University of Macedonia

School of economic and regional studies

Department of Economics

Bachelor Thesis

ON THE CORRELATION BETWEEN COMMODITY AND EQUITY RETURNS

Of

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CONTENTS

ABSTRACT

In this paper, we investigate the correlation between various commodity and equity markets from different countries during the period of the 2000s. We used weekly data to avoid the problem with the differenced time between the markets. We applied the dynamic conditional correlation methodology and ran an OLS estimation with two shock dummies in order to examine the hypothesis that the correlation must be negative during shock periods, as long as the safe heaven hypothesis. Our main findings supports that the correlation between commodity and equity markets tend to be negative during the two crisis, but after the financial crisis of 2008 the correlation seems to be positive due to the financialization of the economy.

INTRODUCTION

The objective of each successful financial investor is to accomplish high returns with low risk. The financial theory suggests, that the best way to do this, is by diversifying portfolios with financial assets that have negative correlation. In the past , the most popular method to create one diversified portfolio was the usage of equities and commodities assets(Gorton and Rouwenhorst, 2006). After the dot-com bubble, at the begging of this century , the investing in commodity markets became more and more popular to the investors, due to the high returns same to those ones from the stock market and also, their negative correlation with the equity markets, which lowered the total risk. Moreover, the safe heaven hypothesis of gold gave an extra motive for investing in commodities such as gold or silver. Although, nowadays their correlation seems to have been changed after the recent financial crisis of 2007-2009 and tend to be positive (Büyükşahin, Haigh and Robe , 2008). All in all, the correlation between commodities and equities doesn't have a constant pattern, it changes through the years, thus more research is needed in order to determine the real relationship between commodity and equity assets.

In this thesis we try to analyze the correlation between various commodity and equity asset, during a period from January 2000 to December 2018. We chose this period of time in order to focus our analysis to the doc-com bubble and the real estate shock in USA , which led to the worldwide financial crisis of 2007-2009. We used the Dynamic Conditional Correlation (DCC) approach established by Engle (2002) which is an extension of the GARCH models to extracted the correlation and then a simple OLS regression between the DCC and the two shocks in order to examine the correlation in that period.

The paper is organized as follows. In section 2 we present the literature review tables, that summarize the previous analysis, that have been made for commodity and equity assets correlation. Section 3 contains the data that we used. Section 4 is devoted to the methodology of the paper. In section 5 one can observe the results from our empirical analysis and finally section 6 concludes and summarizes our main findings.

2.LITERATURE REVIEW

	Title	Author	Methodology	Data	Theme
(1)	The synchronized and long-lasting structural change on commodity markets: Evidence from high frequency data	Bicchetti and Maystre (2013)	Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002) and a moving-window correlations with window widths set to 5 or 15 observations for each considered frequency.	The data used are, tick-level data from January 1998 to December 2011 and they are obtained from Thomson Reuters Tick History (TRTH) database. They used data for E-mini S&P 500 for stock market, light crude oil(WTI) (NYMEX), corn (CBOT), wheat (CBOT), sugar #11(ICE - US), soybeans (CBOT) and live cattle (CME) for the commodity market. The frequencies of the data are 1-hour, 5-minute, 10-second and 1-second.	This article analyses the co-movements between the US stock market and several commodity futures between 1998 and 2011. It computes a DCC model for (i) 1-hour, (ii) 5-minute, (iii) 10-second, and (iv) 1-second frequencies and documents a synchronized structural break, characterized by correlations that have significantly departed from zero to positive territories, since late September 2008. Also the writers support the idea that high frequency trading and algorithmic strategies have an effect on the behavior of commodity prices.

	Title	Author	Methodology	Data	Theme
(2)	On the links between stock and commodity markets' volatility	Creti, Joëts and Mignon (2013)	Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002)	The data are daily spot price series for a large sample of commodities such as energy, precious metals, agricultural, non-ferrous metals, food, oleaginous, exotic and Livestock over the period January 3, 2001–November 28 2011 (source: DataStream, Thomson Financial). They also used data from Commodity Research Bureau (CRB) index and S&P 500 index for the stock market.	This paper investigates the links between price returns for 25 commodities and stocks by paying particular attention to energy raw materials during the financial crisis of 2007-2008.
(3)	On the correlation between commodity and equity returns: Implications for portfolio allocation	Lombardi and Ravazzolo (2016)	Time-varying Bayesian Dynamic Conditional Correlation model based on Engel's (2002) DCC method, rolling windows for mean, variance and correlation. Also for the forecasting exercise they used models such as Random Walk, AR model, Bayesian VAR and Bayesian DCC. The criterions used are, MSPE, KLIC and LS.	The data used are, weekly returns Generated by the Morgan Stanley Capital International global Equity index (MSCI) and the Standard & Poor's Goldman Sachs commodity index (SPGSCI), starting from the first week of January 1980 until the last week of August 2015. Additionally in the forecasting model they used data from SP500, Brent, BCOM and WTI.	This paper investigates the increase of the correlation between equity and commodity returns, blaming for that surging investment in commodity-related products. Moreover, the authors use various measures of correlation and assess what are the implications for asset allocation between the two markets. They also use a forecasting model and run an allocation exercise to verify their results.

	Title	Author	Methodology	Data	Theme
(4)	Conditional Return Correlations between Commodity Futures and Traditional Assets	Chong and Miffre (2008)	GARCH (1, 1) (Hansen and Lunde 2005), developed by Bollerslev (1986), DCC GARCH (1, 1) model proposed by Engel (2002) and maximum likelihood procedure using the algorithm of BFGS.	The data used are, weekly comprise returns and closing prices on the nearby and second nearby contracts of twenty-five commodities (eleven agricultural futures, five energy, four livestock futures and five metal futures) and thirteen traditional asset classes (four from the US, three from global markets and six international bond indices from JP. Morgan). The data set spans the period December 12, 1980 to December 27, 2006.	This article studies the temporal variations in the conditional return correlations between commodity futures and traditional asset classes, it also analyses the link between Treasury-bill portfolios and commodity markets.
(5)	Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold	Mensi, Beljid, Boubaker and Managi (2013)	VAR (1) – GARCH (1, 1) proposed by Ling and McALeer (2003) which includes the multivariate CCC-GARCH of Bollerslev (1990).Also they used quasi - maximum likelihood (QML) to estimate the parameters of the model.	The data used are, daily close returns from the S&P 500 (beverage price), wheat, gold price indexes and two crude oil benchmarks: Cushing West Texas Intermediate (WTI) and Europe's Brent from January 3, 2000 to December 31, 2011. The sources of the data were the US Energy Information Administration, International Grains Council, and S&P 500 websites.	This paper investigates the return links and volatility transmission between the S&P 500 and commodity price indices for energy, food, gold and beverages over the turbulent period from 2000 to 2011. Also analyses the optimal weights and hedge ratios for commodities/S&P 500 portfolio holdings.

	Title	Author	Methodology	Data	Theme
(6)	Commodities and Equities: A “Market of One”?	Büyükşahin , Haigh and Robe (2008)	Rolling historical correlation, exponential smoother, and DCC by log-likelihood for mean-reverting model estimation proposed by Engel (2002). Augmented Dickey Fuller unit root test and recursive cointegration techniques(Johansen, 1998, 1991; Johansen and Juselius,1990)	The data used are, daily, weekly and monthly returns from January 1991 through May 2008, from S&P500 Index (Standard and Poor's), GSCI Index (Goldman Sachs Commodity Index), DJIA Index and DJ-AIG Index (Dow-Jones's). The source of the data was Bloomberg.	This paper analyses the co-movement between commodity and equity markets for a period of 17 years by using Dynamic Conditional Correlation and recursive techniques. They find that the correlation and the co-movement between the returns on commodity and equity investments during periods of extreme returns have not changed significantly through this period of time.
(7)	The relationship between energy and equity markets: evidence from volatility impulse response functions	Olson, Vivian and Wohar (2014)	VAR model with one lag, multivariate GARCH model (BEKK’s specification), hedge ratio for the S&P 500 and each commodity index using the estimated conditional co variances and variance impulse response functions proposed by Hafner and Herwartz’s (2006).	The data used for this paper are weekly returns from S&P 500 and Goldman Sacks Energy Excess Return Index, from January 1, 1985 to April 24, 2013. The source of the data was Thomson’s Data Stream. Also they used weekly return in the Trade Weighted U.S. dollar index: Major currencies from the St. Louis Fred database.	This paper examines the relationship between the energy and equity markets by estimating volatility impulse response functions from a multivariate BEKK model. Their analysis suggests that the energy index is generally a poor hedging instrument.

	Title	Author	Methodology	Data	Theme
(8)	Correlation in commodity futures and equity markets around the world: Long-run trend and short-run fluctuation	Li, Zhang and Du (2011)	DCC model proposed by Engel (2002), log likelihood ratio test, multiple-break unit root test for trend stationary with the use of Monte Carlo Simulations.	The data used are, daily prices from S&P 500 Goldman Sacks Commodity Index (GSCI) and Morgan Stanley Capital International All Country World Investable Index (MSCI ACWI), from January 1, 2000 to December 31, 2010. The source of the data was DataStream.	This paper examines the long-run trends and the short-run fluctuations of the commodity-equity correlation, and it does so to indice from 45 equity markets. They find that commodity investments have more diversification benefits in the long run worldwide.
(9)	Time varying correlation between Islamic equity and commodity returns: implications for portfolio diversification	Khan, Kabir, Bashar and Masih (2015)	Dynamic Conditional Correlations GARCH model proposed by Engle and Sheppard (2001) and Engle (2002).	The data used are daily spot price series extracted from DataStream for the different commodities covering various sectors over the January 3, 2001 - March 28, 2013 period. They investigate 5 different commodity groups; energy, precious metals, agricultural, nonferrous metals and soft's group. An aggregate commodity price index, the DJ Spot commodity Index, is also considered. Regarding the equity market, they used Dow Jones Islamic index.	This article aims at investigating the time varying relationship between Islamic equity and commodity returns in order to examine how combination of Islamic equities and commodities contribute to the benefits of portfolio investors and manager.

