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Hedging strategy for financial variables and commodities

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Abstract

This paper investigates the hedging effectiveness of different hedge types. The S&P 500 index, oil prices, the VIX index, gold prices, bond prices, and CDS spreads are considered. The Dynamic Multivariate GARCH is used to estimate the hedge ratios by separate and complex hedge types from December 2007 to June 2018. This study also performs some statistical works to investigate the relationship between the hedging effectiveness and the commodities prices sensitivity to financial variables. The results show that gold and CDS provide higher hedging effectiveness against equity market losses. Negative correlations between the equity market and VIX are particularly notable, suggesting the economic benefits of diversification.

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1. Introduction

GARCH models are widely used to model and forecast volatility that would affect the value of assets and lead investors to adjust their investment strategy according to the magnitude of risk they expect and the risks to which they are exposed.

Shahzad et *al.* (2017) applied the quantile-on-quantile approach to examine dependence between the quantiles of gold and bonds with the quantile of stock markets. Their empirical findings suggest that gold is a good hedge and diversifier for the stock portfolio. They also show that bonds may act as a safe haven in the stock portfolio. Mensi et *al.* (2017) examined time-varying risk spillover between precious metals and stock markets. They considered four major markets, namely, the USA (S&P 500 index), Japan (Nikkei 225 index), Europe (STOXX 600 index, TSX index), and Asia (DJASIA Index). They analyzed asset allocations, hedge ratios, and hedging strategies. The results show a statistically significant positive conditional correlation between precious metals and stock markets. The conditional correlations between these markets are also time-varying. Moreover, their empirical findings show a greater impact of stock indexes on precious metal prices along with a weak transmission of volatility from precious metals to stock indexes.

One of our main aims, in addition to forecasting and modeling volatility, is to evaluate the effectiveness of different variables to hedge equity markets. The hedging effect of oil price has previously been investigated and confirmed by Pan et *al.* (2014), Arouri et *al.* (2011) and Chang et *al.* (2011) among others. Basher and Sadorsky (2016) used three versions of GARCH models (DCC, ADD, and GO-GARCH) to model the dynamic conditional correlations between emerging market stock prices, oil, gold, VIX, and bonds. They used a rolling window analysis to construct out-of-sample one-step-ahead forecasts of dynamic conditional correlations and optimal hedge ratios. Their findings suggest that oil is the best asset to hedge stock prices.

Thus, gold as a precious metal has attracted the interest of many investors since it acts as a safe haven asset. Many studies have been conducted to examine the ability of this popular precious metal to hedge the equity market, especially in a situation of uncertainty and fluctuation. For instance, Iqbal (2017), Hood and Malik (2013), Baur and Lucey (2010), and Baur and McDermott (2010) extensively examined the hedge and safe haven potential of gold. Their findings converge to support the effectiveness of gold in hedging the equity market in periods of uncertainty. Along the same lines, the studies conducted by Mensei et *al.* (2015) and Ciner et *al.* (2013).

This paper contributes to the current literature by shedding light on the question of whether the U.S. equity market returns can be hedged effectively with commodities and financial variables. We implement multivariate dynamic GARCH models and examine the diversification and hedging effectiveness of including commodities in equity portfolios. Our findings suggest the superiority of the GO-GARCH model in forecasting conditional correlations. Moreover, gold and CDS provide greater hedging effectiveness against the equity market. Negative correlations between the equity market and VIX are particularly notable, suggesting the economic benefits of diversification.

The remainder of the paper is structured as follows. Section 2 deals with the definition of variables and the methodology followed to better examine hedging stock market prices with oil, gold, VIX, bonds, and CDS spreads. Section 3 presents the main empirical findings and discussion. Finally, section 4 concludes.

2. Data and Methodology

This study uses daily data from the U.S. stock market, oil prices, the VIX index, gold prices, bond prices, and CDS spreads. The U.S. stock market (EM) is measured by the S&P 500 index priced in US dollars. Oil prices (OIL) are measured by the WTI crude oil futures contract, a continuous contract expressed in U.S dollars per barrel. The Volatility Index (VIX), which measures implied volatility of the S&P500 index options, has been used since it represents the market expectations of stock market volatility over the next 30 days. Gold prices (GOLD) and bond (BONDS) prices are measured, respectively, by the Chicago Mercantile Exchange continuous futures contract on gold and the Chicago Mercantile Exchange continuous futures contract on the 10-year US Treasury note. CDS spreads theoretically measure a firm's credit risk. The dataset covers the period from 28 December 2007 to 29 June 2018. We apply the Dynamic Conditional Correlation (DCC) model developed by Engle (2002), the Asymmetric Dynamic Conditional Correlation (ADCC) model developed by Capiello et *al.* (2006) and the Generalized Orthogonal- Generalized Auto-Regressive Conditional Heteroskedasticity (GO-GARCH) model developed by Van der Weide (2002). These three GARCH specifications allow us to model the volatility dynamics, the conditional correlations, and the hedge ratios between S&P500 stock market prices, oil prices, gold prices, bond prices, the VIX index and CDS spreads.

Let us consider an $(\mathrm{n} \times 1)$ vector of asset returns denoted r_t, and the AR(1) process for r_t conditional on the information set in time $t-1$ (denoted I_{t-1}), which can be modeled as:

$$r_t = \mu + a r_{t-1} + \varepsilon_t \quad (1)$$

The residuals are defined as:

$$\varepsilon_t = H_t^{1/2} z_t \quad (2)$$

In eq. 2, H_t represents the conditional covariance matrix, while z_t represents an $(n \times 1)$ i.i.d random vector of errors.

