Linkages between Equity and Commodity Markets: Are Emerging Markets Different?

Maria E. de Boyrie
Professor
Department of Finance, MSC 3FIN
College of Business, P.O. BOX 30001
New Mexico State University, Las Cruces, NM 88003
Tel: (575) 646-3201; Fax: (575) 646-2180
E-mail: deboyrie@nmsu.edu

Ivelina Pavlova
Associate Professor
School of Business
2700 Bay Area Blvd., Box 70
University of Houston – Clear Lake, Houston, TX, 77058
Tel: (281) 283-3208
E-mail: pavlova@uhcl.edu

Keywords: Emerging markets, Commodities, Diversification, Dynamic Conditional Correlation

JEL Classification: G15, G11, F15, F36

Linkages between Equity and Commodity Markets: Are Emerging Markets Different?

August 2016

Abstract

The financialization of commodities and their inclusion in financial portfolios as part of a diversification strategy may result in higher correlations and volatility spillovers between commodity and financial markets. Although numerous studies focus their attention on the dependence structure between these two markets in the U.S., few have concentrated their attention on emerging markets. To fill this gap in the literature, we calculate the correlation between equity markets and commodities using the dynamic conditional correlation (DCC) model introduced by Engle (2002), while emphasizing the differences between emerging and developed markets co-movements with commodities. The results reveal that emerging markets, especially those in Asia, show a much lower level of co-movement with commodities than developed markets do. Furthermore, it is found that both agricultural and precious metals commodities offer better diversification possibilities in the less developed markets. Similar to Silvennoinen and Thorp (2013), we also find that increases in the VIX are related to higher commodity-equity correlations, while commodity index investment has limited explanatory power.

Keywords: Emerging markets, Commodities, Diversification, Dynamic Conditional Correlation

JEL Classification: G15, G11, F15, F36

Linkages between Equity and Commodity Markets: Are Emerging Markets Different?

Introduction

Commodities have been considered a valuable asset in portfolio diversification due to their low correlation with other asset classes. The recent slide in oil prices and the much higher positive correlation of crude oil prices with the U.S. equity market are posing a question regarding the diversification potential of commodities. Furthermore, empirical studies show that the financialization of commodities, i.e. the large inflow of funds into commodity markets, has changed the co-movement and volatility spillovers between commodities and equity markets (Adams and Gluck, 2015). While the significant increase of commodity index investment can be traced to 2004, it is argued that the impact of the financialization and the resulting significant increase in risk spillovers became notable after 2008, with the high correlations persisting well into the future. This point is important because higher correlations due to this financialization may threaten the status of commodities as a portfolio diversification tool.

Work by Chong and Miffre (2010), Creti et al. (2013), Mensi et al. (2013) and Silvennoinen and Thorp (2013) investigate the links between commodities and stocks and/or bonds with different results. Whereas Chong and Miffre (2010) find a decrease of the conditional correlations between commodity futures and the S&P 500 and Treasury bills over time, Creti et al. (2013) show an ever evolving and highly volatile correlations between commodities and stocks prices, especially during the financial crisis of 2007/2008. Furthermore, Mensi et al. (2013) find that the past volatility of the S&P 500 strongly influences the oil and gold markets while Silvennoinen and Thorp (2013) report a decrease in diversification benefits due to higher commodity return correlations with equity returns and closer integration due to greater investor interest in

commodities. It is worthwhile to note however, that the literature including emerging market equities is scarce, as evidenced by these and other research works, most of the articles on commodity and equity markets, though, use the S&P 500 index or other developed equity market indices.

In our study, we shift the focus toward emerging markets. While some emerging market countries are exporters of commodities, production and usage vary widely across countries. Eizenman et al. (2016) compare the economic factors affecting emerging markets risk premia and show that the role of factors across regions differs. While Latin American countries tend to be exporters of commodities and to be running current account deficits, Asian countries are found to be importers of commodities needed for manufacturing and a number of them run current account surpluses. These factors may contribute to the manifestation of a different relationship of commodities with emerging markets stocks across continents.

Our analysis contributes to the existing empirical literature by: (1) measuring the dynamic correlations between equity markets and commodities over time including the 2008 crisis and the recent oil price decline which started in 2014; (2) examining the differences between emerging and developed markets co-movements with commodities; (3) evaluating the impact of changes in equity market conditions and the financialization of commodities on the link between commodity and equity returns in the two markets under study (i.e., developed and emerging).

The results reveal differences in correlations of emerging and developed markets and commodities. While developed equity markets exhibit higher correlation with commodities, emerging markets, especially in Asia, reveal much lower level of co-movement. However, adding Latin American stocks to a portfolio including commodities may not be as beneficial. Agriculture and precious metals offer better diversification possibilities with emerging markets, while precious

metals offer better diversification benefits in developed markets. Significant impact of equity market volatility and commodity index investment activity is documented as well.

The rest of the paper is organized as follows. Section 2 offers a brief overview of the most recent related literature, followed by a description of the data and methodology employed in this study. Sections 3 and 4 are followed by the empirical results. The final section offers concluding remarks and implications of our results.

Literature Review

When evaluating the interaction between financial assets/markets and commodities most of the literature focuses on time-varying correlation analysis and the diversification effect that commodities could bring to an investor's portfolio. The main finding that emerges when examining this strand of literature is that the correlation between the commodity and stock markets is time varying with an unclear relationship during the 2007-2008 financial crisis, with possible attribution of this uncertain relation to differences in models, commodities and markets examined and the periods covered in each study.

Even though Malik and Ewing (2009), Chong and Mifree (2010), Sari et al. (2010), Arouri and Nguyen (2010), Belousova and Dorfleitner (2012), Graham et al. (2013) and Zhu et al. (2014) find that commodities are valuable investments from the diversification perspective, some studies cast doubt around the commodity diversification effect due to findings of high correlation between assets or markets and commodities (e.g., Buyukshahin et al. (2010), Li et al. (2011), Filis et al. (2011), Creti et al. (2013), Mensi et al. (2013), Silvennoinen and Thorp (2013), Delatte and Lopez (2013), and Sadorsky (2014), among others).

Malik and Ewing (2009), employing bivariate GARCH models, estimate the mean and conditional variance between five US sector indexes and oil prices between 1992 and 2008. In finding transmission shock between oil and some of the indexes under study, the authors ascertain

the possibility of cross-market hedging by investors. These results are further supported by Chong and Miffre (2010) who show that the dynamic correlations between the rates of return on the S&P 500 and commodities decrease during the crisis period, thus implying diversification benefits in periods of turmoil. Examining the relationship between precious metals, oil prices and the exchange rates, Sari et al. (2010) find diversification benefits by investing in all three type of assets. While attempting to better understand the relationship between stock returns and oil prices, Arouri and Nguyen (2010) determine that there exist diversification benefits by introducing oil assets into a portfolio of stocks. This finding is further supported by Zhu et al. (2014) who find the dependence between crude oil prices and Asia-Pacific stock market returns to be weak. Belousova and Dorfleitner (2012) extend prior work by investigating the contribution to diversification of five commodities to a portfolio of assets. Their findings are mixed in that precious metals and energy help reduce the level of risk and improve return while industrial metals, agriculturals, and livestock only contribute to the reduction of risk. Furthermore, Graham et al. (2013) find no evidence of co-movement between the S&P 500 total return and the S&P GSCI commodity index (and 10 individual sub-indexes), given greater support to the short- and long-term diversification gains provided by commodities.