	Title	Author	Methodology	Data	Theme
(10)	Financial crises and the nature of correlation between commodity and stock markets	Öztek and Öcal (2017)	Smooth transition conditional correlation (STCC) and double smooth transition conditional correlation (DSTCC) models of Silvennoinen and Teräsvirta (2005, 2009).	The data used are, daily price series of agricultural commodity and precious metal sub-indices of S&P GSCI and S & P500 index from January 4, 1990 to December 20, 2012.The data are obtained from Global Financial Data. Weekly return rates calculated by log differencing Thursday 12 closing prices are used in estimations. The extreme returns which are outside the four standard deviations confidence interval around the mean are replaced with their boundary values.	This paper models time-varying correlations between commodity and stock markets to uncover the dynamic nature of correlations during the financialization of commodity markets and in the aftermath of the recent financial crisis. Their results show that commodities work well for diversification in the calm periods due to their heterogeneous structure.

	Title	Author	Methodology	Data	Theme
(11)	Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat	Sadorsky (2014)	VARMA-AGARCH model of McAleer et al. (2009) and the DCC-AGARCH model of Engle (2002). Also, they constructed hedge ratios (Kroner and Sultan 1993) and optimal portfolio weights subject to a no shorting constraint (Kroner and Ng, 1998) for the portfolios.	The data used are, daily data from January 3, 2000 to June 29, 2012 and they are obtained from Data Stream International. For the stock market, they used the MSCI Emerging Markets Index and for the commodity market they used West Texas Intermediate Crude oil, COMEX copper contract prices and International Grains Council wheat price index.	This paper uses VARMA-AGARCH and DCC AGARCH models to model volatilities and conditional correlations between emerging market stock prices, copper prices, oil prices and wheat prices. Also it uses the DCC model to calculate the hedge ratios and the optimal portfolio weights in order to analyze the link between commodity and equity market.
(12)	Linkages between Equity and Commodity Markets: Are Emerging Markets Different?	De Boyrie and Pavlova (2016)	Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002)	The data used are, daily data from January 2006 to January 2016 and they are obtained from DataStream. The commodity indices used are S&P GSCI Index and three sub-indices: S&P GSCI Energy, Agriculture, and Precious Metals. For the stock market, they used the MSCI Emerging markets index and also three regional indices: MSCI Emerging Markets Europe, Asia and Latin America.	This paper investigates the correlation between equity and commodity returns not only in US markets, but also on the emerging markets of Asia, Europe and Latin America. Additionally, it presents the differences between emerging and developed markets co-movements with commodities.

	Title	Author	Methodology	Data	Theme
(13)	The relationship between Asian equity and commodity futures markets	Thuraisamy, Sharma and Ahmed (2013)	BEKK-GARCH (1, 1) model proposed by Engle and Kroner (1995).	The data used are, daily data from July 5, 2005 to December 14, 2011 and they are obtained from Bloomberg Database. Also, they split the sample in two periods, one before the crisis of 2007-2009 and one during the crisis. For the stock market they used indices for 14 Asian countries and for the commodity market they used gold and crude oil.	The purpose of this article is to analyze the relationship between commodity and equity markets in the Asian Market before and during the financial crisis of 2007-2009. Also, it investigates the spillover effects from equity markets to commodity futures.
(14)	The Business Cycle and the Correlation between Stocks and Commodities	Bhardwaj and Dunsby (2012)	Realized correlation and covariance proposed by Andersen et al. (2001) and Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002).	The data used are, daily and weekly data from January 1960 to December 2012 and they are obtained from Commodity Research Bureau (CRB), Bloomberg, London Metals Exchange, U.S. Department of Labor - Bureau of Labor Statistics and Board of Governors of the Federal Reserve System. They used the Dow Jones-UBS Commodity Index and the S&P-GSCI,S&P 500 index, real GDP growth, inflation and the default Spread for USA.	This article analyses the stock-commodity correlation during 1960 to 2012 and proofs the existence of a business cycle component in the correlation. Also, it reports that the business cycle effect can explain the spikes in the stock-commodity correlation in the early 1980s and the late 2000s.

	Title	Author	Methodology	Data	Theme
(15)	Precious metals, cereal, oil and stock market linkages and portfolio risk management: Evidence from Saudi Arabia	Mensi, Hammoudeh and Kang (2015)	The bivariate DCC–FIAPARCH model, which includes the FIGARCH (p, d, q) model of Baillie et al. (1996) and the Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002). Also, they used a modified version of the Inclan and Tiao (1994) ICSS test developed by Sanso et al. (2004) to detect the structural breaks in the unconditional volatility.	The data used are, daily data from June 1, 2005 to August 13, 2014 and they are obtained from Morgan Stanley Capital International. For the stock market they chose Tadawul All-Share Index (TASI) for Saudi Arabia. They used West Texas Intermediate (WTI) crude oil, precious metals (gold and silver) and cereal (wheat, corn and rice) for the commodity market.	This paper investigates the link between commodity and equity markets in Saudi Arabia and draws implications for portfolio risk management.
(16)	Correlation between Islamic stock and Commodity markets: An investigation into the impact of financial crisis and financialization of commodity markets	Khan and Masih (2014)	Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002)	The data used are, daily spot price series extracted from DataStream for the different sector commodities over the January 3, 2001 - March 28, 2013 period. They used 5 different commodities sectors: energy, precious metals, agricultural, non-ferrous metals and soft's spot index. As for the stock market, the selected the Dow Jones Islamic Index.	This paper focuses on commodity markets and their relation with Islamic stock markets during the recent financial crisis and examines the alternative investment opportunities for the investors during that period.

	Title	Author	Methodology	Data	Theme
(17)	Hedging stocks through commodity indexes: a DCC-GARCH approach	Daumas, Aiube and Baidya (2017)	Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002)	The data used, are daily returns of the S&P500, S&P-GSCI, S&P-GSCI Agriculture, S&PGSCI 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.	This paper investigates the links between the S&P500 index and S&P commodities indexes based on the DDC GARCH model, in order to examine the hedge hypothesis between them.
(18)	The dynamic correlation between energy commodities and Islamic stock market: Analysis and forecasting	Chebbi and Derbali (2015)	Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002)	The data used are, daily spot price from 15 March 2011 to 25 December 2014 and they are obtained from Qatar Exchange. The series associated with two strategic commodities, namely crude oil and gas. The stock index considered for this study is the QE Al Rayan Islamic Index.	This article analyses the links between Islamic capital markets and commodities. Their study focuses on gas and crude oil and their relationship with the QE Al Rayan Islamic Index.

	Title	Author	Methodology	Data	Theme
(19)	Co-movement between Commodity Market and Equity Market: Does Commodity Market Change?	Yamori(2010)		The data used are, daily prices from May 31, 1986 to February 28, 2007 and they are obtained from Tokyo Commodity Exchange (TOCOM). Tokyo Commodity Exchange (TOCOM) used as an indicator of the commodity market and they compared it with the Tokyo Stock Exchange Stock Price Index (TOPIX).	This paper, using Japanese market data, presents that the correlation between equity markets and commodity markets have changed significantly through the financial crisis in Autumn of 2008 and analyses the results of this change.
(20)	Links Between Commodity Futures And Stock Market: Diversification Benefits, Financialization and Financial Crises	Demiralay and Ulusoy (2014)	Asymmetric dynamic conditional correlation (ADCC) model proposed by Cappiello et al. (2006). ADCC model is a generalization of DCC-GARCH model of Engle (2002).	The data used are, weekly data of commodity index (Dow Jones-UBS), its sub-indices and S&P 500 stock index from January 3, 1992 to December 27, 2013 and they are obtained from Bloomberg.	This paper, analyzes time-varying correlations between commodity markets and S&P 500 index, employing a recent and novel technique: asymmetric dynamic conditional correlation (ADCC) model, in order to examine the impacts of financial crises on the conditional correlations.

	Title	Author	Methodology	Data	Theme
(21)	Commodity Price Correlation and Time Varying Hedge Ratios	Lahiani and Guesmi (2014)	Return-based DCC-GARCH and range-based DCC-CARR models.	The data used are, weekly data from January 1, 1993 to December 25, 2009 and they are obtained from DataStream. The data consisted of S&P 500, DAX, and Nikkei 225, two precious metal commodities prices (gold and silver), and one crude oil price (WTI).	This paper examines the price volatility and hedging behavior of commodity futures indices and stock market indices. They investigate the weekly hedging strategies generated by return-based and range-based asymmetric dynamic conditional correlation (DCC) processes.
(22)	Crude oil: Commodity or financial asset?	Kolodziej , Kaufmann, Kulatilaka, Bicchetti and Maystre (2014)	OLS for estimating models from rolling windows and the Kalman Filter to estimate time-varying coefficients from the entire sample.	The data used are, daily prices from October 7, 1996 to August 21, 2011, for the West Texas Intermediate (WTI) on the New York Mercantile Exchange, the price of ConocoPhillips stock on the New York Stock Exchange (COP), and the Standard and Poor's 500 index (SP500) and they are obtained from the Thomson-Reuters Tick History database.	This paper examines the relationship between crude oil prices, equity prices, and commodity markets by adding new modification, such as expanding the model to include the equity price for an oil producing firm, ConocoPhillips, which ameliorates omitted variable bias and estimating the expanded model using the Kalman Filter, which reduces uncertainty associated with OLS estimates from rolling windows.

