Commodities and Emerging Markets Stocks in International Portfolios: Measuring Hedging Effectiveness

Pornchai Chunhachinda
Professor of Finance
Faculty of Commerce and Accountancy
Thammasat University
2 Prachan Road
Bangkok 10200 Thailand
Tel: (662) 623-5651-2, 613-2261; Fax: (662) 623-5650
e-mail: pchinda@tu.ac.th

Maria E. de Boyrie
Professor of Finance
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 of Finance
College 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
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Abstract

Our study uses a multivariate DCC-GARCH model to examine the dynamic correlations, portfolio weights and hedging effectiveness of investing in international portfolios with or without commodities. The sample of daily data spanning 1997 to 2017 covers different market conditions. While many emerging market countries are net exporters of commodities and their economies rely heavily on exports of commodities, we show evidence against the belief of some investors that investing in commodities or emerging markets equities provides the same risk exposure. The results of the DCC-GARCH, the optimal portfolio weights, and the hedging effectiveness show that while forming portfolios consisting of the developed markets and the emerging markets stocks can marginally reduce portfolio risk, combining the developed markets equity index and commodities provides a superior hedge throughout the sample period.
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1. Introduction

Over the past decade, financial institutions and retail investors have dramatically increased their exposures to commodities. Between July 2007 and February 2013 alone, commodity investments increased from $170 billion to $410 billion.¹ This increase could be attributed to the belief that commodity prices are more highly correlated with factors such as weather, demographic changes, production, storage, demand patterns, etc. than they are with stocks and bonds market movements. Gorton and Rouwenhosrt (2006) find that commodity futures and equity markets are not driven by similar economic or financial fundamentals, and Liu and Tang (2011) and Szymanowska et al. (2014) have shown weak dependence between the two markets. However, evidence to contradict these findings has been presented by Tang and Xiong (2010), Daskalaki and Skiadopoulos (2011), and Büyükşahin et al. (2010), Li et al. (2011), Silvennoinen and Thorp (2013), Özték & Öcal (2013), Delatte and Lopez (2013), Büyükşahin and Robe (2014), Hammoudeh et al. (2014), González-Pedraz et al. (2015) and Berger and Uddin (2015) who show that commodity and equity returns do indeed move in sync at different points in time. Whereas these findings suggest that diversification through commodities could be of little benefit when investing locally, it could be viewed as an avenue when investing internationally. After all, a high level of positive correlation between emerging markets and commodities would imply an

indistinguishable opportunity for diversification using either emerging market equities or commodities at the international level.

At the height of the financial and European debt crises, i.e., between 2008 and 2012, the correlation between the MSCI Emerging Markets and the Commodity Indexes increased to anywhere between 48 and 65 percent. This increase, due to the reliance of emerging markets on the export of commodities such as minerals, agricultural products and energy resources, indeed led investors to consider investing in either index (i.e., emerging market or commodities) almost identical for diversification purposes. Some of the emerging markets countries included in the MSCI indexes used in our study are indeed leading exporters of commodities. For instance, Brazil is a major exporter of iron ore, soy beans, coffee, oil; Peru’s largest exports are copper, gold, and other metals; whereas Mexico leading exports are oil, oil products and agricultural commodities.\(^2\)

However, with the recent decline in the correlations between emerging markets stock and commodities (i.e., 22 percent on average in the 2013-2015 period), the belief that investing in emerging markets or commodities could provide equivalent exposure has been put into question.

This study contributes to the current empirical literature by shedding light on the question of whether emerging market indexes and commodity indexes can be used interchangeably by passive investors to diversify their portfolios. For this purpose, we implement the multivariate dynamic conditional correlation (DCC) model presented in Sadorsky (2012) and examine the diversification and hedging effectiveness of including commodities or equities from emerging markets into an equity portfolio composed of 23 developed markets. For this purpose, we use daily equity and commodity index data beginning in January 1997 till July 2017, a period which


The findings indirectly support those in the literature that show that commodities do not move in sync with equities, in our case, those from European and Latin American emerging markets. The multivariate dynamic conditional correlation (DCC) results show significant volatility spillovers in both the ARCH (short-term dependence) and GARCH (volatility persistence) terms during the full period, as well as in the three subperiods under study. While the estimated volatility series do not change very quickly given the return innovations, they tend to evolve more rapidly due to past volatilities. Although there is no overall clear pattern, the World Index tends to lead the three emerging market indexes as well as the Commodity Index. The results obtained in the estimation of both optimal hedge ratios and portfolio weights (i.e., cheaper hedges can be found between the World/Commodity Index combination and that an allocation to emerging markets does not equal an allocation to commodities in the case of European and Latin American emerging markets) are further supported by those obtained using the hedging effectiveness measure.