The estimation of the DCC-GARCH model of Engle (2002) can be made in two steps. First, estimating the GARCH parameters and second estimating the conditional correlations.

The $(n \times n)$ conditional covariance matrix H_t can be specified as:

$$H_t = D_t R_t D_t \quad (3)$$

with R_t denoting the conditional correlation matrix and D_t representing a diagonal matrix with time-varying standard deviations on the diagonal. The specifications for D_t and R_t can be written respectively as:

$$D_t = diag\left(h_{1,t}^{1/2}, \dots, h_{n,t}^{1/2}\right) \quad (4)$$

$$R_t = diag\left(q_{1,t}^{-1/2}, \dots, q_{n,t}^{-1/2}\right) Q_t \, diag\left(q_{1,t}^{-1/2}, \dots, q_{n,t}^{-1/2}\right) \quad (5)$$

Where the specification of the asymmetric positive definite matrix Q_t can be written as:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1} \quad (6)$$

where $\bar{Q}$ represents the $(n \times n)$ unconditional correlation matrix of the standardized residual $z_{i,t}$ with $z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$. The parameters associated with the exponential smoothing process used to construct the dynamic conditional correlations denoted by θ_1 and θ_2, are expected to be non-negative. The DCC model is mean-reverting if the sum of these parameters is less than the unity. Finally, the correlation estimator can be computed as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \quad (7)$$

Capiello et *al*. (2006) constructed the Asymmetric DCC GARCH model (ADCC). Hence, the elements of the diagonal matrix H_t became are expressed as:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I\left(\varepsilon_{i,t-1}\right) \quad (8)$$

The indicator function $I\left(\varepsilon_{i,t-1}\right)$ takes value one as long as $\varepsilon_{i,t-1}$ is negative and value if it is positive or null.

Finally, for the ADCC-GARCH model, the dynamics of matrix Q_t are determined by:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{Q}^{-}G) + A'z_{t-1}z'_{t-1}A + B'\,Q_{t-1}B + G'z_t^{-}z'^{-}_tG \quad (9)$$

In eq. 9, A, B and G denote $(n \times n)$ parameters matrices and z_t^{-} represents zero-threshold standardized errors which are equal to z_t if they are negative and zero otherwise. The unconditional matrices of z_t and z_t^{-} are given by $\bar{Q}$ and $\bar{Q}^{-}$, respectively.

The GO-GARH model specifies the returns r_t as follows:

$$r_t = m_t + \varepsilon_t \quad (10)$$

with $m_t$being the conditional mean.

Moreover, the Go-GARCH model maps the returns $(r_t - m_t)$ onto a set of unobservable independent factors denoted by f_t. The error term ε_t can be expressed accordingly as:

$$\varepsilon_t = Af_t \quad (6)$$

In eq. 11, A is the mixing matrix that can be decomposed into an unconditional covariance matrix denoted $\sum$ and an orthogonal (rotational) matrix denoted U. The mixing matrix A can be given accordingly by:

$$A = \textstyle\sum^{1/2}U \quad (12)$$

The assets and the factors (f) are presented in the mixing matrix A in the rows and in the columns, respectively. The specification of the factors is expressed as:

$$f_t = H_t^{1/2}z_t \quad (13)$$

where z_t is a random variable whose characteristics are $E(z_{it}) = 0$ and $E(z_{it}^2) = 1$. The factor conditional variances, namely h_{it}, can be modeled as a GARCH process. Finally, the unconditional distribution of the factors (f) satisfies $E(f_t) = 0$ and $E(f_tf'_t) = I$. By incorporating eq. 11 and eq. 13 into eq. 10, the return r_t is specified as:

$$r_t = m_t + AH_t^{1/2}z_t \quad (14)$$

The conditional covariance matrix of $r_t - m_t$ is given by:

$$\textstyle\sum_t = AH_tA' \quad (15)$$

Note that the GO-GARCH model makes two principal assumptions. The first suggests that matrix A is time-invariant, while the second suggests that matrix H_t is diagonal. Furthermore, the GO-GARCH model requires restricting matrix A to being orthogonal. Van der Weide (2006) estimated the matrix U using nonlinear least squares and the method of moments.

As for the *optimal hedge ratios,* the procedure is as follows. The specification of the return on a hedged portfolio of a spot and futures position denoted $R_{H,t}$ can be written as:

$$R_{H,t} = R_{S,t} - \gamma_tR_{F,t} \quad (16)$$

With γ_t being the hedge ratio, $R_{S,t}$being the return on the spot position and $R_{F,t}$ representing the returns on the future position. The hedge ratio is the number of futures contracts the investor, who is long of the spot position, must sell and similarly, the investor, who is short of the spot position, must buy. The volatility of the hedged portfolio conditional on the information set I_{t-1} is specified as:

$$var(R_{H,t}I_{t-1}) = var(R_{S,t}I_{t-1}) - 2\gamma_tcov(R_{F,t}, R_{S,t}I_{t-1}) + \gamma_t^2var(R_{F,t}I_{t-1}) \quad (17)$$

In this specification, γ_t is thus an $(n\times1)$ matrix of optimal hedge ratios that are assumed to produce lower conditional variance than the hedged portfolio. The optimal hedge ratio conditional on the set of information observed at time t-1 can be computed by setting the partial derivative of the variance equal to zero with respect to the optimal hedge ratios denoted γ_t, as specified in the following equation.

$$\gamma_t^*I_{t-1} = \frac{cov(R_{S,t}, R_{F,t} \mid I_{t-1})}{var(R_{F,t} \mid I_{t-1})} \quad (18)$$

We use the estimated conditional volatility output from the GARCH models to construct the hedge ratios. Considering two assets, A and B, we can hedge a long position in asset A with a short position in asset B.

