}^{o} \gamma_{10i} \Delta er_{,t-i} + \varepsilon_{3t} \quad (5)$$

$$\Delta \boldsymbol{pm} = \delta_0 + \delta_1 oil_{t-1} + \delta_2 equity_{t-1} + \delta_3 pm_{t-1} + \delta_4 im_{t-1} + \delta_5 er_{t-1} + \sum_{i=1}^{p} \delta_{6i} \Delta oil_{t-i} + \sum_{i=1}^{q} \delta_{7i} \Delta equity_{t-i} + \sum_{i=1}^{r} \delta_{8i} \Delta im_{t-i} + \sum_{i=1}^{s} \delta_{9i} \Delta pm_{,t-i} + \sum_{i=1}^{t} \delta_{10i} \Delta er_{,t-i} + \varepsilon_{1t} \quad (6)$$

[2] However, the procedure will crash in the presence of I(2) series.

$$\Delta \boldsymbol{er} = \theta_0 + \theta_1 oil_{t-1} + \theta_2 equity_{t-1} + \theta_3 pm_{t-1} + \theta_4 im_{t-1} + \theta_5 er_{t-1} + \sum_{i=1}^{p} \theta_{6i} \Delta oil_{t-i} + \sum_{i=1}^{q} \theta_{7i} \Delta equity_{t-i} + \sum_{i=1}^{r} \theta_{8i} \Delta im_{t-i} + \sum_{i=1}^{s} \theta_{9i} \Delta pm_{,t-i} + \sum_{i=1}^{t} \theta_{10i} \Delta er_{,t-i} + \varepsilon_{1t} \quad (7)$$

where oil is a proxy for the world oil price, $equity$ is a proxy for the global equity market, im is a proxy for the world industrial metals price, pm is a proxy for the world precious metals price, er is a proxy for the global exchange rate, ε = white noise error term, Δ = first difference operator.

The estimation of the five equations tests for the existence of a long-run relationship among the variables is done by conducting a F-test for the joint significance of the coefficients of the lagged levels of the variables, i.e.:

Oil equation: H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = 0$ against: H_1: $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq 0$,

Equity equation: H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ against: H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$,

Industrial metals equation: H_0: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = 0$ against: H_1: $\gamma_1 \neq \gamma_2 \neq \gamma_3 \neq \gamma_4 \neq \gamma_5 \neq 0$,

Precious metals equation: H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ against: H_1: $\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq 0$,

Exchange rate equation: H_0: $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = 0$ against: H_1: $\theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq 0$,

The F-test has a non-standard distribution which depends upon whether variables included in the ARDL model are I(0) or I(1), the number of regressors and the sample size. Two sets of critical values are given by Pesaran, Shin and Smith (2001). The lower critical bound assumes all the variables are I(0) meaning that there is no cointegration relationship between the examined variables. The upper bound assumes that all the variables are I(1) meaning that there is cointegration among the variables. When the computed F-statistic is greater than the upper bound critical value, then the H0 is rejected and the variables are said to be cointegrated. If the F-statistic is below the lower bound critical value, then the H0 cannot be rejected (there is no cointegration among the variables). When the computed F-statistics falls between the lower and upper bound, then the results are inconclusive.

If the bounds testing procedure identifies cointegration in any of five ARDL models, the second step would be to estimate the long-run and short-run parameters within an error representation model (Ozturk & Acaravci, 2010). The error correction representation of any of the ARDL models with presence of cointegration is formulated as follows:

$$\Delta ly_t = \sum_{i=1}^{k} \vartheta_{1i} \Delta lx_{1,t-i} + \sum_{i=1}^{k} \vartheta_{2i} \Delta lx_{2,t-i} + \sum_{i=1}^{k} \vartheta_{3i} \Delta lx_{3,t-i} + \sum_{i=1}^{k} \vartheta_{4i} \Delta lx_{4,t-i} + \phi ECT_{t-1} + \mu_t \quad (8)$$

Where $ECT_{t-1} = \lambda_1 lx_{1,t-1} + \lambda_2 lx_{2,t-1} + \lambda_1 lx_{3,t-1} + \lambda_1 lx_{4,t-1}$ (9)

y_t represents the dependent variable, $x_{(1\ldots5)}$ are the independent variables, $\lambda_{(1\ldots5)}$ are the long-run coefficients, ϕ is the speed of adjustment parameter and ECT_{t-1} is the residuals that are obtained from the estimated cointegration model of equation (1). The ϕ shows how quickly variables converge to long-run equilibrium after a short term shock and it should have a statistically significant coefficient with a negative sign.

5.3. Short-run relationship analysis: VAR/VECM procedure

There are numerous methods that can be used to analyse short-term dynamic relationship between a set of variables such as, among others, VAR/VEC and simpler OLS models. The former set of models was chosen over simpler OLS techniques due to several reasons described below. As outlined in the theoretical section, there are multiple price transmission channels between the five global markets. These present the problems of endogeneity bias and reverse causality which are central problems for causal inference. When the variables are endogenous, a simple OLS (which can be used when explanatory variables are exogenous to the dependent variable) is likely to be biased as for instance equity market is causing price changes in oil market, but also the oil market is causing price changes in the stock market. Therefore, these dynamic relationships need to be analysed in a more sophisticated way. The vector autoregressive model (VAR) was introduced by Sims (1980), and is an econometric model often used to capture the relationship between such endogenous variables when there is no cointegration between them. They have been mainly used in studying the effects of dynamic relationship between a set of variables through impulse response characteristics and variance decomposition. Importantly, in a VAR system all variables are treated as endogenous and the current value of each variable is a linear combination of its own lagged values and the lagged values of all the other variables in the system (Spajic, 2002). Furthermore, Vector error correction model (VECM) offers a possibility to apply Vector Autoregressive Model (VAR) to integrated multivariate time series since the approach allows isolating short and long run relationships between the five global markets. In turn, ignoring the cointegration relationship and using variables in difference in a VAR framework would lead to biased estimates, as only the short-term fluctuations would be taken into account in the analysis. Therefore, VECM must be estimated in case that cointegration is found in the ARDL procedure.

A five-variable VAR estimated on daily data is used to analyse the interrelationship between the global variables. The model takes the following form:

$$y_t = c + \Phi_1 y_{t-1} + \ \dots . + \Phi_p y_{t-p} + \varepsilon_t \tag{10}$$

where c is a matrix of constants, y_t is a vector of first log differences of oil, equity, industrial metals, precious metals and exchange rate indices, p is the maximum lag order, $\Phi_1 \dots \Phi_p$ are matrices of coefficients to be estimated and ε_t is a vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

In the context of cointegration between the variables, however, VECM model has to be applied instead of the standard VAR. VECM can be formulated as follows:

$$\Delta y_t = \Gamma_1 y_{t-1} + \ \ldots . + \Gamma_{p-1} y_{t-p+1} + \Pi y_{t-p} + v_t \tag{11}$$

where $\Pi = -\left(\mathrm{I} - \Phi_1 - \ldots \Phi_p\right)$ and $\Gamma_i = -(\mathrm{I} - \Phi_1 - \ldots \Phi_i)$ $(\mathrm{I} = 1, \ldots \mathrm{p} - 1)$. Π is a (5x5) matrix with long-run information content, as $\Pi = \alpha\beta'$. α gives us the speed of adjustment to disequilibrium, whereas matrix β contains long-run coefficients. In this multivariate model the error correction term, or cointegrating relationship, contains up to n-1 vectors and is represented by $\beta' * y_{t-1}$, which in turn is embedded in $\Pi * y_{t-p}$.

5.3.1. Impulse response (IR) analysis

Generalized Impulse Responses (GIR) developed by Pesaran and Shin (1996) and Koop, Perasan and Potter (1996) are then used to explore the dynamic relationships between the different markets. Essentially, GIR in a VAR/VECM examine the responsiveness of the dependent variable to shocks in the other variables and are invariant to the ordering of variables in the system. In order to examine this responsiveness, in the previously specified VAR/VECM a unit shock is applied to each particular variable from each equation. In other words, the GIRs not only demonstrate the direction, but it also evaluate the magnitude and duration of the response. If the system is stable it is expected that those shocks would die away gradually. Impulse responses are achieved by writing the VAR as Vector Moving Average (Hill & William Griffiths, 2010).

5.3.2. Forecast error variance decomposition (FEVD) analysis

Another way of characterizing the dynamic behaviour of a VAR system is through Forecast Error Variance Decomposition. The variance decomposition measures the percentage of a variable's forecast error variance that occurs as a result of a shock from a variable in the VAR system. In more technical terms, it explains how much of the s-period-ahead forecast error variance of a particular variable will be explained by the shocks to each explanatory variable for s=1,2,… In this way, one can find the relative importance of a set of variables that affect the variance of another variable, essentially identifying the sources of volatility. There are several ways to apply the variance decomposition technique in a VAR. The method used in this paper is the traditional method which involves "orthogonality assumption". Ordering of the variables in this approach is essential. Proper ordering shows that current innovations in the variable that is placed first affect the rest of the variables. At the same time, the current innovations in variables placed towards the end are not expected to affect the variables in the beginning of the order (Brooks, 2014). Chapter 4 describes a recent theoretical price transmission channel where the initial shock starts from oil and gets transmitted to the other commodities, the stock market and then finally to the currency markets. Having this in mind, the oil index is ordered 1st, the industrial metals index is 2nd, the precious metals index is 3rd, the equity market index is 4th and the exchange rate index is 5th.

5.4. Portfolio optimization: AR-GARCH and DCC-GARCH

As described in the theoretical review, frequent fluctuations in commodities and exchange rates can lead to substantial risk transmission to the global equity market. These transmissions should be accounted for by equity investors when making decisions about portfolio's design and risk management. To build optimal diversification and hedging strategies, a portfolio manager that is heavily invested in the global equity market must firstly have accurate estimations of the time varying variance, covariance and correlation between equity and these other asset classes. The following section firstly describes the methodology to estimate the required parameters. Based on these estimates, the analysis then builds on to provide two practical examples of portfolio diversification and hedging. The first example concerns optimal portfolio diversification in which an equity investor is seeking to minimize risk without reducing expected returns by including one of the other asset classes in his portfolio. The second example concerns optimal hedging strategy, where the equity investor wants to minimise his unhedged portfolio risk by cross-hedging with another asset class as he is worried of unfavourable stock price movements in the near future.

Firstly, GARCH models are naturally suitable for the estimation of the abovementioned parameters. They are a broad category of econometric models used to model correlation structures[3] and time-varying volatility[4] for time series data. The basic way of modelling the correlation structure is to assume a constant relationship among variables in the model. This could be done in the CCC (conditional constant correlation) - GARCH model as proposed by Bollerslev (1990). However, the assumption that the conditional correlations are constant over time could be too restrictive, and for this reason Engle (2002) has proposed a model of dynamic conditional correlation (DCC-GARCH). The key feature is that the conditional correlation matrix is time dependent and the model is suitable for assessing co-movements between the markets as it allows to directly estimate the dynamic cross-market conditional correlations.

To estimate the DCC-GARCH, Engle (2002) proposes a methodology requiring three major computational steps. The first step involves estimating univariate GARCH models for all asset classes in order to derive standardized residuals (and also variances), which are then used as inputs for the DCC-GARCH model. The standardized residuals, calculated in the second step, are simply the estimated model residuals divided by the estimated conditional standard deviation. This process is referred by the literature as "DE-GARCHING" the data (Engle, 2009)[5]. The third step involves creating the DCC-GARCH model which uses the standardized residuals to estimate the dynamic correlation (and also the covariance) between equity and another type of asset.

Finally, the estimated conditional variances, covariances and correlations from the models are used as inputs to build the optimal diversification and hedging strategies which are described in section 5.4.2.

[3] Example: DCC-GARCH, CCC-GARCH, AG DCC-GARCH etc.

[4] Example: GARCH, AVGARCH, NARCH, EGARCH, ZARCH, GJR-GARCH, APARCH, AGARCH, NAGARCH etc.

[5] A wide range of non-GARCH stochastic volatility models can also be used for the DE-GARCHING procedure.

A summary of the whole procedure to calculate the interlinkages and optimize the portfolios can be found in tables A1 and A2 in the appendix.

5.4.1. AR-GARCH and DCC-GARCH estimation

- **Step 1:** GARCH Volatility models

As mentioned above, the first step requires estimating univariate volatility models for each individual market. Price volatility for each index is estimated by fitting an AR (1)-GARCH (1, 1) model to daily log returns. The model for each market takes the following form:

$$\text{[Mean - AR(1)]} \qquad r_t = \mu + \varphi_1 r_{t-1} + u_t \tag{12}$$

$$\text{[Variance - GARCH(1,1)]} \qquad h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{13}$$

$$\text{[Distribution]} \qquad u_t \sim N(0, h_t) \tag{14}$$

In the conditional mean equation $r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$ represents the current daily log returns of an individual asset index, r_{t-1} is the previous period's returns, $\mu = \frac{1}{n}\sum_{i=1}^{n} y_t$ is the sample mean of index returns with *n* being the number of days in the in-sample period, φ_1 is the first-order autocorrelation coefficient for the returns, while u_t is the disturbance term. The latter is commonly referred to as the 'news' because it represents the unanticipated movements in returns in excess of the conditional mean.

In the conditional variance equation, $\mathrm{h_t} = \sigma_\mathrm{t}^2$ is the conditional variance of a market index, ω is the constant term, $\mathrm{u}_{\mathrm{t}-1}^2$ (the ARCH term) is the lag of the squared disturbance term from the mean equation representing the news about volatility in the previous period, $\mathrm{h}_{\mathrm{t}-1}$ (the GARCH term) is the last period's forecast variance. The coefficient α_1 represents the ARCH effect and it measures the degree to which current volatility shock feeds through into next period's volatility. If α_1 is high, it indicates that volatility reacts intensely to recent market movements (Chong, Miffre, & Stevenson, 2008). The parameter β_1 represents the GARCH effect and it measures the persistency of volatility in the market. If the coefficient is high it can be inferred that shocks to conditional variance die after a long time. On the other hand, if β_1 is low and α_1 is high volatility is said to be sharp. The sum of the two coefficients $(\alpha_1 + \beta_1)$ measures the rate at which this effect dies out over time. The significance of α_1 and β_1 provides that trading decisions are significantly influenced by news (both good and bad) and volatility in the preceding time period.

The AR(1)-GARCH(1,1) models are estimated using maximum likelihood estimation (MLE) method. The log-likelihood function is maximized over the in-sample period and is given by:

$$L = \sum_{t=1}^{n} \log\left[\frac{1}{\sqrt{2\pi\sigma^2}} exp\left(\frac{-y_t^2}{2\sigma_t^2}\right)\right] \tag{15}$$

- **Step 2:** Standardized residuals

The residuals from the estimated models are then standardized and used as inputs in the DCC-GARCH. The standardized residuals for any given asset are calculated as follows:

$$s_t = \frac{u_t}{\sqrt{h_t}} \tag{16}$$

- **Step 3:** DCC GARCH models

The standard DCC-GARCH model for two assets *i* and *j* at time *t* is defined on the next page as follows:

$$\begin{cases} \rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \\ q_{i,j,t} = \bar{R}_{i,j}(1-\alpha-\beta) + \alpha s_{i,t-1}s_{j,t-1} + \beta q_{i,j,t-1} \\ q_{i,i,t} = \bar{R}_{i,i}(1-\alpha-\beta) + \alpha(s_{i,t-1})^2 + \beta q_{i,i,t-1} \\ q_{j,j,t} = \bar{R}_{j,j}(1-\alpha-\beta) + \alpha(s_{j,t-1})^2 + \beta q_{j,j,t-1} \\ \omega = \bar{R}_{i,j}(1-\alpha-\beta) \\ \bar{R}_{i,j} = \frac{1}{n}\sum_{t=1}^{n} s_{i,t}s_{j,t} \end{cases} \tag{17}$$

where $\bar{R}_{i,j}$ is the average realized correlation, $s_{i,t-1}$ and $s_{j,t-1}$ are the lagged standardized residuals computed in step 2. They are used to calculate the "quasi-correlations" given by $q_{i,j,t}, q_{i,i,t}, q_{j,j,t}$. However, even though these three elements form a quasi-correlation matrix, they do not ensure that this is a correlation matrix, because the diagonal elements will be 1 on average but they are not estimated to be exactly 1 for every observation. Therefore to convert these *q* processes into a proper time-varying DCC correlation, they must be rescaled. In particular, the diagonal elements $q_{i,i,t}, q_{j,j,t}$ can be used to rescale the quasi-correlations into the DCC conditional correlation. The process is simply:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \tag{18}$$

Furthermore, the term $\bar{R}_{i,j}(1-\alpha-\beta) \equiv \omega$ in the "quasi-correlation" equations is restricted to be a constant. This restriction is known as correlation targeting, which uses an estimate of $\bar{R}_{i,j}$ to reduce the number of unknown parameters to only α and β.

The behaviour of DCC-GARCH models can be described with a non-technical example. Consider a situation in which the correlations a pair of assets i and j evolve over time in response to new information regarding the returns, and as returns on both assets move in the same direction, the correlations will rise above their historical average and remain at that elevated level for some period. Over time, the information that caused the co-movement will decay, and correlations will decrease back to the long-run average. The same process holds for when asset returns move in opposite directions. The "speed" of this adjustment to new information is governed by the two parameters α and β.

As suggested by Engle (2009), the maximum likelihood estimation method is again used to estimate the abovementioned parameters. The log-likelihood function applied to two assets is given by:

$$L_{2,i,j} = -\frac{1}{2}\sum_{t=1}^{n}\left(log\left[1-\rho_{i,j,t}^2\right] + \frac{s_{i,t}^2+s_{j,t}^2-2\rho_{i,j,t}s_{i,t}s_{j,t}}{\left[1-\rho_{i,j,t}^2\right]}\right) \tag{19}$$

5.4.2. Implications for portfolio risk management

This section will explore the financial significance of the results of the GARCH models in terms of asset allocation and risk management.