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.
2. Literature Review

There is a growing number of studies on the benefits of adding commodities as a portfolio diversification tool. Earlier papers such as those by Abanomey and Mathur (1999) and Satyanarayan and Varangis (1996) show that commodity futures contracts add gains to the risk/return profile when added to an international portfolio of bonds and stocks. In particular, Satyanarayan and Varangis (1996) show that adding commodity futures to a portfolio consisting of developed and emerging markets equities leads to a higher efficient frontier than the frontier of a portfolio without commodities. The sample used in their study spans from 1970 to 1992. Jensen et al. (2000) and Jensen et al. (2002) also find that commodity futures have a significant weight in efficient portfolios for the period of study. Using daily commodity index data from 2003 to 2010, Cao et al. (2010), however, argue that there is little benefit of including commodities in a global portfolio. The portfolios in their study consist of US stocks and bonds and emerging markets stocks and bonds, with or without commodities. The efficient frontier of a portfolio without commodities appears higher.

Research focusing on different commodity types, such as Belousova and Dorfleitner (2012), shows that the diversification potential varies by commodity type and market conditions. Agriculture and livestock only reduce risk, while energy and precious metals reduce risk and improve return. A recent study extending this line of the literature is by Bessler and Wolff (2015). Taking the perspective of a US asset manager holding stocks and bonds and adding a commodity index, they have findings similar to Belousova and Dorfleitner, in the sense that agriculture and livestock do not bring much positive effects to portfolios, while the aggregate commodity index, industrial and precious metals and energy enhance portfolio performance. Using rolling Sharpe ratios, Bessler and Wolff (2015) document that the benefits of including individual commodity
groups in a portfolio are time-varying and have decreased over the 2008-2013 period. Furthermore, Graham et al. (2013) find little evidence of co-movement between the S&P500 index and ten sub-indices of the S&P GSCI commodity index.

Most of the literature on stocks and commodities as a hedge focuses on the relationship between developed equity markets and oil or gold. Fewer studies look at the co-movements of emerging markets with commodities. Focusing on Russia in particular, Bhar and Nikolova (2010) use an EGARCH model to show how oil price changes affect Russian equities, while Soucek and Todorova (2012) include both Russia and China in their analysis. The latter study documents an enhanced risk-return profile when oil is combined with Chinese equities. Batten et al. (2017) study the relation between oil, gas and coal and Asian markets (Japan and China) and find evidence of integration of Asian markets with the energy portfolio. Under a different setting, de Boyrie and Pavlova (2016) use a DCC GARCH model to fit conditional volatility dynamics and compare the co-movements of emerging and developed markets with commodities. They document differences in the correlations both across commodity sub-indices and over time. Their results show that emerging markets, especially those in Asia, exhibit less co-movement with commodities than developed markets do.

Two other studies involving emerging markets are those by Sadorsky (2014) and Basher and Sadorsky (2016). Sadorsky (2014) uses VARMA-AGARCH and DCC-AGARCH framework to model volatility and conditional correlations. The data series include emerging market stock prices, copper prices, oil prices and wheat prices. His results suggest that oil provides the cheapest hedge for emerging market equities, while copper is the least attractive hedge option. In a later study, Basher and Sadorsky (2016) use the MSCI emerging markets index and oil, VIX, gold, and bonds to find optimal portfolio weights and hedge ratios in DCC, ADDC and GO-GARCH
settings. Similar to their earlier findings, oil is the most effective hedge for emerging market stocks under most circumstances. However, they note that different GARCH models provide different hedging effectiveness depending on the assets considered, e.g., GO-GARCH model’s hedge ratios are most effective when emerging market stocks are hedged with gold.