Nonetheless, Buyukshahin et al. (2010) find that correlations among assets and commodities tend to increase after the beginning of the financial crisis, instilling doubt about the effect of diversification through the use of commodities. While examining the commodity-equity correlation Li et al. (2011) find that 43 of the 45 indexes under study had increasing correlation during the financial crisis of 2007-2008. Filis et al. (2011) and Creti et al. (2013) both used (DCC) GARCH methodology to investigate the time-varying correlation between the stock market and oil prices and the stock prices and 25 commodities, respectively and find that such correlation not only exists but that it evolves over time. Furthermore, Creti et al. (2013) report the presence of

high volatility since the financial crisis. Of the commodities under study by Creti et al., the authors determined that oil, coffee, and cocoa are speculative in nature, gold was determined to be used as a safe-heaven. Delatte and Lopez (2013) also finds that the correlation between commodity and stock markets is time-varying but occurs most of the time and not only during times of distress.

Using a slightly different model (i.e., the double smooth transition conditional correlation model), Silvennoinen and Thorp (2013) estimate the changes in correlation between stocks, bonds and commodity future returns with similar results to those stated before; that is, increasing correlation over time with significant reduction of diversification benefits across the three markets. Applying a VAR-GARCH model, Mensi et al. (2013) discovers that the highest conditional correlations are between the S&P 500 and both the gold and WTI indexes.

An interesting point to note is that most work in the areas of directional volatility spillover, hedging and diversification benefits from the use of commodities has been done from the point of view of developed markets, and little work can be found that focuses on emerging markets. Of those studies that can be found, several focus on the effect of oil prices on stock markets. For example, Basher and Sadorsky (2006) use an international multi-factor model to determine the existence of a strong relationship between oil price risk and the return of stock prices in emerging markets. Soytas et al. (2009) analyze the possible relationship between the world oil price and the Turkish interest rate, Turkish lira-US dollar exchange rate, and domestic spot gold and silver prices in both the short- and long-term. Overall, oil prices were found to have no predictive power over the price of precious metals, the interest rate or the exchange rate market in the country under study and vice-versa. Masih et al. (2011) study the effects of crude oil prices on the Korean economy during the Asian crisis using modern time series techniques in a cointegrating framework. The authors find that oil price volatility indeed dominates real stock returns. Basher et al. (2012) estimate the dynamic relationship between oil prices, exchange rates and emerging market stock

prices and discern that positive shocks to oil prices reduce both emerging market's stock prices and US dollar exchange rates in the short run while an increase in the stock prices of emerging markets increases oil prices. Sardosky (2014) studies the interrelationship between stock prices in emerging markets and copper, oil and wheat prices. Overall the results show that stock and oil prices exhibit leverage effects with oil providing the cheapest hedge for stock prices. Only Graham et al. (2016) makes a connection between companies in developed markets and commodities by concluding that these companies may have a larger exposure to commodity returns if they have significant exposure in emerging markets.

Methodology

The methodology used in this paper to model the evolution of correlations between commodities and equities is the dynamic conditional correlation (DCC) model introduced by Engle (2002). This model builds on the framework of ARCH/GARCH-type models, developed by Engle (1982) and Bollerslev (1986), respectively. Assume that r_t is a vector consisting of two return series, *A(L)* is the lag polynomial and ε_t is the error term vector, the return and conditional variance can represented as follows:

$$A(L)r_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim N(0, H_t) \tag{1}$$

$$H_t = D_t R_t D_t \tag{2}$$

where $D_t = diag\left|\sqrt{h_{1t}}\sqrt{h_{2t}}\right|$, a diagonal matrix of time-varying standard deviations estimated from the univariate GARCH (1,1) models and R_t is the time-varying conditional correlation matrix. That is, in the first stage of the DCC estimation, univariate GARCH models are fit for each of the two return series. In the second stage, the standardized residuals from the previous stage are used to obtain the conditional correlation coefficients. The GARCH (1,1) variance is represented by

$$h_t = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{t-1} \tag{3}$$

where $\omega_i > 0, \alpha_i, \beta_i > 0, \alpha_i + \beta_i < 1$. The ω term presents the weighted long-run variance, while the α and β coefficients determine the short-term dynamics of the volatility series resulting from the equation.

The time-varying correlation matrix R_t can be decomposed into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4}$$

where Q_t is the symmetric positive definite matrix of the conditional variances-covariances and Q_t^{*-1} is an inverted diagonal matrix consisting of the square root of the diagonal elements of Q_t.

$$Q_t^{*-1} = \begin{bmatrix} \frac{1}{\sqrt{q_{11t}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{22t}}} \end{bmatrix} \tag{5}$$

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_2 \varepsilon_{t-1} \varepsilon'_{t-1} + \theta_2 Q_{t-1} \tag{6}$$

If both parameter estimates for θ_1 and θ_2 are significant, this indicates that the conditional correlation is not constant. While θ_1 measures the effect of past shocks on current conditional correlation, θ_2 measures the impact of past correlations.

The dynamic conditional correlation between assets 1 and 2 at time *t* are given by

$$\rho_{12t} = \frac{q_{12t}}{\sqrt{q_{11t} q_{22t}}}. \tag{7}$$

The coefficients in the DCC model are estimated by a two-step maximum likelihood method, where the maximum likelihood function is expressed as

$$L = -\frac{1}{2} \sum_{t=1}^{T} (2 \log(2\pi) + 2log|D_t| + log|R_t| + \varepsilon'_t R_t^{-1} \varepsilon_t). \tag{8}$$

Data

Daily equity and commodity index data are gathered from Datstream beginning in January 2006 till January 2016. The indices are denominated in USD. The commodity indices included are S&P GSCI Commodities and three sub-indices: S&P GSCI Energy, S&P GSCI Agriculture, and S&P GSCI Precious Metals. The S&P GSCI is a major investable commodity index, which is also weighed based on world's production and adjusted for futures trading volume.[1] Total return indices are used which measure the returns from investing in commodity futures contracts with the closest settlement date on a fully-collateralized basis. Twenty-four physical commodity futures are included in the GSCI commodity index and the five sectors they span are energy, agriculture, livestock, industrial metals and precious metals. As of January 2016, the index was heavily weighted in energy, with about 25% in WTI crude oil, 25% in Brent crude oil, 7% in gas oil, while gold had about 2.42% weight (Table A.2.). The three sub-indices we use are also world-production based and are rebalanced annually. The index is rolled from the nearby to the next futures contract between the fifth and the ninth business days of the month.