Following the diligence outlined by Kroner and Ng (1998), the first situation considers an equity investor who wants to diversify his portfolio with another asset class *j* which could be either petroleum, industrial metals, precious metals or the US dollar index. The investor's objective is then to minimize risk of his two-asset portfolio without reducing its expected returns. According to Kroner and Ng (1998), the optimal holding weight of index *j* in a one dollar portfolio of equity and *j* holdings at time *t* is given by:

$$w_t^j = \frac{h_t^{equity}-h_t^{j,equity}}{h_t^j-2h_t^{j,equity}+h_t^{equity}} \tag{20}$$

When short selling is not allowed, the optimization approach imposes the following constraints on the optimal weight of the other asset:

$$\begin{cases} w_t^{*j} = 0,\ if\ w_t^j < 0 \\ w_t^{*j} = 0,\ if\ w_t^j < 0 \\ w_t^{*j} = 1,\ if\ w_t^j > 1 \end{cases} \tag{21}$$

Where w_t^{*j} is the optimal weight of holding index j in a \$1 portfolio of a two asset holding (petroleum and equity index) at time t, the terms h_t^{equity} and h_t^j refer respectively to the conditional variance of the equity index and the *j* index, and $h_t^{j,equity}$ is the conditional covariance between the returns on *j* and equity indices at time t. The optimal portfolio weight of the stock market index is (1- w_t^{*j}). All the required series are derived from the DCC-GARCH models.

The variance reduction ratio (VR) is constructed in order to check the effectiveness of portfolio diversification:

$$\mathrm{VR} = \frac{VAR\ undiversified - VAR\ diversified}{VAR\ undiversified} \tag{22}$$

where $VAR\ undiversified$ is the variance of the returns on the equity-only portfolio, while $VAR\ diversified$ is the variance of the returns of the equity-*j* portfolio. The optimum weights are used in order to calculate the variance of the diversified portfolio. Higher VR ratio indicates greater effectiveness in terms of variance reduction.

As evident in the theoretical review, his unhedged global equity portfolio has risk exposure to any of the abovementioned markets. Therefore, the second situation considers a pure equity investor who wants to completely minimise his portfolio risk as he is worried of the possibility of unfavourable stock price movements that could be caused by either petroleum, industrial metals, precious metals or the dollar index. The investor could hedge this exposure by selling an appropriate $ amount of the other asset class that he has exposure to. In order to find an optimal hedging strategy, the analysis follows Cecchetti, Cumby, and Figlewski (1988) and Kroner and Sultan (1993). To minimize the risk of such an unhedged portfolio, a long position of one-dollar on the equity index must be hedged by a short position of \$$\beta$ dollars on the other asset, where \$$\beta$ is given by:

$$\beta_t^{equity} = \frac{h_t^{j,equity}}{h_t^j} \tag{23}$$

A positive value of β_t^{equity} means that the investor could reduce the volatility of the unhedged portfolio by holding a short position in another asset class. On the contrary, a negative value would mean that the investor should hold a long position in the other asset class[6]. A short position implies that the *j* market returns tend to increase when the unhedged global equity returns increase, while a long position would mean *j* market returns tend to decrease as the unhedged returns increase.

6. Data

The following section provides an overview of the sample periods and the data that are being used to evaluate the dynamic cross-asset linkages and to construct the different portfolio optimization examples. All data is of daily frequency and is obtained via Datastream and measured in US dollar.

The empirical investigation focuses on the two major periods: the pre-OPEC breakdown period (June 1, 2012 to October 1, 2014) and the OPEC breakdown period (October 1, 2014 to May 20, 2016). These periods were chosen in order to investigate whether the dynamics between the global markets change before and after the OPEC breakdown that occurred at the end of 2014. The breaking point was chosen to be October 2014 since around that time it became obvious that despite sliding oil prices the organization will not cut production in the hope to drive higher-cost producers in the US and elsewhere out of business (Financial Times, 2016).

The dataset consists of diversified proxies for five different global asset classes, namely oil prices, industrial metals prices, precious metals prices, equity prices and a broad measure of US dollar exchange

[6] It is important to note that if the hedge ratio varies a lot over time, then the investor has to rebalance the portfolio more often.

rate against a broad basket of world currencies. Using such global variables avoids country specific effects that may be inherent to domestic industrial specialization, foreign exchange regimes, financial developments and market sizes. That makes them ideal for analyzing the dynamic cross-linkages between the abovementioned markets and reaching conclusions valid in a global context.

Firstly, the Morgan Stanley Capital International All Country World Investable Market Index (MSCI ACWI IMI) is selected as a proxy for the global equity index. It is a free float-adjusted, market-capitalization weighted index, designed to measure the equity market performance of developed and emerging markets. It covers over 9,000 securities across large, mid and small cap size segments and across style and sector segments in 45 developed and emerging markets. MSCI is used instead of S&P500 because world commodity prices tend to interact with the global financial variables via the world economy and not just the US economy (Hammoudeh & Bhar, 2011).

Secondly, three specific Bloomberg commodity indices are employed as proxies for global commodity price levels[7]. All of the indices track the spot prices on physical commodities on the commodity markets. In particular, the Bloomberg Petroleum Index is chosen as a proxy for the world oil price. The sub-index includes the volume/liquidity weighted spot prices of Brent crude oil, WTI crude oil, ultra-low sulfur diesel and unleaded gasoline[8]. Furthermore, the Bloomberg Industrial Metals Index is picked to represent the world non-ferrous metals prices. The sub-index includes the volume weighted spot prices of the most traded metals such as aluminium, copper, lead, nickel, tin and zinc. The Bloomberg Precious Metals Index is preferred as a proxy for world precious metals prices. The sub-index includes the volume weighted spot prices of gold, platinum and silver. For the purpose of index calculation, Bloomberg utilize the prices and volume of contracts traded on the COMEX division of the New York Mercantile Exchange and also London Mercantile Exchange (LME).

Lastly, in order to capture the pattern in global exchange rates, the study uses the Federal Reserve Trade Weighted US Dollar Index which proxies for dollar strength against a basket of 26 other global currencies. The exchange rate index aggregates and summarizes information contained in a collection of bilateral foreign exchange rates. More specifically, the index gives importance - or weight - to currencies most widely used in international trade. It includes the currencies of the Euro Area, Canada, Japan, Mexico, China, United Kingdom, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Switzerland, Thailand, Philippines, Australia, Indonesia, India, Israel, Saudi Arabia, Russia, Sweden, Argentina, Venezuela, Chile and Colombia. A rise in the index means that the value of the US dollar appreciates compared to the rest of the currencies.

Table 2 below exhibits the descriptive statistics for the index prices of the five asset classes over the respective sample periods and Figure B1 in the appendix plots their values and percentage returns. The

[7] For more information see: https://www.etfsecurities.com/Documents/Index%20Methodology%20-%20Dow%20Jones-UBS%20Commodity%20Indexes.pdf

[8] For more information on the weighting procedure see pages 9 and 48: https://www.etfsecurities.com/Documents/Index%20Methodology%20-%20Dow%20Jones-UBS%20Commodity%20Indexes.pdf

first difference between the two periods is the mean price, which, with the exception of the currency market, has decreased for all asset-classes. The second striking difference between the two periods can be found in the standard deviation of the variables. Unexpectedly, during the pre OPEC-breakdown period, the standard deviation of precious metals is found to be the highest among the five indices, followed by equity, oil and industrial metals and lastly exchange rates. That is, during the first period precious metals were generally more risky than all the other asset-classes. During the second period, however, the standard deviation of oil and industrial metals is way higher than the rest of the asset classes implying a drastic increase of risk in those markets. This increase of risk also coincides with substantially lower prices hinting about the presence of a structural break in the oil market.

Period: June 1, 2012 - October 1, 2014

	Oil	**Industrial metals**	**Equity**	**Precious metals**	**Exchange rate**
Mean	392.17	205.70	374.26	445.80	101.50
Median	394.90	203.40	373.85	416.15	101.79
Maximum	430.44	232.77	433.79	577.40	106.29
Minimum	326.92	186.33	291.15	359.02	98.34
Std. Dev.	17.40	10.96	37.65	65.22	1.56
Skewness	-0.72	0.54	-0.19	0.53	-0.07
Kurtosis	3.69	2.45	1.92	1.71	2.59
Jarque-Bera	64.41	37.28	33.34	70.89	4.69
# of obs	608	608	608	608	608

Period: October 1, 2014 - May 20, 2016

	Oil	**Industrial metals**	**Equity**	**Precious metals**	**Exchange rate**
Mean	209.77	168.40	344.74	409.29	117.04
Median	198.78	163.19	348.61	410.64	117.88
Maximum	356.24	208.27	386.27	442.70	126.24
Minimum	118.45	133.82	305.20	353.35	105.55
Std. Dev.	50.57	21.94	18.69	20.20	5.13
Skewness	0.69	0.20	-0.25	-0.53	-0.49
Kurtosis	3.17	1.69	2.26	2.67	2.51
Jarque-Bera	34.44	33.40	14.31	22.09	21.73
# of obs	428	428	428	428	428

Table 2. *Descriptive statistics of the variables during the two analysed periods. Notes: Oil stands for BBG Petroleum spot index, Industrial metals stands for BBG Industrial metals spot index, Equity stands for MSCI World ACWI index, Precious metals stands for BBG Precious metals spot index, Exchange rate stands for the broad U.S. Dollar trade weighted index, Skew shows the skewness level, and Kurt shows the kurtosis level in the data, Jarque-Bera (JB) represents the Jarque-Bera test for normality*[9].

[9] *Kurtosis is defined as follows:* $Kurtosis = (\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \frac{(x_i - \overline{x})^4}{s}) - \frac{3(n-1)^2}{(n-2)(n-3)}$

The kurtosis of the variables is positive, even though its magnitude is different across all markets and periods. During the first period, with the exception of oil the kurtosis of all asset-classes is less than 3 meaning that their distribution is platykurtic, indicating fewer and less extreme outliers than does the normal distribution. On the other hand, the distribution of oil price in both periods is leptokurtic since it is higher than 3, meaning that it has more extreme observations than a normal distribution. Furthermore, the distributions of all asset-classes appear to be asymmetric. For instance, the skewness of the distribution of oil has shifted from negative to positive. This means that during the first period, the price of oil had a left skewed distribution with most values concentrated on the right of the mean and extreme values on the left tail, while during the second period the distribution of oil has become right skewed. The opposite trend is observed for the skewness of precious metals. Furthermore, exchange rate and equity prices exhibit right skewed distributions during both periods, while industrial metals are left skewed. All in all, these properties show signs that the distributions of the five-asset classes are non-normal. The significance of the Jarque–Bera test statistics further confirms that the distributions are non-normal.

7. Results I – interlinkages between the asset classes

This chapter presents the results of all the required tests and computations in order to assess the dynamic cross-linkages across the five markets. It then provides a discussion of the results and proceeds with portfolio optimizations.

7.1. Unit root tests

Before testing for the presence of long and short-term relationship between the five markets, one has to determine the time series properties of the variables. Firstly, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests are conducted using logarithms of the levels of all series to check for unit roots. The output of both tests and periods is provided in Table 3 below:

Skewness is defined as follows: $Skewness = \frac{n}{(n-1)(n-2)} \sum (\frac{(x_i - \overline{x})}{s})^3$

Jarque-Bera is defined as follows: $JB = \frac{n-k+1}{6} (Skew^2 + \frac{1}{4} (Kurt - 3)^2)$

where s is the standard deviation, k is the number of regressors, n the number of observations and $\overline{x}$ *is the mean.*

Period: June 1,2012 - October 1,2014

Log level		ADF	PP
C	Oil	-3.168**	-3.071**
	Industrial metals	-2.340	-2.287
	Equity	-2.291	-2.303
	Precious metals	-0.832	-0.761
	Exchange rate	-0.679	-0.739
C & T	Oil	-2.895	-2.765
	Industrial metals	-2.479	-2.431
	Equity	-4.257	-3.848
	Precious metals	-2.214	-2.126
	Exchange rate	-3.026	-3.081

First log differences		ADF	PP
C	Oil	-27.038***	-27.066***
	Industrial metals	-26.157***	-26.160***
	Equity	-21.128***	-20.875***
	Precious metals	-26.931***	-26.903***
	Exchange rate	-24.393***	-24.392***
C & T	Oil	-27.097***	-27.166***
	Industrial metals	-26.136***	-26.139***
	Equity	-21.195***	-20.949***
	Precious metals	-26.915***	-26.888***
	Exchange rate	-24.510***	-24.526***

Series	Final outcome
Oil	I(0)/I(1)
Industrial metals	I(1)
Equity	I(1)
Precious metals	I(1)
Exchange rate	I(1)

Period: October 1,2014 - May 20,2016

Log level		ADF	PP
C	Oil	-2.372	-2.381
	Industrial metals	-1.197	-1.153
	Equity	-1.990	-1.809
	Precious metals	-2.082	-2.082
	Exchange rate	-1.990	-2.003
C & T	Oil	-1.697	-1.546
	Industrial metals	-2.184	-2.047
	Equity	-2.738	-2.425
	Precious metals	-1.931	-1.931
	Exchange rate	-1.745	-1.736

First log differences		ADF	PP
C	Oil	-22.933***	-22.903***
	Industrial metals	-22.407***	-22.407***
	Equity	-16.849***	-16.643***
	Precious metals	-22.153***	-22.188***
	Exchange rate	-20.549***	-20.551***
C & T	Oil	-23.080***	-23.081***
	Industrial metals	-22.385***	-22.385***
	Equity	-16.834***	-16.624***
	Precious metals	-22.162***	-22.195***
	Exchange rate	-20.623***	-20.642***

Series	Final outcome
Oil	I(1)
Industrial metals	I(1)
Equity	I(1)
Precious metals	I(1)
Exchange rate	I(1)

Table 3. *ADF and PP unit root tests results. Notes: Lag lengths are determined via Schwartz Information Criterion. C denotes constant, and C&T denotes constant and trend. Subscripts *,** and *** represent significance of results at 10%,5%, and 1% significance level, respectively. The variables are in the top tables are expressed in logarithmic form. The variables are in the top tables are expressed in first logarithmic differences.*

Firstly, the top panel shows the output of the tests conducted on the levels of the variables. Allowing for drift and trend the ADF test fails to reject the null hypothesis for all series with the exception of oil allowing for constant during the first period. The PP test confirms the result of ADF test by rejecting the null of stationarity in the series for almost all of the indices. The only exception is oil with constant in the first period which is I (0), i.e. does not contain unit root. Overall, the results are somewhat inconclusive for oil in the first period, and this is precisely the situation that ARDL bounds testing procedure is designed for. Secondly, panel B shows the output of the tests conducted on the first difference of the variables. The results show that all series in first differences reject the null hypothesis at the 1% significance level, implying that all series in first differences are stationary.

7.2. Estimation of the long-term interactions across the markets through ARDL modelling

7.2.1. Models specification

In order to investigate the long-term relationship between the different asset prices, this paper makes use of the ARDL bounds testing procedure. As already mentioned, the test is based on the assumption that the variables are I(0) or I(1). Therefore, the procedure is appropriate since no I(2) series were found by the unit root tests. In particular, per each period, a system of five ARDLs models is estimated as shown in the methodology section. To determine the optimal lag length, the Aikake Information Criteria (AIC) is chosen over Schwarz Information Criterion (SC) because the latter tends to select a simpler model specification than the former and one runs the risk of under-fitting the models (Giles, 2015). In total, for each model 14406 model specifications were considered as the maximum number of lags for the dependent variable and the principal regressors was set to 6. The results of the model specification are shown in the second column in Table 4, while Tables C1 and C2 in the appendix show how well some other specifications performed in terms of minimizing AIC.

Before looking at the results of the cointegration, it is important to firstly check if the errors of the model are serially independent and whether the estimated coefficients are stable. Firstly, if the errors are not serially independent, the parameter estimates will not be consistent. By observing the correlograms of the residuals in Tables C1 and C2, it is confirmed that no autocorrelation exists. The higher than 5% p-values strongly suggest that there is no evidence of autocorrelation in the models' residuals. Second, stability of short-run and long-run coefficients is examined by employing cumulative sum (CUSUM) test. The null hypothesis of all coefficients in the given regression are stable cannot be rejected since the plots of CUSUM statistics stay within the critical bonds of 5% level of significance (Tables C1 & C2). Overall, these tests indicate the model coefficients are stable and that problems such as autocorrelation and model misspecification do not exist and the study can proceed to the next step of analysing the long-term equilibrium relationship between the different markets.

7.2.2. Discussion about the long-term relationship across the five asset classes

The outcome of the ARDL bounds testing method for both periods is presented in Table 4 below. The results of the procedure show that the calculated F-statistics are insignificant at the 1% level for both periods implying that the null hypothesis of no cointegration cannot be rejected. The lack of cointegration in the models implies that there are no long-term equilibrium relationships among the analyzed markets for both periods under investigation. That is, oil prices, industrial metals prices, precious metal prices, world equity and global exchange rates are not collectively driving forces of each other in the long run. These results do not confirm the initial predictions in Hypotheses 1-4. This implies that the markets have their own fundamentals in the long run and that investors do not view any of these asset classes as long-run substitutes. In other words, these markets are not that sensitive to common macroeconomic factors in the long-run. This could be justified by the fact that oil is controlled by oil-producing countries and it has its own seasonality, inventories and hedging strategies, also precious metals are considered to be safe heaven assets and respond strongly to inflationary pressures, while industrial metals, much like oil, have their own idiosyncratic market dynamics. The lack of cointegration could also reflect an increasing disparity in economic, monetary and hedging uses between these markets in the long-run.