Kang et al. (2016) extend the emerging markets and commodities strand of research by examining BRICS (Brazil, Russia, India, China, South Africa) equities co-movement with oil and gold. Using a trivariate DCC-FIAPARCH model, they estimate dynamic correlations as well as optimal weights and hedge ratios. As the BRICS equities are more volatile than developed markets, Kang et al. (2016) show that oil is not an effective hedge, while gold can be used effectively to hedge exposure in BRICS.

3. Data

To emphasize the differences between the World (developed countries only), Emerging, Emerging European and Emerging Latin American markets co-movements with commodities, the daily equity, and U.S. dollar denominated commodity index data series are gathered from Datastream between January 1997 and July 2017. To capture the fluctuations of developed and emerging equity markets, we use the MSCI World index consists of large- and mid-cap companies covering about 85% of the market capitalization of 23 developed markets, the MSCI Emerging Markets index (23 emerging markets), The MSCI Emerging Markets Europe (6 countries) and the MSCI Emerging Markets Latin America (5 countries). Country weights in the MCSI World Index are dominated by five countries - United States (58.72%), Japan (8.96%), United Kingdom (7.41%), France (3.72%), Switzerland (3.60%) and Other (17.58%). The MSCI Emerging Market Index is also dominated by five countries: China (17.58%, South Korea (15.57%), Taiwan (12.10%), India (8.73%) and South Africa (6.79%) with the remaining 18 countries accounting for
30.25% of the index. Russia (48.72%), Turkey (19.24%), Poland (18.40%), Greece (7.18%) and Hungary (3.74%) are the main constituents of the MSCI Emerging Markets Europe Index. Finally, the weights of the five countries that make up the MSCI Emerging Markets Latin America are as follows: Brazil (46.07%), Mexico (37.59%), Chile (10.05%), Colombia (3.46%) and Peru (2.83%).

The commodity index used in this study is the S&P GSCI Commodity Index. It consists of 24 physical commodity futures, and it is weighed based on world’s production and adjusted for futures trading volume. It comprises five sectors, mainly energy (71.25% of the index, with 24.47% and 24.70% assigned to WTI and Brent Crude, respectively), agriculture (13.34%), livestock (5.96%), industrial metals (6.73%) and precious metals (2.76%) sectors. The index is rolled from the nearby to the next futures contract between the fifth and the ninth business days of the month. Total return indices which are used measure the returns from investing in commodity futures contracts with the closest settlement date on a fully-collateralized basis.

Given that each portfolio under study consists of the MSCI World index and one other index, Bai and Perron’s (1998, 2003) tests is used to determine the major structural breaks in this index. Although the test can find multiple structural breaks, for manageability purposes, only the two major breaks (7/11/2005 and 7/11/2013) as specified by using unequal weighting scheme (WD max test) are utilized.³

Graphs of the time series returns for each index are presented in Figure 1. Volatility appears to be higher for all indexes during the recession period established by NBER (9/4/2007-6/30/2009). The equity indexes with the highest volatility of return are those of the emerging

³ On July 7, 2005, coordinated terrorist bomb blasts struck London’s public transportation system. On July 10, 2005, Hurricane Dennis entered the U.S. mainland through Florida, causing billions of dollars in damage. On July 8, 2015, Egyptian army raids a sit in protest taking palace in Cairo (42 people killed and hundreds injured) after then President Mursi was ousted on June 22, 2013. On July 11, 2015, a wave of bombs and gun attacks killed 30 people in Iraq.
markets (i.e., European Emerging Markets followed by Latin American Emerging Markets and Emerging Markets). Separate mini-volatility episodes can be observed in 1997 and 1998, the period that covers the Asian and Russian crises and the end of 2011, caused by weakness in the global economy and the Eurozone debt crisis that motivated the fear of sovereign defaults and imposed severe financing strains on banks. The largest changes in index return from day to day seem to be in the commodity markets with sharp declines on 9/24/2001, 5/5/2011 and 11/28/2014, all of them due to the decline in crude oil prices. During the second half of 2013 and 2014, commodity, returns were at the lowest level due to growing supply and weak demand. Nonetheless, over this period, the MSCI equity indexes under study only outperformed that of MSCI commodities index 50% of the time.

