Hedging stocks through commodity indexes: a DCC-GARCH approach

Leandro Dias Daumas
Faculty of Economic Sciences - State University of Rio de Janeiro
Fernando Antonio Lucena Aiube
Faculty of Economic Sciences - State University of Rio de Janeiro
Tara Keshar Nanda Baidya
Postgraduate Program of Administration - UNIGRANRIO

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Abstract

In this paper we investigate the links between the S&P500 index and S&P commodities indexes. Many assets in financial markets mimic these indexes and some have been responsible for huge amounts of new capital in commodity markets in the last decade. Based on the DDC-GARCH model we estimated the conditional correlations among these classes of assets focusing in the main events that occurred in equity and commodity markets. We found an increased level of correlations between S&P500 and commodities indexes after 2004. The increased correlations prevailed in the months following 2008 financial crises. An identical behavior was observed during the plunge of commodity prices in 2014. Although during these financialization periods the characteristic of commodities as diversification assets weakened, Precious Metals index preserved this property during most of the periods. According to our findings, the financialization persists nowadays.

Keywords: Hedging, commodity indexes, DCC GARCH, financialization

JEL Classification: C58, G01, G11, Q02

1 Introduction

The role of commodities in the world goes beyond their relevance as inputs in most economic activities. It is a well-known fact that commodities are assets useful to hedge positions in equities (Erb and Harvey (2006) [16]). Commodity returns are negatively correlated with stock and bond returns and positively correlated with inflation (Gorton and Rouwenhorst (2006) [19]). For example, Levine et al. (2016) [26] analyzed a sample from 1877 to 2015 documenting the main stylized facts of commodity returns. They concluded that commodity future prices have low correlation with stocks and bonds and that these futures are relevant for portfolio diversification.

Nowadays, the access of agents to commodities markets is different from the traditional way. The presence of investors in commodity markets has increased through commodity indexes and commodity exchange traded funds (ETF). Traditionally, investors gained exposure to commodities by taking positions in futures markets. Speculators received a risk premium in a long position to hedge commodity producers, or in a short position to hedge commodity consumers. Using these new instruments investors can take positions in different types of indexes that track index funds like Standard and Poor's-Goldman Sachs Commodity Index (S&P-GSCI) or Dow-Jones-UBS Commodity Index (DJ-UBS). On the other hand, these tracking funds take positions directly in future markets or with swap dealers that will enter in futures. The availability of new financial instruments has brought unconventional participants to commodity markets.

The inflow of new capital in commodity markets was due to a class of players called commodity index traders (CITs). Their main goal was diversification and capturing the escalation of commodity prices that was pushed by the demand of emerging markets at the beginning of the last decade. Irwin and Sanders [22] reported an increase in commodity markets from \$15 billion in 2003 to \$ 250 billion in 2009. Index traders treated commodities like any other financial investment (Cheng and Xiong (2014) [9]). This huge flow of capital into commodity markets through new index instruments promoted the escalation of commodity prices even more in the last decade. The high prices in commodity markets attracted the attention of authorities and policymakers concerned with prices of energy and food (Adams and Glück (2015) [1]). These developments are known as financialization of commodity markets as named by Domanski and Heath (2007) [14]. This means that commodities are moving more in sync with financial markets. The increased presence of hedge funds and speculators in commodity markets after 2004 has changed the role of commodities as hedging assets. The financialization phenomenon of commodity markets not only brought more volatility, but also modified the behavior of correlation with stocks as well. Figure 1 presents empirical cross-correlation among Energy, Agriculture, Industrial Metals and Precious Metals indexes. The correlations were computed considering a two-month moving window from 2002 to 2010. One can easily observe that the pattern of the correlations changed after 2004.

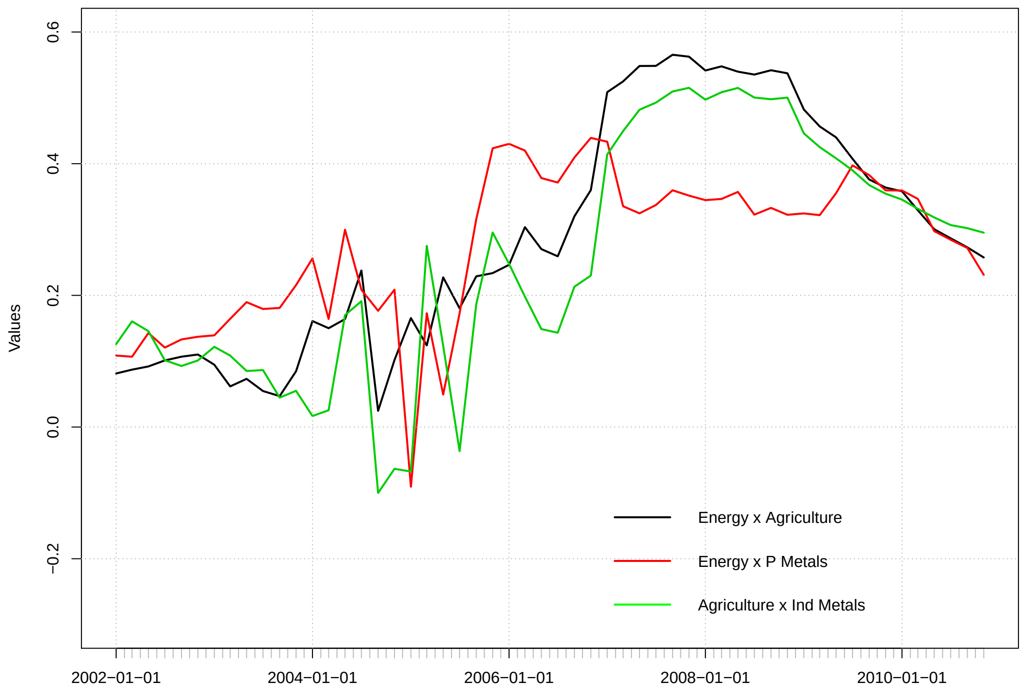

Figure 1: Some cross-correlations - Energy, Agriculture, Industrial Metals and Precious Metals

The consequence of these changes is that the diversification benefits has declined and the management of portfolios has also changed. The literature on financialization is huge. We mention Irwin and Sanders (2011) [22], Fattouh et al (2013) [17], Kaufmann and Ulman (2009) [24], Kaufmann (2011) [23], Alquist and Gervais (2013) [2], Singleton (2014) [35], Silvennoinen and Thorp (2013)

[34], Manera et al (2013) [27], among others.

A major debate in the finance the literature emerged with the surge of commodity prices and the high level of volatility observed. Many researchers claim that the fundamentals of supply and demand are the causes of this behavior of commodity prices (Fattouh et al (2013) [17], Alquist and Gervais (2013) [2], Manera et al (2013) [27], Kilian and Murphy (2014) [25]). There is also a group of researchers who found little evidence that traders such as hedge funds and swap dealers influenced prices in commodity markets, such as Büyüksahin et al (2011) [7] in oil markets and Brunetti et al (2016) [5] in several commodity markets. Hamilton and Wu (2015) [21] found little evidence that index-fund investing caused significant changes in the commodity futures market. On the other hand, other researchers attribute the escalation of commodity prices to the speculative trading behavior of commodity index funds (Singleton (2014), [35], Kaufmann and Ulman (2009) [24], Kaufmann (2011) [23], Mou (2011) [30]). However Irwin and Sanders [22] call attention to the fact that data and methods used in these types of studies are subject to criticisms. A survey of the financialization of commodity markets can be found in Cheng and Xiong (2014) [9]. It is clear there is no consensus about the increase in trading activity and the surge of prices in commodity markets. However, there is a convergence position related to an increase of volatility and also an increase in correlation between commodity future and equity markets (see for example, Sadorsky (2014) [33], Creti et al (2013) [12] and Tang and Xiong (2012) [36]).