Period: June 1,2012 - October 1,2014

Cointegration hypothesis	Lag structure	F-stat	Outcome
F(**Oil**|Industrial metals, Equity, Precious metals, Exchange rate)	2-1-1-1-0	2.383	No cointegration
F(**Industrial metals**|Oil, Equity, Precious metals, Exchange rate)	1-2-4-1-2	2.206	No cointegration
F(**Precious metals**|Oil, Industrial metals, Equity, Exchange rate)	2-1-1-1-5	3.381	No cointegration
F(**Equity**|Oil, Industrial metals, Precious metals, Exchange rate)	2-1-1-4-1	2.837	No cointegration
F(**Exchange rate**|Oil, Industrial metals, Equity, Precious metals)	1-0-1-1-3	3.083	No cointegration

Period: October 1,2014 - May 20,2016

Cointegration hypothesis	Lag structure	F-stat	Outcome
F(**Oil**|Industrial metals, Equity, Precious metals, Exchange rate)	3-6-0-3-1	3.205	No cointegration
F(**Industrial metals**|Oil, Equity, Precious metals, Exchange rate)	2-4-5-1-1	1.999	No cointegration
F(**Precious metals**|Oil, Industrial metals, Equity, Exchange rate)	3-0-1-2-1	2.533	No cointegration
F(**Equity**|Oil, Industrial metals, Precious metals, Exchange rate)	3-1-1-4-1	1.839	No cointegration
F(**Exchange rate**|Oil, Industrial metals, Equity, Precious metals)	6-1-2-3-5	2.888	No cointegration

Table 4. *ARDL bounds testing procedure results. Notes: lag lengths are determined via AIC. F-statistics denotes the F-stat of the model with unrestricted intercept and no trend. Asymptotic critical value bounds to check the outcome of the test are obtained from (Perasan and Perasan, 1997). The results are below the critical lower bound of I(0)=3.516 at 1% level of significance, meaning that there is no cointegration in any of the equations for both periods. Subscripts *,** and *** represent significance of results at 10%,5%, and 1% significance level, respectively.*

The absence of long-term relationship does not mean that there are no short-term dynamic interactions across the markets. Since all series are stationary when first-differenced and there is no cointegration among the variables, the short-run interactions in the next section can be estimated by employing a VAR model as outlined in the methodology chapter.

7.3. Estimation of the short-term interactions across the markets through VAR modelling

7.3.1. Models specification

To analyse the dynamic relationships between the markets from the short-term perspective, this paper makes use of two VAR models - one per each period. Before proceeding with the results, it is important to check whether the models are well specified. Firstly, an appropriate number of lags is determined via several lag determination criteria. Secondly, serial correlation in the residuals is investigated and resolved by adding the necessary extra number of lags. The next step of the VAR's specification is investigation on the dynamic stability of the models. It is important for the VAR to be dynamically stable, otherwise key statistics such as the impulse response error bands will not be reliable. The final step would be the estimation of impulse response functions and forecast error variance decomposition in order to analyse the short-term dynamics across the different markets.

Six lag length criteria are used to find the optimal lag length - the Schwarz Information Criterion (SC), the Hannan-Quinn Criterion (HQ), the Akaike Information Criterion (AIC), the likelihood ratio (LR) test and the Final Prediction error (FPE). The optimal number of lags for both periods would be chosen by the most commonly selected lag order by the different criteria. In case all criteria show different results, the optimal lag length would be set to the criterion that shows the least number of lags and then the residuals will be checked for serial correlation in case the model is under-fitted or omitting important information. Table C3 in the appendix summarizes the output of the different criteria. For both periods, the chosen amount of lags is 1 based on the most commonly selected lag order strategy.

The second step is to investigate whether these models suffer from autocorrelation in the residuals. For this purpose, a Lagrange Multiplier Autocorrelation (LM) test is used (Johansen, 1995). The test has a null hypothesis that there is no serial correlation up to the respective lag. The whole output can be seen in Table C4. It is apparent that there is still some serial correlation left in the residuals for the second period at lag length 1 as the null hypothesis is rejected at the 5% level. This problem in the second period was removed by increasing the number of lags until the serial correlation in the residuals was resolved. Therefore, the lag length was increased to 3. Further robustness checks on the chosen VARs based on the Portmanteau Tests for Autocorrelations (Ljung & Box, 1978) revealed that the residuals were serially uncorrelated (Table C5). The insignificance of the p-value shows that the null hypothesis of no serial correlation of order 3 cannot be rejected. This provided more assurance that the VAR systems in both periods do not suffer from the problem of omitted relevant variables.

To ensure the stability of the models, the study employs the AR root stability test (Lutkepohl, 1991). The estimated VAR is stable if all the inverse roots of AR characteristic polynomial have modules less than one and lie inside the unit circle of the AR graph. In the models, as shown in Figure C1, there are no roots lying outside the unit circle suggesting that the two models are stable. That is, the influence of the shock for all variables decreases over time. Overall, the tests indicate the models are stable and the study can proceed to analysing the short-term dynamics across the different markets through the impulse response functions and forecast error variance decomposition.

7.3.2. Discussion about the short-term interactions across the five asset classes

Figures D1 and D2 in the appendix show the estimated impulse response functions. Tables 5-9 below present only the statistically significant impulse response results for expository purposes and easier interpretation.

Impulse responses to d(Oil) shock

Period: June 1, 2012 - October 1, 2014

Day	d(Ind. metals)	d(Pr. metals)	d(Equity)	d(Ex. rate)
1	**0.0036**	**0.0036**	**0.0025**	**-0.0007**
	0.000	0.000	0.000	0.000
2			**0.0006**	
			0.000	

Period: October 1, 2014 - May 2016

Day	d(Ind. metals)	d(Pr. metals)	d(Equity)	d(Ex. rate)
1	**0.0045**	**0.0018**	**0.0033**	**-0.0012**
	0.001	0.001	0.000	0.000
2			**0.0009**	
⋮			0.000	
4		**0.0016**		
		0.001		

Table 5. *Impulse response functions of the different asset classes to one standard-deviation shocks in Oil returns. Notes: the table presents only the significant results. The non-significant ones are left out for expository purposes. The bolded numbers represent the impulse responses, while the grey numbers represent the response standard errors.*

As seen in Table 5, world equity, industrial metals and precious metals have significant positive reaction to one standard-deviation shock in oil returns where the reactions decrease significantly after 1 day. These results are in line with Hypotheses 5. On a global level, unexpected oil price increases have a positive short-term effect on the other commodities and the world equity market. Essentially, positive oil return can reflect improvements in world economic growth which can boost other commodity prices by increasing their industrial demand. Secondly, during the current historically low commodity prices, negative oil returns directly influence the bottom lines of many energy producing companies hindering their stock prices relatively more than the contemporaneous boost in the stock markets of energy consuming companies. On that note, Financial Times (2016) report that after 2014 cheaper oil severely hurt energy exporting nations and did not recreate the lost dynamism in Europe, China, the US and Japan as initially expected. This could be one of the reasons why on an aggregate global level oil has positive relationship with world equity index. On the other hand, the impact of oil shocks on the global exchange rate is significantly negative. This finding is supported by the Riksbank's (2016) argument that increase in oil improves the current account balances of oil net exporters causing their currencies to appreciate against the US dollar giving the negative reaction of the global exchange rate to unexpected shocks to oil price returns.

Furthermore, looking the second period in Table 5, it could be observed that with the exception of precious metals all the other markets became much more responsive to oil return shocks, confirming the predictions in Hypothesis 8. Essentially, this implies that during the second period, in which oil prices plunged to historical lows, bad news in the oil market can cause significant short-term liquidation across world equity, metals and energy exporters' currencies against the US dollar. This finding is supported by CME group (2016) suggestion that credit fears of defaulting energy companies have prompted stocks and net exporters' currencies to be more heavily driven by movements in oil prices than they normally are. This further justifies the positive relationship between global oil prices and world equity prices. Another interesting finding is that the responsiveness of oil to the rest of the markets significantly weakens during the second period suggesting that oil became a more isolated market. In essence, after OPEC decided to maintain market share instead of lowering production, the oil market has become more reactive to its' own supply and demand dynamics than to developments in the other markets.

Impulse responses to d(Ind. metal) shock

	Period: June 1, 2012 - October 1, 2014					Period: October 1, 2014 - May 2016			
Day	d(Oil)	d(Pr. metals)	d(Equity)	d(Ex. rate)	Day	d(Oil)	d(Pr. metals)	d(Equity)	d(Ex. rate)
1	**0.0039**	**0.0055**	**0.0028**	**-0.0010**	1	**0.0101**	**0.0031**	**0.0030**	**-0.0013**
	0.000	0.000	0.000	0.000		0.001	0.001	0.000	0.000

Table 6. *Impulse response functions of the different asset classes to one standard-deviation shocks in Industrial metal returns. Notes: the table presents only the significant results. The non-significant ones are left out for expository purposes. The bolded numbers represent the impulse responses, while the grey numbers represent the response standard errors.*

Looking at Table 6, it could be observed that the short-run impact of shocks to industrial metals on oil, precious metals and world equity is positive and significant (in line with Hypothesis 5). Apart from that, as expected the response of the global exchange rate to shocks in industrial metals is negative. Firstly, the positive effect on oil and world equity could be caused by the fact that the investors view industrial metals price movements as a proxy for world economic growth. Secondly, the positive effect on precious metals and the negative effect on the US dollar against other 26 other global currencies could be attributed to hedging behaviour on the part of traders. In particular, unexpected increase in industrial metals prices could translate into higher expected inflation which would influence traders to “fly to safety” to protect their wealth by buying safer assets such as precious metals. As for the exchange rate, to reap gains from inflationary trends, traders usually buy currencies of commodity producing countries against the US dollar. This justifies the negative relationship industrial metals returns and the USD. Also, industrial metals are often viewed by traders as a proxy for global economic growth and therefore unexpected increase in their prices could boost the global equity market. This highlights the large influence of global activity upon the relationships between these variables.

Impulse responses to d(Pr. metal) shock

	Period: June 1, 2012 - October 1, 2014					Period: October 1, 2014 - May 2016			
Day	d(Oil)	d(Ind. metals)	d(Equity)	d(Ex. rate)	Day	d(Oil)	d(Ind. metals)	d(Equity)	d(Ex. rate)
1	**0.0032**	**0.0045**	**0.0015**	**-0.0010**	1	**0.0041**	**0.0032**	**-**	**-0.0016**
	0.000	0.000	0.000	0.000		0.001	0.001		0.000

Table 7. *Impulse response functions of the different asset classes to one standard-deviation shocks in Precious metal returns. The table presents only the significant results. The non-significant ones are left out for expository purposes. The bolded numbers represent the impulse responses, while the grey numbers represent the response standard errors.*

Looking at Table 7, it could be observed that there is a positive short-run impact of shocks to precious metals on oil, industrial metals and world equity, while the response of the global exchange rate is significantly negative (in line with Hypothesis 5). These effects are very similar to the ones found for shocks to industrial metals. However there is one substantial difference, namely during the second period, shocks to precious metals returns do not have any significant impact on the world equity returns. A plausible explanation could be the fact that short-term movements in precious metals prices are frequently driven by speculation. This results in merely an income transfer from commodity-consuming to commodity-producing countries, and this is neutral for the world economy as a whole.

Impulse responses to d(Equity) shock

Period: June 1, 2012 - October 1, 2014

Day	d(Oil)	d(Ind. metals)	d(Pr. metals)	d(Ex. rate)
1	**0.0045**	**0.0045**	**0.0029**	**-0.0013**
	0.000	0.000	0.000	0.000

Period: October 1, 2014 - May 2016

Days	d(Oil)	d(Ind. metals)	d(Pr. metals)	d(Ex. rate)
1	**0.0109**	**0.0045**	**-**	**-0.0012**
	0.001	0.001		0.000

Table 8. *Impulse response functions of the different asset classes to one standard-deviation shocks in Equity returns. Notes: the table presents only the significant results. The non-significant ones are left out for expository purposes. The bolded numbers represent the IRs, while the grey numbers represent the response standard errors.*

Fourth, Table 8 shows that the impact of world equity shocks on oil, industrial and precious metals is significant and positive where the effect dies out quickly by the second day (in line with Hypothesis 6). As stated earlier, one reason for this could be that a rise in global stock prices can reflect improvements in the world economy which increases the risk appetite of various market participants. This rise in turn contributes to an economic recovery through increase in investors' wealth and consequently boosts commodity prices by increasing their industrial demand. This facilitates hedge funds and institutional managers to include commodities in their portfolio further pushing up the price. Interestingly, during the second period precious metals do not respond to world equity shocks. A plausible interpretation of the fact that precious metals have become relatively isolated from equity shocks could be due to the quantitative easing programs implemented by the major central banks. In essence, investors now prefer to use bonds instead of precious metals as a safe haven asset during equity market turbulence.

Impulse responses to d(Ex. rate) shock

Period: June 1, 2012 - October 1, 2014

Days	d(Oil)	d(Ind. metals)	d(Pr. metals)	d(Equity)
1	**-0.0033**	**-0.0044**	**-0.0055**	**-0.0035**
	0.000	0.000	0.000	0.000
2			**0.0016**	
			0.001	

Period: October 1, 2014 - May 2016

Days	d(Oil)	d(Ind. metals)	d(Pr. metals)	d(Equity)
1	**-0.0094**	**-0.0045**	**-0.0055**	**-0.0028**
	0.001	0.001	0.001	0.000

Table 9. *Impulse response functions of the different asset classes to one standard-deviation shocks in the Global Exchange rate returns. Notes: the table presents only the significant results. The non-significant ones are left out for expository purposes. The bolded numbers represent the impulse responses, while the grey numbers represent the response standard errors.*

Lastly, although short-lived, in line with Hypothesis 7 innovations to the global exchange rate have a negative effect on the rest of the markets (Table 9). This is logical since commodities and stocks that are traded on the world markets are priced in U.S. dollars. For instance, an unexpected decline of other currencies relative to the U.S. dollar (i.e. increase in the global exchange rate) makes commodities more expensive for non-US consumers. As a result, non-US consumers may reduce demand for commodities and thereby cause prices to soften. At the same time commodity producers tend to increase supply in order to take advantage of the stronger currency. This puts further downward pressure on the prices thus giving the negative effects of shocks to the global exchange rate on commodity markets.

All in all, it could be observed that most of the dynamic effects between the markets are short-lived as the speed of the return to long-term equilibrium for each asset class happens within a few days. This emphasises the efficiency of the markets and the importance of the existing fundamental market forces.

Next, the study turns to variance decomposition analysis. The variance decomposition of the forecast error gives the percentage of variation in each variable that is explained due to its own shocks versus shocks from other markets. Ordering of the variables is given in section 5.3.2. Table 10 reports the average 20 days forecast error variance decomposition of respective asset-class returns to each of the Choleski-factored shocks during both periods, while Figures D3 and D4 in the appendix show the variance decompositions of the five different variables over different forecasting horizons (in days).

Period: June 1,2012 - October 1,2014

To/From	d(Oil) shock	d(Industrial metals) shock	d(Precious metals) shock	d(Equity) shock	d(Exchange rate) shock
d(Oil)	97,8	0,5	0,5	0,8	0,4
d(Industrial metals)	12,9	84,4	0,8	0,4	1,6
d(Precious metals)	8,6	13,8	75,5	0,5	1,6
d(Equity)	16,3	10,8	0,4	72,0	0,6
d(Exchange rate)	8,7	12,5	7,7	14,5	56,6

Period: October 1,2014 - May 20,2016

To/From	d(Oil) shock	d(Industrial metals) shock	d(Precious metals) shock	d(Equity) shock	d(Exchange rate) shock
d(Oil)	96,0	1,1	0,5	2,0	0,3
d(Industrial metals)	16,0	81,3	1,7	0,5	0,5
d(Precious metals)	2,7	5,5	90,6	0,8	0,4
d(Equity)	17,2	6,7	3,1	72,3	0,6
d(Exchange rate)	12,9	7,1	15,0	6,1	58,9

Table 10. *Average 20 days forecast error variance decomposition of respective asset-class returns to each of the Choleski-factored shocks. Notes: the order of the variables in the VAR specification is (Oil, Industrial metals, Precious metals, Equity, Exchange rate).*

Looking at the first column in Table 10, it could be observed that during the first period, oil price shocks cause respectively 16.3%, 12.9%, 8.7% and 8.6% of the variation in the world financial market, industrial metals, the global exchange rate and precious metals. During the second period, the share attributable to oil price shocks increases to respectively 17.2%, 16% and 12.9% for the former three asset classes, but fell to 2.7% for precious metals. Those findings are exactly in line with the impulse response results and indicate that after the OPEC strategy change, financial, currency and other industrial commodity markets have become increasingly more influenced by oil movements. These results confirm the predictions in Hypothesis 9.

The results for industrial metals shocks also reveal very interesting findings. With the exception of oil, all the other markets were much more affected by industrial metals shocks during the first period. More specifically, before the end of 2014, industrial metals were influencing precious metals the most by around 14% of their total variation. This is logical since the two metal groups share similar industrial application and market dynamics, but are also involved in inflation hedging strategies and portfolio allocations of various investors. However, after the end of 2014, the effects of industrial metals shocks on the financial, currency and precious metals prices decreased by around a half. This could reflect the fact that during the second period investors have started worrying more about the risk of growth-damaging deflation stemming from the historically low oil prices.

The second column shows the results for precious metals shocks to itself and the rest of the markets. One striking result is the influence of precious metals shocks on the global exchange rate variance which is on average respectively 7.7% and 15% during the first and second period. This can potentially be attributed to the effect of precious metals shocks on the current account balances of large metal producing nations such as Russia, China, Australia, Canada and South Africa. The effects of precious metal shocks to the rest of the markets during both periods is relatively small within the range of 0.5% to 3.1%. What is also surprising is that precious metals became less influenced by other markets during the second period as the effect of shocks to its own variance increased from 75.5% to 90.6%.

World equity market shocks to the commodity markets have somewhat weak effect ranging from a minimum of 0.4% for industrial metals to a maximum of 2% for oil. On the other hand, much like precious metals, the global stock market shocks have a very strong effect on the global exchange rate variance ranging from 14.5% during the first period to 6.1% during the second period. The strong influence of the world equity market on the global exchange rate can be explained by the investment behavior of market participants during times of elevated financial risk. A good example here can be the recent 2015 Chinese stock market crash or the Greek bailout case which posed enormous risk to the European financial system. During such times, investors rush to buy safer asset such as the U.S. dollar to protect their wealth.

Lastly, as observed in the last column, exchange rate shocks do not influence the rest of the markets that much during the short run. The currency market shocks explain only around 1% of the other asset-classes. However, it is possible the effects of US dollar shocks on dollar denominated assets need longer time to materialise. This could be a subject of future research.

8. Results II – Equity portfolio optimizations

The significant risk and return transmissions that were found among the five asset classes must be accounted for when making decisions about portfolio's design and risk management. This chapter shows how diversification and cross-asset hedging strategies can be carried out to efficiently minimize the risk of global equity portfolios. To show how diversification strategies can be effectively used, the analysis assumes a global equity investor who is fully invested in the global stock markets but wishes to include one more asset class in his portfolio in order to minimize his risk while keeping returns the same. To show how hedging strategy can be effectively used, the second example considers the same equity investor wants to minimise his unhedged portfolio risk by cross-hedging with another asset class as he is worried of unfavourable stock price movements in the near future. The chapter initially introduces the estimated volatility models and then presents and discusses the results from the portfolio optimization exercises.