The MSCI indices selected reflect equity returns in developed and emerging markets. The MSCI World index consists of large-cap and mid-cap companies covering about 85% of the market capitalization of 23 developed markets[2]. As of January 2016 the top constituents were Apple, Microsoft Corp., Exxon Mobil Corp., and General Electric. US companies accounted for more than 58% of the country weights of the MSCI World Index. The index is reviewed quarterly, while rebalancing occurs semiannually. To capture the fluctuations of equity markets in emerging markets, we use the MSCI Emerging markets index (23 emerging markets) and also three regional indices: MSCI Emerging Markets Europe (6 countries), MSCI Emerging Markets Asia (8

[1] http://us.spindices.com/index-family/commodities/sp-gsci
[2] https://www.msci.com/world

countries), and MSCI Emerging Markets Latin America (5 markets). Country weights in each in each of the selected indices is provided in table A1. Similarly to the MSCI World, the indices capture approximately 85% of the float-adjusted market capitalization in each country. Figure 1 and figure 2 present the evolution of the commodity and equity indices levels over the sample period. The GSCI commodity index shown in figure 1 has a notable spike in 2008 (the price of crude oil reached $147 per barrel I July 2008), followed by a dramatic decrease towards the end of 2008 and beginning of 2009 and again a big drop starting in the second half of 2014. Large swings in the level of equity indices are noted in figure 2 as well, since our period includes the 2008 Global Financial Crisis.

Table 1 reports descriptive statistics of the index returns data in percent. The returns are defined as $r_t = \ln(P_t/P_{t-1})$, where P_t is the index price at time t. The MSCI World and the MSCI Emerging Markets (EM) Asia are the two equity indices with positive average return over the 2006-2016 period, while from the commodity indices the Precious Metals index is the only one with a positive mean return over the sample period. The maximum daily return for the GSCI world index is 9%, while the minimum is -7%. The highest range of returns among the stock indices is noted for the EM Europe and Latin America indices. The GSCI Energy and Precious Metals indices have the largest range of daily returns, from -9.6% to 9.8% and -10.1% to 8.8%, respectively. The EM Europe index is most volatile among the equity indices and the Energy index has the highest standard deviation among the commodities. Table 1 also shows the skewness, kurtosis and Jarque-Bera test for normality. All returns series are negatively skewed. The evidence in the table suggests that returns distributions exhibit significant departures from normality.

The results in the table 2 show the unconditional correlations between the equity and commodity indices. Some of the lowest correlations of the equity indices are with Precious Metals, for instance, the correlations the EM Asia is only 13% and with the World index is 17%.

Agricultural commodities also exhibit relatively low correlations with stocks, about 16% with Asian stocks and about 32% with developed equity markets (MSCI World). Energy commodity seem to have higher correlations with both emerging and developed markets, with the exceptions of EM Asia. Within the equity indices group, we note relatively high correlations between developed and emerging markets, whereas within the commodity indices correlations are much lower (28% between Agriculture and Precious Metals). The unconditional return correlations suggest that while commodity returns have potential for diversifying risk in a portfolio including stocks, the diversification potential differs based on the markets involved.

Empirical Results

Commodities and Developed Markets

The pairwise dynamic conditional correlations of commodity and equity market indices are presented in figure 3. Starting with the correlations of MSCI world index with commodities, we note that the correlations display relatively large fluctuations over time. The MSCI World index comprises of developed markets such as the UK, US, Japan, France, etc. Prior to 2008 correlations vary relatively less and are mostly positive but less than 50%. The global financial crisis causes a large swing, with correlations initially going negative and over time reaching almost 80%. Correlations keep relatively high till 2014, with the exception of one large decrease in 2011. The correlation of developed equity markets with energy commodities follows almost the same pattern, positive correlations interrupted by episodes of negative correlations going to almost -20% in 2008 and 2011. These findings are consistent with studies investigating the link between the S&P 500 index and energy commodities such as Creti et al. (2013), Filis et al. (2011). According to Creti et al. (2013) the initial drop in correlations during the 2008 crisis could be due to “flight to quality”, i.e. investors are trying to escape from the collapsing equity markets by investing into different asset classes, such as commodities. The subsequent increase in correlations of commodities in

general and of energy commodities with developed equity markets in late 2008 and early 2009 could be explained by an aggregate demand shock (Filis et al., 2011). The 2008 financial crisis resulted in a recession, which consequently caused the decline in oil prices (Filis et al., 2011), and can be seen in the rise of the correlation with the energy commodity index.

Agricultural commodities and precious metals present a slightly different pattern in correlation dynamics with developed equity markets (Figure 3). Correlations with agricultural commodities rarely exceed 20% prior to 2008 crisis and after that they rarely go above 40%. The global financial crisis is also surrounded by higher volatility in this case, but the spike in 2011 is much less. Correlations with agricultural commodities are positive throughout the sample period. Precious metals, however, present multiple periods of negative correlations with developed equity market returns (MSCI World index). The multiple instances of correlations below zero could be attributed to the safe-haven role of gold, i.e. when stock prices drop, investors buy gold (Creti et al., 2013; Baur and McDermott, 2010).

Commodities and Emerging Markets

Turning to the emerging markets equities and commodities correlations (MSCI Emerging Markets and GSCI Commodities), we note that the relations appear less volatile. While larger swings are noted in 2008 and 2011, the range is smaller in comparison with developed markets and commodities. Furthermore, the MSCI Emerging Markets and GSCI commodity index correlation does not become negative at any point during our sample. The correlations between emerging markets and energy commodities again seem more volatile than with the overall commodity index, but again a major difference is that there is no negative correlations recorded during the sample period. These dissimilarities between emerging and developed equity markets may stem from the different role of commodities in emerging market economies. The countries with largest weight in the MSCI Emerging markets index are China, South Korea, Taiwan, India

and South Africa. While commodities are a major source of export revenue in some developing countries, China is a major net importer of commodities. Roache (2012) shows that China has impact on the prices of base metals and oil in the short run, and overall, growth in China has had an increasing influence on commodity prices.

Lastly, we address the correlations of Asian, European and Latin American stocks with commodity indices. Comparing the three regions, the overall correlations with commodities are lowest and least volatile in the case of MSCI EM Asia. The correlations with the Agriculture sector index is relatively lower for all three regions, but shows the least number of swings and does not exceed 20% in the case of MSCI EM Asia. The conditional correlation of Latin American stocks and the overall commodity index, as well as the Energy sector, are time-varying and ranging from close to zero in 2008 and 2011 to over 60%. High correlations are noted in the period after 2014 as crude oil prices began deteriorating. An earlier study by Johnson and Soenen (2009) supports the view that stock markets of South American countries are heavily influenced by commodity prices and that Argentinian, Brazilian and Peruvian equities are impacted by commodity price swings in the same day during the period of their study.

Overall, the results presented in figure 3 support the notion that the correlations of emerging stock markets and commodities are time-varying, and also differ by region. While Asian equities and commodities offer a better diversification opportunity, including Latin American stocks in a portfolio that already has commodities in it will not be as valuable. To add to the graphical presentation of correlation dynamics, table 3 reports the estimates of the univariate GARCH specifications for each series and the DCC coefficients (eq. 1, 3 and 6). All DCC coefficients (eq. 6) show evidence of time varying conditional correlation and a sum close to 1 for most of the series, indicating persistence in volatility.