New theoretical tools have been developed in the past decade to conduct this type of analysis. New advances have been made in GARCH models in the direction of multivariate series, as in Engle (2002) [15], McAleer et al. (2009) [29] and McAller et al (2008) [28] to mention a few. The main motivation in this direction is to study the relation between volatility (variance) and co-volatilities (covariances) of several assets/markets. From the practical point of view, the interest was to understand how volatility is transmitted from one market (asset) to another, since the financial markets have been closely integrated in the last 20 years worldwide. One investigation related to this problem is whether the correlations between asset returns change over time. Furthermore, the research on the dynamic behavior of correlations in the context of strong movements of financial markets is a crucial point for the management of portfolios.

In this paper we investigate the dynamic correlation among S&P500 and different commodity indexes using the dynamic conditional correlation DCC GARCH approach formulated by Engle (2002) [15]. The paper is organized as following; Section 2 presents a brief literature review; Section 3 presents the methodology; Section 4 exhibits the data used; Section 5 shows the results. Section 6 discusses hedging performance over the period analyzed; and Section 7 concludes.

2 Literature review

The empirical literature on commodities is well documented. There are many similarities between commodities and equity markets. The main stylized facts of equity series are present in commodity time series. Commodity returns have stationary behavior, weak linear dependence and strong nonlinear dependence, excess of kurtosis (fat tails) and conditional heteroskedastic behavior. All these points enable the study of commodity time series through volatility models of the GARCH family. In this manner, the links between the co-movements of commodities can be analyzed using these models. Most of the literature focuses on the dynamics of equities and specific commodities. Oil and agriculture commodities are the most studied since they are the most relevant in energy and food, sectors respectively. Links and spillover effects between equities, commodities, and other assets are commonly analyzed. The investigation of linkages between oil and financial markets can be found in Sadorsky (1999) [32], Filis et al. (2011) [18], Arouri et al. (2011) [3], Chang et al. (2013) [8], and

Hamilton (2008) [20], in addition to some references already cited the in previous section.

Manera et al. (2013) [27] used the DCC-GARCH model to evaluate the spillover impact of macroeconomic factors, agriculture and energy commodities. They used weekly returns from 1986 to 2010. They found that some macroeconomic variables seem to significantly affect commodity futures. Moreover, they found possible spillovers across commodities, observing that oil and gas markets positively affect other energy commodities. Also, they concluded that the dynamic correlation always increased after 2004 (in energy markets they even doubled) and that financial speculation was weakly significant in modeling commodity returns. Creti et al. (2013) [12] investigated the conditional correlation for 25 commodities and stocks over the period from January 2001 to November 2011 using the DCC-GARCH model. The focus was on the linkage between each commodity and the S&P500. They found high volatility in conditional correlation throughout the period, especially during the sub-prime crisis in 2008. Also, they noticed speculative movements in commodities like crude oil, cocoa and coffee. Their main conclusion was that only gold had negative correlation with stocks most of the time and that the financialization of commodity markets reduced their potential use in diversification, with main exceptions for gold, coffee and cocoa. Sadorsky (2014) [33] compared the performance of VARMA-AGARCH of McAleer et al. (2009) [29] and DCC-AGARCH of Engle (2002) [15], examining the correlations of emerging market stock prices and the prices of copper, oil and wheat. He found better performance with dynamic conditional correlation and proceeded using DCC-GARCH to compute hedging ratios and portfolio weights.

Chong and Miffre (2010) [11] investigated the hedging of equities and Treasury bills with 25 different future contracts of commodities based on weekly prices from 1981 to 2006. They used DCC-GARCH to estimate the conditional correlations. Based on the data sampled they found evidence that the conditional correlation of S&P500 and commodity futures decreased over time. This suggests that commodities are instruments for strategic asset allocation and that this conclusion is extended to short-term interest rate securities. It is important to note that this conclusion was based on the on a sample until 2006, so the more recent phenomenon of financialization (2004 onwards) probably had less influence on the results. Choi and Hammoudeh (2010) [10] analyzed the volatility behavior of oil as an industrial commodity and the stock market. They used GARCH switching approach to study volatility regimes and DCC GARCH to estimate conditional correlations. Based on data from 1990 to 2006 they found increasing correlations since the 2003 Iraq war but decreasing correlation with S&P500. Again, the sample until 2006 covers a short period of financialization. Büyüksahin et al (2008) [6], using dynamic correlation and cointegration techniques and a sample from 1991 to 2008, found no evidence of increase in the co-movement between equities and commodities returns. Demiralay and Ulusoy (2014) [13] analyzed links between commodity markets and the S&P500 index. They studied Dow Jones-UBS commodity index and its sub-indexes to check conditional correlations with S&P500 through asymmetric dynamic correlation (ADCC) GARCH model. The study was based on univariate exponential GARCH (EGARCH) model, using weekly returns from 1992 to 2013. They found that correlations between equity and commodity indexes are highly volatile and increased during the financial crisis, deteriorating the diversification benefits.

The goal of this paper is to analyze the role of commodity indexes as an asset to hedge exposure to positions in equity markets (proxied by the S&P500), focusing on the main events that occurred in equity and commodity markets. It contributes to the empirical literature in two ways. First, we analyze the hedging of equity markets using the S&P500 and commodity indexes covering the most relevant sectors of commodity markets. As mentioned before, commodity indexes as new financial instruments brought popularity to this market increasing its overall liquidity. Second, we use a time series period covering not only important crises in equity markets in the last 18 years, but also encompassing the recent downward movement of commodity prices. In this manner, we investigate the investors' hedging behavior, capturing the movements of ups and downs in both markets.

3 Methodology

To investigate the dynamic correlation between equity and commodity markets we rely on DCC-GARCH. Let y_t be the log-return of the index series. The model is written as

$$\Phi(L)\, y_{it} = \mu_i + \Theta(L)\, \epsilon_{it} \qquad i = 1, \ldots, n \qquad t = 1, \ldots, T \tag{1a}$$

$$\epsilon_{it} = \sigma_{it}\nu_{it} \qquad \nu_{it} \sim Std \quad t(0,1) \tag{1b}$$

$$\ln \sigma_{it}^2 = \omega_i + \sum_{j=1}^{q} \alpha_{ij}\epsilon_{it-1} + \gamma_{ij}\left(|\epsilon_{it-1}| - E\left(|\epsilon_{it-1}|\right)\right) + \sum_{j=1}^{p} \beta_i \ln \sigma_{it-1}^2, \tag{1c}$$

where L is the lag operator in the AR and MA polynomials $\Phi(L) = 1 - \phi_1 L - \ldots - \phi_r L^r$ and $\Theta(L) = 1 + \theta_1 L + \ldots + \theta_s L^s$, respectively. ϵ_t is the innovation and the equation (1c) represents the EGARCH(p,q) model [1] proposed by Nelson (1991) [31]. The EGARCH model captures the asymmetric effect or leverage effect. This asymmetry means that a negative shock on price series at time t brings more volatility at time $t+1$ than a positive shock of the same size. In this equation α captures the sign effect and γ the size effect.