The portfolio optimization examples are calculated based on the methodology described in section 5.4 and Figure A2. In particular, the analysis firstly builds 5 univariate AR-GARCH and 4 DCC-GARCH models in order to calculate the parameters needed for the portfolio optimizations. The estimated univariate AR- GARCH and pairwise DCC GARCH models can be found in Table 11.

AR(1)-GARCH(1,1)

		Oil		**Industrial metals**		**Equity**		**Precious metals**		**Exchange rate**	
		Coef	z-stat	Coef	z-stat	Coef	z-stat	Coef	z-stat	Coef	z-stat
mean	μ	-0.02	-0,55	-0,02	-0,74	0,04	1.85**	-0,03	-0,93	0,01	2.07**
	φ_1	-0.08	-2.55***	-0,07	-2.13**	0,16	4.17***	-0,06	-1.78*	0,00	0,02
variance	ω	0,01	2.48***	0,01	1.66*	0,02	3.08***	0,06	4.71***	0,00	1,17
	α_1	0,05	6.53***	0,02	3.52***	0,09	5.43***	0,05	10.33***	0,04	3.41***
	β_1	0,95	128.10***	0,97	95.78***	0,87	35.36***	0,91	102.28***	0,95	73.20***

DCC

		Equity	
		Coef	z-stat
Oil	α^{DCC}	0.01	3.19***
	β^{DCC}	0.98	141.73***
Industrial metals	α^{DCC}	0.01	2.02**
	β^{DCC}	0.97	66.77***
Precious metals	α^{DCC}	0.02	3.07***
	β^{DCC}	0.97	99.20***
Exchange rate	α^{DCC}	0.01	5.73***
	β^{DCC}	0.99	36784***

Table 11. *Univariate AR(1)-GARCH(1,1) estimates and pairwise bivariate DCC model estimates for the global equity index. The sample period is between June 1, 2012 and May 20, 2016. Notes: the reported z-stat numbers are the test statistics and asterisks indicate significance at the 10% (*), 5% (**), and 1% (***) level.*

The ARCH (α) and GARCH (β) estimates of the conditional variance are statistically significant for all univariate models. The degree of short run persistence α, is generally small (less than 0.1), while the β estimates are generally high and close to one for all asset classes. These results indicate shocks to conditional variance of the broad exchange rate, world equity, oil and metals prices die after a long time. Furthermore, the DCC estimates of the conditional correlations between the volatilities of world equity and all other asset class returns are shown in the bottom part of the table. The estimates of the DCC parameters, α^{DCC} and β^{DCC}, are statistically significant in all cases. This indicates that DCC-GARCH is the right model to use since the significance of both coefficients means that the assumption of constant conditional correlation between world equity and the other indices is not supported empirically. Lastly, the time varying conditional correlations between world equity and the rest of the asset classes are given in Figure 1.

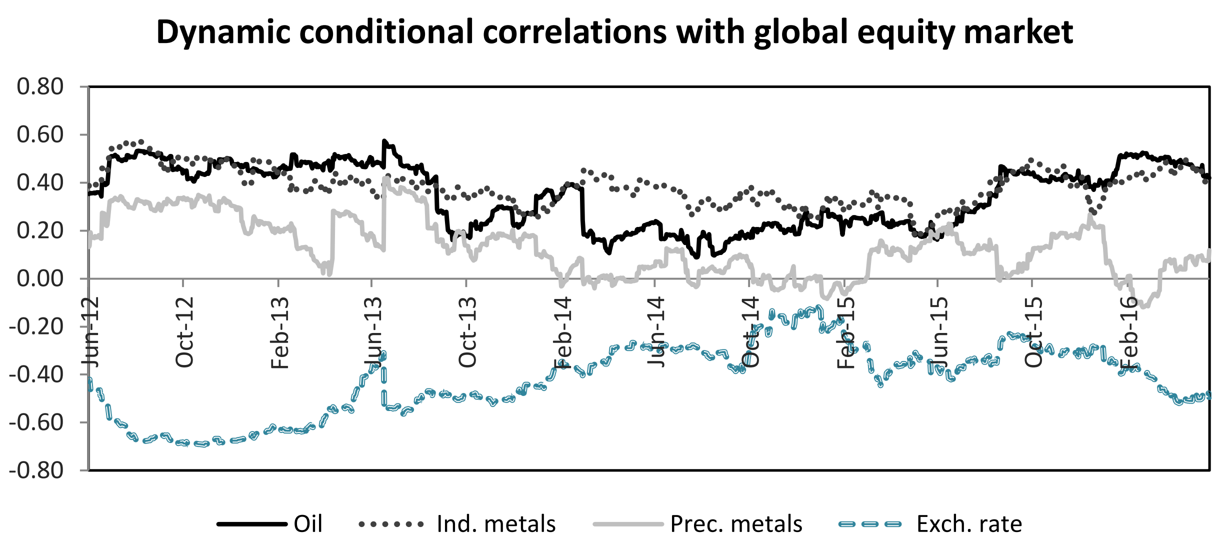


Figure 1. *Dynamic conditional correlation between equity-oil, equity-industrial metals, equity-precious metals, equity-exchange rate returns.*

It can be observed that the correlations between the asset classes significantly change over time, further strengthening the case for using DCC-GARCH modelling. All correlations have the expected sign. Interestingly, in Figures B1 in the appendix it could be seen that in June 2015, after several months of stable and recovering oil prices, oil prices started sliding again. At that moment, the correlation between the global stocks and world oil prices began to steadily increase reaching a maximum of 0.53 in February 2016 (in line with Hypothesis 10). As with the impulse response and variance decomposition, this finding again suggests that credit fears of defaulting energy companies have prompted global stocks to be much more heavily driven by movements in oil prices than they normally are. Higher correlations also mean that the diversification benefits of combining these assets in a multi-asset class portfolio are disappearing and hedging strategies become much more expensive.

By looking at Table 12 below, it could be observed that diversifying with the global exchange rate is the best way to decrease your risk while keeping returns the same as indicated by the highest *VR ratios* of around 0.80 in both periods. In other words, the ratio shows that it is very beneficial for a pure-equity portfolio manager to consider investing in a broad effective exchange rate because in this way, at a given level of return, his portfolio risk can be reduced by 83%.

	Period 1	Period 2
w_t^{oil}	0,16	0,07
w_t^{im}	0,20	0,23
w_t^{pm}	0,19	0,29
w_t^{er}	0,86	0,80

	Period 1	Period 2
VR oil	0,10	-0,32
VR im	0,12	0,13
VR pm	0,15	0,27
VR er	0,89	0,83

Table 12. Optimal weights (for the second asset) and the Variance reduction index for an equity-oil, equity-industrial metals, equity-precious metals, equity-exchange rate portfolios. Notes: **Period 1** refers June 1, 2012 – Oct 1, 2014, while **Period 2** refers to Oct 1, 2014 – 20 May 2016.

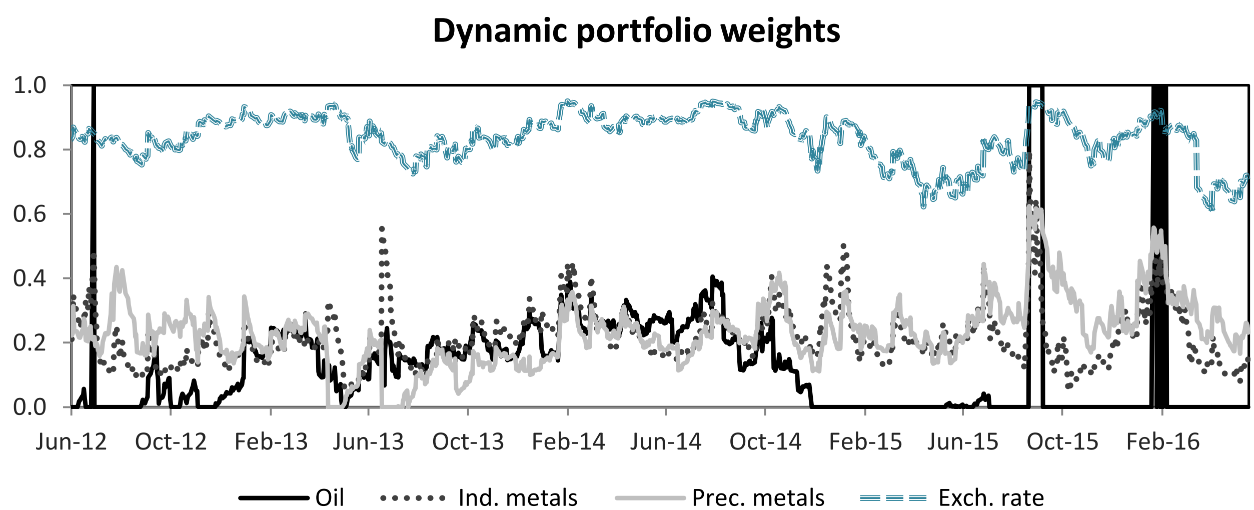


Figure 2. *Time-varying portfolio weights for oil, industrial metals, precious metals and the broad US dollar exchange rate.*

An interesting insight for the same portfolio is further given by the optimal weights, which can also be seen in Figure 2. They show that the portfolio is dominated by the global exchange rate since 80% of the capital should be invested into the US dollar trade weighted index, while 20% should be in the world equity index. Overall, this finding does not confirm the predictions of Hypothesis 11, but the result can be explained by the fact that the global exchange rate index is already a much diversified index and also not very volatile by construction as observed in the data description section. Further, the two metal indices have positive *VR ratios* suggesting that they could also be a good addition to an all global equity portfolio. In particular, the relatively high *VR pm* ratio of 0.27 is reflecting the low correlation between global equity and global precious metals prices. To lower his portfolio risk without the hurting the returns, the optimal portfolio weights suggest that a global equity investor should currently consider putting either ~20% of his capital into industrial metals or ~30% of his capital into precious metals. Not surprisingly, *VR oil* is very small in the first period and even negative in the second period suggesting that equity investors should currently avoid adding any oil derivatives to their portfolio since this strategy would only increase the riskiness of the portfolio without bringing any extra returns. As seen by the time-varying portfolio weights in Figure 2, with the exception of a few short periods, throughout almost the whole time after the OPEC breakdown it does not make any sense to be invested in oil as the weights are 0%.

Looking at the right panel of Table 13 below, it could be observed that the average risk-minimizing hedge ratio for the equity/precious metals portfolio is 0.03, which means that one dollar long position in the global equity market should be shorted by 3 dollar cents in the precious metals market[10]. In line with Hypothesis 12, it is the most highly effective and inexpensive hedge since an investor has to short only 3 cents in the precious metals index to achieve minimization of the variance of his portfolio. Alternatively, an equity investor could short ~20 cents worth of oil or industrial metals to achieve similar result. Lastly, to minimize his portfolio risk he could instead go long 20 cents in the global currency index as indicated by the negative value of the *Beta er* parameter.

	Period 1	**Period 2**
Beta oil	0,16	0,21
Beta im	0,17	0,22
Beta pm	0,08	0,03
Beta er	-0,21	-0,20

Table 13. *Average hedge ratios for an equity-oil, equity-industrial metals, equity-precious metals, equity-exchange rate portfolios.* ***Period 1*** *refers June 1, 2012 – Oct 1, 2014, while* ***Period 2*** *refers to Oct 1, 2014 – 20 May 2016.*

All in all, the results suggest that for a pure global equity investor the most optimal portfolio construction in terms of risk and return is to invest 20% of his capital in the world equity index and the remaining 80% in the global currency market represented by the broad US dollar index. In this way, while keeping his portfolio returns the same, the investor will be able to reduce his portfolio risk by around 80%. On the other hand, considering an investor holding a one dollar long position in global equity, the most effective strategy that he can use to minimize the risk associated with global equity price fluctuations is to short 3 dollar cents of precious metals. Finally, the equity investor should currently stay out of the oil markets as buying derivatives based on a broad oil index would only increase the riskiness of the portfolio without bringing any extra returns.

[10] A positive value of β means that the investor could reduce the volatility of the unhedged portfolio by holding a short position in another asset class. On the contrary, a negative value would mean that the investor should hold a long position in the other asset class.

9. Conclusion

There are numerous studies related to the interactions between individual commodities and the financial and currency markets of different countries around the world (Chakraborty & Bordoloi, 2012; Kawamoto, Kimura, Morishita, & Higashi, 2011; Fratzscher, Schneider, & Robays, 2014; Soytas, Sari, Hammoudeh, & Hacihasanoglu, 2010; Sari, Hammoudeh, & Soytas, 2010; Hammoudeh & Alesia, 2004; Ciner, 2013; Wang, Abhankyar, & Xu 2013; Lizardo & Mollick, 2010; Kilian & Park, 2009). The results on these relationships are mixed in so far as most of the research papers have been conducted using individual commodities and individual country stock markets and currency exchange rates. There is a substantial lack of literature concerning the interactions of these five asset classes on an aggregated global level. Therefore, this study investigates the recent long and short-term relationships between the global equity, commodity and currency markets. The analysis is generally conducted through ARDL, VAR and GARCH techniques and is separated in two periods. The first period covers June 2012 until October 2014. This time is characterized by sliding industrial metals prices and high oil prices. The second period is between October 2014 and May 2016 during which oil price plummeted more than 60% as it became clear that OPEC would not cut oil production in order to keep its share in the world oil markets and drive out US shale producers and other higher cost producers.

Firstly, the ARDL analysis shows no evidence of long-term equilibrium relationships among the analysed markets for either period, meaning that oil, industrial metals, precious metal, world equity and global currency markets are not collectively driving forces of each other in the long run, therefore rejecting Hypotheses 1-4. These results for instance differ from other studies find long-term relationship between individual commodities and other country-level currency and stock markets such as Baffes (2007), Zhang and Wei (2010), Creti, Ftiti, and Guesmi (2014), Wang and Huang (2010). The lack of any unique cointegration between the global markets could be contributed to the idiosyncratic-market specific forces driving their prices or to time-varying risk appetite of market participants preventing these asset classes to have sustainable long-term relationship.

Secondly, concerning the short-term relationship, the VAR impulse response functions identify numerous dynamic interactions between the five markets (equity, oil, industrial metals, precious metals and currency) in the short term for both periods. There are significant positive two-way interactions between the global prices of oil, industrial metals, precious metals and world equity markets confirming hypotheses 5 and 6. Most of these price responses to innovations in the other markets disappear quickly, only after the first day. One reason for the positive short-run price dynamics between the individual commodity groups is that they have industrial application in the same sectors. Also, through the cost-push channel - metals' extraction, refining and transportation is highly energy intensive making the prices of energy and metals dependent on each other. Another reason is that price movements of these global commodities partly reflect changes in world economic outlook and are thus influenced by common macroeconomic factors making movements in their prices somewhat tied together.

Moreover, improvements in the global macroeconomic outlook will also stimulate financial markets, as the stock prices are formed by both expectations of the idiosyncratic company prospects and also overall economic conditions. This directly explains the positive price interactions between these globally traded commodities and the world stock market. Finally, according to Coleman and Levin (2006), Masters and White (2008a, 2008b) the positive price responsiveness between commodities and financial markets is due to the inclusion of those assets in the same investment portfolios by hedge funds and institutional investors.

On the other hand, there are significant negative two-way negative price interactions between these four markets and the global exchange rate in line with Hypotheses 5-7. When the dollar increases in value against other currencies, it makes dollar-denominated assets (such as the ones this study analyses) more expensive for consumers or potential buyers who operate using other currencies. This then decreases the dollar-denominated asset demand and decreases their prices.

Next, based on the VAR forecast error variance decomposition, it was found that world equity markets, industrial metals and the global exchange rate are more heavily driven by movements in oil prices during the second period. Furthermore, the DCC-GARCH modelling revealed that after June 2015 the correlation between the global stocks and world oil prices began to steadily increase reaching a maximum of 0.53 in February 2016. These results provide evidence that oil has a bigger influence on the abovementioned world markets after the OPEC breakdown as the investors have started worrying more about the risk of growth-damaging deflation stemming from the historically low oil prices thus confirming Hypotheses 8-10. Credit fears of defaulting energy companies and the unknown exposures of banks to those companies have led the global stock market to correlate much more tightly with fluctuations in the price of crude oil, while the deteriorating current account balances of oil net exporters cause their currencies to depreciate against the US dollar.

Finally, the portfolio optimization results based on the univariate AR(1)-GARCH(1,1) and pairwise DCC-GARCH models suggest that a pure global equity investor should consider restructuring his portfolio by investing 20% of his capital in the world equity index and the remaining 80% in the global currency market in order to minimize his risk, while keeping returns constant. In this way, keeping his portfolio returns the same, the investor will be able to reduce his portfolio risk by around 80%. This result is not in line with Hypothesis 11 which predicted that precious metals index gives the best diversification strategy due to its low correlation with equity markets. On the other hand, assuming that this investor is holding a one dollar long position in global equity, the most effective strategy that he can use to minimize the risk associated with global equity price fluctuations is to short 3 dollar cents of precious metals confirming Hypothesis 12. Finally, the equity investor should currently stay out of the oil markets as buying derivatives based on a broad oil index would only increase the riskiness of the portfolio without bringing any extra returns.

All in all, this study examines the rich dynamic interactions between five global markets and provides practical examples for global equity portfolio managers and policy makers in regards to optimal asset allocation, portfolio risk management and diversification benefits among these markets. The discovered dynamic interdependencies among global currency, commodities and equity prices are of fundamental importance for either investment or policy decisions. The fact that after October 2014, 3 out of the 4 markets are more heavily influenced by innovations in the oil price raises the need for further research by academics and policy makers and for more sophisticated commodity risk hedging strategies by international equity investors.