Correlation Determinants

Few studies have documented that the links between equities and commodities can change in a volatile financial environment. For instance, Chong and Miffre (2010) regress conditional correlations on volatility of different asset markets and find that correlation between some commodities and the S&P 500 decrease during periods of market turbulence. A more recent study by Silvennoinen and Thorp (2013) finds that, on the contrary, correlations of the S&P 500 and commodity futures increased during the 2008 crisis and shows that as the VIX index increases, correlation increase as well. Silvennoinen and Thorp (2013) also show that futures markets positions of non-commercial traders long positions (open interest) affect correlations. Creti et al. (2013) also highlight the differences in the correlations between S&P 500 and commodities during the 2008 financial crisis and attribute it to the financialization of commodity markets.

To evaluate the impact of the financialization of commodities and changes in equity market conditions on the link between commodity and equity returns, we save the DCC time series estimates of the correlations of each equity index with each commodity index and run the following regression:

$$\hat{\rho}_{i,jt} = \gamma_0 + \gamma_1 \hat{\rho}_{i,jt-1} + \delta_1 NII_t + \delta_2 VIX_t + \upsilon_t \quad (9)$$

where $\hat{\rho}_{i,j}$ is the Z transformed monthly correlation between market *i* and commodity *j* at time *t*, NII_t denotes Net Index Investment and VIX_t denotes changes in the CBOE VIX index, reflecting expected market volatility over the next 30 days. The Net Index Investment data is gathered by the Commodity Futures Trading Commission (CFTC) and is released to the public monthly. Index investment is considered by the CFTC to be a passive investment strategy to gain exposure to commodity price fluctuations by investors such as index funds, pension funds, hedge funds, mutual funds, ETFs, ETNs, among others. The CFTC gathers data on the total notional value of each fund's commodity index business. The data includes the number of futures contracts for all U.S. markets with more than $0.5 billion notional value per month. NII data is available from December 2007 till November 2015.

The estimates from equation (9) are reported in table 4. Net Index Investment has limited explanatory power and appears negative and significant at 10% only in five cases, and in particular, in three

of these instance it affects the correlations with agricultural commodities. The VIX appears positive and significant in explaining the correlations between MSCI EM and agricultural commodities, as well as between Asian equities and agricultural commodities and commodities in general. High levels of the VIX are also associated with higher correlations between Latin American equities and energy commodities. These results are largely consistent with Silvennoinen and Thorp (2013), who use a different methodology but also find that increases in the VIX are related to higher commodity-equity correlations, while higher open interest of non-commercial traders indicates subsequent declines in correlations for some commodities. A notable exception to the influence of the VIX towards higher correlations is the impact of the VIX on correlations of precious metals and equity markets. Higher levels of market turbulence are associated with safe-haven effects, when gold and equity prices move in the opposite direction.

Conclusion

This paper investigates the links between emerging and developed equity markets co-movements with commodities through the use of the dynamic conditional correlation methodology developed by Engle (2002). It contributes to the current literature in several ways. Primarily, this study analyzes the differences between the co-movements of both types of markets with commodities. Secondarily, it evaluates the impact of the financialization of commodities and changes in equity market conditions on the link between commodity and equity returns by examining the relationship between the DCC time series estimates for bilateral correlations and the CBOE VIX index and total commodity index activity. The study and findings are of relevance to policymakers who are concerned with the effect of commodity prices and volatility on inflation and to portfolio investors who combine commodities with, or use them as substitutes for bonds and stocks in their asset allocation, an allocation to less risky and more liquid assets due to the phenomenon better known as “flight-to-quality” or “flight-to-liquidity” during periods of crisis (Berber et al., 2007; Chong and Miffre, 2010; and Silvennoinen and Thorp, 2013).

The main findings for the period between 2006 and 2016 can be summarized as follows. Using two different MSCI indexes and three MSCI sub-indexes and the S&P GSCI Commodities index and three S&P GSCI sub-indices to proxy for equity market and commodity returns, respectively, it is determined that while commodity returns have potential for diversifying risk in a portfolio including stocks, the diversification potential differs based on the markets involved. For example, although there exist low correlations between equity markets and precious metals and agricultural commodities, high correlations between equity markets and energy commodities are observed. Second, the pairwise dynamic conditional correlations between developed markets and energy commodities show large fluctuations over time, especially during the 2008 financial crisis in which correlations increased, and at times became negative, and remained fairly high until 2014. One exception is the economic crisis of 2011 where a decrease was noted. A somewhat similar case occurs between equities and agricultural commodities and precious metals where correlations increase during the crises periods (2008 and 2011) but in a much lower proportion than energy. In the case of emerging markets, there exists less volatility than in developed markets and the correlations are positive throughout the study period, especially in the case of Asia. With regards to energy sector in developing economies, high correlations are noted in the period after 2014 as crude oil prices began deteriorating. These findings corroborate the "flight-to-quality" or "flight-to-liquidity" hypotheses proposed in earlier studies. Third, higher commodity index investment indicates subsequent declines in correlations with agricultural commodities, while increases in the VIX are related to higher commodity-equity correlations in most cases. These findings are in line with those of Silvennoinen and Thorp (2013) who find closer integration between the equity and commodity markets.

Overall, our findings show that during periods of crisis, investors can benefit by adding commodities such as energy (in the case of developed markets) and precious metals (in both

developed and emerging markets) to their portfolios due to their negative correlations with market returns.

References

Aizenman, J., Jinjarak, Y., & Park, D. (2016). Fundamentals and sovereign risk of emerging markets. *Pacific Economic Review*, *21*(2), 151-177.

Arouri, M. E. H., & Nguyen, D.K. (2010). Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. *Energy Policy*, 38(8), 4528-4539.

Basher, S. A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. *Global Finance Journal*, 17(2), 224-251.

Basher, S.A., Haug, A. A., & Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. *Energy Economics*, 34(1), 227-240.

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, *34*(8), 1886-1898.

Belousova, J., & Dorfleitner, G. (2012). On the diversification benefits of commodities from the perspective of euro investors. *Journal of Banking & Finance*, 36(9), 2455-2472.

Beber, A., Brandt, M.W., & Kavajecz, K.A. (2007). Flight-to-quality or flight- to-liquidity? Evidence from the Euro-Area bond market. Review of Financial Studies, 22(3), 925–957.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327.

Büyüksahin, B., Haigh, M.S., & Robe, M.A. (2010). Commodities and Equities: Ever a "Market of One"? *Journal of Alternative Investments*, 12(3), 76-95.

Chong, J., & Miffre, J. (2010). Conditional correlation and volatility in commodity futures and traditional asset markets. *Journal of Alternative Investments*, 12(3), 61–75.

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

Delatte, A. L., & Lopez, C. (2013). Commodity and equity markets: Some stylized facts from a copula approach. *Journal of Banking & Finance*, *37*(12), 5346-5356.

Engle, R. F. (1982). A general approach to Lagrange multiplier model diagnostics. *Journal of Econometrics*, *20*(1), 83-104.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339-350.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, 20(3), 152-164.

Graham, M., Kiviaho, J., & Nikkinen, J. (2013). Short-term and long-term dependencies of the S&P 500 index and commodity prices. *Quantitative Finance*, 13(4), 583-592.

Graham, M., Peltomaki, J., & Piljak, V. (2016). Global economic activity as an explicator of emerging market equity returns. *Research in International Business Finance*, 36, 424-435.