The DCC-GARCH model is estimated in two steps. First the parameters in equation 1c describing the EGARCH(p,q) are estimated. In the second step correlations are estimated. The $n \times n$ conditional covariance matrix H_t is defined as

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

where R_t is the time-varying conditional correlation matrix, which must be invertible and positive definite and $D_t = diag(\sigma_{11t}, ..., \sigma_{nnt})$ is a diagonal matrix whose elements are the conditional standard deviations obtained in a previous univariate EGARCH (p,q) model.

To assure that R_t will be invertible and positive definite, an approximation matrix Q_t can be modeled as:

$$Q_t = (1 - a - b)\overline{Q} + a\nu_{t-1}\nu_{t-1}' + bQ_{t-1}, \tag{3}$$

where a and b are non-negative such that $a + b < 1$ to ensure stationarity and positive definiteness of Q_t and $\overline{Q}$ is the unconditional matrix of standardized errors ν_t. By this procedure, the correlation matrix is shown to be

$$R_t = diag(Q_t)^{-1/2} Q_t\, diag(Q_t)^{-1/2} \tag{4}$$

Like for the univariate model, DCC-GARCH parameters are estimated by the maximum likelihood estimation (MLE), whose function is composed of:

$$\begin{aligned}
LL =& \frac{1}{2}\sum_{i=1}^{T}(n\log(2\pi) + 2\log|D_t| + \log|R_t| + \nu_t R_t^{-1}\nu_t) \\
=& \frac{1}{2}\sum_{i=1}^{T}(n\log(2\pi) + 2\log|D_t| + \epsilon_t D_t^{-1} D_t^{-1}\epsilon_t) - \frac{1}{2}\sum_{i=1}^{T}(\nu_t'\nu_t + \log|R_t| + \nu_t' R_t^{-1}\nu_t') \\
=& LL_V(\eta_1) + LL_R(\eta_1, \eta_2),
\end{aligned}$$

[1] The EGARCH model in (1c) was selected among many GARCH models according the AIC and BIC criteria. There are three cases (GSCI, Agriculture and Industrial Metals) in which the standard GARCH model (Bollerslev (1986) [4]) performed better and was used. The order (p, q) of each model was selected in the same way.

where $LL_V(\eta_1)$ is the volatility component composed by parameters η_1 and $LL_R(\eta_1, \eta_2)$ is the correlation component estimated by parameters: η_1 and η_2.

4 Data Description

The selected data consist of daily returns of the S&P500, S&P-GSCI, S&P-GSCI Agriculture, S&P-GSCI Energy, S&P-GSCI Industrial Metals, S&P-GSCI Livestock and S&P-GSCI Precious Metals, from January 1999 to June 2017. The data were provided by S&P Dow Jones Indexes. The S&P-GSCI (formerly known as Goldman Sachs Commodities Index) was created in 1991 by the investment bank Goldman Sachs as a tradable asset for investors and also to measure the commodity market performance. In 2007, the index became a property of Standard and Poor's which has published it since then. The computation of the index takes into account world production. In other words, each commodity has a weight in S&P-GSCI based on the relevance in the global economy, which explains why energy commodities are the heaviest ones in the index composition followed by metals, agriculture and livestock commodities.

Regarding the sub-indexes, Agriculture includes wheat, corn, coffee, sugar, cocoa and cotton in the basis data. Energy is composed by crude oil and natural gas. Livestock includes commodities like lean hogs, live cattle and feeder cattle. Industrial Metals takes into account aluminum, copper, lead, nickel and zinc, while Precious Metals represents gold and silver.

The Standard and Poor's 500, or simply S&P500, is based on the 500 largest companies in the United States in term of market capitalization. The Dow Jones stock index was created in 1927 and the basis was expanded to 500 companies 30 years later. It provides an extensive record of information about the stock market. In this work, this indicator represents the equity market dynamic.

Table 1 describes the main statistics of the data sampled. One can note that Energy has the highest standard deviation while Livestock has the lowest. The S&P500 registered the highest daily surge (11.6%) and Energy suffered from the worst drop (-13.4%). Additionally, skewness has small negative values except for Agriculture. All kurtosis values are above three, meaning distribution with fat tails.

Figure 2 exhibits S&P500 and GSCI indexes from 01/03/2000 to 6/30/2017 normalized by their respective average indexes in 1999.

5 Results

Table 6 in the Appendix exhibits the estimation results for the model in equation (1) and also for the DCC-GARCH equation (3). The Appendix also presents figures in the dynamic conditional correlation between each index and the S&P500 that were estimated from DCC-GARCH. GSCI, Agriculture and Industrial Metals indexes were better fit using the classical GARCH(1,1) model. The remaining indexes had a better adjustment using the EGARCH model. Also, all coefficients are significant at 1%, except the parameter ω of the Agriculture index, which is significant at 5%.

From the figures in the Appendix, one can observe that the correlations in all indexes are highly volatiles which is an expected result according to the empirical literature mentioned above. Prior to 2005, the correlation was negative most of the time in almost all indexes (except for Industrial Metals and Livestock). During the period between 2005 and the 2008 financial crisis, there was increasing correlation (except for Precious Metals). From 2006 to 2009, a positive correlation prevailed. The

Table 1: Descriptive Statistics - Return series

	S&P500	GSCI	Agriculture	Energy	I. Metals	Livestock	P. Metals
Mean	2.2E-04	3.3E-04	1.9E-04	4.8E-04	3.0E-04	2.0E-04	3.8E-04
Std. Dev	0.012	0.015	0.013	0.020	0.014	0.009	0.012
Max	0.116	0.075	0.074	0.103	0.079	0.047	0.092
Min	-0.090	-0.088	-0.074	-0.134	-0.087	-0.042	-0.096
Skewness	-0.002	-0.124	0.006	-0.054	-0.129	-0.057	-0.118
Kurtosis	11.247	5.445	5.437	5.217	5.897	3.726	8.924
JB	13,220	1,175	1,155	959	1,645	105.28	6,832
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	57.121	14.395	11.638	16.736	30.829	33.972	11.891
	(0.000)	(0.156)	(0.310)	(0.080)	(0.001)	(0.000)	(0.292)
$Q^2(10)$	3,624	1,359	1,007	1,000	1,705	338	387
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH(10)	1,192	565	450	439	640	185	227
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-16.476	-15.476	-16.537	-15.380	-15.708	-16.015	-16.814
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: JB stands for Jarque-Bera test, $Q\,(10)$ and $Q^2\,(10)$ denote Ljung-Box statistics with 10 lags for returns and squared returns, respectively. ARCH is the LM-ARCH test with 10 lags and ADF denotes Augmented Dickey-Fuller unit root test. The p-values are in parentheses.

period from 2004 to 2009 crisis was the first period of the financialization of commodity markets (conditional correlations increased, see Table 2). This means that the characteristic of commodities as diversification asset for equity investors weakened.