	Title	Author	Methodology	Data	Theme
(23)	Is Gold the Best Hedge and a Safe Haven Under Changing Stock Market Volatility	Hood and Malik (2013)	Regression model proposed by Baur and McDermott (2010)	The data used are, daily closing spot prices for gold, silver, platinum, S&P 500 Index and VIX. All the data used in the paper was obtained from Bloomberg. The data covers a period from November 30, 1995 to November 30, 2010.	This paper investigates the role of gold and other precious metals relative to volatility of stock markets and VIX as a hedge and safe haven using data from the US stock market. Also, they examine a portfolio analysis with interesting results.
(24)	Correlations and cross-correlations in the Brazilian agrarian commodities and stocks	Siqueira Jr, T.Stosic, Bejan, B.Stosic (2010)	Detrended Fluctuation Analysis (DFA) introduced by Peng (1994) and Detrended Cross-Correlation Analysis (DCCA) introduced by Podobnik and Stanley (2008).	The data used, are daily prices from August 10, 2000 to April 30, 2008,for cotton ,sugar, soybean, coffee, cattle, Brazil's TELECOM S.A. (brto4), Usinas Sid de MG S.A. (usim5), Gás de São Paulo (cgas5) and Itaus Investimentos S.A. (itsa4).The sources of the data were cepea esalq usp and BOVESPA.	This article investigates the auto-correlations and cross-correlations of the volatility time series in the Brazilian stock and commodity market, using the recently introduced Detrended Cross-Correlation Analysis.

	Title	Author	Methodology	Data	Theme
(25)	Commodity Futures Indices and Traditional Asset Markets in India: DCC Evidence for Portfolio Diversification Benefits	Lagesh, Kasim and Paul (2014)	Dynamic Conditional Correlation (DCC) GARCH model proposed by Engel (2002)	The data used are, daily data from June 7, 2005 to September 30, 2011 and they are obtained from MCX India, Clearing Corporation of India Limited and the National Stock Exchange of India. The commodities used are, COMDEX, an index representing all commodities, MCXMETAL, MCXENERGY and MCXAGRI. As a as proxy of the Indian stock market, they selected the S&P CNX Nifty Index. Also they used the long-term bond index and Treasury bill index. They split the sample into two periods one, before the crisis and one during the crisis of 2007-2009.	This article investigates the potential for portfolio diversification benefits of commodity futures in the Indian context. Moreover, they calculated the DCC correlation between commodities and stocks, bond and Treasure bills before and during the financial crisis of 2007-2009 and found interesting results.

3.DATA

We analyzed the correlation between different stock markets and several commodity markets between January 3 2000 and December 28 2018, using weekly data from Quantl, Fred St Louis, London Stock Exchange, Gold World Council and Yahoo Finance. More specifically, we used weekly closing prices for S&P 500 INDEX (USA), DAX INDEX (GERMANY), NIKKEI 225 INDEX (JAPAN) and FTSE 100 INDEX (UK) and weekly spot prices for WTI OIL, BRENT CRUDE OIL, GOLD and SILVER.

We used the logarithmic values for each variable, in order to achieve better economic results and then calculate the log returns.

$$R_t = \mathrm{Log}\ (X_t) - \mathrm{Log}\ (X_{t-1})$$

where

X_t: variables price at time t

X_{t-1}: variables price at time t-1

DATA SUMMARY

Firstly, we plotted the log variables and their log returns and then we presented the descriptive statistics for each log return.

3.1 DATA EXPLANATION

TABLE 1

VARIABLES	DEFINITION	SOURCE
LOGBRENT	LOG (BRENT_PRICES)	Fred St Louis
BRENT_R	LOG(BRENT_PRICES)-LOG(BRENT_PRICES(-1))	
LOGDAX	LOG (DAX_PRICES)	Yahoo Finance
DAX_R	LOG(DAX_PRICES)-LOG(DAX_PRICES(-1))	
LOGFTSE100	LOG (FTSE100_PRICES)	London Stock Exchange
FTSE100_R	LOG(FTSE100_PRICES)-LOG(FTSE100_PRICES(-1))	
LOGGOLD	LOG (GOLD_PRICES)	Gold World Council
GOLD_R	LOG(GOLD_PRICES)-LOG(GOLD_PRICES(-1))	
LOGNIKKEI	LOG (NIKKEI_PRICES)	Yahoo Finance
NIKKEI_R	LOG(NIKKEI_PRICES)-LOG(NIKKEI_PRICES(-1))	
LOGSILVER	LOG (SILVER_PRICES)	Quantl
SILVER_R	LOG(SILVER_PRICES)-LOG(SILVER_PRICES(-1))	
LOGSP500	LOG (SP500_PRICES)	Yahoo Finance
SP500_R	LOG(SP500_PRICES)-LOG(SP500_PRICES(-1))	
LOGWTI	LOG (WTI_PRICES)	Fred St Louis
WTI_R	LOG(WTI_PRICES)-LOG(WTI_PRICES(-1))	

3.2 GRAPHS

BRENT

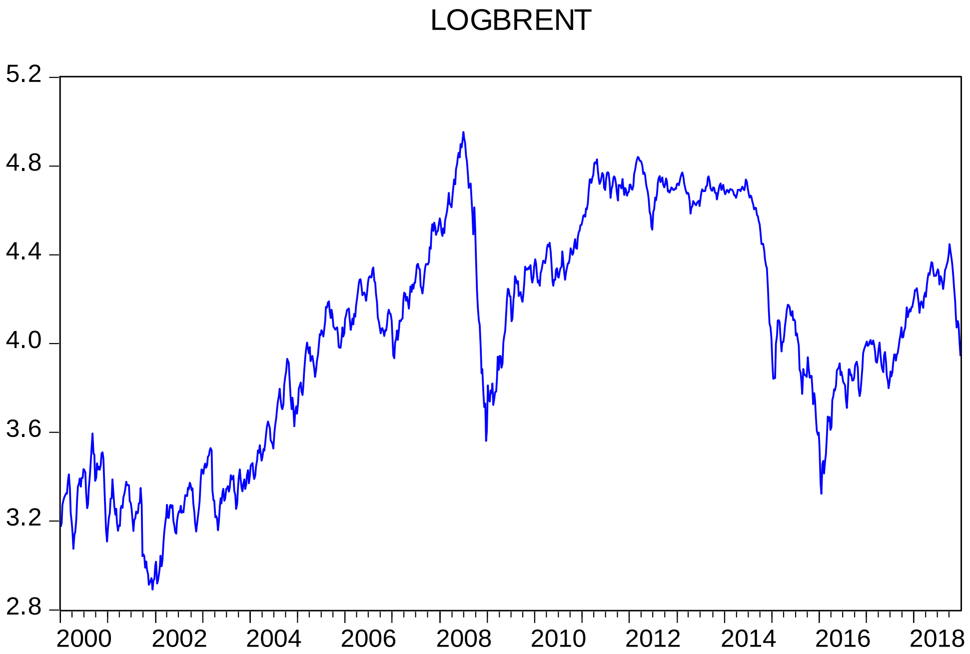


Figure 1

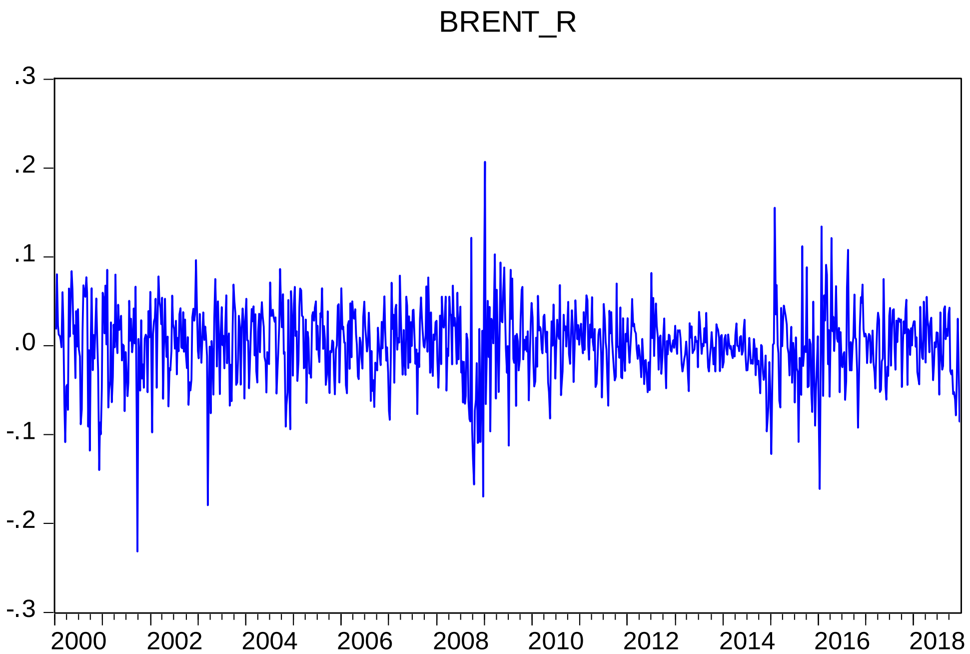


Figure 2

Figure 1 illustrates the natural logarithm of BRENT line graph and we can see that the index has a trend. Figure 2 represents the BRENT's returns.