Johnson, R., & Soenen, L. (2009). Commodity prices and stock market behavior in South American countries in the short run. *Emerging Markets Finance and Trade*, *45*(4), 69-82.

Li, X., Zhang, B., & Du, Z. (2011). Correlation in commodity futures and equity markets around the world: Long-run trend and short-run fluctuation (November 16, 2011). Available at SSRN: http://ssrn.com/abstract=2011178 or http://dx.doi.org/10.2139/ssrn.2011178

Malik, F., & Ewing, B.T. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis*, 18(3), 95-100.

Masih, R., Peters, S., & De Mello, L. (2011). Oil price volatility and stock price fluctuations in an emerging market: Evidence from South Korea. *Energy Economics*, 33(5), 975-986.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling*, 2, 15-22.

Roache, S. K. (2012). *China's Impact on World Commodity Markets* (No. 12/115). International Monetary Fund.

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

Sari, R., Hammoudeh, S., & Soytas, U. (2010). Dynamics of oil price, precious metal prices, and exchange rate. *Energy Economics*, 32(2), 351-362.

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

Soytas, U., Sari, R., Hammoudeh, S. & Hacihasanoglu, E. (2009). World oil prices, precious metal prices and macroeconomy in Turkey. *Energy Policy*, 37(12), 5557-5566.

Zhu, H-M., Li, R., & Li, S. (2014). Modelling dynamic dependence between crude oil prices and Asia-Pacific stock market returns. *International Review of Economics & Finance*, 29, 208-223.

Table 1. Descriptive Statistics (returns)

	MSCI World	MSCI EM	MSCI EM Asia	MSCI EM Europe	MSCI EM LatAm	GSCI Commodities	GSCI Agriculture	GSCI Energy	GSCI Precious Metals
Mean	0.007	-0.002	0.009	-0.035	-0.014	-0.050	-0.009	-0.073	0.023
Median	0.081	0.067	0.054	0.039	0.045	0.007	-0.041	0.006	0.050
Maximum	9.097	10.073	12.652	18.601	15.364	7.216	7.157	9.805	8.763
Minimum	-7.325	-9.994	-11.993	-19.926	-15.060	-8.649	-7.475	-9.609	-10.105
Std. Dev.	1.133	1.389	1.449	2.148	1.933	1.523	1.435	1.943	1.366
Skewness	-0.469	-0.531	-0.468	-0.461	-0.322	-0.296	-0.138	-0.237	-0.455
Kurtosis	11.225	10.985	11.117	13.899	11.764	6.147	5.102	6.007	7.651
Jarque-Bera	7192.845	6810.177	7006.505	12556.960	8104.399	1076.557	471.677	972.815	2357.229
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sum	16.848	-4.077	21.580	-87.807	-34.345	-125.498	-23.571	-184.641	57.948
Sum Sq. Dev.	3229.74	4854.539	5286.928	11616.48	9411.432	5839.884	5182.063	9508.701	4699.264

Table 2. Correlations

	MSCI World	MSCI EM	MSCI EM Asia	MSCI EM Europe	MSCI EM LatAm	GSCI Commodities	GSCI Agriculture	GSCI Energy	GSCI Precious Metals
MSCI World	1								
MSCI EM	0.74	1							
MSCI EM Asia	0.51	0.90	1						
MSCI EM Europe	0.71	0.81	0.57	1					
MSCI EM LatAm	0.80	0.78	0.48	0.69	1				
GSCI Commodities	0.50	0.45	0.29	0.48	0.51	1			
GSCI Agriculture	0.32	0.29	0.16	0.30	0.35	0.54	1		
GSCI Energy	0.46	0.41	0.26	0.43	0.46	0.98	0.41	1	
GSCI Precious Metals	0.17	0.22	0.13	0.22	0.22	0.39	0.28	0.32	1

Table 3.a. Univariate GARCH Model Estimates

Coef.	MSCI World		MSCI EM		MSCI EM Asia		MSCI EM Europe		MSCI EM Latin America	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
μ	**0.049**	0.015	**0.040**	0.018	**0.051**	0.019	**0.016**	0.030	0.029	0.028
ω	**0.013**	0.004	**0.021**	0.006	**0.015**	0.005	**0.063**	0.014	**0.039**	0.013
α	**0.101**	0.014	**0.102**	0.018	**0.090**	0.015	**0.085**	0.010	**0.080**	0.015
β	**0.889**	0.014	**0.888**	0.016	**0.906**	0.012	**0.899**	0.011	**0.908**	0.015
Coef.	GSCI Commodities		GSCI Agriculture		GSCI Energy		GSCI Precious Metals			
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error		
μ	-0.021	0.022	-0.030	0.025	-0.016	0.028	0.0220	0.0246		
ω	0.006	0.003	0.012	0.007	0.011	0.006	0.0261	0.0150		
α	**0.045**	0.008	**0.046**	0.009	**0.047**	0.009	**0.0506**	0.0214		
β	**0.954**	0.008	**0.948**	0.010	**0.951**	0.008	**0.9356**	0.0261		

Table 3.b. DCC Estimates

	GSCI Commodities		GSCI Agriculture		GSCI Energy		GSCI Precious Metals	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
MSCI World								
θ_1	**0.029**	0.005	**0.017**	0.006	**0.032**	0.005	**0.0398**	0.0069
θ_2	**0.967**	0.006	**0.974**	0.010	**0.964**	0.006	**0.9373**	0.0123
MSCI EM								
θ_1	**0.012**	0.003	**0.006**	0.003	**0.014**	0.004	**0.0253**	0.0068
θ_2	**0.986**	0.004	**0.990**	0.004	**0.983**	0.005	**0.9466**	0.0179
MSCI EM Asia								
θ_1	**0.007**	0.003	0.008	0.008	**0.007**	0.003	**0.007**	0.003
θ_2	**0.990**	0.005	**0.930**	0.074	**0.990**	0.005	**0.989**	0.007
MSCI EM Europe								
θ_1	**0.016**	0.003	**0.009**	0.003	**0.017**	0.004	**0.029**	0.007
θ_2	**0.983**	0.004	**0.988**	0.004	**0.981**	0.004	**0.933**	0.019
MSCI EM Latin America								
θ_1	**0.017**	0.003	**0.010**	0.004	**0.019**	0.004	**0.033**	0.007
θ_2	**0.981**	0.004	**0.985**	0.005	**0.979**	0.004	**0.943**	0.013

Numbers in bold denote significance at 5% or higher.

Table 4. Determinants of correlation coefficients. Monthly regression model estimates of the regression of equation (9) with first order AR (1).