Descriptive statistics for all returns are presented in Table 1. Of the five indexes under study, all equity indexes present a positive mean return over the full sample period, with the exceptions of the commodities index. The maximum and minimum daily returns found are for Europe in the full period and two subperiods, followed by those of the Latin America. It is only during the second subperiod (7/11/2005-7/10/2013) that the Latin American market presents the highest and lowest returns. The most volatile index is that of European emerging markets. When focusing on the subperiods, the highest and lowest means, as well as the highest volatility can be found during the first subperiod (1/1/1997-7/10/05). While all returns series are negatively skewed (with the exception on commodities during the last subperiod), the return distributions display significant departures from normality. The unconditional correlations between the equity and the commodity index are presented in Table 2. With regards to the world and emerging markets equity indexes, there exist a high correlation between the World and Latin American markets (72%) and between Emerging Markets and Latin America (75%). Looking solely at the commodity index,
Table 2 displays the relatively low correlations (between 30% and 32%) with all equity indexes during the full period, but somewhat higher during the second-subperiod (between 46% and 50%). Overall, the highest correlation can be found during the period covering the financial and European crises (i.e., the second subperiod) followed by the period covering July of 2013 and later. These results suggest that some diversification potential comes from the inclusion of commodities in a portfolio.

4. Methodology

In this study, the multivariate dynamic conditional correlation model (DCC) presented in Sadorsky (2012) is employed to model the volatility dynamics between commodities and equities in developed and emerging markets. The DCC model is estimated in two steps. The first step uses the univariate GARCH model to estimate the variances; while the second utilizes the standardized residuals estimated in step one to model the correlations. To allow for autocorrelations and cross-autocorrelations in the returns, a VAR(1) is used to model the returns. The time varying variances and covariances are modeled using a multivariate GARCH model. Following Ling and McAleer (2003), the conditional variance, which is assumed to be VARMA-GARCH(1,1), is modeled by using the dynamic conditional correlation models for the diagonal. As such, the return ($r_{it}$) for the series under study, the relationship between the error term ($\varepsilon_{it}$) and the conditional variance ($h_{it}$), and the conditional variance specified as a GARCH (1,1) process with VARMA terms can be expressed as:

$$r_{it} = m_{i0} + \sum_{j=1}^{3} m_{ij} r_{it-1} + \varepsilon_{it}, \quad \varepsilon_{it} | I_{it-1} \sim N(0, h_{it}), \ i = 1,2,3$$

(1)

$$\varepsilon_{it} = \nu_{it} h_{it}^{1/2}, \quad \nu_{it} \sim N(0,1)$$

(2)

$$h_{it} = c_{it} + \sum_{j=1}^{3} \alpha_{ij} \varepsilon_{jt-1}^{2} + \sum_{j=1}^{3} \beta_{ij} h_{jt-1}$$

(3)
where $I_{t-1}$ represents the market information available at time $t-1$.

The dynamic conditional correlation (DCC) model introduced by Engle (2002) builds on the framework of ARCH/GARCH-type models, developed by Engle (1982) and Bollerslev (1986), respectively. The model first estimates the GARCH parameters, followed by the estimation of the correlations. A 3x3 conditional covariance matrix ($H_t$) is estimated using a conditional correlation matrix ($R_t$) and a diagonal matrix ($D_t$) with time-varying standard deviations in the diagonal. By defining $Q_t$ to be a symmetric positive definite matrix, $\bar{Q}$ to be 3x3 unconditional correlation matrix of the standard residuals $\xi_{it}$, and restrict the parameters $\theta_1$ and $\theta_2$ to be nonnegative with a sum of less than one, we can define

$$H_t = D_t R_t D_t$$  \hspace{1cm} (4)

$$D_t = diag(h_{11t}^{1/2}, ... h_{33t}^{1/2})$$  \hspace{1cm} (5)

$$R_t = diag(q_{11t}^{-1/2}, ... q_{33t}^{-1/2})Q_t diag(q_{11t}^{-1/2}, ... q_{33t}^{-1/2})$$  \hspace{1cm} (6)