DAX

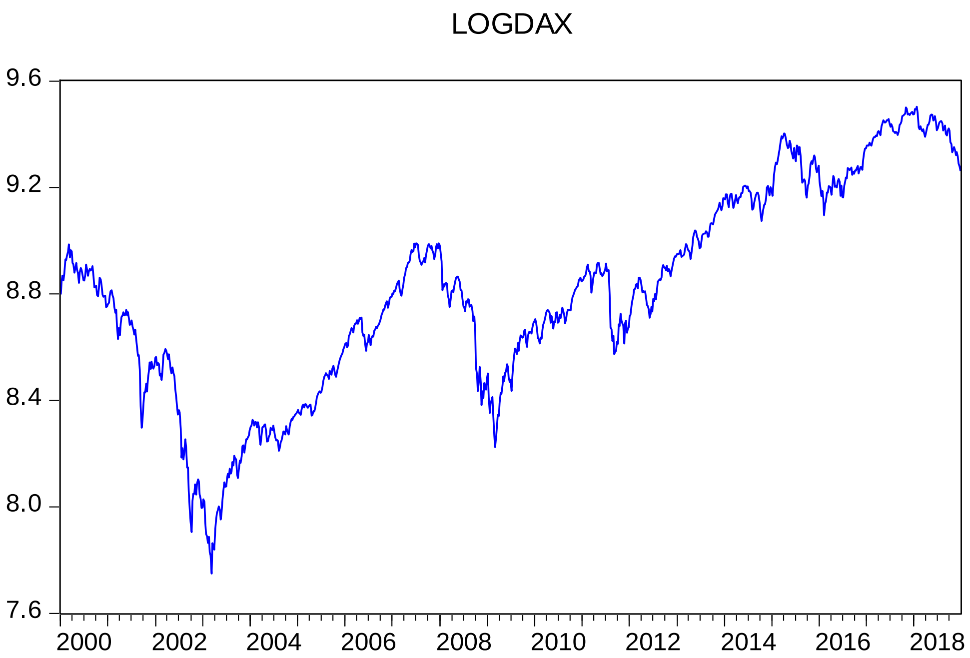


Figure 3

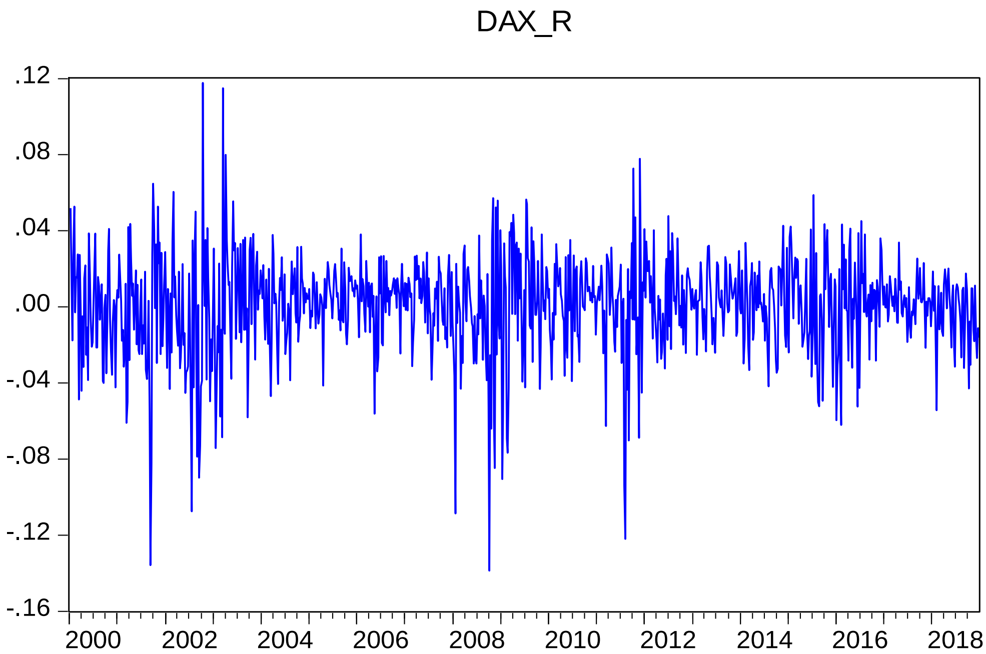


Figure 4

Figure 3 illustrates the natural logarithm of DAX line graph and we can see that the index has a trend. Figure 4 represents the DAX's returns.

FTSE100

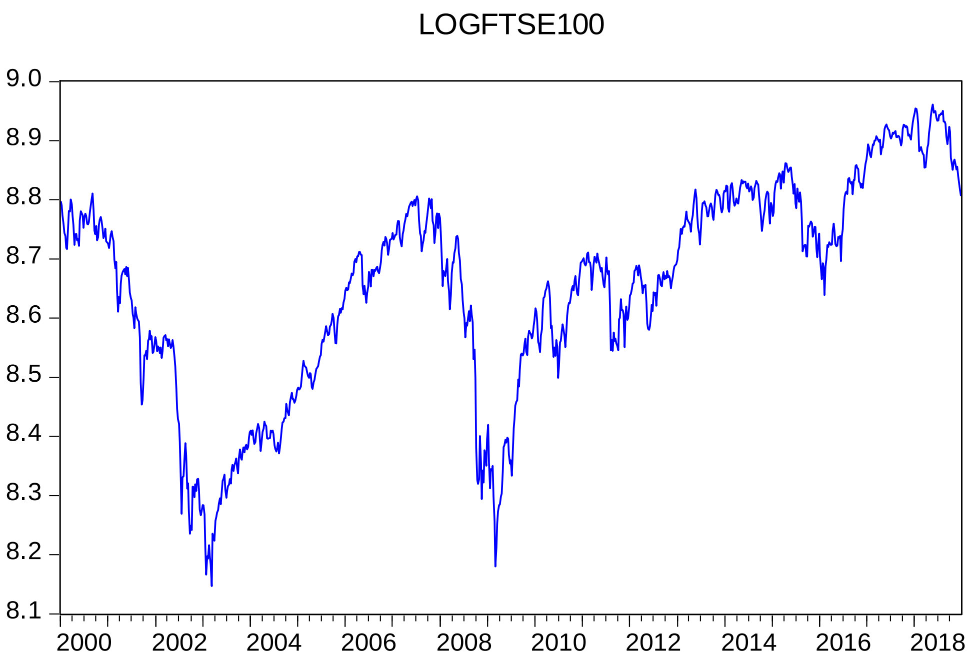


Figure 5

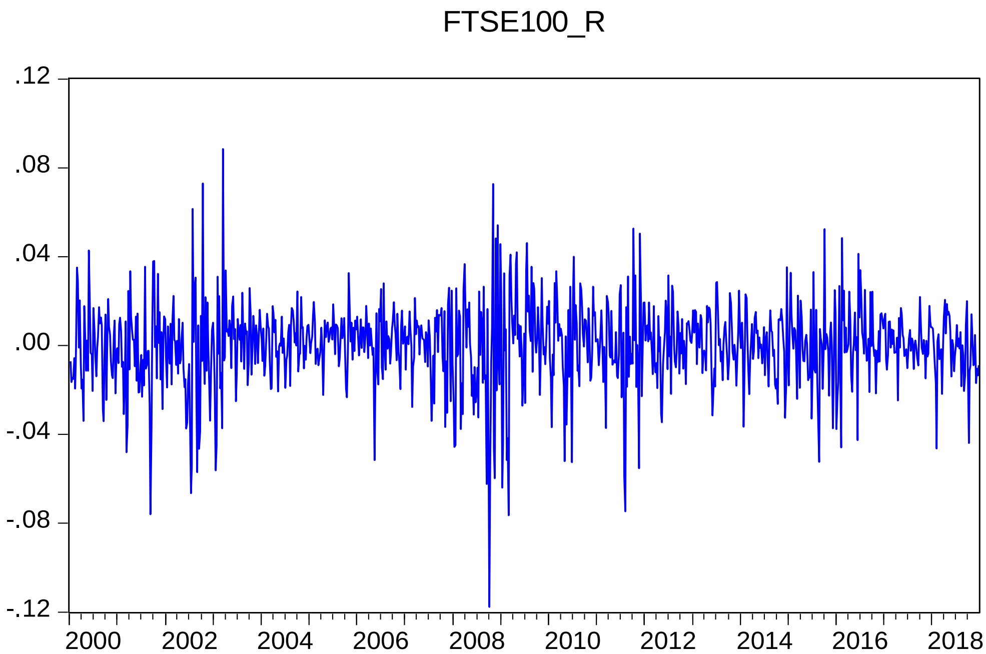


Figure 6

Figure 5 illustrates the natural logarithm of FTSE100 line graph and we can see that the index has a trend. Figure 6 represents the FTSE100's returns.