Correlation between	Constant		NETIDEXINV		VIX		AR1_1	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
MSCI World - GSCI commodities	0.4040	0.2622	-0.0029	0.0019	0.0108	0.0082	**0.8495**	0.0572
MSCI World - GSCI Agriculture	***0.5225***	0.2844	***-0.0038***	0.0020	0.0049	0.0088	**0.8050**	0.0621
MSCI World - GSCI Energy	0.3950	0.2910	-0.0028	0.0021	0.0107	0.009	**0.8042**	0.0634
MSCI World - GSCI Precious Metals	-0.0558	0.3853	0.0004	0.0028	***-0.0203***	0.0116	**0.6156**	0.0821
MSCI EM - GSCI commodities	***0.3069***	0.184	***-0.0022***	0.0013	0.0089	0.0057	**0.9337**	0.0396
MSCI EM - GSCI Agriculture	***0.2678***	0.1598	***-0.0019***	0.0012	**0.0097**	0.0049	**0.9423**	0.0344
MSCI EM - GSCI Energy	0.3203	0.2123	-0.0023	0.0015	0.0087	0.0065	**0.9012**	0.0457
MSCI EM - GSCI Precious Metals	-0.2519	0.4528	0.0018	0.0033	-0.0149	0.0135	**0.4105**	0.0967
MSCI EM Asia - GSCI commodities	0.2301	0.1969	-0.0017	0.0014	**0.0118**	0.006	**0.9343**	0.0425
MSCI EM Asia - GSCI Agriculture	0.3484	0.4629	-0.0025	0.0033	**0.0426**	0.0147	**0.2810**	0.1033
MSCI EM Asia - GSCI Energy	0.2599	0.2025	-0.0019	0.0015	***0.0108***	0.0062	**0.9225**	0.0436
MSCI EM Asia - GSCI Precious Metals	-0.4304	0.3046	0.0029	0.0022	0.0080	0.0082	**0.7747**	0.0659
MSCI EM Europe - GSCI commodities	0.3180	0.1836	***-0.0022***	0.0013	0.0035	0.0056	**0.9256**	0.0394
MSCI EM Europe - GSCI Agriculture	***0.2913***	0.1720	***-0.0021***	0.0012	0.0042	0.0052	**0.9259**	0.0368
MSCI EM Europe - GSCI Energy	0.3149	0.2007	-0.0022	0.0014	0.0037	0.0061	**0.9064**	0.0431
MSCI EM Europe - GSCI Precious Metals	0.0640	0.4679	-0.0005	0.0034	-0.0220	0.0142	**0.2981**	0.1004
MSCI EM LatAm - GSCI commodities	-0.0200	0.0562	0.1186	0.1086	0.0578	0.1077	**0.9048**	0.0454
MSCI EM LatAm - GSCI Agriculture	0.3257	0.2004	-0.0024	0.0014	-0.0029	0.0058	**0.8950**	0.0429
MSCI EM LatAm - GSCI Energy	**0.4330**	0.2124	-0.0030	0.0015	**0.0037**	0.0065	**0.8785**	0.0458
MSCI EM LatAm - GSCI Precious Metals	-0.0393	0.4051	0.0002	0.0029	**-0.0308**	0.0123	**0.5540**	0.0865

Numbers in bold denote significance at 5% or higher, numbers in bold italic denote significance at 10%.