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \xi_{t-1}' \xi_{t-1} + \theta_2 Q_{t-1}$$ \hspace{1cm} (7)

and the correlation estimator as

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}}. \hspace{1cm} (8)$$

Following the work of Kroner and Sultan (1993), a risk minimizing hedge ratio, based on the minimization of the variance of the portfolio return, is obtained using conditional variance and covariance obtained using the model above, that is,

$$\beta_{i,j,t} = \frac{h_{i,j,t}}{h_{j,j,t}} \hspace{1cm} (9)$$

where $\beta_{i,j,t}$ stands for the hedge ratio where a long position in one index (i) can be hedged with a short position in the other index (j), $h_{i,j,t}$ is the conditional covariance between index (i) and index (j) at time $t$ and $h_{j,j,t}$ is the conditional variance of index (j) at time $t$. 
The optimal portfolio weights are estimated per work presented by Kroner and Ng (1998). In this instance, the weights are constructed using once again the conditional volatilities from the DCC-GARCH model and minimizing the risk of the portfolio while assuming the expected return of each index to be zero. As such,

\[ w_{ij,t} = \frac{h_{ij,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \]  \hspace{1cm} (10)

where \( w_{ij,t} \) is defined as the weight of the first index in a one dollar portfolio composed of index (i) and index (j) at time t, the weight of the second index is estimated as \( 1 - w_{ij,t} \), and

\[
w_{ij,t} = \begin{cases} 
0, & \text{if } w_{ij,t} < 0 \\
w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\
1, & \text{if } w_{ij,t} > 1
\end{cases}
\]

To determine the effectiveness of the hedge, the realized hedging errors presented by Ku, Chen and Chen (2007) are estimated using the variance of the returns of a portfolio consisting of the World Index and any of the three emerging markets indexes (i.e., Emerging, Europe or Latin America) or the Commodity index \( (\sigma_{hedged}^2) \) and the variance of return on a portfolio of either the World Index or one of the three emerging market indexes \( (\sigma_{unhedged}^2) \).

\[
HE = \frac{\sigma_{unhedged}^2 - \sigma_{hedged}^2}{\sigma_{unhedged}^2} \]  \hspace{1cm} (11)

The higher the hedging effectiveness (HE), the greater the portfolio risk reduction.

5. Empirical Results
The results of the multivariate DCC-GARCH model, the hedge ratios, the optimal portfolio weights and the hedging effectiveness are reported in the next sub-sections. Portfolios are formed
consisting of the developed markets and either commodity or one of three emerging markets stock indexes.

5.1 Return and Volatility Dependencies

The results obtained using the multivariate dynamic conditional correlation (DCC) are presented in Table 3. The mean equations suggest the possibility of forecasting the World index return using the emerging and Latin American market returns during the full period (1/1/1997 - 7/27/2017) and the first- and second-subsample (i.e., 1/1/1997 - 7/10/2005 and 7/11/2005 - 7/10/2013) periods due to the persistence in the returns. It is only during the full period and after July of 2013 that the European emerging markets can be used to forecast the equity returns in developed markets. The estimated coefficients of commodities \(m_{1,2}\) in all equations are consistently insignificant, signifying its inability to establish a positive relationship between the equity MCSI index for the World and its prior period return. While no significant relationship is found within the first and third subperiods (i.e., 1/1/1997 - 7/10/2005 and 7/11/2013 - 7/27/2017) developed market returns, a positive relationship from the developed markets to commodities \(m_{2,1}\) is observed in the remaining two periods. In most cases, the developed market returns can be used to forecast the returns of the three emerging markets under study.

Significant volatility spillovers in both the short- \(\alpha_{ij} \text{ or } \alpha_{ji}\) and long-term \(\beta_{ji} \text{ or } \beta_{ij}\) coefficients can be found during the three subperiods, as well as during the full period. In the short-term, most of the volatility transmission from the emerging and Latin American markets to the developed markets during the first and second subperiods, and the third subperiod, respectively. In the full period, short-term transmissions occur from developed markets to two of the emerging markets (i.e., excluding the Latin American markets) as well as to commodities. The transmission to the emerging and European emerging markets can also be observed in the first and
second subperiods) and to emerging markets and commodities in the third subperiod. There also appears to be a positive relationship from the developed markets to commodities in the second subperiod. All relationships are positive except for the that of the emerging markets to the developed markets during the second subperiod. The small size of the ARCH \((a_{ij} or a_{ji})\) coefficients suggests that the estimated volatility does not change very quickly given the return innovations.