GOLD

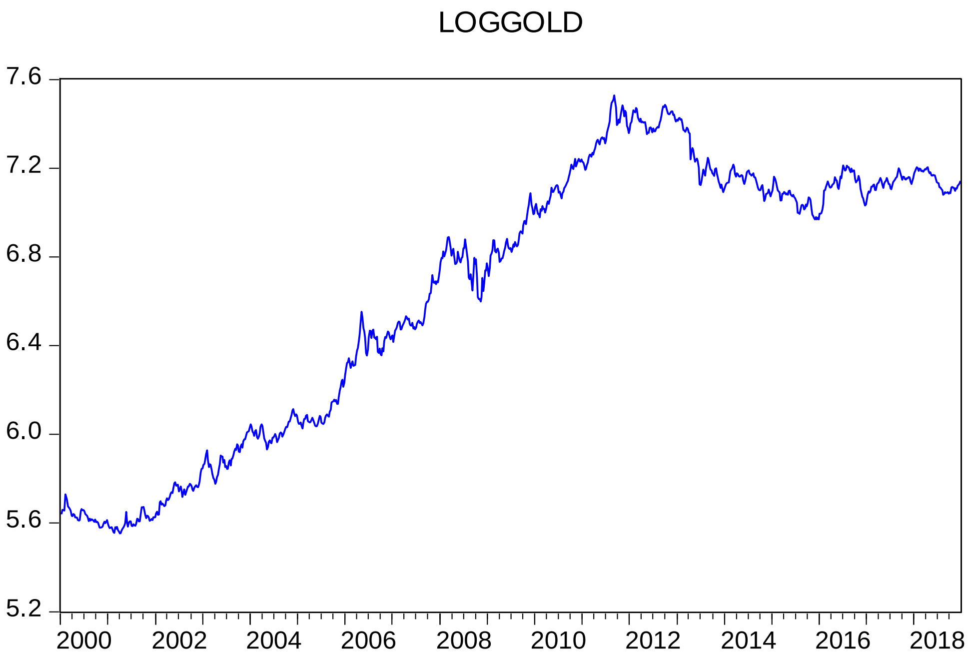


Figure 7

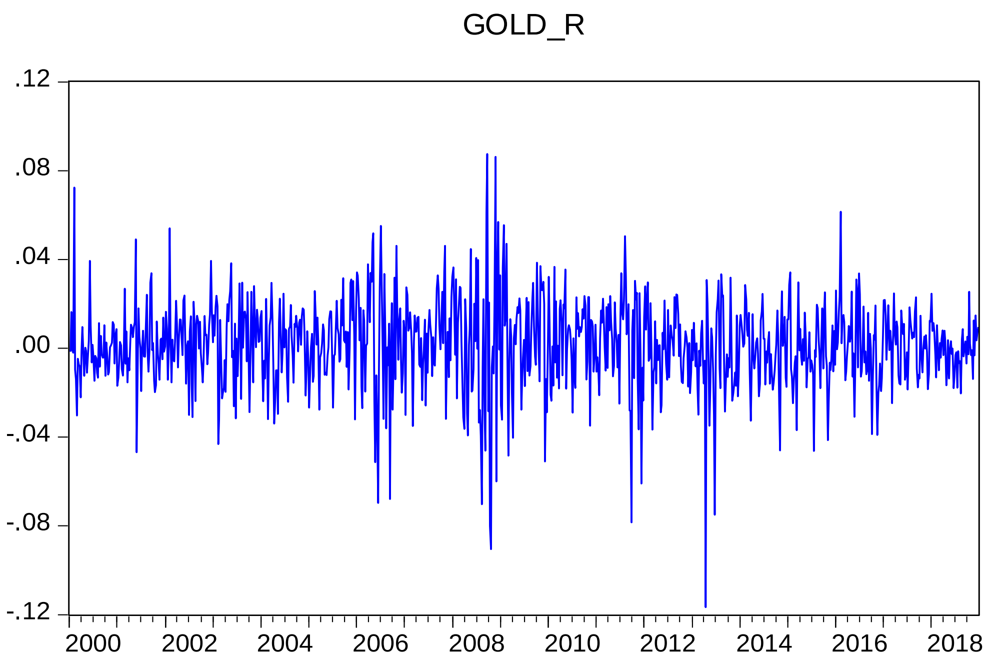


Figure 8

Figure 7 illustrates the natural logarithm of GOLD line graph and we can see that the index has a trend. Figure 8 represents the GOLD's returns.

NIKKEI

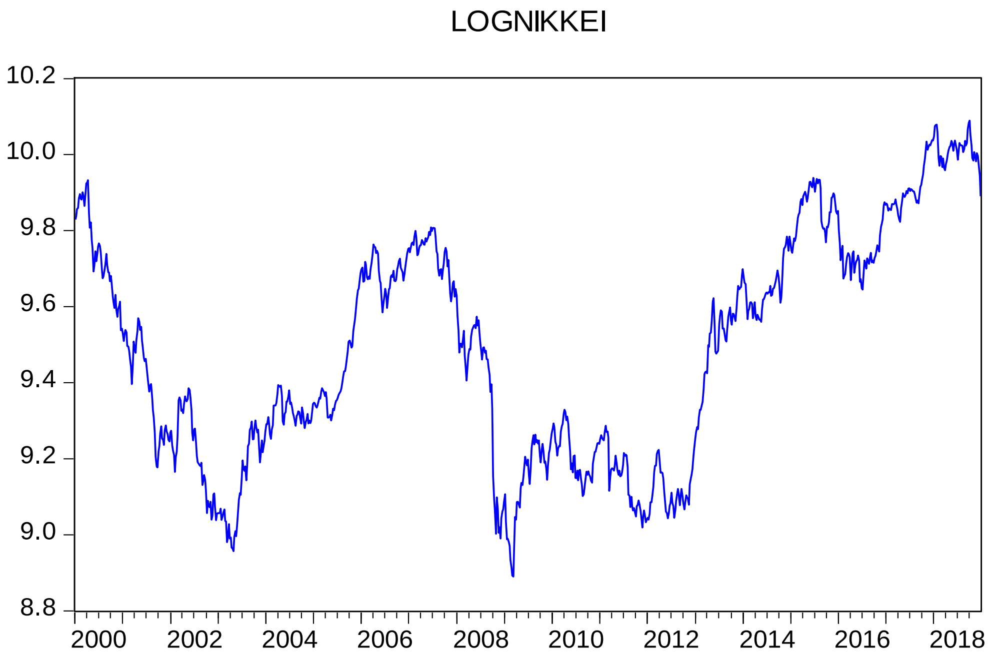


Figure 9

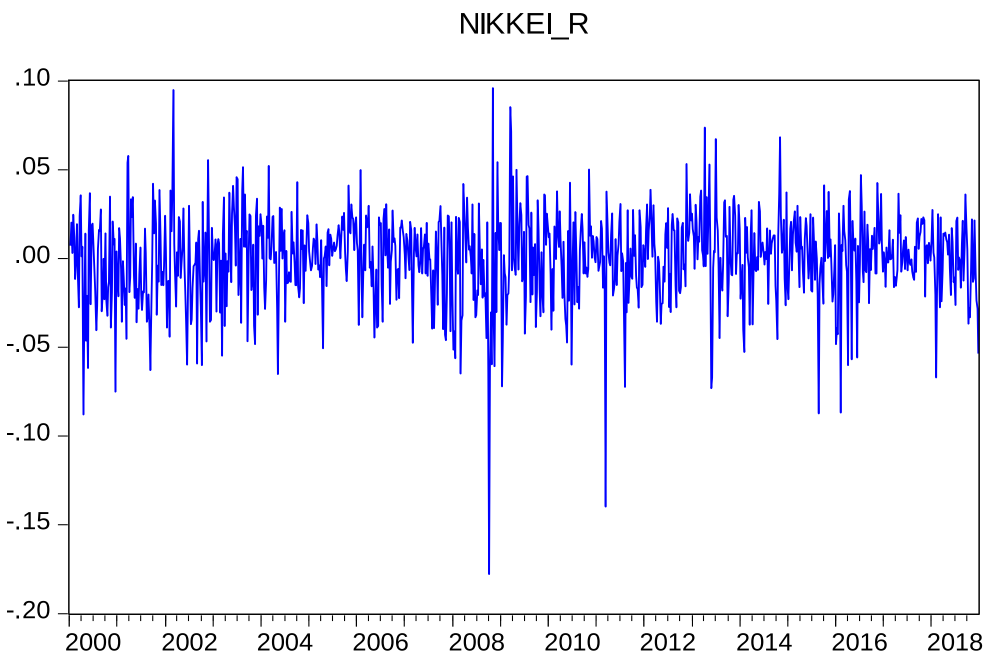


Figure 10

Figure 9 illustrates the natural logarithm of NIKKEI line graph and we can see that the index has a trend. Figure 10 represents the NIKKEI's returns.

SILVER

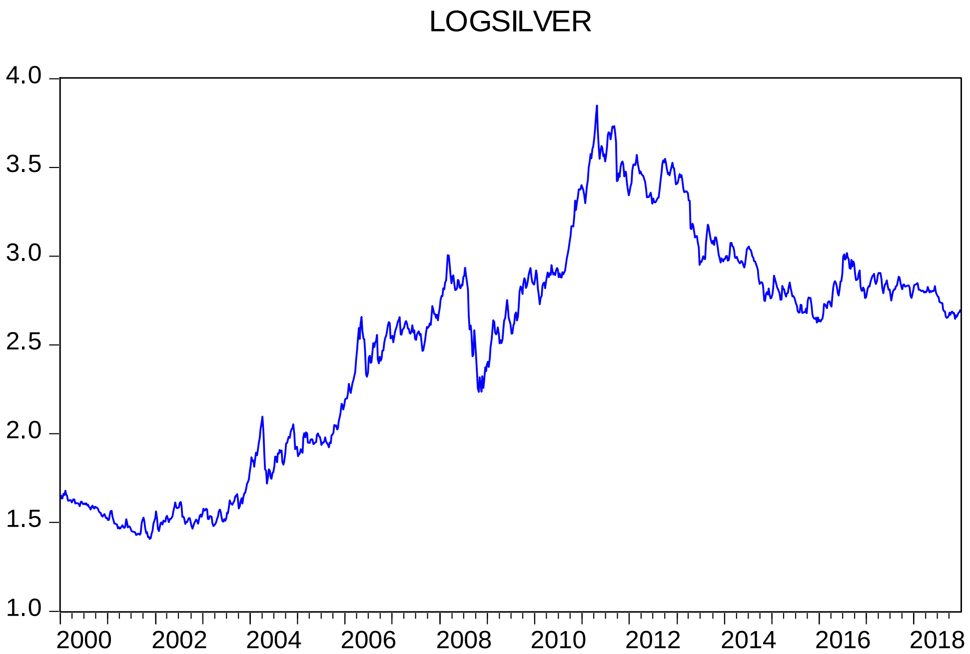


Figure 11

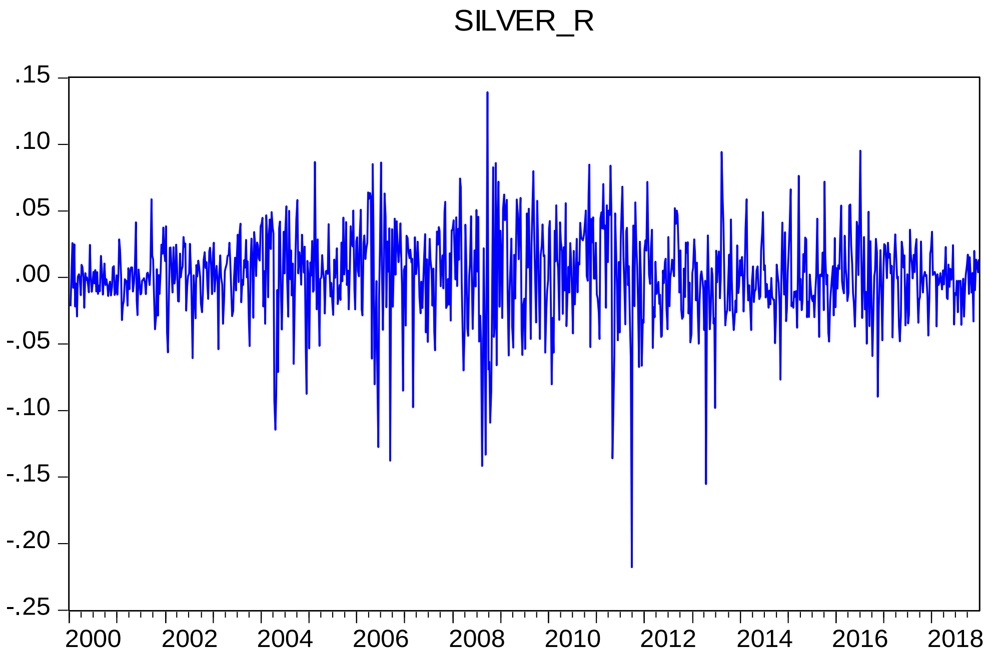


Figure 12

Figure 11 illustrates the natural logarithm of SILVER line graph and we can see that the index has a trend. Figure 12 represents the SILVER’s returns.