Let $\gamma_t^* \mid I_{t-1}$ be the hedge ratio between spot and future prices conditional on the information set I_{t-1}, $h_{SF,t}$ is the conditional covariance between spot and future and $h_{F,t}$ is the conditional variance of future returns.

Thus, the hedge ratio between spot and futures can easily be computed as:

$$\gamma_t^* \mid I_{t-1} = h_{SF,t}/h_{F,t} \tag{19}$$

The Hedging Effectiveness index (HE) is used to measure the performance of the different optimal hedge ratios, estimated using the different GARCH models and is computed as:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \tag{20}$$

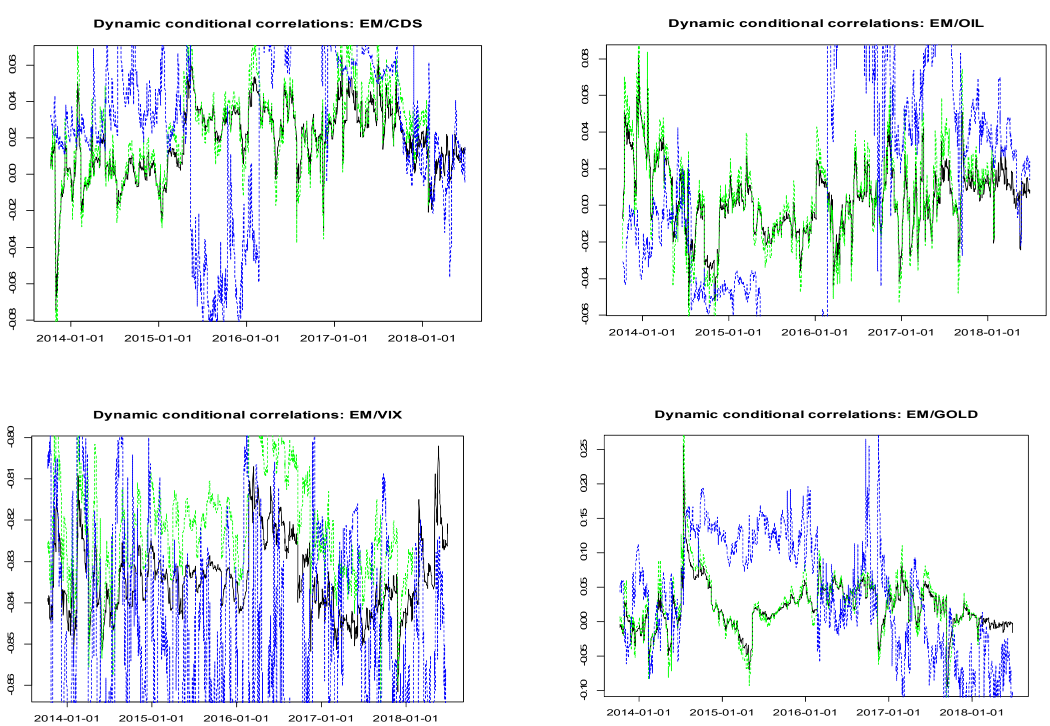
Note, that the hedging effectiveness is higher as long as the HE index is higher.

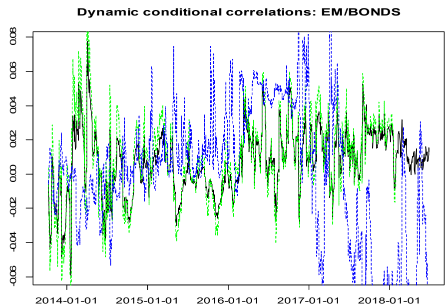
3. Empirical results

3.1 Conditional correlations

Figure 1 plots the dynamic conditional correlations between EM and each of the independent variables for the three models: DCC, ADCC, and GO-GARCH. The results illustrate similar trends for the DCC and ADCC models. Significant differences are observed, however, between the results of the GO-GARCH and both the DCC and ADCC models. The dynamic correlations between EM and CDS were trending upwards from about mid-2013 until mid-2017. Over the subsequent period until mid-2018, the trends exhibited were mainly downward. For the correlations between EM and Oil, we observe a sharp downward trend over the period from mid-2013 until about October 2015, and a relatively smooth upward trend for the rest of the period until June 2018. A smooth upward trend was observed for the correlations between EM and VIX from mid-2013 until the first quarter of 2016. A sharp upward trend followed by a sharp downward trend was then detected over the two periods from early 2016 until about May 2017, and from May 2017 to June 2018, respectively.

Figure1: Rolling one-step-ahead conditional correlations





Note: Black dashed line: DCC, Green dashed line: ADCC, Blue dashed line: GO-GARCH.

Overall, the dynamic correlations from DCC and ADCC models seem to provide similar trends that are sharply distinguished from those of the GO-GARCH model. In fact, the DCC and ADCC models appear to produce quite smoothed dynamic correlations compared to the GO-GARCH that produces high volatile correlations.