In the long-term, positive unidirectional transmission exists in all instances except for the emerging markets in the full period, implying that past values of the conditional volatility in the case of all indexes can be used to forecast future volatility. Furthermore, the three emerging markets are also found to lead the developed markets in one or more of the sub-samples but not in the full period. Developed markets lead all three markets (emerging in the full period, second and third subperiods, Emerging markets in the second subperiod and Latin American emerging markets in the full period) and commodities in all periods but the first sub-sample (i.e., between 1/1/1997 and 7/10/2005). There exist negative volatility transmissions in four instances in the long-term – from the emerging and Latin American markets to developed markets and from developed markets to the European emerging markets and commodities. Although there is no overall clear pattern, the World Index tends to lead in all periods under study. The Commodities Index fails to lead in all instances.

In all periods under study, own volatility long-term (GARCH) persistence \((\beta_{ii})\) is found to be larger than those of the own conditional ARCH effects \((\alpha_{ii})\) or own conditional short-term persistence in all but one case, meaning that the estimated volatility series tend to evolve more rapidly due to past volatility rather than to return innovations. The values of the DCC coefficients
(\theta_1 \text{ and } \theta_2) \text{ are all positive and add up to less than one, indicative of mean reversion of the dynamic conditional correlations.}

Figure 2 reports the time-varying dynamic conditional correlations estimated using the VAR(1)-GARCH(1,1) model for the five indexes over the full period (1/1/1997-7/27/2017). Throughout the sample period, correlations remain positive between all three emerging market indexes and the developed markets. Negative correlations are observed between the World Index and the Commodity Index up to the end of 2005 and then during the financial crisis of 2000-2008. The large decrease in correlations during the crisis period indicates that diversification into commodities worked best during this period. Other decreases in correlation can be observed throughout the first sub-sample, in 2011 and after the second half of 2013, followed by an in the second half of 2015. Furthermore, the graphs also show that the highest conditional correlations are found between the World Index and all three emerging market indexes. Given that the correlations between the World Index and the Commodity Index consistently fall below those of the World Index and the three emerging market indexes, it is safe to ascertain that the first set of indexes provide greater diversification benefits than the second set.

5.2 Optimal Hedge Ratios and Portfolio Weights

Equations (9) and (10) are used to estimate the optimal hedge ratio and portfolio weights for all possible index combinations, respectively. Results are presented in Table 4. In all instances, a $1 position in the first index (i.e., World) can be hedged with the average value of the hedge ratio of a short position in the second index (i.e., any of the three emerging market indexes or the Commodity Index). For example, between 1997 and 2007, the average hedge ratio for the World/Commodities combination is 0.18 which means that a $1 long position in the World Index can be hedged with 18 cents of a short position in the Commodity Index. Since a lower value of
the hedge ratio indicates a cheaper hedge, it is noted that the cheaper hedges for the World/Emerging and World/Latin American markets combinations can be found in between 7/11/2013 and 7/27/2017, and for the World/European emerging markets and the World/Commodities combination between 1/1/1997 and 7/10/2005.

While the optimal portfolio weights vary over time, the optimal weight of World/Commodity increased the most during the second sub-sample. This anomalous increase could be explained by a significant increase in the demand for commodities – or “flight to safety” due to the financial crisis of 2007/2008 and the European debt crisis. However, this hedge ratio is still the cheapest of those studied during this period. Figure 3 further denotes the need of portfolio managers to rebalance the portfolios more often during the crisis periods as evidenced by the widest variations in hedge ratios. Of all the possible combinations shown in the graphs, the combination between all three emerging market indexes and the World Index have some of the highest hedge ratios. Negative hedge ratios are commonly observed up to the end of 2004 and then briefly in 2008 between the Commodities and World Indexes, requiring a portfolio manager to go long in the World Index to hedge against the long position in the Commodities Index.