Table 2 presents the statistics of correlations obtained from DCC-GARCH model. Panel A exhibits the statistics for the overall period. Panel B exhibits the statistics before 2004. Panel C shows the results for the period from 2004 to 2008-2009 (financial crisis). Panel D focuses on 2008 and, Panel E presents the results of the second half of 2014 onwards. Industrial Metals is the index that is most related to the market index and Precious Metals is the least correlated. Agriculture had the least reduction in the overall period, while the Livestock index had the least in 2008. Before 2004, conditional correlations with S&P500 were on average much lower than the overall period. And the period 2004 to 2009 was marked by an increase in correlations. The same result was found by Manera et al (2013) [27]. Moreover, from the second half of 2014 onwards, the correlations increased (in many cases even greater than the overall period), with the exception of the Precious Metals index. The upper graph in Figure 3 focuses on 2008, exhibiting conditional correlation between S&P500 and GSCI indexes.

Focusing on 2008, many interesting points can be observed. Before the Lehman Brothers bankruptcy on September 15, 2008, all correlations indexes were negative. For example, on May 2008 the GSCI index was negatively correlated with S&P500 and decreased to a minimum level (in 2008) of -0.408 on 7/3/2008. On 9/15/2008 the correlation was -0.09 and from October onwards the correlation increased. Amid the uncertainties of 2008, the normal link between the commodity indexes and S&P500 index was lost for a short period of time.

The indexes had minimum correlation values before 9/15/2008 and on this date correlations were

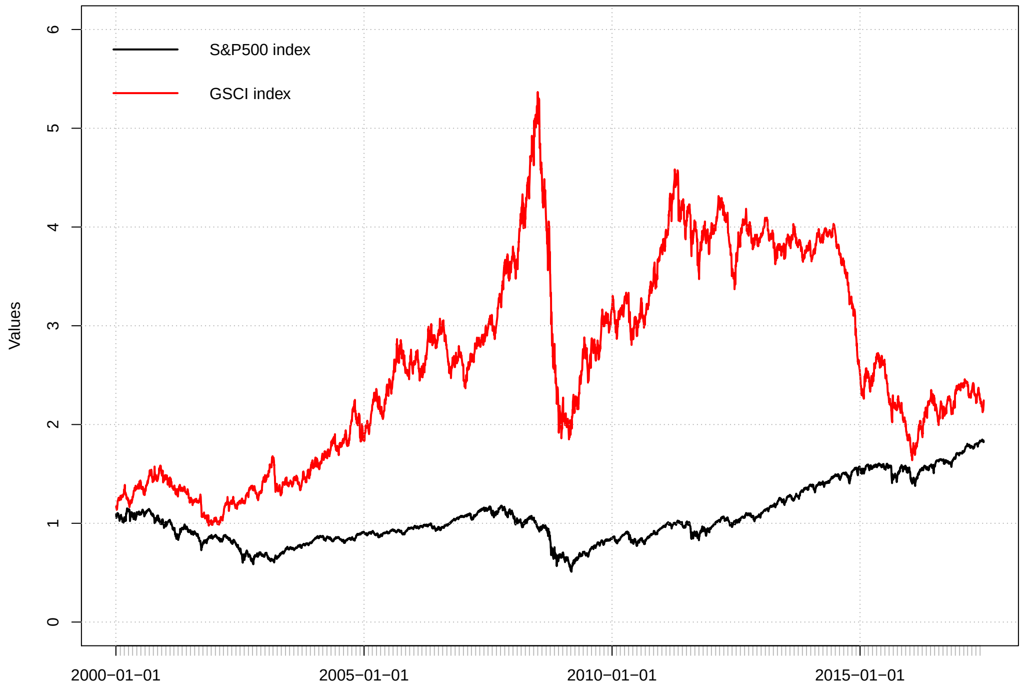

Figure 2: S&P500 and GSCI indexes

rising (see upper graph in Figure 3 for the GSCI case). The exception is the Precious Metals index, which reached the minimum correlation level more recently. It seems that the market turmoil of September 2008 triggered a herding behavior in which investors were looking for a diversification strategy through commodities (commodity indexes were increasing).

The figures in the Appendix show that after September 2008, the conditional correlations continued to increase and reached the highest levels observed in the whole sample analyzed. The finding that conditional correlations increased strongly during crisis is in line with the results in Creti et al (2013) [12], Demiralay and Ulusoy (2014) [13] and Sadorsky (2014) [33]. This means that financialization continued to be observed and again commodities were not a safe-haven for diversification as historically had been considered. This financialization period was even stronger than that before the crisis.

The lower graph of Figure 3 depicts another critical moment that deserves attention, the year when commodity prices plunged. In the beginning of 2014, the correlation between the S&P500 and GSCI was around 0.3. Then the correlation decreased until mid-2014. In the second half of 2014, most commodity prices plunged. This behavior can be explained by the appreciation of the US dollar against the euro as a consequence of European sovereign debt crisis (see Tokic (2015) [37], who examines the case of oil). At this time, the conditional correlation started a rising period and commodities lost their diversification value, except for Precious Metals, which stayed at low levels most part of the time.

Interestingly, before the disruption period of equities (2008) and before the drop of commodity prices (in the second half of 2014), the correlation decreased, exhibiting its classic behavior as an asset appropriate for hedging exposure to equities. Moreover, during the financial crisis (from September 2008 onwards) and during the commodity price downward movement (second half of

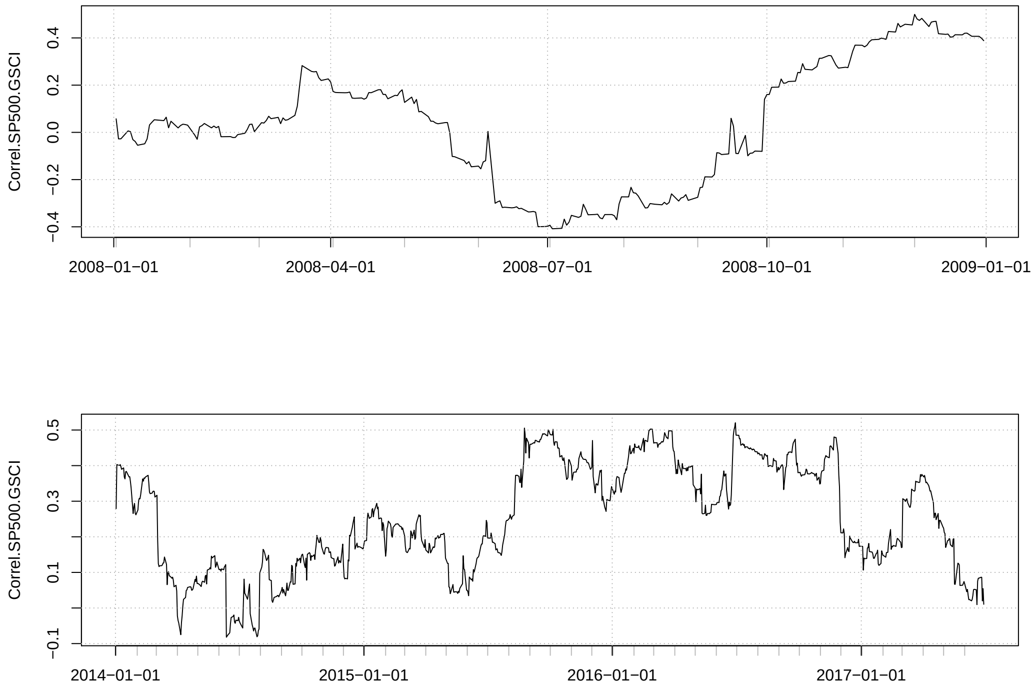

Figure 3: Conditional correlations between S&P500 and GSCI indexes

2014), the correlations with S&P500 increased. More recently, one observes, based on conditional correlation levels, that the financialization phenomenon still holds, with most indexes exhibiting a positive correlation (around 0.2) with the S&P500 index. The exception is the Precious Metals index, which preserved its main characteristic of a safe-haven asset. It seems that financialization was not a passing phenomenon.