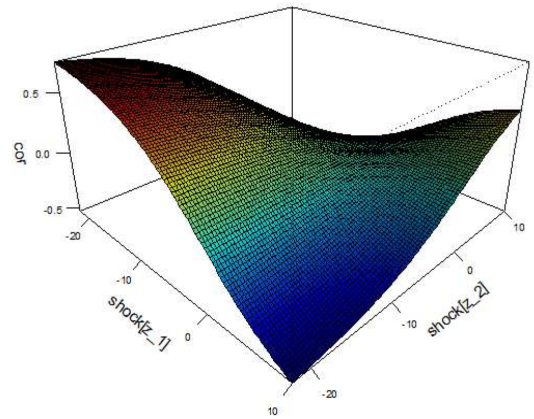
The dynamic conditional correlations between EM and CDS were almost positive for the different GARCH models from late 2014 until June 2018. Negative dynamic correlations were observed, however, especially for the years 2013-2014. Positive correlations imply that the U.S equity market tends to react positively to developments in the CDS market since the CDS implies considerable protection against default. The negative correlation between the U.S equity market and the CDS market can be explained by the fact that investors perceive the increase in CDS spreads as an indicator of deterioration in companies' creditworthiness.

The DCC and ADCC models show higher positive dynamic conditional correlations until about mid-2015, and different waves of positive and negative dynamic conditional correlations between EM and Oil over the rest of the period of analysis. The dynamic conditional correlations provided by the GO-GARCH model were almost negative over the first period until early 2016 and almost positive over the rest of the sample period. The correlations displayed by the GO-GARCH model are strongly distinguishable compared to those of the DCC and ADCC models, with clearly lower net coefficients over the first half of the sample period and higher net coefficients over the second half. Moreover, the DCC and ADCC models display similar correlations with higher absolute coefficients for the ADCC model. Variability of the negative and positive dynamic correlations between Oil and EM may be due to variability in the USA's need to import, although the USA remains one of the greatest net importers. More specifically, even an increase in the extraction of oil and natural gas from shale in recent years has at times been insufficient to meet the USA's oil import needs. Oil and natural gas extraction remain variables that could be the result of significant variability in industrial production, in oil prices and oil demand-supply shocks.

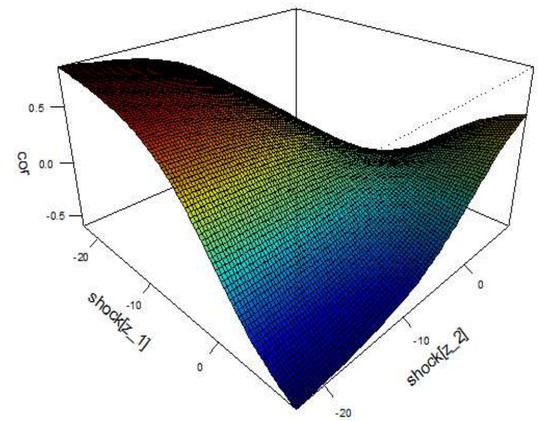
Negative dynamic conditional correlations were detected between EM and VIX for the different GARCH models, suggesting that an increase in volatility or uncertainty results in lower equity market returns. In other words, an increase in volatility results in the equity market losing money. This is strong evidence that the two variables, EM and VIX, express significant diversification benefits.

Strong fluctuations between positive and negative dynamic correlations, between EM and GOLD, and between EM and BONDS were observed. This is explained by various external factors. A regional or local cultural affinity for gold, for instance, can explain the positive correlation between gold and equity markets largely. This affinity with gold is a special characteristic of the population's lifestyle in most emerging and developing counties, such as China, Southeast Asia, and North Africa. While it is not the case for the USA, increased demand for gold in China and India is one of the main factors explaining the positive correlation between gold and the S&P500 equity market.

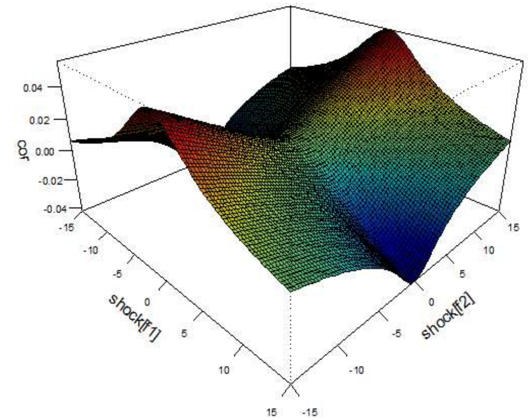
DCC - News impact correlation surface between EM and CDS



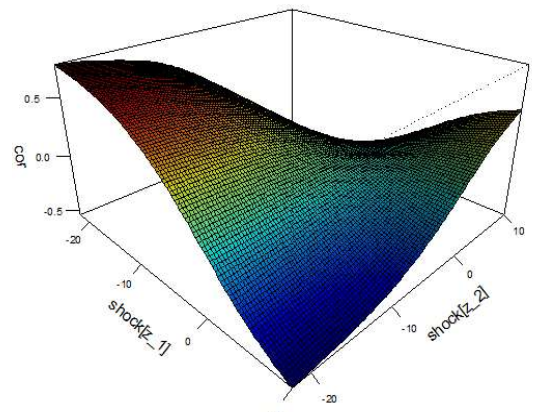
ADCC - News impact correlation surface between EM and CDS