Figure 1. Commodities Index Levels

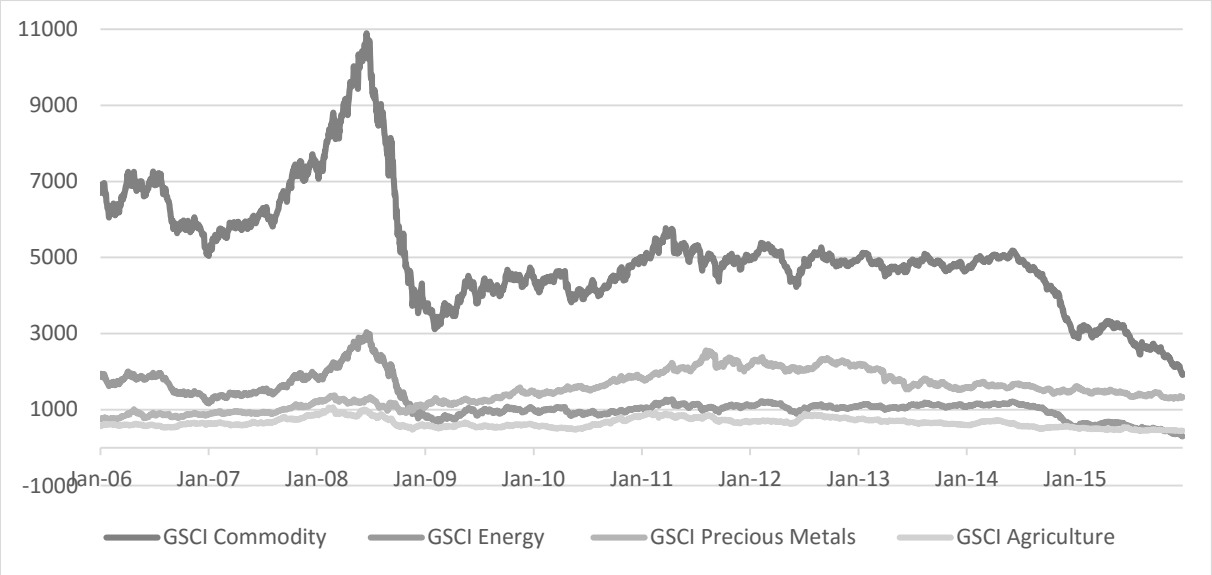


Figure 2. Equity Index Levels

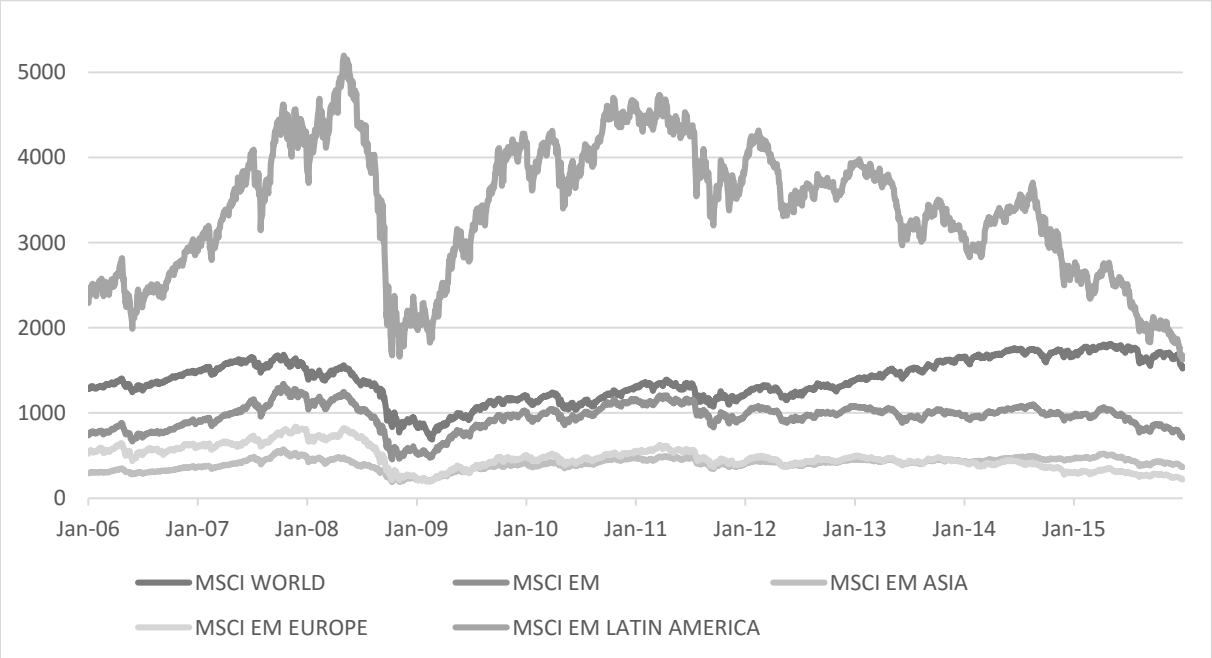


Figure 3. Dynamic Conditional Correlations

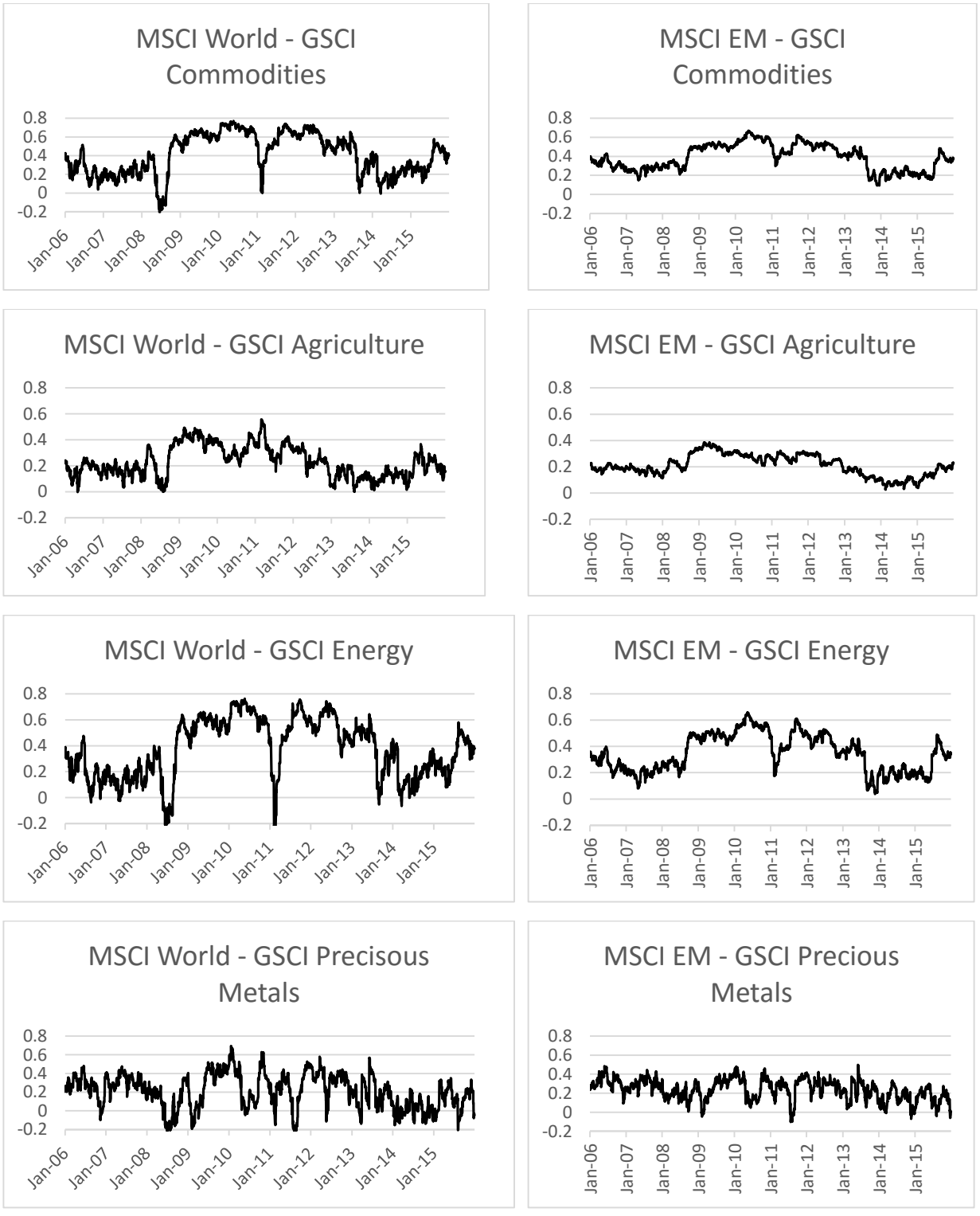
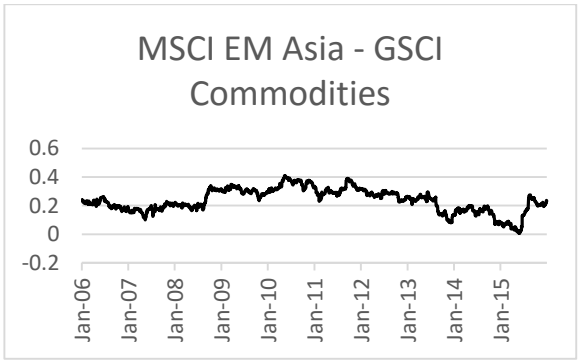
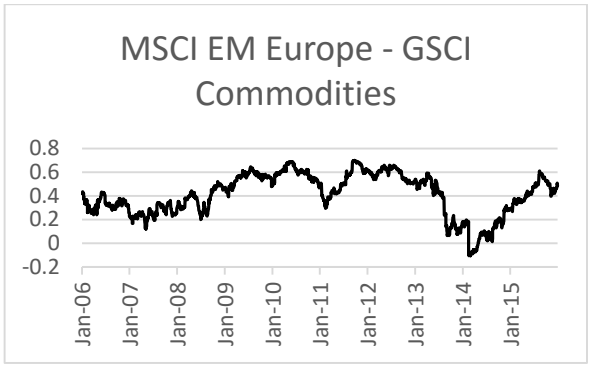
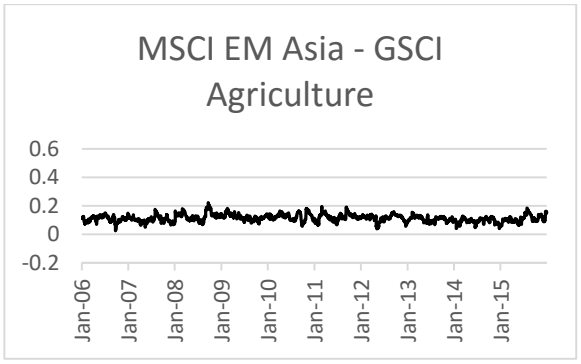
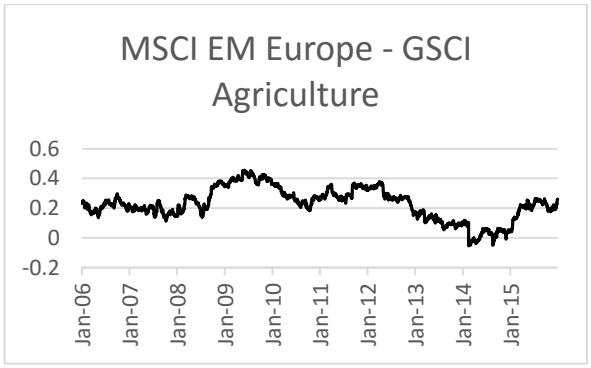


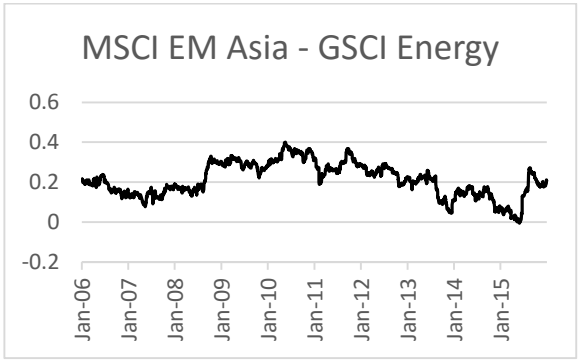
Figure 3. Dynamic Conditional Correlations - Ctd.