When attempting to figure out whether commodities are good substitutes for emerging market equities in portfolio formation, optimal portfolio weights need to be examined. As presented in Table 4, an investor is better off investing a larger portion of his/her portfolio in the World Index in all instances. Of all four possible portfolios studied, it appears that the most effective diversification index is that of emerging markets except for the subperiod which includes the two latest crises in the which commodities appeared to be a better diversification instrument. However, it is worthwhile to note that the optimal portfolio weights for emerging markets and commodities differ at most by 22% in the full period and the first and third subperiods.
5.3 Hedging Effectiveness

To further determine whether the Commodity Index can be used as a substitute for any of the three emerging market indexes in portfolio formation, the hedging effectiveness ratios are calculated using equation (11). As previously noted, this ratio estimates the percentage increase or decrease in the overall portfolio risk created by investing in the World Index and any of the three emerging market indexes or commodities.

The hedging effectiveness ratio estimates presented in Table 4 displays a wide range.

Combining the World Index with a Latin American or European emerging market index seldom reduces the risk of the portfolio but does increase it in most instances. Combining developed market stocks with the overall emerging markets index seems to reduce the risk of the portfolio but not by as much as when combining developed market stocks with commodities.

The overall findings lead us to conclude that when it comes to diversification, adding commodities to a portfolio of developed market equities still helps to reduce its risk. These findings are in line with prior results from Belousova and Dorfleitner (2012) and Bessler and Wolff (2015) showing the diversification potential of commodities within different frameworks. However, combining securities from emerging markets to a portfolio containing securities from developed markets might not have the same effect as commodities. Once again, the findings corroborate the idea that the MSCI Commodities Index is not identical, and cannot thus be used as a proxy to the MSCI Emerging Markets, MSCI Emerging Markets Europe, and MSCI Emerging Markets -Latin America Indexes.

6. Conclusion

Using over 20 years of daily data, this study takes the perspective of a developed equity market investor combining emerging market equities and commodities in a portfolio. We examine the
evolution of the conditional correlations between the equity and commodity indexes and find large fluctuations of correlations and volatility spillovers across those markets during the 1997 - 2017 period. More notably, we observe that the correlations between the developed equities and commodities consistently stay below the correlations of developed and emerging markets equities. While prior studies mostly focus on particular commodity and the S&P 500 index, our study differs from the literature in the setup and direct comparison of the hedging effectiveness emerging market stocks and commodities.

The results of the multivariate DCC-GARCH model, the hedge ratios, the optimal portfolio weights and the hedging effectiveness show that while forming portfolios consisting of the developed markets index and the emerging market index can marginally reduce the portfolio risk during times of tranquility, it does not reduce risk as much as when the developed markets index and commodities are combined. During all periods studied, commodities provide a cheaper hedge than the emerging market equities.

Our findings can be useful for portfolio managers assessing diversification opportunities. The first half of 2017 marked a notable increase in emerging markets returns and an increased interest of investors in global investing. However, from a hedging perspective, an investment strategy focused on developed and emerging markets may entail greater risk and lower hedging effectiveness compared to investing in developed markets and commodities.
References


Figure 1. Time Series Plots of Equity and Commodity Indexes (Returns)

Figure 2. Time-varying Conditional Correlation Coefficients – Full Period (1/1/1997 – 7/27/2017)

Figure 3. Time-varying Hedge Ratios
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<td><strong>Full Period (1/1/1997 - 7/27/2017)</strong></td>
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<td>MSCI World</td>
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<td>-7.325</td>
<td>0.993</td>
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<td>752.614</td>
<td>12784.724</td>
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Table 2. Correlations

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Table 3. Multivariate GARCH Parameter Estimates

Values highlighted, in italics and underlined are significant at the 5% level. m stands for mean, subscript i or j = 1 stands for MSCI World index, subscript 2 for emerging markets, emerging markets (Europe), emerging markets (Latin America) or Commodities. $m_{10}, m_{20}$ represent the equation’s constants. $\alpha(i,j)$ represents the ARCH impact of volatility j on volatility i while $\beta(i,j)$ represent the GARCH impact of volatility j on volatility i. All figures are rounded to two decimal places.

<table>
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<th>Latin America</th>
<th>Commodities Markets</th>
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Table 4. Summary Statistics - Hedge Ratio (Long/Short), Portfolio Weights and Hedging Effectiveness

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<td>Std. Dev.</td>
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