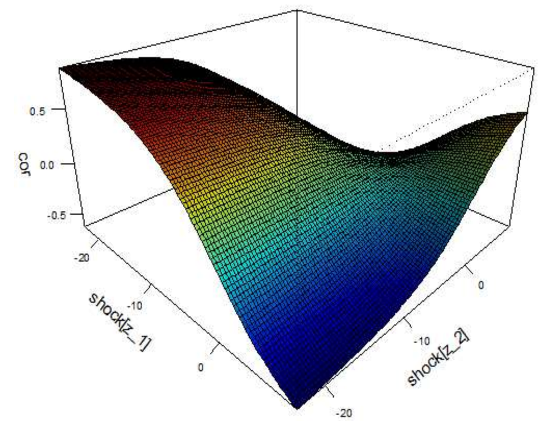
GO-GARCH - News impact correlation surface between EM and CDS



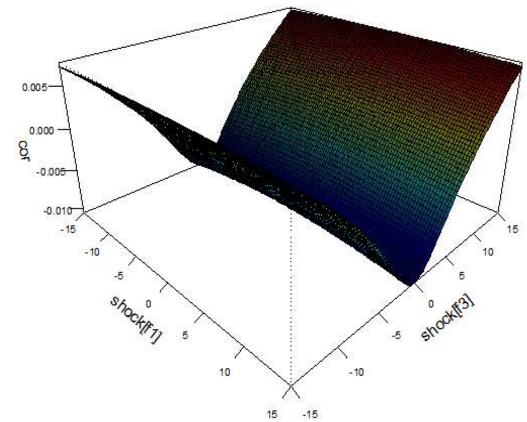
DCC - News impact correlation surface between EM and OIL



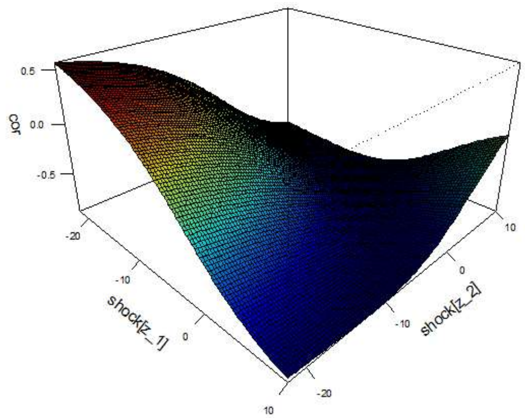
ADCC - News impact correlation surface between EM and OIL



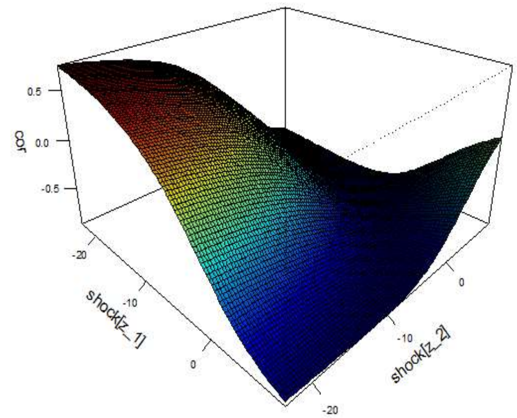
GO-GARCH - News impact correlation surface between EM and OIL



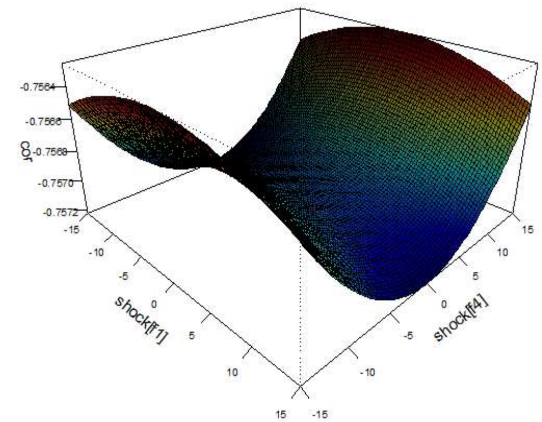
DCC - News impact correlation surface between EM and VIX



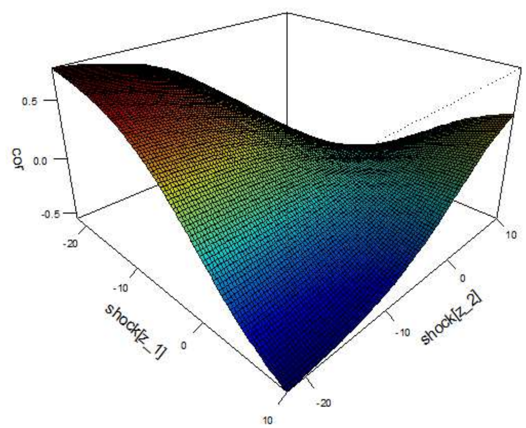
ADCC - News impact correlation surface between EM and VIX



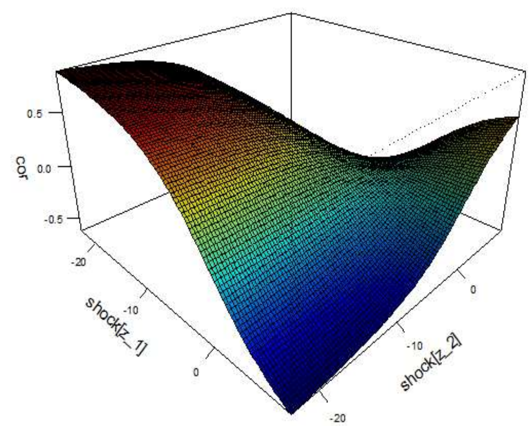
GO-GARCH - News impact correlation surface between EM and VIX