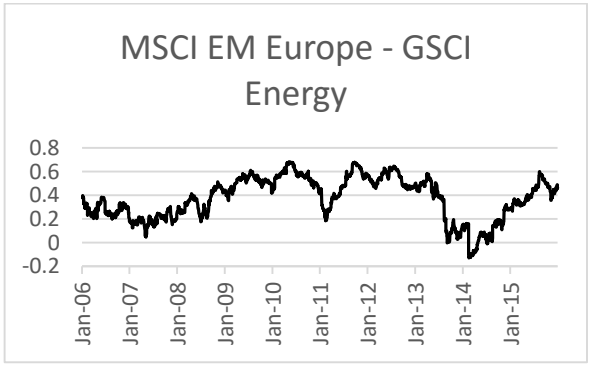












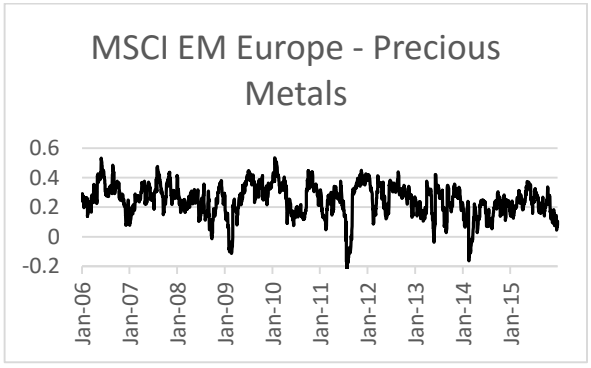
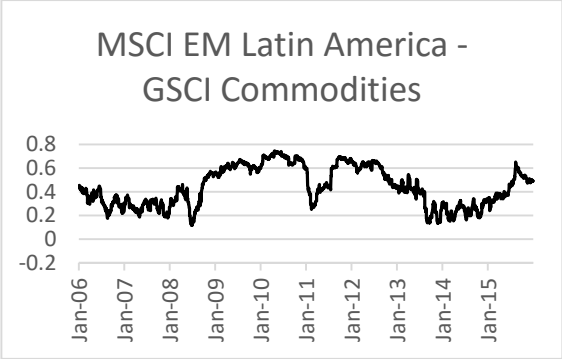
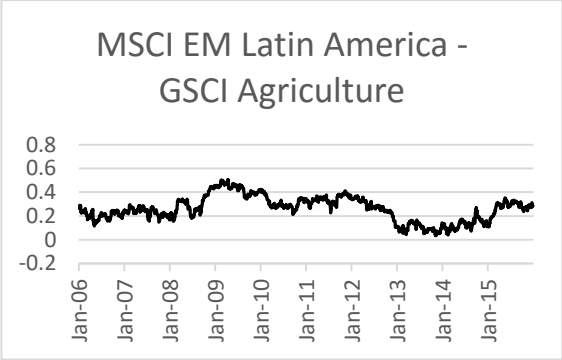
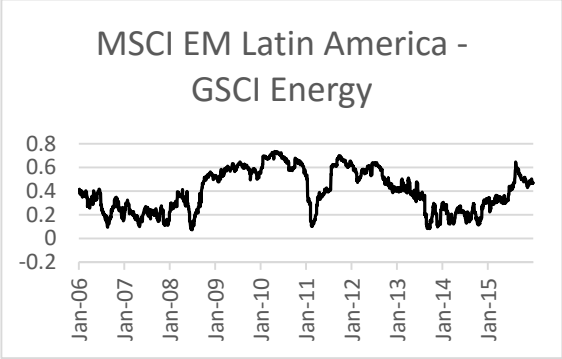
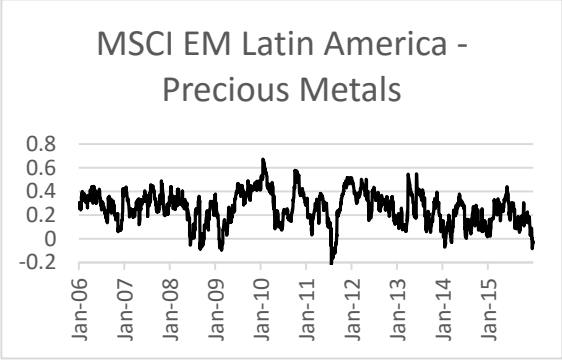


Figure 3. Dynamic Conditional Correlations - Ctd.









Appendix

Table A1. MSCI Indices Country Weights

MSCI Index	Country	Weight
World	United States	58.72%
	Japan	8.96%
	United Kingdom	7.41%
	France	3.72%
	Switzerland	3.60%
	Other	17.58%
Emerging Markets	China	26.56%
	South Korea	15.57
	Taiwan	12.10%
	India	8.73%
	South Africa	6.79%
	Other	30.25%
Emerging Markets Europe	Russia	48.72%
	Turkey	19.24%
	Poland	18.40%
	Greece	7.18%
	Hungary	3.74%
	Other	2.70%
Emerging Markets Asia	China	36.78%
	South Korea	21.55%
	Taiwan	16.75%
	India	12.09%
	Malaysia	4.52%
	Other	8.32%
Emerging Markets Latin America	Brazil	46.07%
	Mexico	37.59%
	Chile	10.05%
	Colombia	3.46%
	Peru	2.83%

Table A2. S&P GSCI Index Commodity Weights

S&P GSCI Index Category	Commodity	Weight
Agriculture	Chicago Wheat	2.96%
	Kansas Wheat	0.76%
	Corn	3.42%
	Soybeans	2.73%
	Coffee	0.68%
	Sugar	1.42%
	Cocoa	0.30%
	Cotton	1.07%
Livestock	Live Cattle	3.11%
	Feeder Cattle	0.73%
	Lean Hogs	2.12%
Energy	WTI Crude Oil	24.47%
	Brent Crude Oil	24.70%
	Gas Oil	7.38%
	Heating Oil	5.83%
	RBOB Gasoline	5.73%
	Natural Gas	3.14%
Industrial Metals	Aluminum	1.99%
	LME Copper	3.12%
	Lead	0.47%
	Nickel	0.56%
	Zinc	0.59%
Precious Metals	Gold	2.42%
	Silver	0.34%