Finally, we highlight the conditional cross correlations with the Energy index and Agriculture index. The particular importance of energy and agricultural commodities is their use as inputs production processes and food prices, respectively. In the overall period, both Energy and Agriculture indexes had the smallest conditional correlations with the Livestock index. The conditional cross correlations among indexes increased after the 2008 disruption in financial markets. To save space, we omit further results, which are available on request.

6 Hedging applications

To analyze the hedging properties of each index we compute three different metrics. First we compute the fraction of the whole period sampled in which the conditional correlation was below zero.

$$R = \frac{\# n_{hedge}}{n}, \tag{5}$$

where $\# n_{hedge}$ is the number of observations below zero and n is the sample size. This ratio was applied to all the period (overall) and for sub-periods chosen according to the main events: 1999 to 2002 (dot.com bubble and 11^{th} September), 2003 to 2007 (Iraq war and financialization period), 2008 (subprime crisis), 2009 to mid-2014 (post-subprime crisis), mid-2014 to 2017 (plunge of commodity prices and European sovereign debt crisis). Computing the R ratio through these periods enables

Table 2: Conditional correlations statistics: S&P500 and commodity indexes

	Mean	Std. error	Minimum	Maximum
Panel A (Overall)				
GSCI	0.186	0.261	-0.409	0.714
Agriculture	0.117	0.161	-0.280	0.551
Energy	0.167	0.262	-0.423	0.681
Ind. Metals	0.247	0.182	-0.288	0.688
Livestock	0.082	0.136	-0.357	0.438
P. Metals	0.010	0.214	-0.647	0.629
Panel B (before 2004)				
GSCI	0.009	0.168	-0.409	0.399
Agriculture	0.039	0.124	-0.254	0.348
Energy	-0.001	0.167	-0.397	0.432
Ind. Metals	0.167	0.130	-0.195	0.453
Livestock	0.056	0.099	-0.235	0.319
P. Metals	-0.101	0.157	-0.487	0.235
Panel C (2004 to 2009)				
GSCI	0.098	0.239	-0.408	0.650
Agriculture	0.113	0.175	-0.280	0.551
Energy	0.079	0.239	-0.423	0.628
Ind.Metals	0.195	0.190	-0.288	0.662
Livestock	0.057	0.159	-0.357	0.439
P.Metals	0.059	0.174	-0.408	0.488
Panel D (year 2008)				
GSCI	0.031	0.256	-0.408	0.500
Agriculture	0.054	0.163	-0.208	0.363
Energy	0.024	0.260	-0.423	0.505
Ind. Metals	0.121	0.179	-0.288	0.407
Livestock	0.101	0.137	-0.196	0.358
P. Metals	-0.112	0.170	-0.408	0.233
Panel E (July 2014 - June 2017)				
GSCI	0.267	0.145	-0.081	0.520
Agriculture	0.145	0.099	-0.143	0.370
Energy	0.243	0.150	-0.100	0.529
Ind.Metals	0.245	0.111	-0.106	0.546
Livestock	0.124	0.108	-0.162	0.403
P.Metals	-0.131	0.158	-0.647	0.288

Table 3: R ratio - fraction of negative correlation

Panel A (Overall/sub-periods)						
	Overall	99-02	03-07	2008	09-mid-14	mid-14-17
GSCI	0.242	0.322	0.513	0.409	0.029	0.018
Agriculture	0.252	0.425	0.297	0.452	0.144	0.079
Energy	0.279	0.353	0.589	0.417	0.048	0.040
Ind. Metals	0.079	0.122	0.121	0.258	0.005	0.028
Livestock	0.273	0.297	0.439	0.270	0.176	0.143
Precious Metals	0.492	0.636	0.410	0.631	0.267	0.803
Panel B (year 2008)						
	Jan-Feb	Mar-Apr	May-Jun	Jul-Aug	Sep-Oct	Nov-Dec
GSCI	0.366	0.000	0.672	1.000	0.409	0.000
Agriculture	0.804	0.000	0.537	0.930	0.455	0.000
Energy	0.390	0.000	0.693	1.000	0.409	0.000
Ind. Metals	0.000	0.000	0.450	1.000	0.136	0.000
Livestock	0.244	0.000	0.317	0.860	0.455	0.000
P. Metals	0.073	0.238	0.929	1.000	1.000	0.488

us to assess differences in hedging possibilities during different economic events.

The computation above is exhibited in Table 3. Panel A has the overall sample and sub-periods. Panel B contains the results for the year 2008 in bimonthly periods (in this case the denominator is the number of days in every two months). In Panel A, the index that was correlated negatively with S&P500 for the longest period was Precious Metals (almost 50% of the time), while Industrial Metals was the least useful for hedging purposes. The remaining indexes had almost equal values. This pattern of Industrial Metals repeats in all sub-periods. This behavior is expected since Industrial Metals are heavily correlated with equities since their consumption increases with the industry growth. Notice that in the period from mid-14 to 2017 (when commodity prices plunged), all indexes were positive most of the time, except for Precious Metals. In 2008, all indexes were negative longer than in the overall sample, except for Livestock. From Panel B one can observe that just before September, the conditional correlations were mostly negatively correlated with S&P500. At the end of 2008, all indexes except Precious Metals had positive conditional correlations.

Second, since we have computed variances and covariances, we can build the hedge ratios. Following Kroner and Sultan (1993), one can compute the optimal hedge ratio given by the conditional moments as:

$$\hat{\beta}_{ij,t} = \frac{\hat{\sigma}^2_{ij,t}}{\hat{\sigma}_{j,t}}, \tag{6}$$

where $\hat{\sigma}_{ij,t}$ is the covariance between i and j at t and $\sigma^2_{j,t}$ is the variance of j at t. The hedge ratio $\hat{\beta}_{ij}$ means that a long position in an asset i can be hedged with a short position in another asset j. In other words it means the optimal number of futures contracts in the investor's portfolio. Table 4 presents the results from equation (6). A \$1 long position in S&P500 can be hedged by a \$0.15 short position in GSCI on average. The negative sign means the reverse position. In absolute terms the cheapest hedge is obtained with Precious Metals, the second cheapest hedge is obtained with the Agriculture and the most expensive is with Industrial Metals. When accounting for the variability cost of the hedge ratio Agriculture has the lowest standard error deviation while the GSCI has the highest. As mentioned in Sadorsky (2014), [33] the high variability of the hedge ratio obtained above implies that the positions should be updated regularly, however this is an expensive cost strategy.