Appendix A. Conceptual framework

Figure A1. *Empirical framework for examining the dynamic linkages between the global markets. Notes: ARDL refers to Autoregressive Distributed Lag model, VECM refers to Vector Error Correction Model and VAR refers to Vector Autoregression Model.*

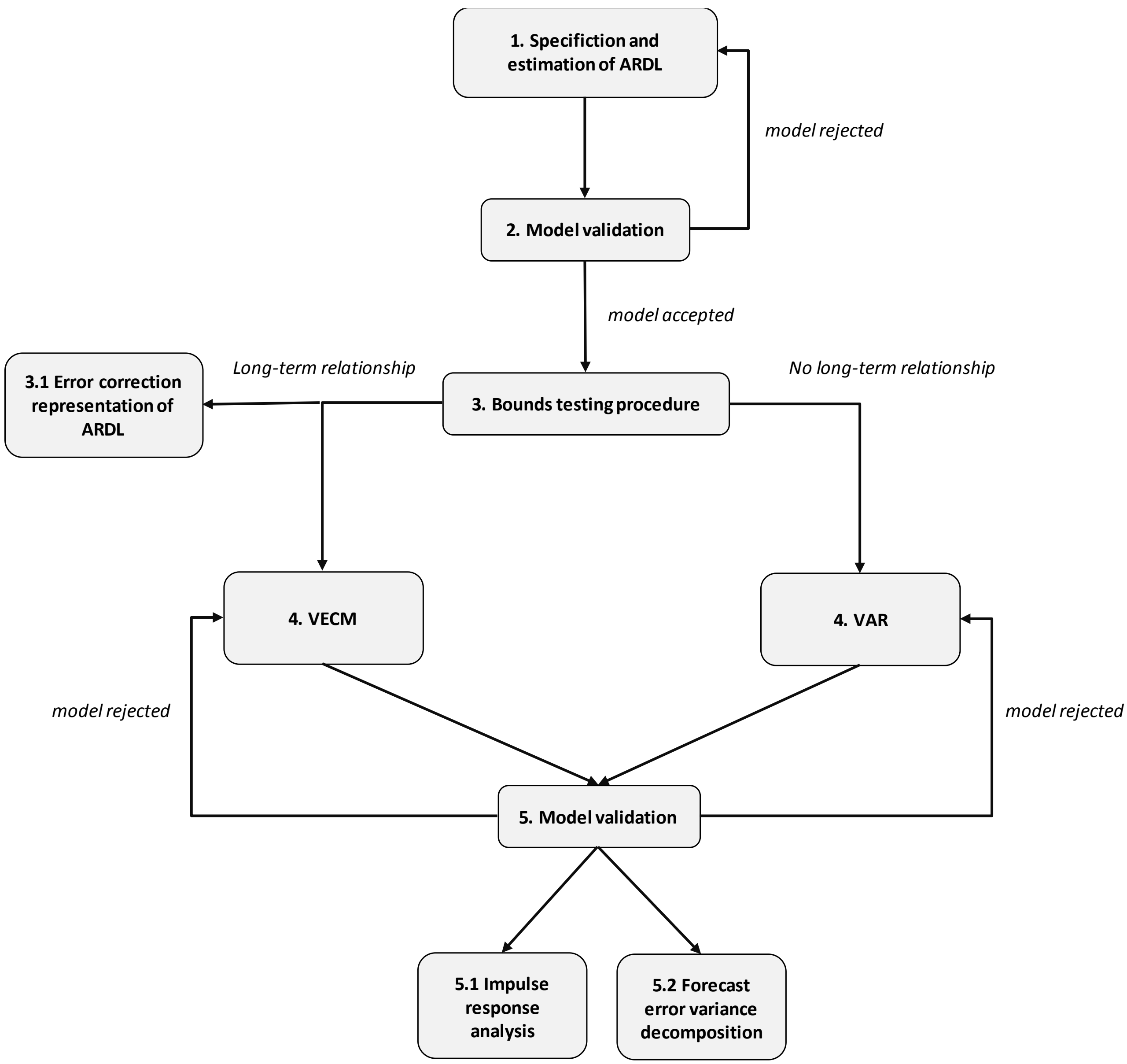
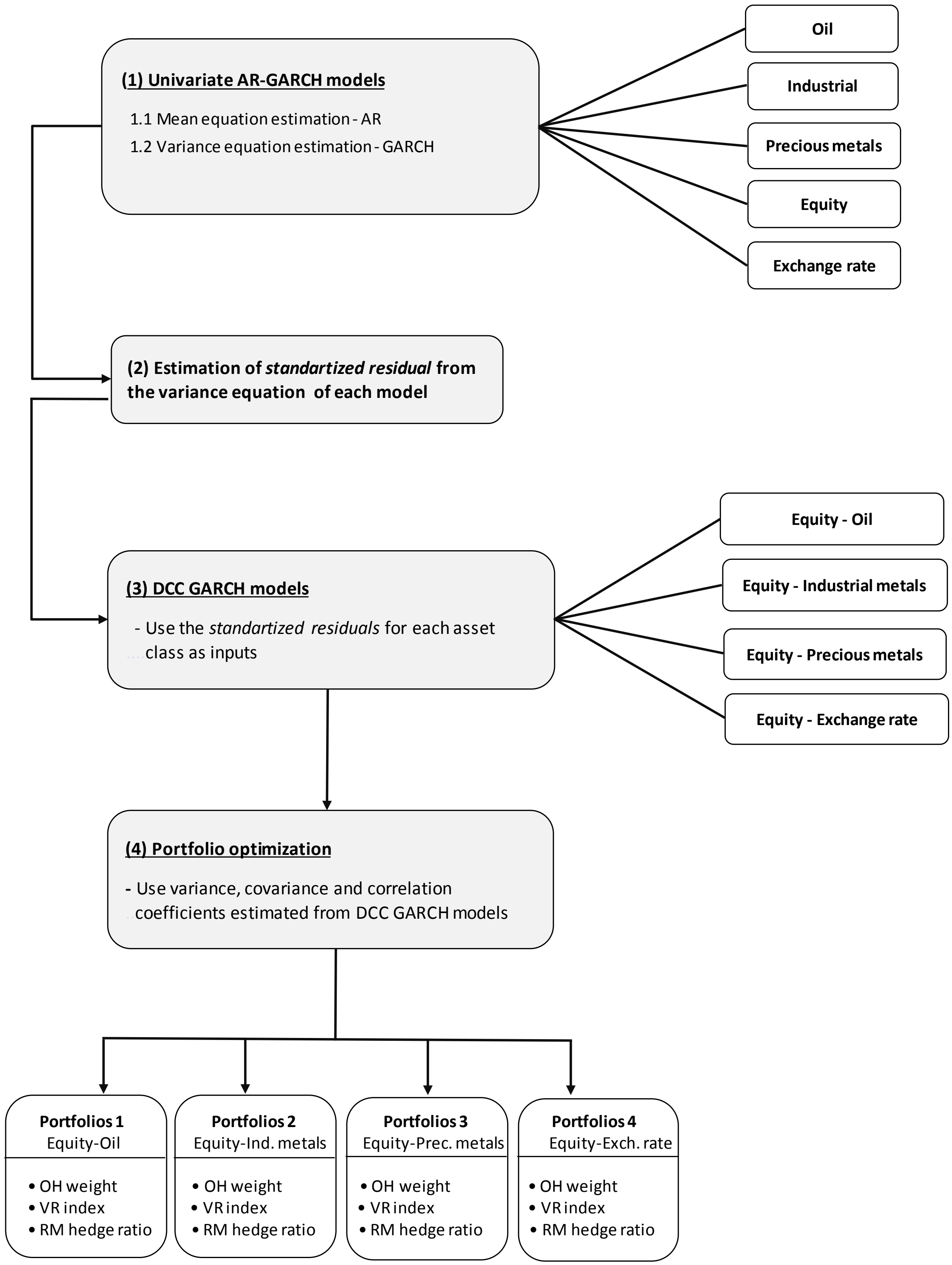


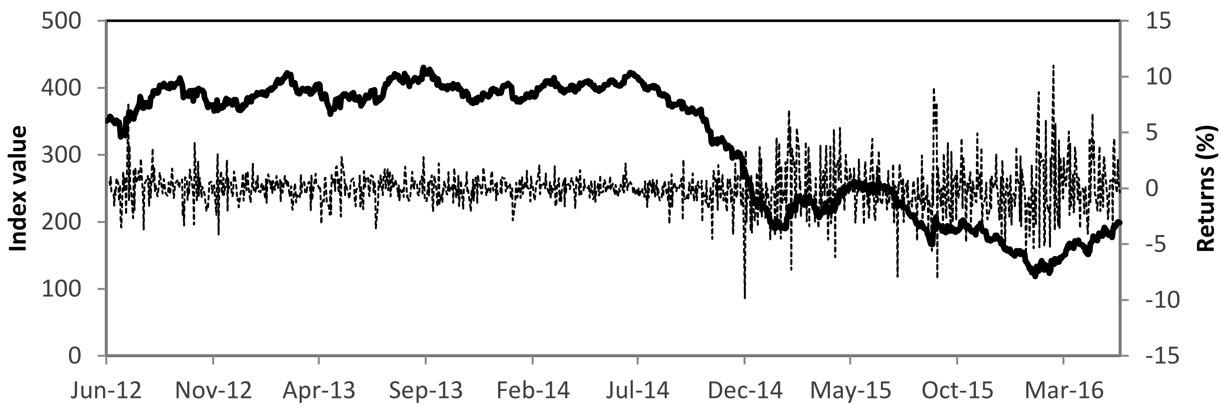
Figure A2. *Empirical framework for designing portfolio optimizations. Notes: OH weight refers to the optimal holdings of asset j in an equity-j portfolio, VR refers to the variance reduction index, RM refers to the risk minimizing hedge ratio.*



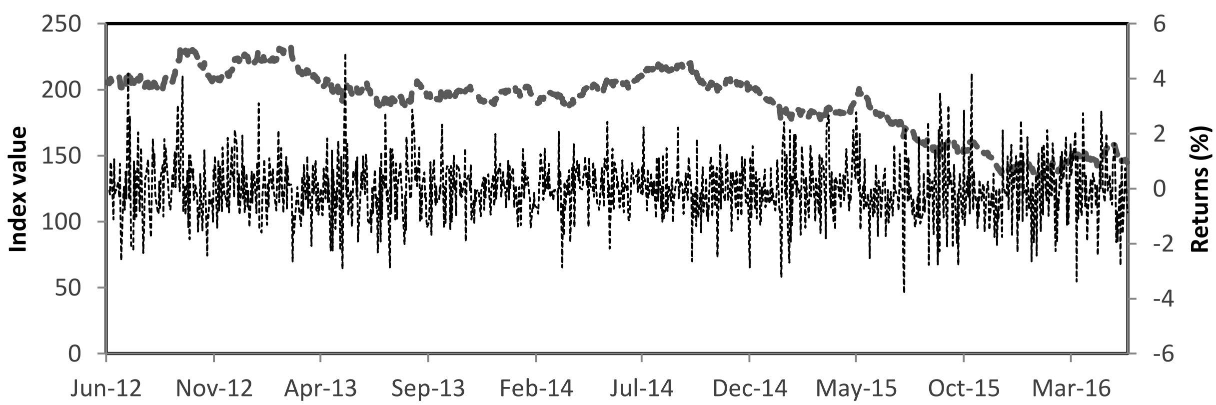
Appendix B. Data representation

Figure B1. *Index values and percentage returns of the different asset indices. Notes: the vertical axis on the left-hand side shows the index value, while the vertical axis on the right-hand side shows the percentage returns across the different asset classes between June 1, 2012 - May 20, 2016.*

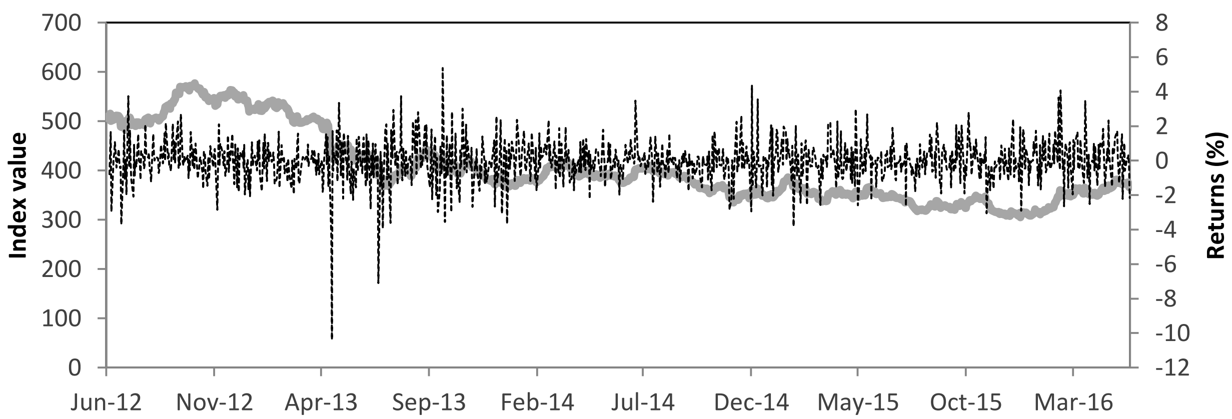
Oil



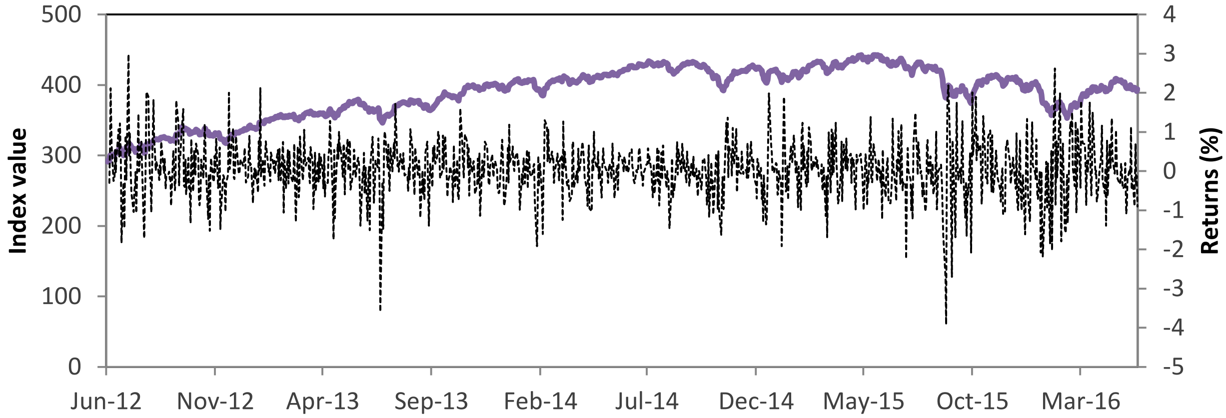
Industrial metals



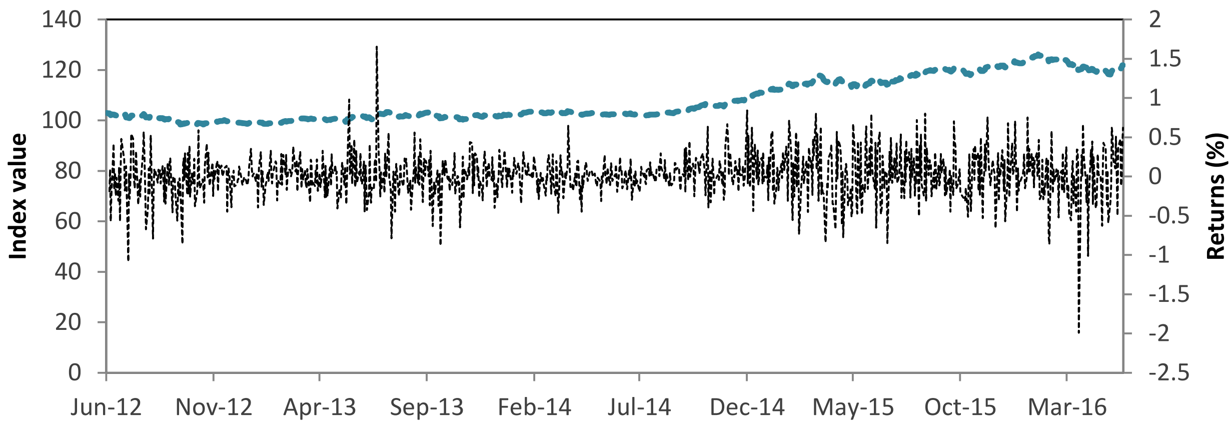
Precious metals



World equity



Global exchange rate



Appendix C. Models validation

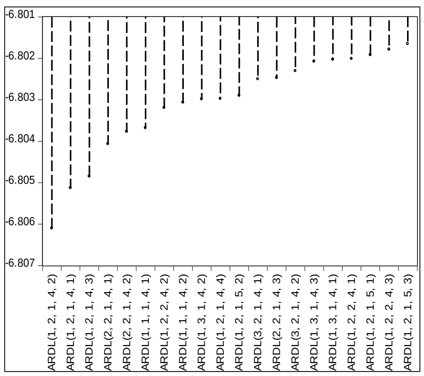
Table C1. *ARDL model verifications based on different criteria for the first period (June 1, 2012 – October 1, 2014).*