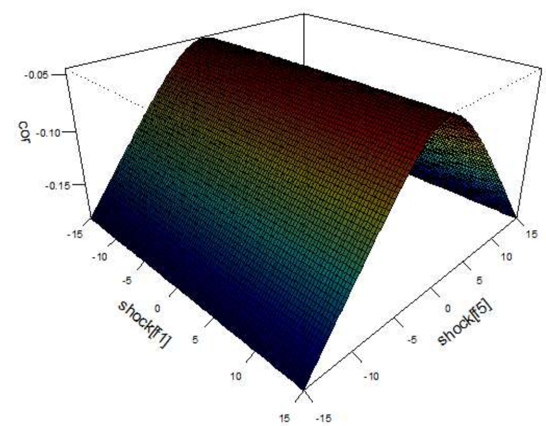
DCC - News impact correlation surface between EM and GOLD



ADCC - News impact correlation surface between EM and GOLD



GO-GARCH - News impact correlation surface between EM and GOLD



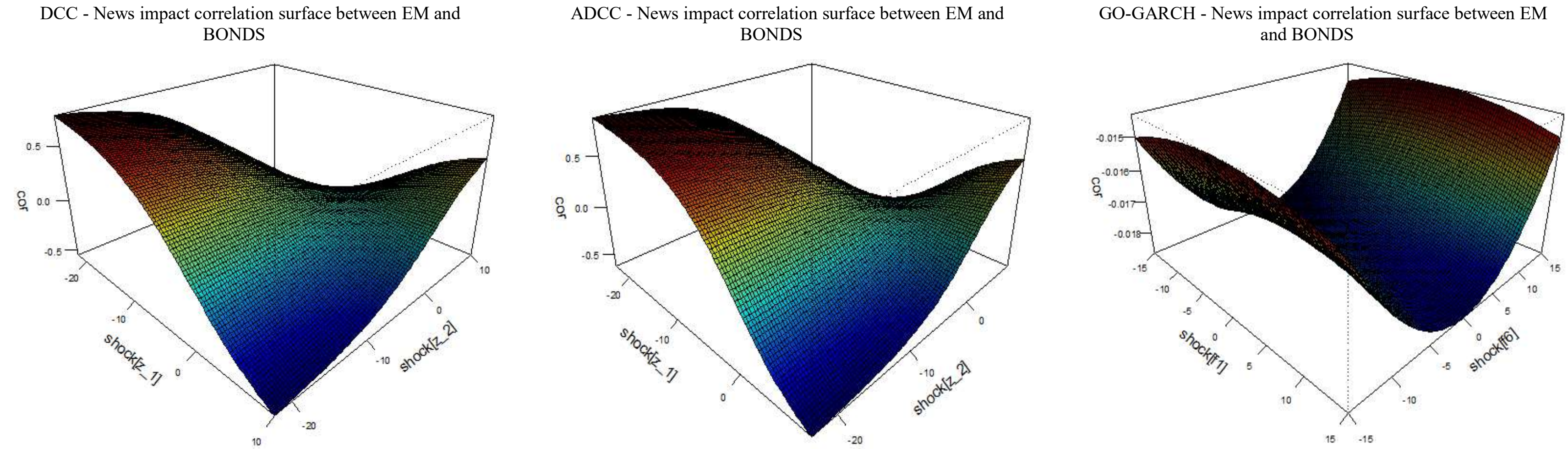


Figure 2: News impact correlation surfaces between EM and each of CDS, OIL, VIX, GOLD and BONDS

Table 1: Correlation between correlations

	EM/CDS	EM/OIL	EM/VIX	EM/GOLD	EM/BONDS
DCC/ADCC	0.9684	0.9610	0.9597	0.9716	0.9628
DCC/GO-GARCH	0.1139	0.1364	0.1937	-0.0694	0.1285
ADCC/GO-GARCH	0.0966	0.0966	0.2570	-0.0259	0.0859

Notes: DCC and ADCC estimated using a multivariate normal (MVNORM) distribution. GO-GARCH estimated using a multivariate affine negative inverse Gaussian (MANIG) distribution. All specifications include a constant and an AR(1) term in the mean equation.

It is also commonly believed that gold gives investors a better inflation hedge and more security in periods of turbulence and uncertainty since it is a safe haven asset and constitutes a good source of wealth. Thus, under such conditions, the equity market expresses a positive response to an increase in gold prices. Besides, a negative correlation between the equity market and gold can be explained by the fact that in the case of certainty and lower turbulence, investment in gold becomes less attractive for investors. In fact, in such circumstances, investors prefer to invest in more risky assets and underinvest in gold.

For the EM and BONDS pairs, positive dynamic correlations are generally reported. Some waves of negative correlation were also detected, especially over the period from mid-2013 to late 2016. Positive associations between the two variables may act as a solid indicator for investors' risk–on/off trading strategy to asset allocation. As for negative correlations, these may be explained by the so-called "Bernanke put", which suggests a lower yield on 10-year treasury bonds that characterizes most emerging and developed economies.