Table 4: Kroner and Sultan's hedge ratio statistics for S&P500 with each index

	Mean	Std. error	Minimum	Maximum
GSCI	0.150	0.221	-0.399	1.033
Agriculture	0.097	0.153	-0.415	0.927
Energy	0.103	0.171	-0.368	0.795
Ind. Metals	0.206	0.188	-0.373	1.308
Livestock	0.109	0.202	-0.443	1.140
Precious Metals	-0.016	0.209	-1.002	0.719

Table 5: Kroner and Ng's portfolio weight statistics for S&P500 with each index

	Mean	Std. error	Minimum	Maximum
GSCI	0.673	0.219	0	1
Agriculture	0.596	0.225	0.031	1
Energy	0.802	0.166	0.135	1
Ind. Metals	0.649	0.261	0	1
Livestock	0.464	0.216	0	0.988
Precious Metals	0.579	0.216	0.078	1

Finally, an important application of multivariate models is to build optimal portfolios. Following Kroner and Ng (1998) we can obtain the optimal portfolio weights by

$$w_{ij,t} = \frac{\hat{\sigma}_{j,t}^2 - \hat{\sigma}_{ij,t}}{\hat{\sigma}_{i,t}^2 - 2\hat{\sigma}_{ij,t} + \hat{\sigma}_{j,t}^2} \tag{7a}$$

$$w_{ij,t} = \begin{cases} 0, & \text{if} \quad w_{ij,t} < 0 \\ w_{ij,t}, & \text{if} \quad 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if} \quad w_{ij,t} > 1 \end{cases} \tag{7b}$$

where the $w_{ij,t}$ is the weight of asset i in a portfolio composed of assets i and j at time t. Table 5 summarizes the portfolio weights. In a portfolio including S&P500 and GSCI, the average weight is 0.67, indicating that this fraction is invested in the S&P500 index and 0.33 is invested in the GSCI index. The highest proportion of S&P500 in a two-asset portfolio with commodity indexes analyzed is with Energy. The lowest proportion is with Livestock, on average. In terms of variability of the weight, Energy has the lowest standard deviation. To save space, we do not to exhibit the results in Tables 3, 4 and 5 for Energy, Agriculture and Precious Metals as we did before in Table **??**. They are available on request.

7 Conclusions

In this paper we use the DCC-GARCH model to analyze the conditional correlations among commodity indexes and S&P500. The main focus is on the investigation of hedging performance, highlighting the 2008 financial crisis and the downward movement of commodity prices in 2014.

Commodity indexes have become very popular financial assets in the last decade. They are used by unconventional commodity players as a typical financial asset such as stocks or bonds. This trend brought an unprecedented amount of new investment in commodity markets, a phenomenon called financialization of commodities. The escalation of commodity prices is attributed by many researchers as a consequence of financialization. Furthermore, the new behavior of investors in commodity markets has changed the volatility and the correlation between commodities and equities with consequences for portfolio management.

We found that before 2004, the conditional correlations were much lower than in the following periods, confirming the financialization phenomenon. Moreover, Precious Metals index has the lowest correlation with S&P500. It provided the best strategy for hedging, beingg negatively correlated most of the time with the S&P500. On the other hand, the Industrial Metals index had the highest correlation. During 2008, all indexes had low correlations on average. Just before the Lehman Brothers bankruptcy, all indexes were negative most of the time and were useful for hedging equity positions. After the turmoil in the financial markets, the correlations skyrocketed and most of them were positive (except for Precious Metals index). Again financialization occurred, with an unfavorable conditions for hedging with commodities (except for Precious Metals). In the second half of 2014, when commodities plunged, the correlation increased and again financialization was observed. More recently (2016 and 2017), one observes high correlation between indexes and the S&P500 can be observed, which can be a sign that financialization continues to weaken diversification and hedging strategies.

Finally, the results obtained from the hedging performance in the analyzed period indicate that the Precious Metals index is the cheapest hedge for the S&P500 while the most expensive is Industrial Metals. The highest proportion of S&P500 in a two-asset portfolio occurs with the Energy index.

To summarize, we can conclude that (i) the financialization and the increased correlations that started in 2004 weakened the use of commodities as a diversification asset in equities portfolios; (ii) during the financial crises in 2008 and also during the plunge of commodities in 2014, the correlations were even higher than in the first period of financialization, with adverse consequences for their use to hedge equities; (iii) despite the occurrence of these events in 2008 and 2014, the Precious Metals index preserved its main characteristic of an appropriate asset for diversification during most of the time period; and, (iv) more recently, the high level of correlations persists, suggesting that financialization has become a stylized fact of commodity markets.

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8 Appendix

Table 6: Estimation results

Coefficient	S&P500	GSCI	Agriculture	Energy	Ind Metals	Livestock	P Metals	DCC
μ	3.8E-04						4.6E-04	
	(4.0E-04)						(7.1E-04)	
ϕ_1						0.056		
						(3.1E-04)		
θ_1	-0.063		0.046		-0.055			
	(4.6E-04)		(0.002)		(4.2E-05)			
ω	-0.148		1.0E-06					
	(0.000)		(0.034)					
α_1	-0.258	0.038	0.047	-0.030	0.042	-0.028	0.030	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(2.3E-05)	(5.3E-05)	
α_2	0.116							
	(0.000)							
β_1	0.985	0.959	0.947	0.996	0.953	0.999	0.994	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
β_2						-0.110		
						(0.000)		
β_3						0.097		
						(0.000)		
γ_1	-0.078			0.091		0.083	0.095	
	(0.003)			(0.000)		(0.000)	(0.000)	
γ_2	0.193							
	(0.000)							
a								0.029
								(0.000)
b								0.969
								(0.000)
df	7.950	10.047	10.150	9.422	8.892	20.200	4.609	9.385
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: df means degrees of freedom for the standard t distribution and for DCC df means degrees of freedom for the multivariate standard t distribution. In parenthesis are the p-values.