Panel A — Top 20 models based on AIC

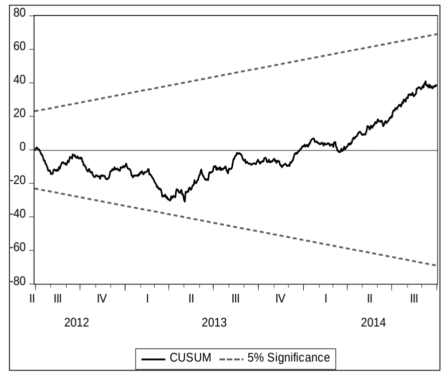
Panel B — ARDL residual correlogram

Panel C — Cumulative sum (CUSUM) test

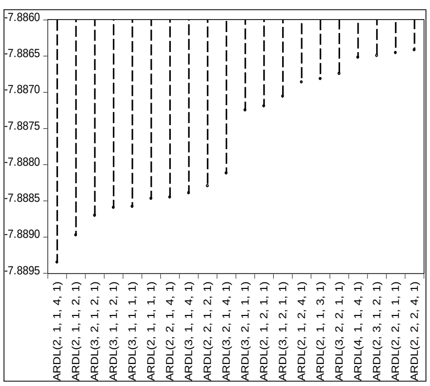
Industrial metals



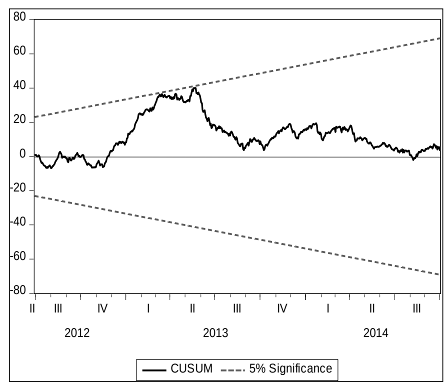
	AC	PAC	Q-Stat	Prob*
1	-0.04	-0.04	0.75	0.39
2	0.04	0.04	1.84	0.40
3	0.00	0.00	1.84	0.61
4	0.04	0.04	2.70	0.61
5	-0.04	-0.03	3.45	0.63
6	0.06	0.05	5.34	0.50
7	0.07	0.08	8.40	0.30
8	-0.05	-0.06	10.19	0.25
9	0.03	0.03	10.86	0.29
10	-0.03	-0.03	11.31	0.33
11	0.07	0.07	14.73	0.20
12	-0.04	-0.03	15.88	0.20
13	0.02	-0.01	16.05	0.25
14	-0.01	0.00	16.14	0.31
15	-0.03	-0.04	16.76	0.33
16	-0.02	-0.02	16.95	0.39
17	0.03	0.03	17.67	0.41
18	0.01	0.00	17.69	0.48
19	0.00	0.01	17.70	0.54
20	-0.01	-0.02	17.75	0.60



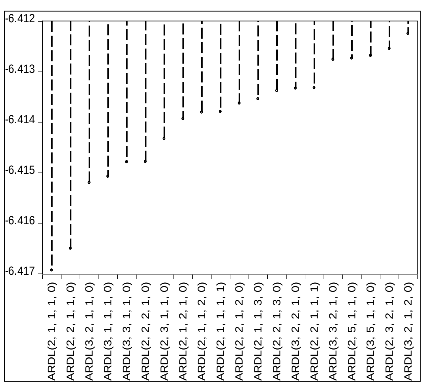
World Equity



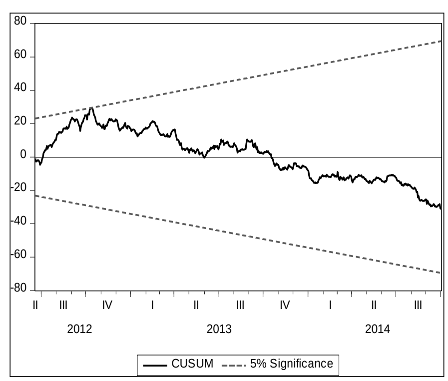
	AC	PAC	Q-Stat	Prob*
1	-0.02	-0.02	0.21	0.64
2	0.05	0.05	1.49	0.47
3	0.00	0.00	1.50	0.68
4	-0.03	-0.03	1.88	0.76
5	-0.01	-0.01	1.92	0.86
6	0.04	0.05	3.07	0.80
7	0.06	0.06	5.28	0.63
8	0.02	0.01	5.41	0.71
9	0.09	0.08	10.06	0.35
10	-0.02	-0.01	10.27	0.42
11	-0.01	-0.02	10.36	0.50
12	-0.03	-0.03	10.86	0.54
13	-0.02	-0.02	11.13	0.60
14	-0.08	-0.09	15.34	0.36
15	0.03	0.02	15.94	0.39
16	-0.03	-0.03	16.41	0.43
17	0.00	0.00	16.41	0.50
18	-0.02	-0.02	16.55	0.55
19	-0.04	-0.03	17.33	0.57
20	0.06	0.07	19.23	0.51



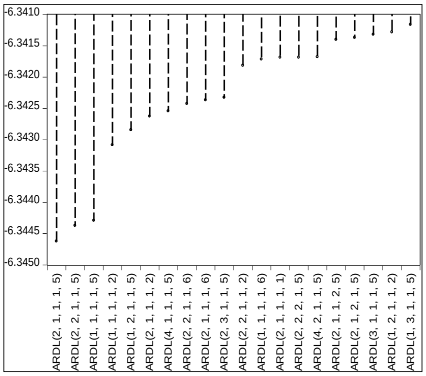
Oil



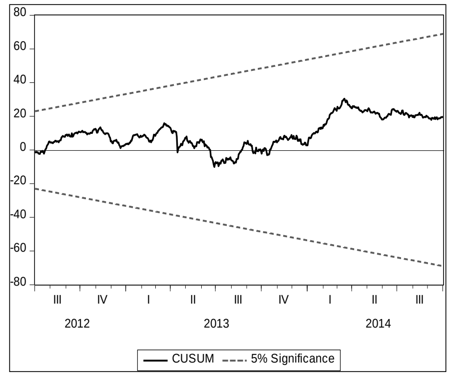
	AC	PAC	Q-Stat	Prob*
1	0.02	0.02	0.20	0.66
2	0.05	0.05	1.74	0.42
3	0.03	0.03	2.31	0.51
4	0.01	0.00	2.33	0.68
5	-0.04	-0.04	3.30	0.65
6	0.09	0.09	8.02	0.24
7	-0.03	-0.03	8.56	0.29
8	0.01	0.00	8.60	0.38
9	0.06	0.06	10.70	0.30
10	-0.06	-0.06	12.90	0.23
11	-0.01	0.00	12.93	0.30
12	-0.02	-0.03	13.17	0.36
13	-0.01	0.00	13.29	0.43
14	-0.10	-0.10	19.53	0.15
15	-0.03	-0.04	20.11	0.17
16	-0.09	-0.07	25.22	0.07
17	-0.04	-0.04	26.25	0.07
18	0.00	0.02	26.26	0.09
19	0.03	0.04	26.74	0.11
20	0.02	0.04	27.08	0.13



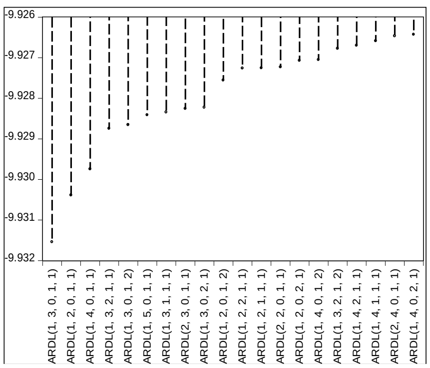
Precious metals



	AC	PAC	Q-Stat	Prob*
1	-0.01	-0.01	0.05	0.82
2	0.02	0.02	0.32	0.85
3	0.08	0.08	4.38	0.22
4	-0.04	-0.04	5.40	0.25
5	-0.01	-0.01	5.42	0.37
6	0.02	0.01	5.57	0.47
7	0.02	0.03	5.79	0.56
8	-0.03	-0.03	6.42	0.60
9	0.04	0.03	7.17	0.62
10	-0.03	-0.03	7.79	0.65
11	-0.02	-0.01	7.93	0.72
12	0.03	0.03	8.61	0.74
13	-0.03	-0.02	9.13	0.76
14	0.05	0.05	10.95	0.69
15	-0.01	-0.01	10.98	0.75
16	0.03	0.03	11.44	0.78
17	-0.06	-0.07	13.55	0.70
18	-0.06	-0.06	15.41	0.63
19	-0.04	-0.05	16.57	0.62
20	-0.03	-0.02	17.23	0.64



Global exchange rate



	AC	PAC	Q-Stat	Prob*
1	-0.02	-0.02	0.15	0.70
2	0.04	0.04	0.89	0.64
3	0.01	0.01	0.91	0.82
4	-0.06	-0.06	3.28	0.51
5	-0.04	-0.04	4.17	0.53
6	0.05	0.05	5.42	0.49
7	-0.06	-0.06	7.61	0.37
8	0.06	0.05	9.99	0.27
9	0.09	0.09	14.47	0.11
10	-0.03	-0.02	14.86	0.14
11	0.02	0.01	15.06	0.18
12	-0.02	-0.02	15.36	0.22
13	-0.06	-0.04	17.51	0.18
14	0.00	-0.01	17.51	0.23
15	-0.08	-0.07	21.02	0.14
16	0.01	0.02	21.07	0.18
17	0.03	0.01	21.50	0.21
18	-0.02	-0.02	21.70	0.25
19	-0.02	-0.02	21.85	0.29
20	-0.05	-0.06	23.55	0.26

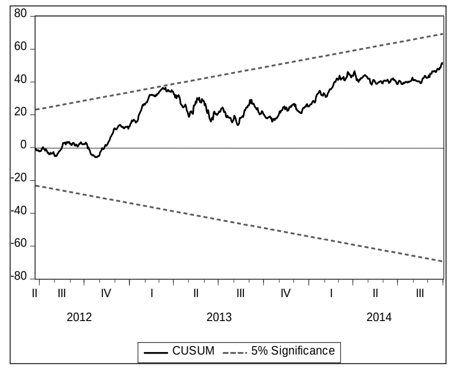


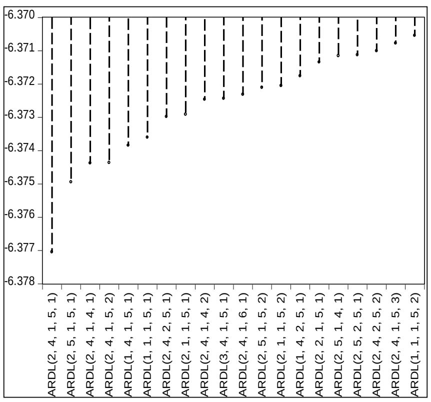
Table C2. *ARDL model verifications based on different criteria for the second period (October 1, 2014-May 20, 2016).*

Panel A — **Top 20 models based on AIC**

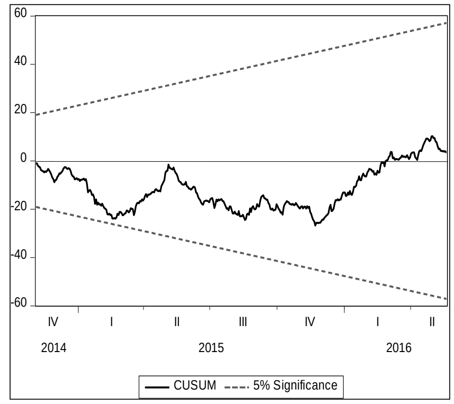
Panel B — **ARDL residual correlogram**

Panel C — **Cumulative sum (CUSUM) test**

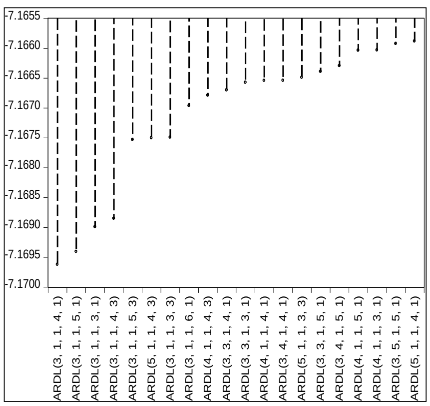
Industrial metals



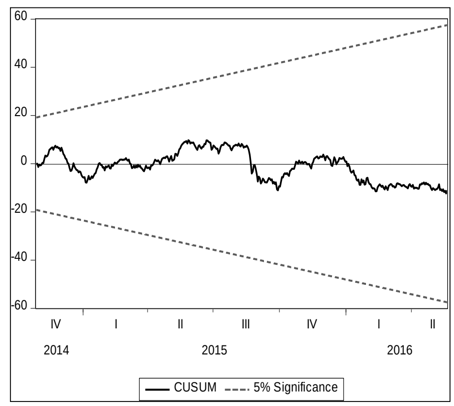
	AC	PAC	Q-Stat	Prob*
1	0.00	0.00	0.01	0.94
2	0.01	0.01	0.03	0.99
3	-0.02	-0.02	0.20	0.98
4	0.01	0.01	0.21	1.00
5	0.05	0.05	1.44	0.92
6	0.00	0.00	1.45	0.96
7	0.01	0.01	1.46	0.98
8	-0.01	-0.01	1.49	0.99
9	-0.01	-0.01	1.51	1.00
10	-0.02	-0.03	1.74	1.00
11	0.00	0.00	1.74	1.00
12	0.00	0.00	1.75	1.00
13	0.05	0.05	2.96	1.00
14	-0.04	-0.03	3.51	1.00
15	-0.03	-0.03	3.85	1.00
16	-0.11	-0.11	8.84	0.92
17	-0.02	-0.02	9.03	0.94
18	0.03	0.02	9.34	0.95
19	0.03	0.04	9.83	0.96
20	0.05	0.05	10.83	0.95



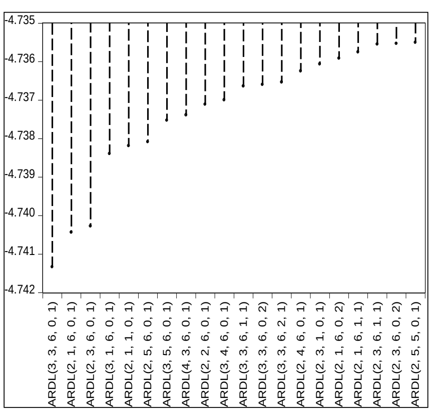
World Equity



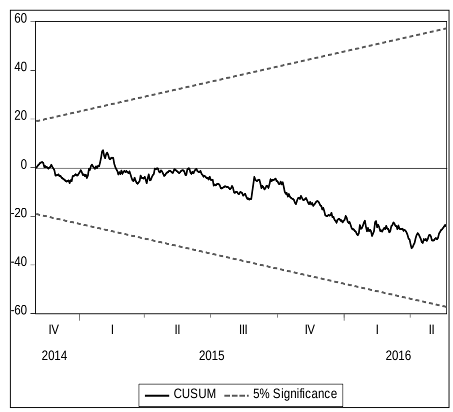
	AC	PAC	Q-Stat	Prob*
1	0.01	0.01	0.01	0.91
2	-0.04	-0.04	0.76	0.69
3	0.03	0.03	1.22	0.75
4	-0.01	-0.01	1.24	0.87
5	0.00	0.00	1.24	0.94
6	-0.04	-0.04	1.84	0.93
7	-0.06	-0.05	3.14	0.87
8	-0.01	-0.01	3.18	0.92
9	0.00	0.00	3.18	0.96
10	-0.07	-0.07	5.52	0.85
11	-0.02	-0.02	5.67	0.89
12	0.01	0.00	5.69	0.93
13	0.00	-0.01	5.70	0.96
14	-0.01	-0.02	5.78	0.97
15	0.03	0.02	6.08	0.98
16	-0.09	-0.10	9.41	0.90
17	0.01	0.01	9.49	0.92
18	0.02	0.01	9.65	0.94
19	0.00	0.00	9.66	0.96
20	0.08	0.07	12.51	0.90



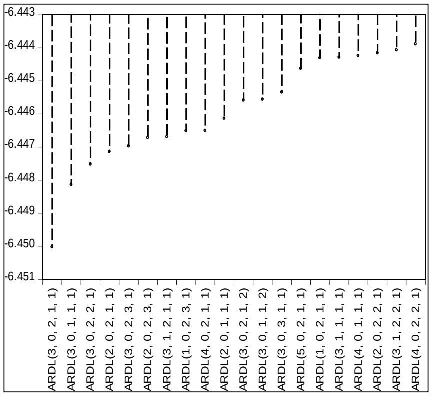
Oil



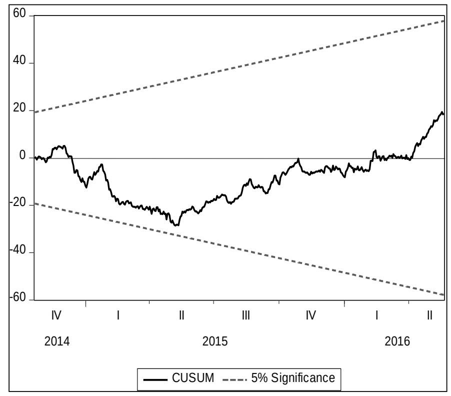
	AC	PAC	Q-Stat	Prob*
1	0.00	0.00	0.00	0.95
2	0.00	0.00	0.00	1.00
3	-0.03	-0.03	0.42	0.94
4	0.00	0.00	0.42	0.98
5	0.08	0.08	3.22	0.67
6	-0.07	-0.07	5.46	0.49
7	-0.08	-0.08	8.35	0.30
8	0.04	0.05	9.16	0.33
9	-0.11	-0.12	14.66	0.10
10	0.11	0.10	19.98	0.13
11	0.02	0.04	20.21	0.14
12	0.01	0.01	20.27	0.16
13	0.06	0.05	21.90	0.16
14	0.05	0.07	22.80	0.16
15	0.02	-0.01	22.91	0.19
16	0.04	0.04	23.58	0.20
17	-0.03	0.01	23.90	0.12
18	0.07	0.05	26.04	0.10
19	-0.11	-0.09	31.07	0.14
20	-0.04	-0.03	31.94	0.14



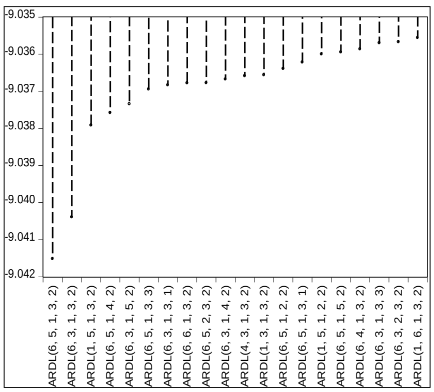
Precious metals



	AC	PAC	Q-Stat	Prob*
1	0.00	0.00	0.01	0.93
2	0.00	0.00	0.01	1.00
3	0.05	0.05	0.93	0.82
4	0.05	0.05	2.20	0.70
5	-0.04	-0.04	2.93	0.71
6	0.05	0.05	4.20	0.65
7	-0.01	-0.02	4.28	0.75
8	0.02	0.03	4.52	0.81
9	-0.07	-0.07	6.82	0.66
10	-0.04	-0.04	7.42	0.69
11	-0.04	-0.03	7.99	0.71
12	0.01	0.01	8.07	0.78
13	0.06	0.08	9.65	0.72
14	-0.07	-0.07	11.53	0.64
15	-0.07	-0.07	13.83	0.54
16	-0.03	-0.04	14.31	0.58
17	-0.08	-0.07	16.86	0.46
18	-0.05	-0.03	17.77	0.47
19	-0.02	-0.03	17.91	0.53
20	-0.06	-0.05	19.43	0.49