Table 1 summarizes the correlations between dynamic conditional correlations produced by the different GARCH specifications. DCC-GARCH and ADCC-GARCH produce higher correlations between conditional correlations. Go-GARCH, however, produces lower dynamic conditional correlations compared to those produced by both DCC and ADCC models. The lowest correlations are mainly observed between dynamic conditional correlations produced by ADCC-GARCH and GO-GARCH. Taken together, these results join those produced from the one-step-ahead dynamic conditions correlations, displayed in Figure 2.

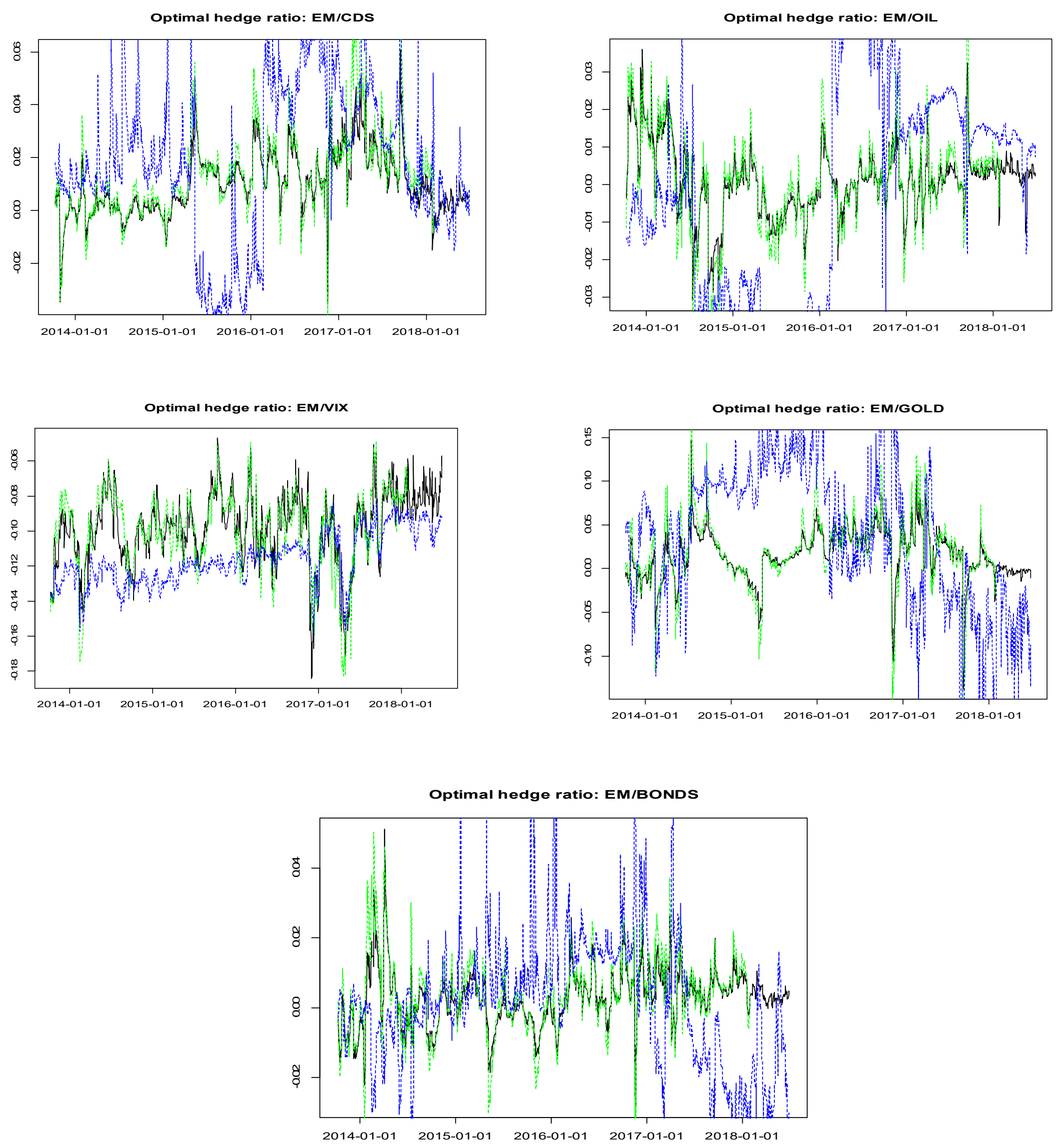
Figure 2 displays the news impact correlation surfaces. DCC and ADCC models show a similar shape. In particular, news impact correlation surfaces produced from the DCC and ADCC models trace out positive to negative patterns along the Z_1 axis linked to EM shocks. Negative to positive patterns are also observed for each pair along the Z_2 axis. Moreover, for both the DCC and ADCC models, and for each pair, the news impact correlation surfaces are convex and show strong evidence of asymmetry. Conversely, the GO-GARCH produces, first, news impact correlation surfaces that are very different from those produced by both DCC and ADCC models. Second, the news impact correlation surfaces produced from the GO-GARCH model show more (perfect) symmetry in the EM shock impact and each of the sample variables on the dynamic correlations between EM, and each of these variables. This symmetry can be explained by the orthogonalized GO-GARCH factors. Finally, while the news impact correlation surface produced from GO-GARCH is concave for the EM/GOLD pair, those related to the other pairs are more convex.