SP500

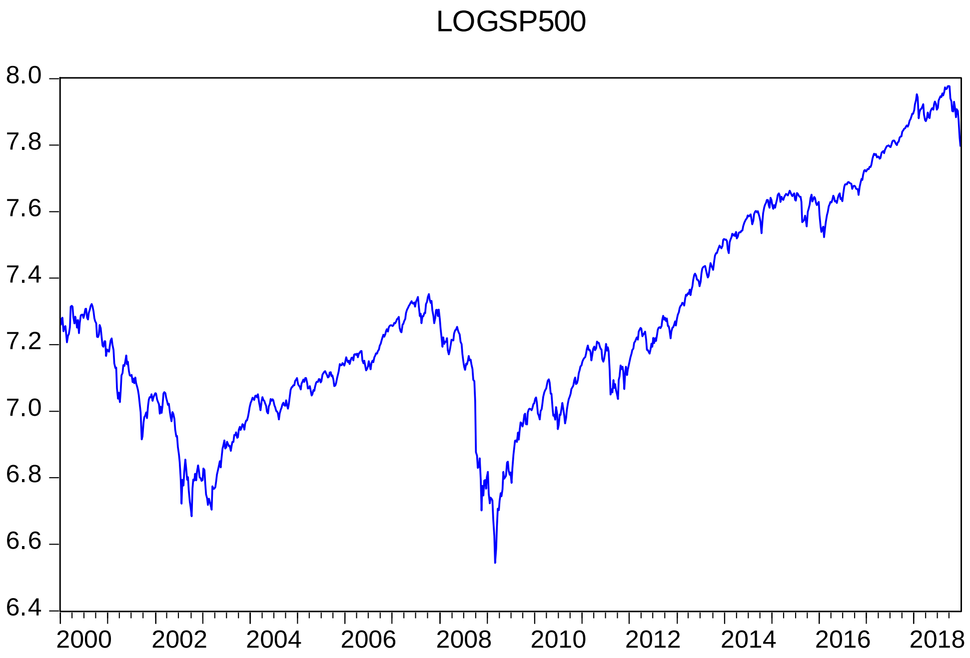


Figure 13

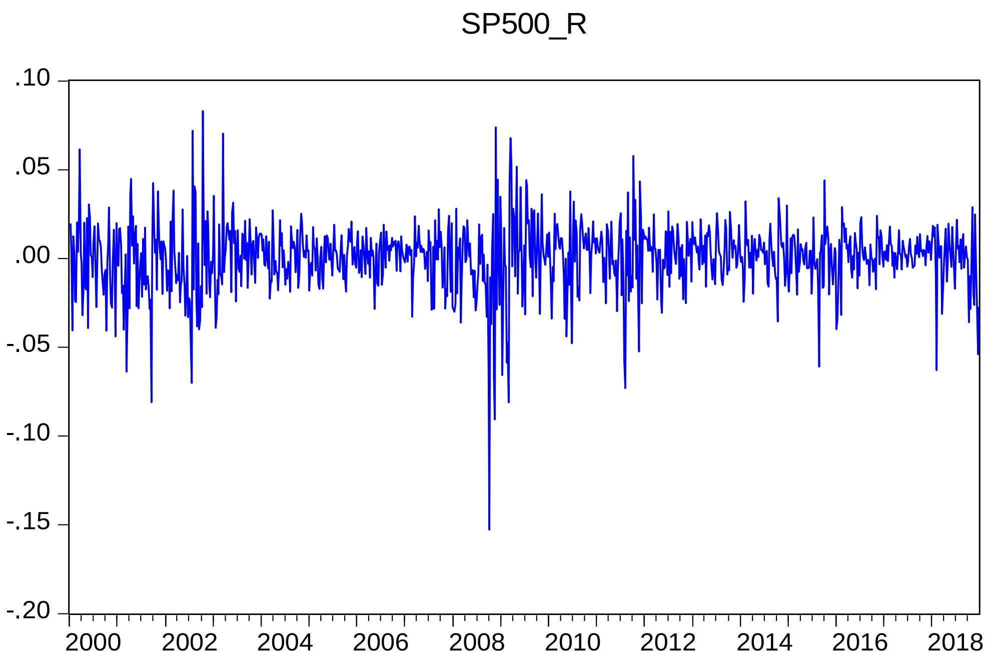


Figure 14

Figure 13 illustrates the natural logarithm of SP500 line graph and we can see that the index has a trend. Figure 14 represents the SP500's returns.

WTI

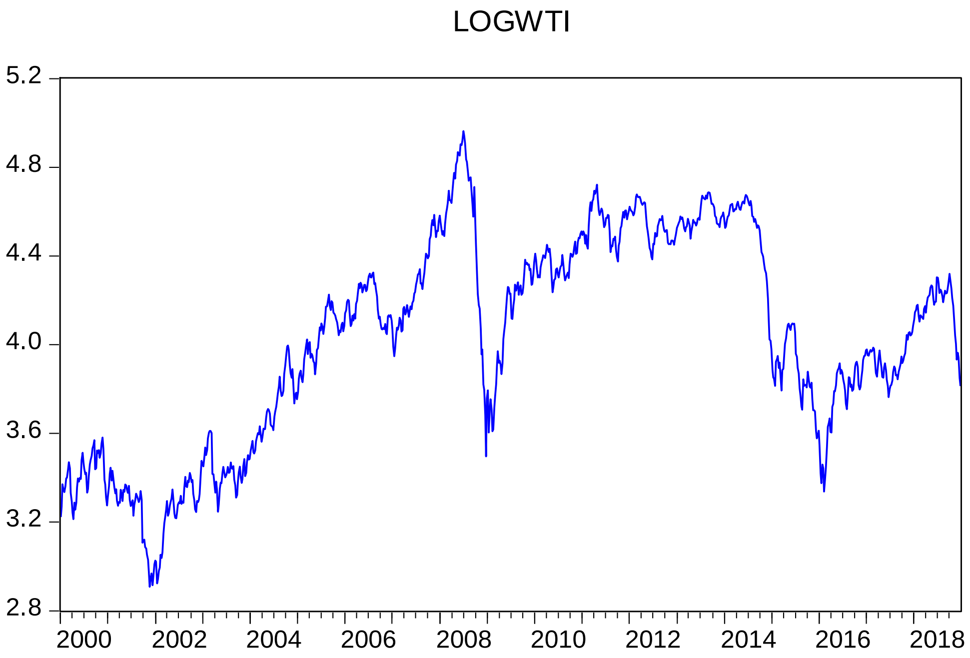


Figure 15

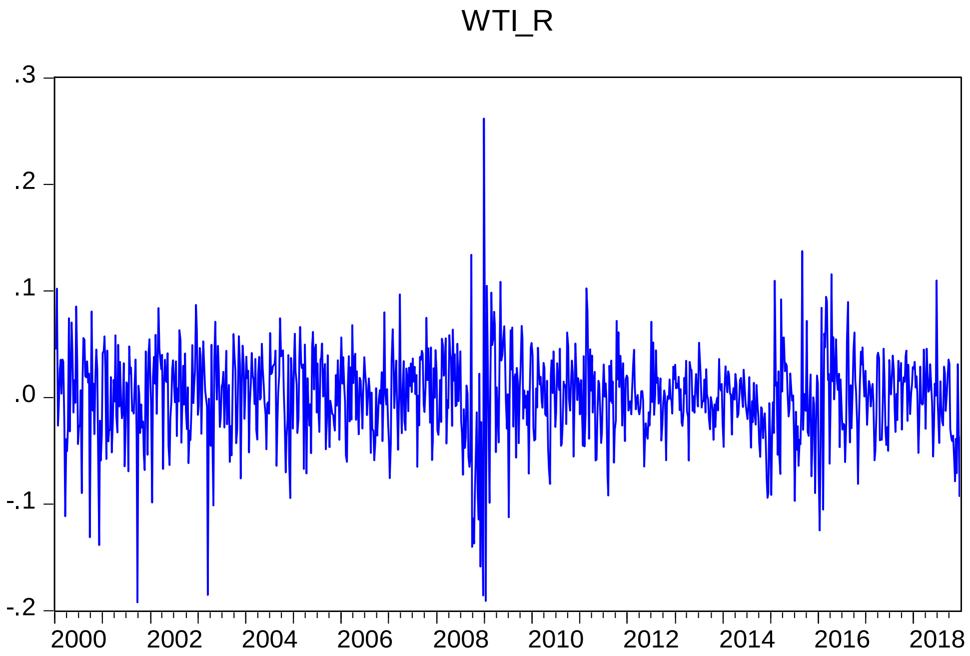


Figure 16

Figure 15 illustrates the natural logarithm of WTI line graph and we can see that the index has a trend. Figure 16 represents the WTI's returns.