Global exchange rate



	AC	PAC	Q-Stat	Prob*
1	0.00	0.00	0.00	0.96
2	-0.01	-0.01	0.01	0.99
3	-0.01	-0.01	0.03	1.00
4	-0.01	-0.01	0.06	1.00
5	-0.04	-0.04	0.76	0.98
6	0.03	0.03	1.04	0.98
7	-0.05	-0.05	2.25	0.95
8	0.03	0.03	2.59	0.96
9	0.04	0.04	3.35	0.95
10	0.05	0.05	4.39	0.93
11	0.01	0.01	4.46	0.95
12	-0.02	-0.02	4.59	0.97
13	0.01	0.02	4.63	0.98
14	-0.02	-0.02	4.80	0.99
15	-0.02	-0.02	5.03	0.99
16	0.02	0.03	5.27	0.99
17	-0.05	-0.05	6.22	0.99
18	-0.02	-0.02	6.35	1.00
19	-0.07	-0.08	8.28	0.98
20	0.01	0.01	8.32	0.99

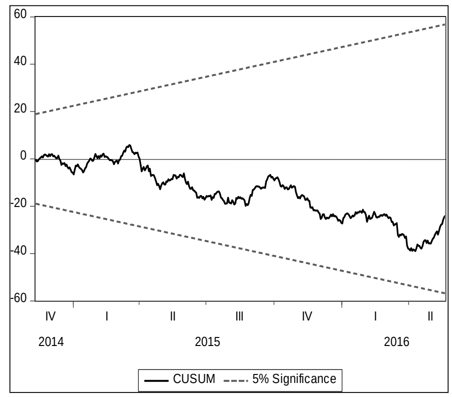


Table C3. *Results from the different VAR lag length criteria. Notes: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.*

Period: June 1,2012 - October 1,2014

Lag	LogL	LR	FPE	AIC	SC	HQ
0	10900.48	NA	1.03E-22	-36.44	-36.40*	-36.43*
1	10930.68	59.80*	1.01e-22*	-36.45*	-36.24	-36.37
2	10941.92	22.07	1.06E-22	-36.41	-36.01	-36.25
3	10955.37	26.18	1.10E-22	-36.37	-35.78	-36.14
4	10969.08	26.45	1.14E-22	-36.33	-35.56	-36.03
5	10976.40	14.00	1.21E-22	-36.28	-35.32	-35.90
6	10993.51	32.46	1.24E-22	-36.25	-35.11	-35.81
7	11006.41	24.23	1.30E-22	-36.21	-34.89	-35.69
8	11024.08	32.92	1.33E-22	-36.18	-34.68	-35.60
9	11037.18	24.18	1.38E-22	-36.14	-34.45	-35.49
10	11054.62	31.91	1.42E-22	-36.12	-34.25	-35.39

Period: October 1,2014 - May 20,2016

Lag	LogL	LR	FPE	AIC	SC	HQ
0	6863.46	NA	3.56E-21	-32.89	-32.85*	-32.86*
1	6891.06	54.40*	3.52e-21*	-32.91*	-32.62	-32.79
2	6910.28	37.43	3.62E-21	-32.88	-32.35	-32.67
3	6924.57	27.48	3.81E-21	-32.83	-32.05	-32.52
4	6937.59	24.73	4.04E-21	-32.77	-31.75	-32.37
5	6952.20	27.39	4.24E-21	-32.72	-31.46	-32.22
6	6963.59	21.10	4.53E-21	-32.66	-31.16	-32.06
7	6974.23	19.43	4.86E-21	-32.59	-30.85	-31.90
8	6984.56	18.63	5.22E-21	-32.52	-30.53	-31.73
9	7003.85	34.32	5.37E-21	-32.49	-30.26	-31.61
10	7020.02	28.38	5.61E-21	-32.45	-29.98	-31.47

Table C4. *VAR LM serial correlation test. Notes: Null Hypothesis: no serial correlation at lag order h. Probs from chi-square with 25 df.*

Period: June 1,2012 - October 1,2014

Lags	LM-Stat	Prob
1	21.92	0.64
2	23.59	0.54
3	22.52	0.61
4	27.07	0.35
5	17.66	0.86
6	32.58	0.14
7	18.63	0.81
8	29.45	0.25
9	23.51	0.55
10	30.55	0.20

*Results based on the model with 1 lag

Period: October 1,2014 - May 20,2016

Lags	LM-Stat	Prob
1	41.90	**0.02**
2	36.57	0.06
3	29.02	0.26
4	26.41	0.39
5	32.30	0.15
6	23.29	0.56
7	23.23	0.56
8	23.87	0.53
9	28.93	0.27
10	33.73	0.11

Results based on the model with 1 lag

Lags	LM-Stat	Prob
1	25.59	0.43
2	28.57	0.28
3	20.09	0.74
4	20.46	0.72
5	30.11	0.22
6	23.66	0.54
7	21.25	0.68
8	20.13	0.74
9	24.95	0.47
10	30.71	0.20

Results based on the model with 3 lag

Table C5. *VAR residual Portmanteau tests for autocorrelations. Notes: the test is valid only for lags larger than the VAR lag order. df is degrees of freedom for (approximate) chi-square distribution. Null Hypothesis: no residual autocorrelations up to lag h.*

Period: June 1,2012 - October 1,2014

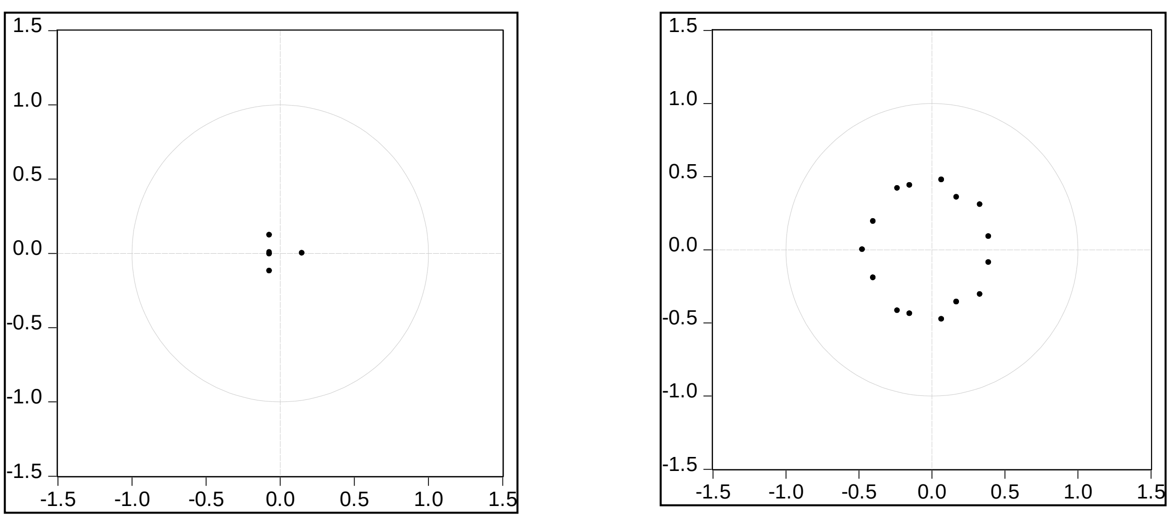
Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.49	NA*	0.49	NA*	NA*
2	23.73	0.54	23.80	0.53	25
3	46.19	0.63	46.38	0.62	50
4	73.21	0.54	73.58	0.52	75
5	90.75	0.74	91.26	0.72	100

Period: October 1,2014 - May 20,2016

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.47	NA*	0.47	NA*	NA*
2	1.45	NA*	1.46	NA*	NA*
3	2.71	NA*	2.72	NA*	NA*
4	22.62	0.60	22.82	0.59	25
5	52.52	0.38	53.08	0.36	50

Figure C1. *This figure shows the Inverse Roots of AR Characteristic Polynomial for both periods. Notes: Roots lying within the unit circle indicates that the models are dynamically stable.*

Period: June 1,2012 - October 1,2014 **Period: October 1,2014 - May 20,2016**



Appendix D. GIRF and FEVD Results

Figure D1. *Impulse response functions during June 1, 2012 – Oct 1, 2014. Notes: the first, second, third, fourth and fifth columns respectively represent the dynamic effects of an oil shock, an industrial metals shock, a precious metal shock, a world equity shock, and a global exchange rate shock on each variable. The black lines illustrate the estimated impulse responses, and the grey dotted lines show two standard error bands.*

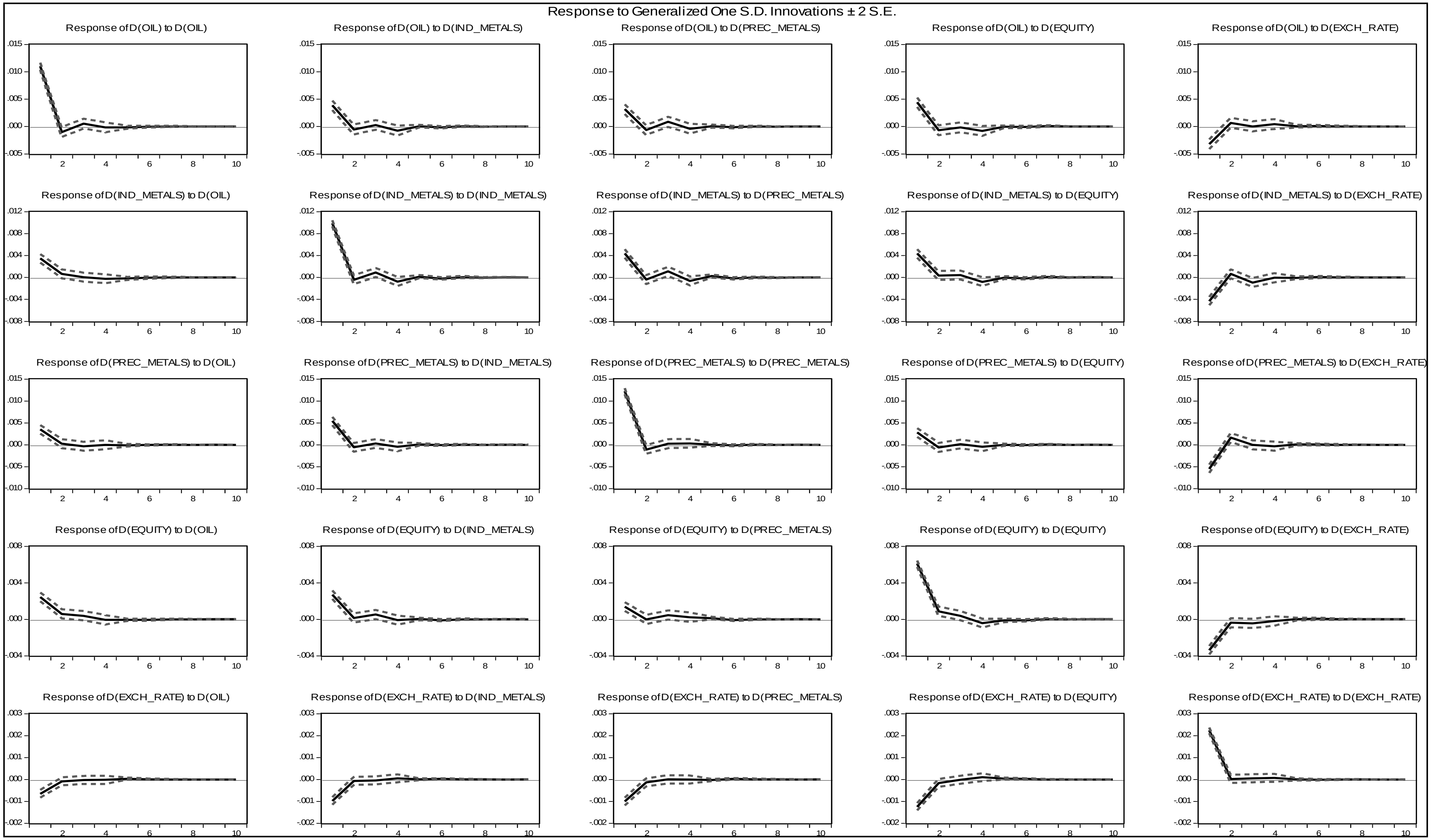


Figure D2. *Impulse response functions during Oct 1, 2014 – May 20, 2016.*

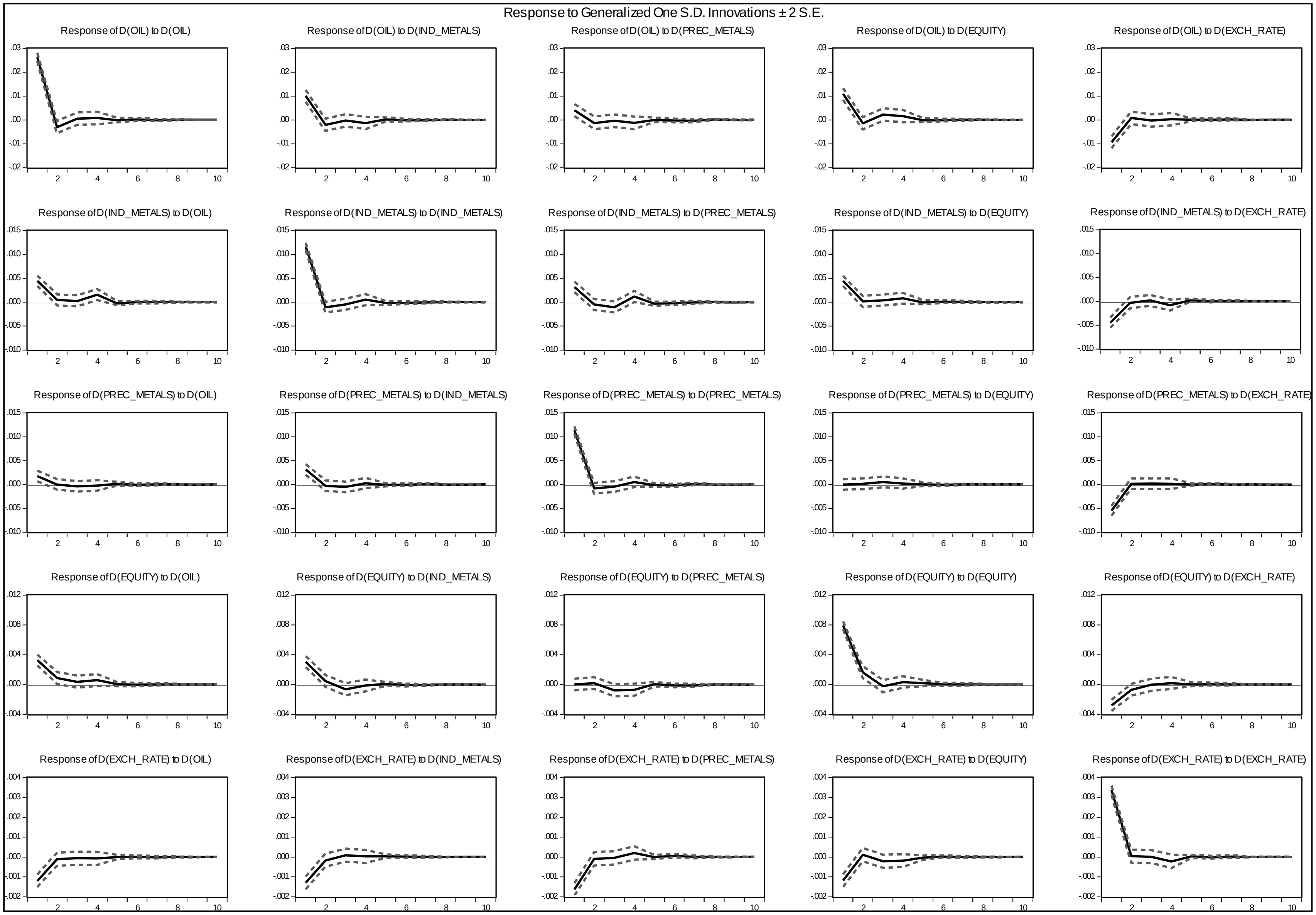
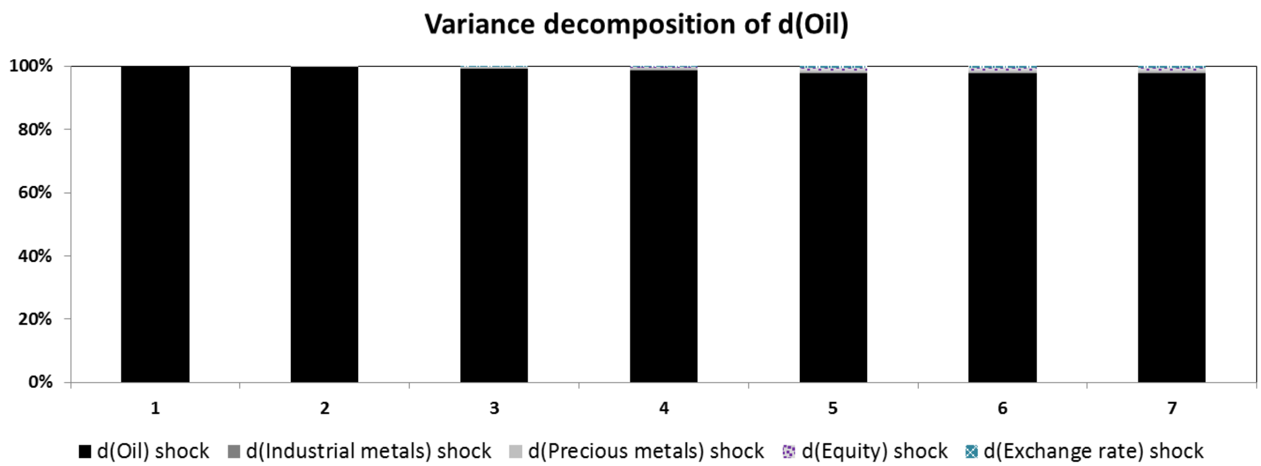
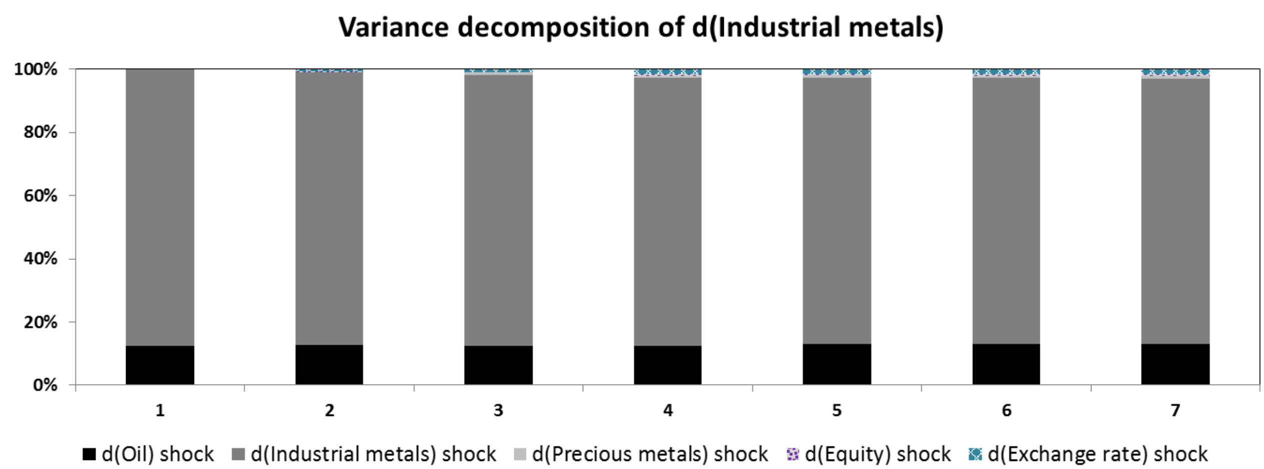
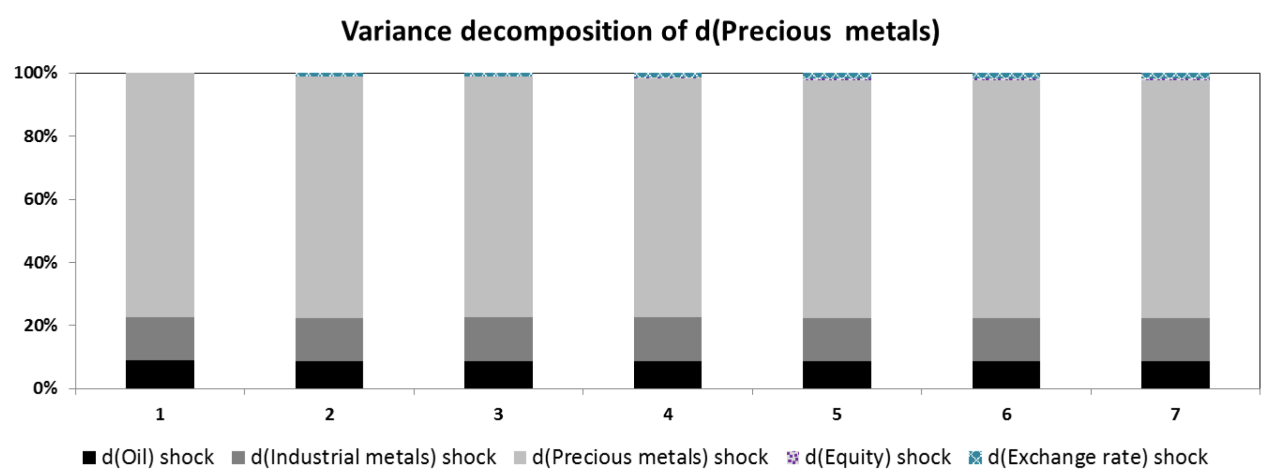
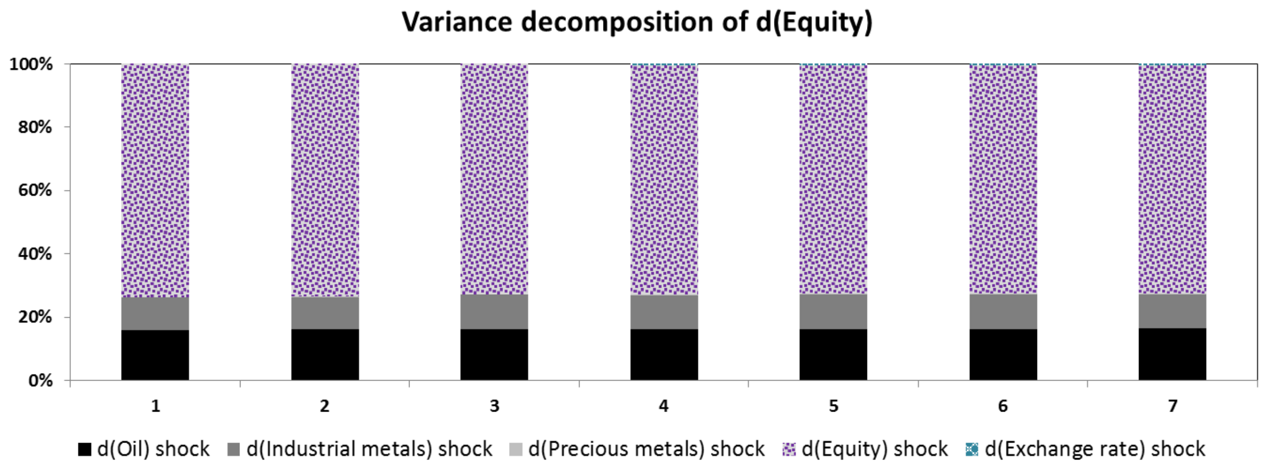