3.2 Optimal hedge ratios

The optimal hedge ratios produced by the three GARCH models and computed between the EM and a position for each of the CDS, OIL, VIX, GOLD, and BONDS are plotted in Figure 3. A common result is that for the different pairs, apart from EM/VIX, the hedge ratios produced by the GO-GARCH exhibit higher volatility compared to those produced by either the DCC or the ADCC models. Moreover, for each pair, DCC and ADCC models have similar hedge ratio distributions. Moreover, for the EM/CDS pair, the hedge ratios produced by the different GARCH models (DCC, ADCC, and GO-GARCH) are mostly positive. This suggests that the CDS can hedge the equity market in periods of uncertainty. For the two EM/GOLD and EM/BONDS pair, the GO-GARCH produces higher (lower) optimal hedge ratios, suggesting high (low) hedging effectiveness over the period extending from mid-2013 till about the first quarter of 2017 (from the end of the first quarter of 2017 until June 2018, respectively). For the EM/CDS pair, the GO-GARCH provides higher hedging effectiveness over almost the whole period from mid-2013 to June 2014 except for the subperiod from about May 2015 to January/February 2016. For the EM/OIL pair, both the DCC and the ADCC models provide higher hedging effectiveness compared to the GO-GARCH over the period from June 2013 until about late 2016 and lower hedging effectiveness over the period from late 2016 until June

2018. Regarding the EM/VIX pair, the DCC and ADCC models provide higher hedging effectiveness compared to the GO-GARCH over the whole period from June 2013 until June 2018. Also, compared to the other pairs, the EM/GOLD pair provides the highest hedging effectiveness. This can easily be explained by the fact that in periods of high turbulence, gold is more attractive to investors as it constitutes a good source of wealth and a safe haven asset. The EM/VIX pair shows the lowest hedging effectiveness for the three GARCH models. This is not surprising as the VIX index is unable to provide a hedging strategy for the equity market. The lower hedge ratios related to this pair imply significant diversification benefits, however, rather than hedging effectiveness.

Figure 3: Rolling one-step-ahead optimal hedge ratios



Note: Black dashed line: DCC, Green dashed line: ADCC, Blue dashed line: GO-GARCH.

As for the EM/BONDS pair, we show different waves of higher and lower effective hedge produced by the DCC, ADCC, and GO-GARCH models. This may indicate that BONDS are probably unable to provide a better hedging strategy to the equity market, possibly due to low-interest rates. Note that lower interest rates are generally observed in developed countries to which the United States, the focus of this study, belongs.

Finally, from Table 2, reporting the correlations between the hedge ratios produced by the three GARCH models for each pair, we can easily deduce that higher correlations between the hedge ratios are produced by the DCC and ADCC models. The hedge ratios produced by the GO-GARCH model have a lower correlation with those produced by both the DCC and the ADCC models. These results are consistent with those displayed in Figure 3, suggesting that the different pairs have a similar distribution of the hedge ratios produced by the DCC and ADCC models, which are very different from those produced by the GO-GARCH.

Table 2: Correlations between hedge ratios

	EM/HML	EM/OIL	EM/VIX	EM/GOLD	EM/BONDS
DCC/ADCC	0.9032	0.9501	0.9674	0.9158	0.9149
DCC/GO-GARCH	-0.2197	0.3025	0.2887	0.3650	0.3552
ADCC/GO-GARCH	-0.0522	0.2017	0.3551	0.4258	0.2189

Notes: Forecasts calculated from fixed-width rolling analysis that produces 1,000 one-step forecasts. Models are refitted every 20 observations. DCC and ADCC estimated using a multivariate t (MVT) distribution. GO-GARCH estimated using a multivariate affine negative inverse Gaussian distribution. All specifications include a constant and an AR(1) term in the mean equation.

Taken together, the results discussed above offer several implications. First, negative dynamic correlations between EM and VIX as well as lower hedging effectiveness of VIX indicate that VIX is probably unable to provide a hedging strategy against the USA equity market losses. This provides strong evidence of the immense economic benefits gained from optimal diversification. Second, due to the lower interest rates generally observed in the US market, bonds are unable to provide a hedging strategy to the equity market. Third, both CDS and GOLD provide a better hedging strategy in the equity market. The highest hedging effectiveness is related to GOLD. In periods of high turbulence and uncertainty, GOLD provides the best hedging strategy to equity markets and is more attractive for investors. The CDS provides an alternative hedging strategy that is appreciated as it provides the second most effective hedging potential. Oil provides smoother hedging effectiveness, possibly due to the high variability of oil prices and the frequency of oil supply and demand shocks.

4. Conclusion

This paper investigates dynamic conditional correlation and hedging effectiveness between commodity markets (Oil and GOLD) and financial variables (VIX, BONDS, and CDS). The results from the one-step-ahead forecasts of dynamic conditional correlations and optimal hedge suggest a strong economic benefit of diversification as the dynamic conditional correlations between the equity market and VIX indices are statistically and negatively significant, followed by high hedging effectiveness of both GOLD and CDS. GOLD is commonly shown to be a safe haven asset, while CDS provides better information about credit risk that would affect an enterprise. The results suggest, moreover, the superiority of the GO-GARCH model in predicting and forecasting the conditional dynamics of stock market returns.

These findings have strong implications for investors, market makers, analysts, and policymakers. In the U.S equity market, a consequence of the Subprime crisis, financial institutions, and retail investors dramatically increased their exposure to commodities. Our results highlight that especially in periods of crisis and high turbulence, investors can gain more profit by holding more gold than risky assets in their portfolios. They are also encouraged to invest in a highly-diversified portfolio to take advantage of the economic benefits of diversification.

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