3.3 DESCRIPTIVE STATISTICS

Table 2

	BRENT_R	DAX_R	FTSE100_R	GOLD_R	NIKKEI_R	SILVER_R	SP500_R	WTI_R
Mean	0.000777	0.000469	8.90E-06	0.001513	6.22E-05	0.001054	0.000542	0.000596
Median	0.003557	0.002939	0.001324	0.002105	0.002176	0.001611	0.002750	0.003332
Maximum	0.206977	0.117668	0.088479	0.087530	0.096007	0.139301	0.083078	0.261874
Minimum	-0.231604	-0.138715	-0.117725	-0.116598	-0.177819	-0.217729	-0.152785	-0.192338
Std. Dev.	0.042020	0.026098	0.018958	0.019798	0.025307	0.033412	0.019307	0.042101
Skewness	-0.425745	-0.733942	-0.561141	-0.411687	-0.748798	-0.742898	-0.908346	-0.354576
Kurtosis	5.344959	6.415746	6.503137	6.189374	6.806793	6.719712	9.358280	6.196734
Jarque-Bera	256.7345	570.1577	558.1736	447.5647	690.2968	661.8089	1803.784	442.2826
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.769062	0.464539	0.008807	1.497738	0.061611	1.043647	0.536798	0.589820
Sum Sq. Dev.	1.746242	0.673598	0.355447	0.387661	0.633401	1.104083	0.368670	1.753027
Observations	990	990	990	990	990	990	990	990

The above table summarizes the descriptive statistics for each variable. In order to have normal distribution the skewness must be about zero and the kurtosis must be about 3. As we can see the skewness is near zero in most of the variables, but the kurtosis is bigger than 3 in all of them, so there is not enough strong evidence for normal distribution.

4.METHODOLOGY

The basic methodology that we use in our analysis is a multivariate GARCH model with time varying conditional correlation. To begin with we applied the unit root test (ADF) in the log returns and we tested for autocorrelation, by using correlogram. The results from the previous analysis can be seen in the results section. Then, we applied the DCC model proposed by Engle (2002). The DCC model is estimated in two steps. In the first step we estimate the GARCH parameters and in the second we estimate the correlation. For the estimation we used the maximum likelihood method and tried to maximize the likelihood function. Also, in the estimation of the quasicorrelation matrix Q_t we utilized a mean-reverting model which is also a GARCH (1, 1) model Engle (2002). Finally, with the results from the DCC correlations we ran an estimation with two dummy variables, bubble dummy and estate dummy. These dummies represented the two shocks occurred during the period we investigated. Bubble dummy represented the dot.com shock in 2000-2002 and estate dummy represented the financial crisis in 2007-2009.

4.1 ADF TEST

Augmented Dickey Fuller tests the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is stationarity but in our analysis is trend-stationarity. The test continues as follows :

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \dots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t,$$

where α is a constant, β the coefficient on a time trend and p the lag order of the autoregressive process. The unit root test is carried out under the null hypothesis $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$. ε_t is the error term. We run the estimation and then we save the $\gamma^{\wedge}$.Then we calculate the DF stat :

$$\mathrm{DF_t} = \frac{\gamma^{\wedge}}{SE(\gamma^{\wedge})}$$

If $|DF_T|$ > *t*-values , we reject the null hypothesis and we accept the alternative one. Also, if the *p*-value of the test is smaller than 0,05 ,we also accept the alternative hypothesis.

If $|DF_T|$ < *t*-values , we reject the alternative hypothesis and we accept the null hypothesis. Also, if the *p*-value of the test is more than 0,05 ,we also accept the null hypothesis.

4.2 GARCH (1,1)

The GARCH (1,1) model can be written as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1}$$

where

σ_t^2: is the variance in time t

ε_{t-1}: is the error term of previous period

σ^2_{t-1}: is the variance of the previous period

α_0: is a constant term

α_1: is a coefficient

β_1: is a coefficient

Also , these conditions must be valid $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta_1 > 0$ and $\alpha_1 + \beta_1 < 1$.

4.3 DCC MODEL

The DCC GARCH model can be written as follows:

$$H_t = D_t R_t D_t$$

where

H_t: is the conditional covariance matrix

R_t: is the conditional correlation matrix

D_t: is a diagonal matrix with time varying standard deviations on the diagonal

$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$

Q_t: is symmetric positive definite matrix

$Q_t = (1- \theta_1 – \theta_2) \bar{Q} + \theta_1 e_{t-1} e'_{t-1} + \theta_2 Q_{t-1}$

$\bar{Q}$: is the unconditional correlation matrix of standardized residuals e_{it}

$\theta_1 > 0$, $\theta_2 > 0$ and $\theta_1 + \theta_2 < 1$

The correlation estimator is:

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

4.4 DCC VS DUMMIES MODEL

The equation we used in order to investigate the correlation between commodities and equities during the shocks in 2000-2002 and 2007-2009 can be written as follows:

$$RHO\_12\_i_t = c + d_1 buble\_dummy + d_2\, estate\_dummy + u_t$$

where

$RHO\_12\_i_t$: is the DCC correlation result for each relationship

c : is a constant term

d_1: is a coefficient

d_1: is a coefficient

u_t : is the error term.

We constructed the correlation matrix for the variables in Eviews and then we applied the DCC GARCH (1, 1) methodology in Eviews. Finally we ran the equation with the two shock dummies with OLS estimation. You can see results from our analysis in the results section.

5.RESULTS

5.1 UNIT ROOT TEST ADF

TABLE 1

Variables	Probability
BRENT_R	0,0000
DAX_R	0,0000
FTSE100_R	0,0000
GOLD_R	0,0000
NIKKEI_R	0,0000
SILVER_R	0,0000
SP500_R	0,0000
WTI_R	0,0000

After the ADF test for the first log difference variables, we found that all are stationary, thus we accepted the alternative hypothesis.

If probability is smaller than 0,05 then we must accept the H1: Variable is stationary.

If the returns are stationary then the indexes have a unit root. Our results follow the theory and proof that commodity and equity prices are I(1) variables.

5.2 AUTOCORRELATION TEST

TABLE 2

BRENT_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.252	0.252	62.898	0.000
		2	0.028	-0.037	63.690	0.000
		3	0.070	0.077	68.525	0.000
		4	-0.045	-0.087	70.532	0.000
		5	0.017	0.058	70.836	0.000
		6	-0.008	-0.038	70.904	0.000
		7	-0.041	-0.019	72.590	0.000
		8	0.035	0.044	73.841	0.000
		9	0.003	-0.013	73.852	0.000
		10	0.039	0.050	75.380	0.000
		11	0.022	-0.014	75.856	0.000
		12	0.008	0.018	75.914	0.000
		13	-0.003	-0.023	75.925	0.000
		14	0.018	0.033	76.256	0.000
		15	-0.022	-0.039	76.729	0.000
		16	-0.038	-0.021	78.182	0.000
		17	0.009	0.024	78.256	0.000
		18	-0.028	-0.037	79.033	0.000
		19	-0.034	-0.016	80.225	0.000
		20	-0.007	-0.004	80.269	0.000
		21	-0.001	0.013	80.271	0.000
		22	0.052	0.046	83.040	0.000
		23	0.001	-0.027	83.041	0.000
		24	0.006	0.020	83.076	0.000

The evidence of autocorrelation is strong in our variable , because all the *p-values* is smaller than 0,05 and we accept the H1, that variable has autocorrelation.

TABLE 3

DAX_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.155	0.155	23.768	0.000
		2	-0.005	-0.030	23.798	0.000
		3	0.015	0.022	24.036	0.000
		4	0.012	0.007	24.190	0.000
		5	0.037	0.036	25.577	0.000
		6	0.023	0.012	26.125	0.000
		7	-0.059	-0.065	29.604	0.000
		8	0.007	0.027	29.658	0.000
		9	-0.023	-0.034	30.208	0.000
		10	-0.017	-0.007	30.514	0.001
		11	0.030	0.033	31.447	0.001
		12	-0.009	-0.016	31.523	0.002
		13	0.025	0.034	32.165	0.002
		14	0.027	0.014	32.908	0.003
		15	0.013	0.013	33.088	0.005
		16	-0.001	-0.010	33.088	0.007
		17	0.039	0.039	34.609	0.007
		18	-0.011	-0.022	34.733	0.010
		19	-0.008	-0.008	34.805	0.015
		20	0.051	0.058	37.466	0.010
		21	0.057	0.042	40.707	0.006
		22	0.053	0.041	43.581	0.004
		23	0.019	0.006	43.952	0.005
		24	-0.043	-0.044	45.874	0.005

The evidence of autocorrelation is strong in our variable , because all the *p-values* is smaller than 0,05 and we accept the H1 that, variable has autocorrelation.

TABLE 4

FTSE 100_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.157	0.157	24.516	0.000
		2	-0.033	-0.059	25.600	0.000
		3	-0.042	-0.028	27.332	0.000
		4	-0.057	-0.049	30.530	0.000
		5	0.013	0.027	30.692	0.000
		6	-0.012	-0.025	30.833	0.000
		7	-0.062	-0.059	34.616	0.000
		8	0.027	0.045	35.355	0.000
		9	-0.013	-0.029	35.515	0.000
		10	-0.049	-0.047	37.891	0.000
		11	0.011	0.022	38.004	0.000
		12	-0.006	-0.011	38.040	0.000
		13	0.058	0.056	41.424	0.000
		14	0.026	0.000	42.111	0.000
		15	0.037	0.047	43.517	0.000
		16	0.038	0.024	44.990	0.000
		17	0.008	0.004	45.059	0.000
		18	0.017	0.026	45.340	0.000
		19	-0.015	-0.019	45.562	0.001
		20	0.026	0.044	46.261	0.001
		21	0.058	0.047	49.614	0.000
		22	0.056	0.050	52.758	0.000
		23	-0.010	-0.015	52.858	0.000
		24	-0.030	-0.016	53.783	0.000

The evidence of autocorrelation is strong in our variable , because all *the p-values* is smaller than 0,05 and we accept the H1 that, variable has autocorrelation.