Figure D3. *20 days forecast error variance decomposition of respective asset-class returns to each of the Choleski-factored shocks. Notes: the sample period is June 1, 2012 – Oct 1, 2014. The order of the variables in the VAR specification is (Oil, Industrial metals, Precious metals, Equity, Exchange rate).*








Variance decomposition of d(Equity)
100%
80%
60%
40%
20%
0%
1
2
3
4
5
6
7
d(Oil) shock
d(Industrial metals) shock
d(Precious metals) shock
d(Equity) shock
d(Exchange rate) shock

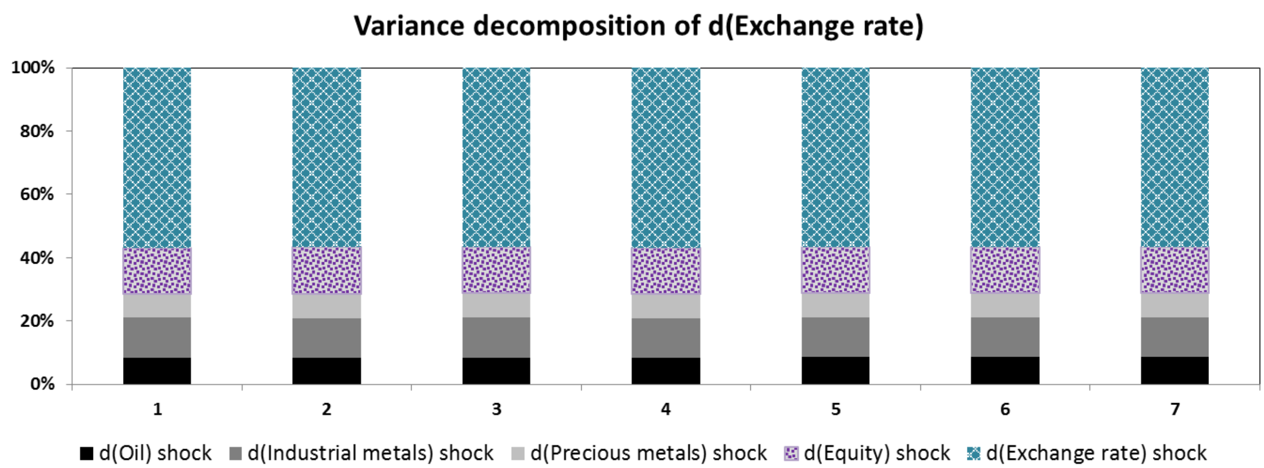
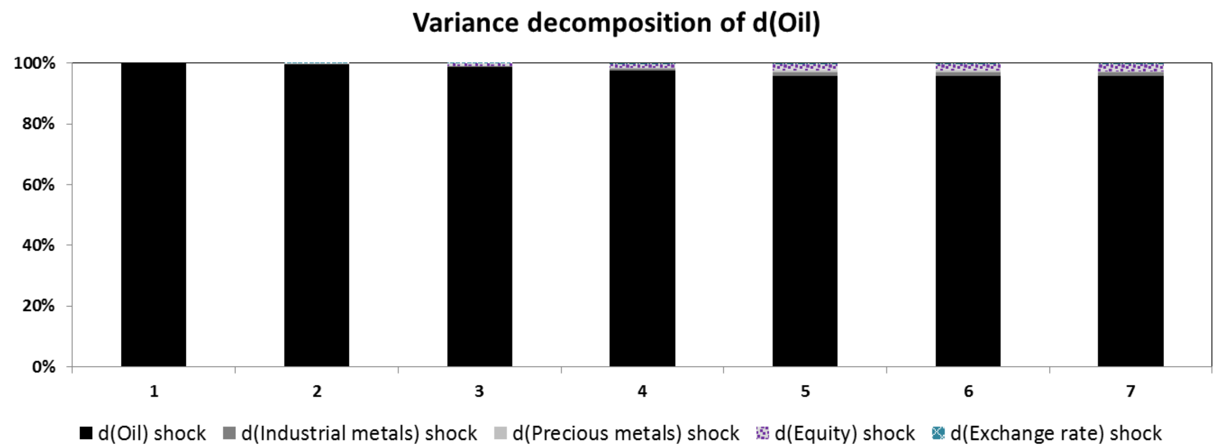
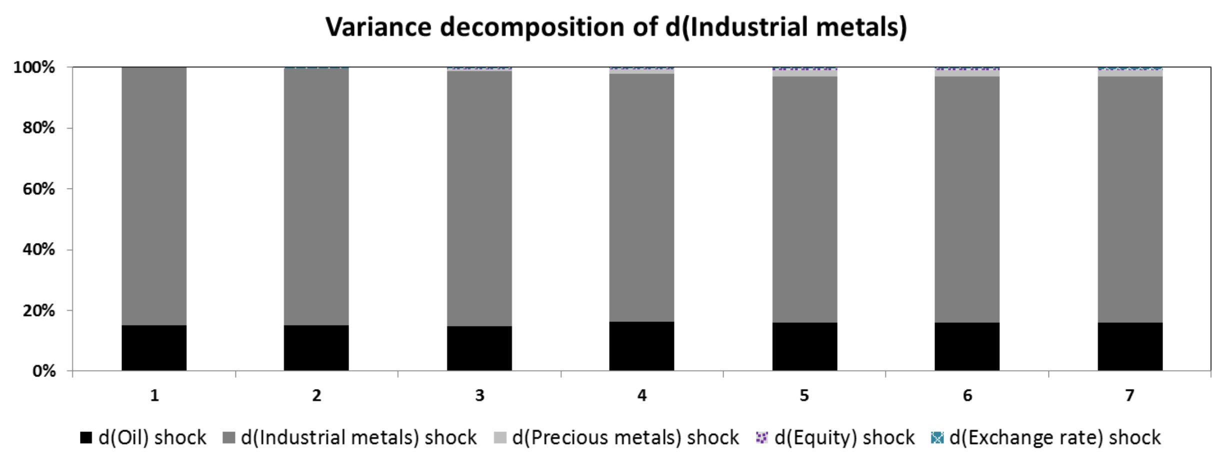
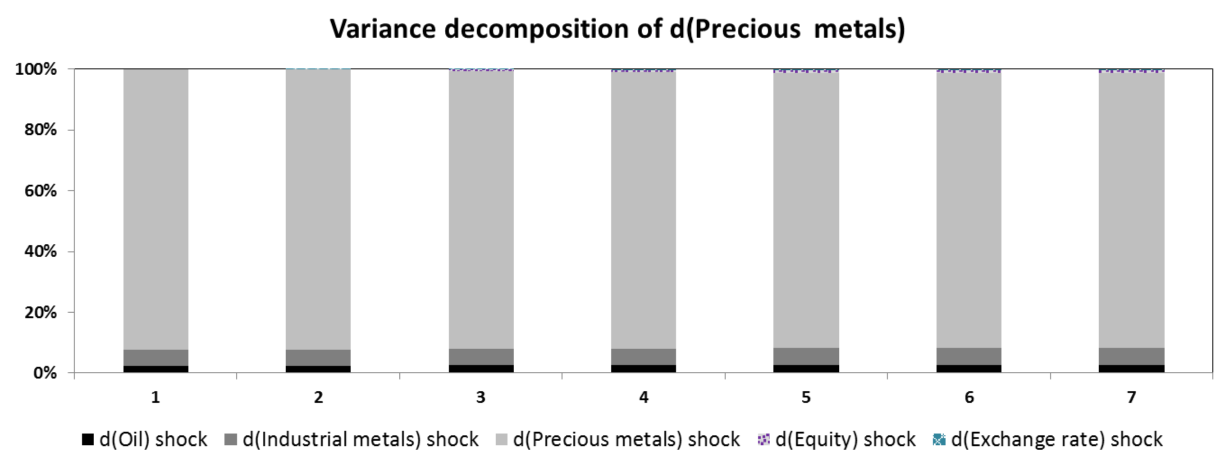
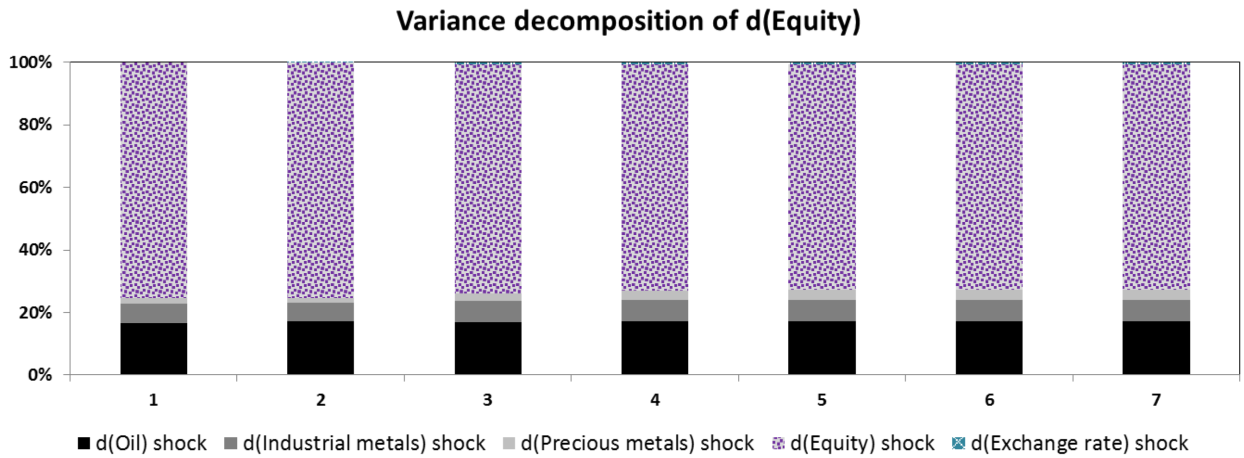

Variance decomposition of d(Exchange rate)
100%
80%
60%
40%
20%
0%
1
2
3
4
5
6
7
d(Oil) shock
d(Industrial metals) shock
d(Precious metals) shock
d(Equity) shock
d(Exchange rate) shock

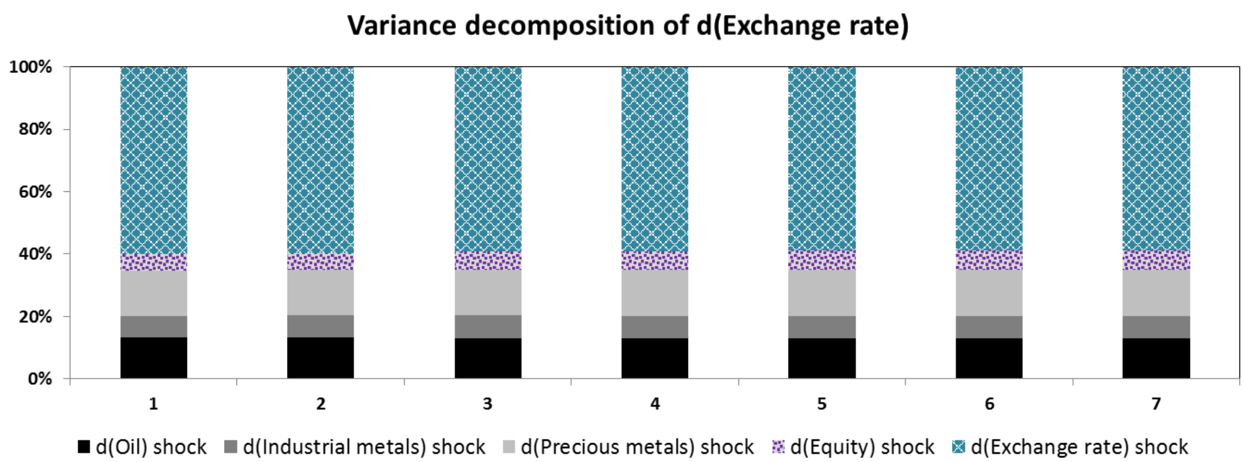
Figure D4. *20 days forecast error variance decomposition of respective asset-class returns to each of the Choleski-factored shocks. Notes: the sample period is Oct 1, 2014 – May 20, 2016. The order of the variables in the VAR specification is (Oil, Industrial metals, Precious metals, Equity, Exchange rate).*








Variance decomposition of d(Equity)
100%
80%
60%
40%
20%
0%
1
2
3
4
5
6
7
d(Oil) shock
d(Industrial metals) shock
d(Precious metals) shock
d(Equity) shock
d(Exchange rate) shock


Variance decomposition of d(Exchange rate)
100%
80%
60%
40%
20%
0%
1
2
3
4
5
6
7
d(Oil) shock
d(Industrial metals) shock
d(Precious metals) shock
d(Equity) shock
d(Exchange rate) shock

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