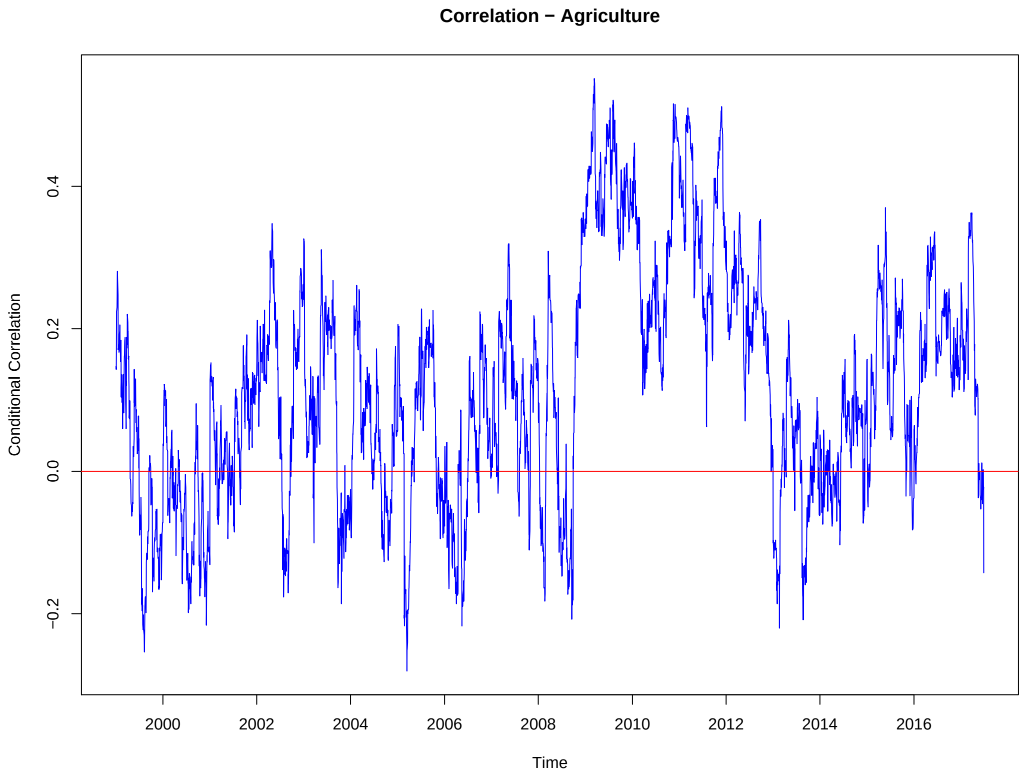

Figure 4: S&P500 index *versus* Agriculture index

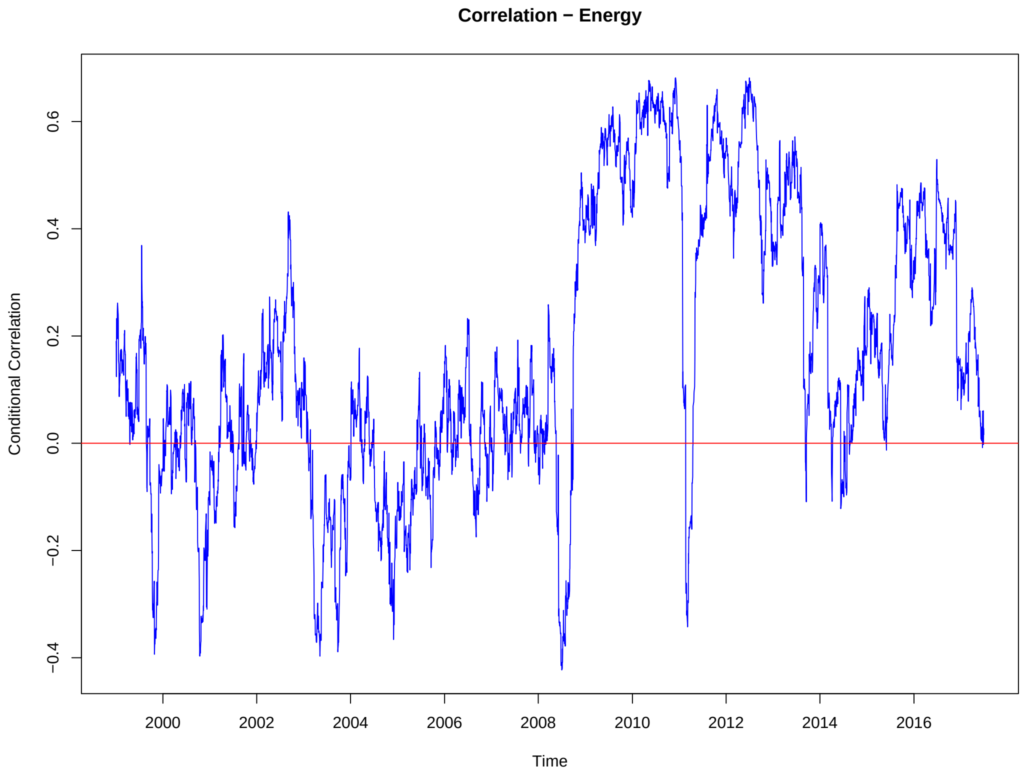

Figure 5: S&P500 index *versus* Energy index

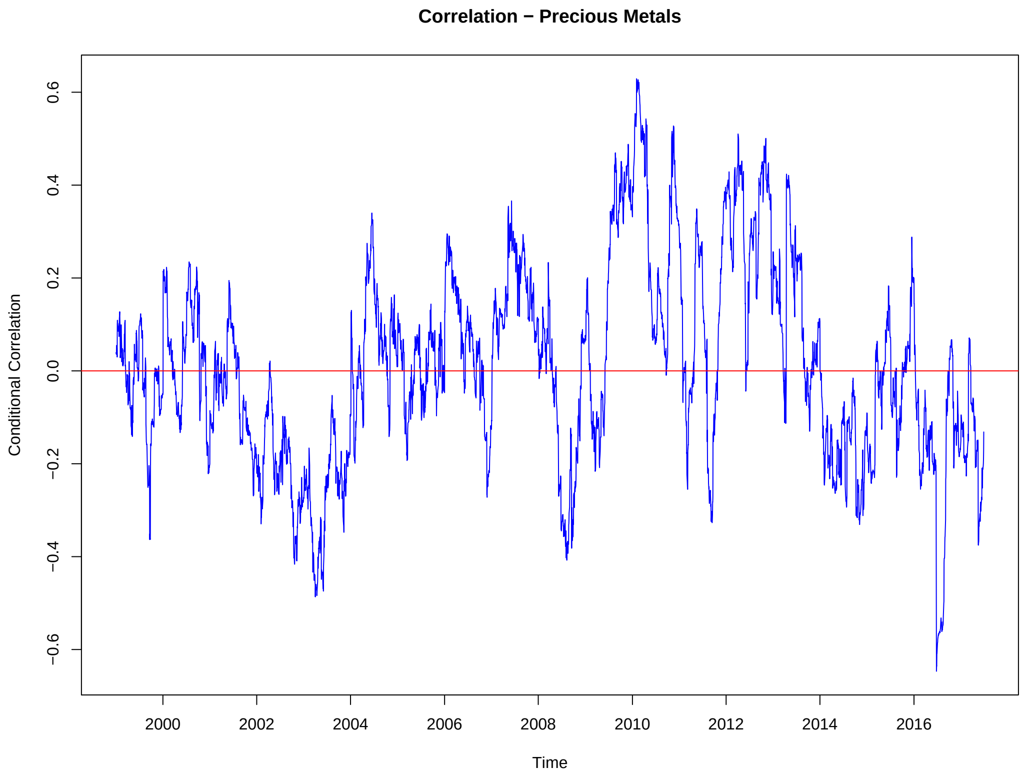

Figure 6: S&P500 index *versus* Precious Metals index

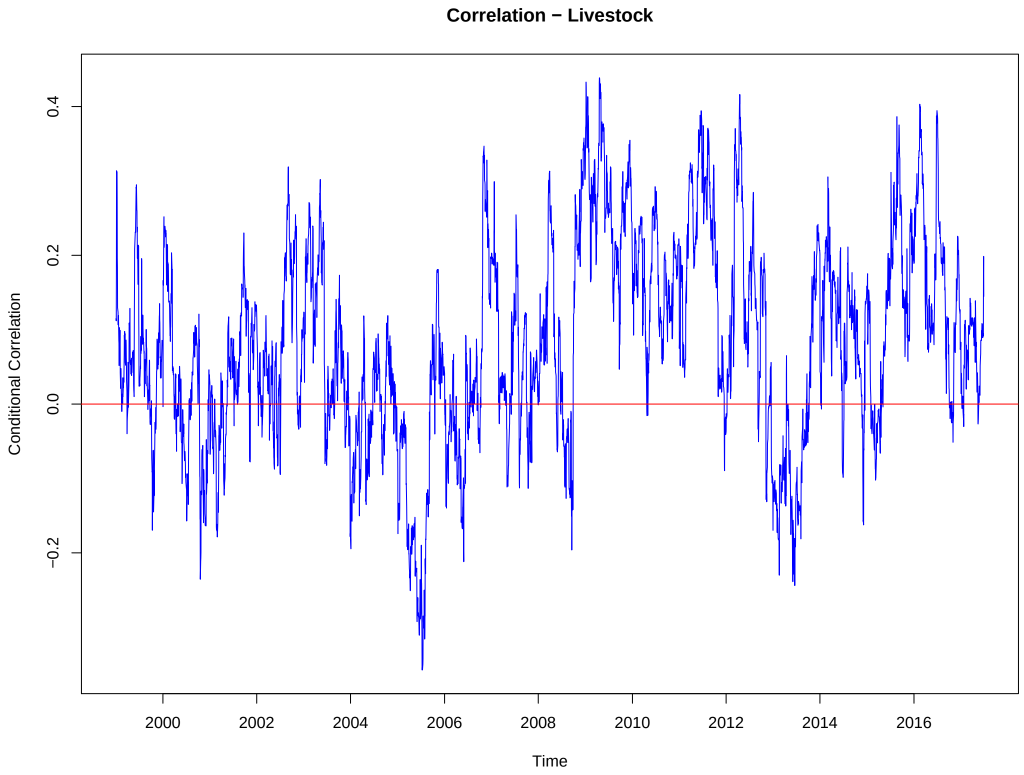

Figure 7: S&P500 index *versus* Livestock index

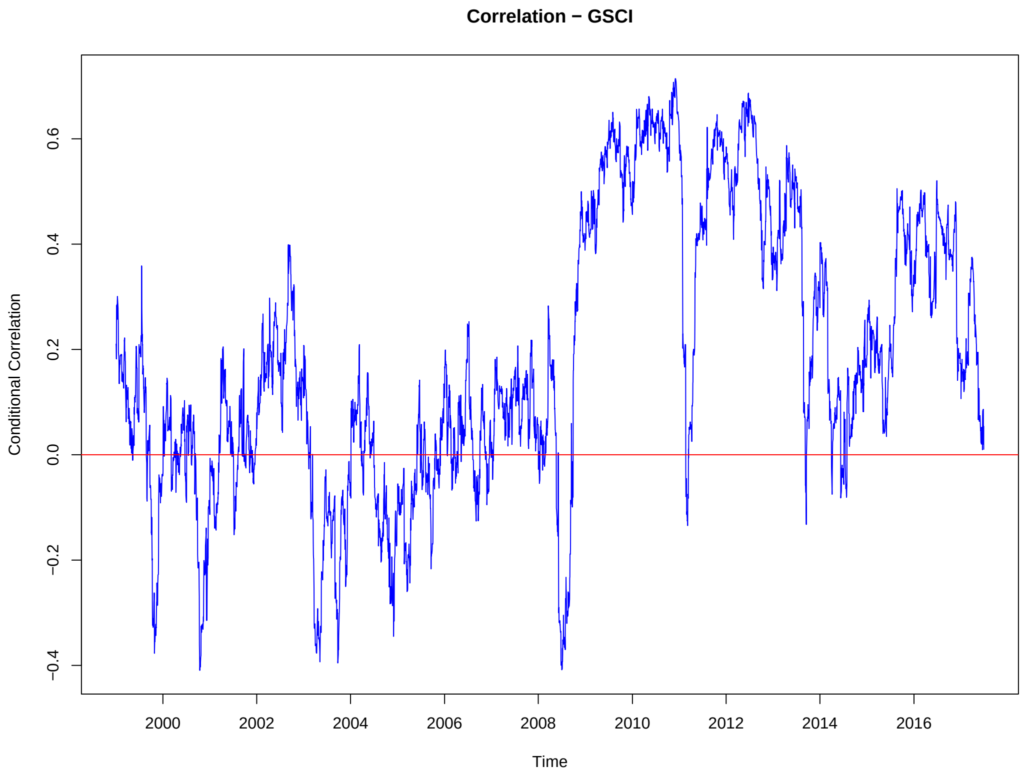

Figure 8: S&P500 index *versus* S&P-GSCI index

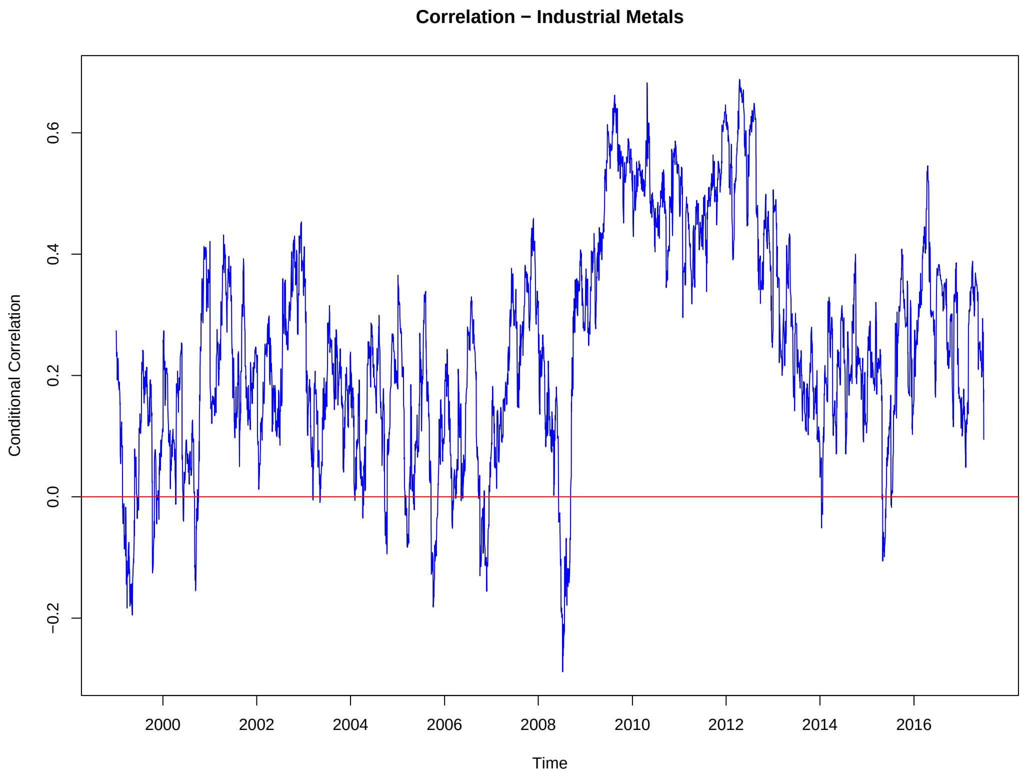

Figure 9: S&P500 *versus* Industrial Metals