TABLE 5

GOLD_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.210	0.210	43.785	0.000
		2	-0.058	-0.107	47.142	0.000
		3	-0.002	0.036	47.147	0.000
		4	-0.047	-0.064	49.334	0.000
		5	-0.081	-0.057	55.880	0.000
		6	-0.040	-0.019	57.483	0.000
		7	-0.051	-0.052	60.078	0.000
		8	-0.029	-0.011	60.909	0.000
		9	0.019	0.015	61.287	0.000
		10	0.006	-0.012	61.320	0.000
		11	-0.024	-0.028	61.883	0.000
		12	0.088	0.096	69.612	0.000
		13	0.056	0.007	72.769	0.000
		14	-0.039	-0.040	74.290	0.000
		15	-0.035	-0.019	75.559	0.000
		16	0.046	0.059	77.703	0.000
		17	0.019	0.006	78.064	0.000
		18	-0.011	-0.006	78.184	0.000
		19	0.043	0.052	80.026	0.000
		20	-0.026	-0.047	80.734	0.000
		21	0.009	0.039	80.820	0.000
		22	-0.005	-0.029	80.840	0.000
		23	-0.004	0.024	80.856	0.000
		24	0.024	0.021	81.454	0.000

The evidence of autocorrelation is strong in our variable , because all the *p-values* is smaller than 0,05 and we accept the H1, that variable has autocorrelation.

TABLE 6

NIKKEI_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.207	0.207	42.368	0.000
		2	-0.026	-0.072	43.054	0.000
		3	0.036	0.060	44.345	0.000
		4	-0.027	-0.052	45.061	0.000
		5	0.029	0.054	45.900	0.000
		6	-0.000	-0.027	45.900	0.000
		7	-0.013	0.001	46.072	0.000
		8	0.039	0.037	47.618	0.000
		9	0.007	-0.008	47.666	0.000
		10	0.007	0.012	47.719	0.000
		11	0.010	0.002	47.828	0.000
		12	0.047	0.053	50.078	0.000
		13	-0.009	-0.037	50.161	0.000
		14	0.031	0.052	51.124	0.000
		15	0.035	0.010	52.385	0.000
		16	-0.028	-0.031	53.172	0.000
		17	0.039	0.050	54.694	0.000
		18	-0.026	-0.051	55.354	0.000
		19	0.004	0.034	55.369	0.000
		20	0.071	0.047	60.473	0.000
		21	0.058	0.051	63.903	0.000
		22	0.024	-0.005	64.479	0.000
		23	-0.052	-0.058	67.208	0.000
		24	-0.108	-0.088	79.079	0.000

The evidence of autocorrelation is strong in our variable , because all the *p-values* is smaller than 0,05 and we accept the H1, that variable has autocorrelation.

TABLE 7

SILVER_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.252	0.252	62.973	0.000
		2	-0.025	-0.094	63.583	0.000
		3	-0.008	0.024	63.644	0.000
		4	-0.039	-0.049	65.155	0.000
		5	-0.048	-0.027	67.445	0.000
		6	-0.001	0.015	67.445	0.000
		7	0.014	0.007	67.653	0.000
		8	0.022	0.018	68.152	0.000
		9	-0.015	-0.029	68.370	0.000
		10	-0.071	-0.062	73.353	0.000
		11	-0.034	0.000	74.481	0.000
		12	0.018	0.023	74.810	0.000
		13	0.019	0.008	75.162	0.000
		14	0.018	0.008	75.480	0.000
		15	-0.001	-0.015	75.481	0.000
		16	0.024	0.033	76.079	0.000
		17	0.032	0.022	77.099	0.000
		18	-0.007	-0.015	77.149	0.000
		19	0.028	0.039	77.938	0.000
		20	0.040	0.016	79.521	0.000
		21	0.037	0.030	80.924	0.000
		22	-0.070	-0.089	85.932	0.000
		23	-0.037	0.013	87.329	0.000
		24	-0.020	-0.021	87.755	0.000

The evidence of autocorrelation is strong in our variable , because all the *p-values* is smaller than 0,05 and we accept the H1, that variable has autocorrelation.

TABLE 8

SP500_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.143	0.143	20.339	0.000
		2	-0.002	-0.023	20.345	0.000
		3	0.030	0.034	21.226	0.000
		4	-0.042	-0.052	22.943	0.000
		5	0.007	0.022	22.985	0.000
		6	0.066	0.061	27.381	0.000
		7	-0.091	-0.109	35.617	0.000
		8	0.037	0.069	37.023	0.000
		9	-0.030	-0.056	37.931	0.000
		10	-0.034	-0.006	39.074	0.000
		11	0.065	0.060	43.323	0.000
		12	0.004	-0.014	43.341	0.000
		13	0.001	0.019	43.343	0.000
		14	0.042	0.016	45.153	0.000
		15	0.059	0.076	48.658	0.000
		16	0.042	0.014	50.463	0.000
		17	0.039	0.022	52.026	0.000
		18	-0.034	-0.030	53.203	0.000
		19	-0.014	-0.011	53.387	0.000
		20	0.054	0.064	56.333	0.000
		21	0.060	0.045	59.973	0.000
		22	0.056	0.045	63.140	0.000
		23	0.005	-0.016	63.165	0.000
		24	-0.035	-0.018	64.430	0.000

The evidence of autocorrelation is strong in our variable , because all the *p-values* is smaller than 0,05 and we accept the H1, that variable has autocorrelation.

TABLE 9

WTI_R CORRELOGRAM

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.188	0.188	35.019	0.000
		2	-0.041	-0.079	36.719	0.000
		3	0.091	0.119	44.949	0.000
		4	0.014	-0.034	45.132	0.000
		5	0.039	0.061	46.674	0.000
		6	-0.010	-0.045	46.771	0.000
		7	0.002	0.024	46.774	0.000
		8	0.112	0.098	59.264	0.000
		9	0.059	0.024	62.795	0.000
		10	-0.005	-0.009	62.816	0.000
		11	-0.019	-0.032	63.179	0.000
		12	0.000	0.004	63.179	0.000
		13	-0.011	-0.023	63.291	0.000
		14	0.018	0.034	63.622	0.000
		15	-0.053	-0.071	66.488	0.000
		16	-0.055	-0.033	69.570	0.000
		17	0.022	0.016	70.064	0.000
		18	0.034	0.036	71.234	0.000
		19	-0.046	-0.050	73.374	0.000
		20	-0.072	-0.049	78.607	0.000
		21	0.024	0.044	79.206	0.000
		22	0.062	0.044	83.048	0.000
		23	-0.018	-0.017	83.385	0.000
		24	-0.040	-0.018	84.976	0.000

The evidence of autocorrelation is strong in our variable , because all the *p-values* is smaller than 0,05 and we accept the H1, that variable has autocorrelation.

5.3 CORRELATION MATRIX

TABLE 10

Covariance analysis and correlation Observations 990								
DAX_R		BRENT_R		GOLD_R		SILVER_R		WTI_R
Covariance		0,000211		-1,18E-05		0,000124		0,000204
Correlation		0,192272		-0,022926		0,141909		0,186288
t-Statistic		6,158479		-0,720808		4,506139		5,959809
Probability		0,0000		0,4712		0,0000		0,0000
FTSE100_R		BRENT_R		GOLD_R		SILVER_R		WTI_R
Covariance		0,000212		1,07E-05		0,000123		0,000212
Correlation		0,266019		0,028443		0,193903		0,265439
t-Statistic		8,674179		0,894387		6,212762		8,653831
Probability		0,0000		0,3713		0,0000		0,0000
NIKKEI_R		BRENT_R		GOLD_R		SILVER_R		WTI_R
Covariance		0,000248		-1,50E-05		0,000126		0,000226
Correlation		0,233398		-0,029891		0,148643		0,212768
t-Statistic		7,544659		-0,939971		4,724690		6,844537
Probability		0,0000		0,3475		0,0000		0,0000
SP500_R		BRENT_R		GOLD_R		SILVER_R		WTI_R
Covariance		0,000206		1,55E05		0,000118		0,000200
Correlation		0,254731		0,040691		0,183518		0,245870
t-Statistic		8,279970		1,280090		5,868100		7,973049
Probability		0,0000		0,2008		0,0000		0,0000

Brent has a positive correlation with Dax, Ftse100, Nikkei and Sp500, because *t-stat* is bigger than 1,96 , thus we accept the H1, that we do have correlation and it is positive.

Gold has no correlation with Dax, Ftse100, Nikkei and Sp500, because *t-stat* is smaller than 1,96 , thus we accept the H0, that we don not have correlation.

Silver has a positive correlation with Dax, Ftse100, Nikkei and Sp500, because *t-stat* is bigger than 1,96, therefor we accept the H1, that we have correlation and it is positive.

Wti has a positive correlation with Dax, Ftse100, Nikkei and Sp500, because *t-stat* is bigger than 1,96 , thus we accept the H1, that we have correlation and it is positive.

5.4 DCC GARCH 1,1 RESULTS

TABLE 11

DCC GARCH 1,1	THETAS	COEFFICIENTS	PROBABILITIES
BRENT_R-DAX_R	Theta(1)	0,065661	0,0003
BRENT_R-DAX_R	Theta(2)	0,911633	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
BRENT_R-FTSE100_R	Theta(1)	0,036784	0,0091
BRENT_R-FTSE100_R	Theta(2)	0,955200	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
BRENT_R-NIKKEI_R	Theta(1)	0,088671	0,0002
BRENT_R-NIKKEI_R	Theta(2)	0,834204	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
BRENT_R-SP500_R	Theta(1)	0,052812	0,0000
BRENT_R-SP500_R	Theta(2)	0,937725	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
GOLD_R-DAX_R	Theta(1)	0,057868	0,0217
GOLD_R-DAX_R	Theta(2)	0,901174	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
GOLD_R-FTSE100_R	Theta(1)	0,025875	0,3566
GOLD_R-FTSE100_R	Theta(2)	0,926091	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
GOLD_R-NIKKEI_R	Theta(1)	0,007241	NA
GOLD_R-NIKKEI_R	Theta(2)	1,037751	NA
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is not met			
GOLD_R-SP500_R	Theta(1)	0,050797	0,0210
GOLD_R-SP500_R	Theta(2)	0,895809	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
SILVER_R-DAX_R	Theta(1)	0,047128	0,1143
SILVER_R-DAX_R	Theta(2)	0,903350	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
SILVER_R-FTSE100_R	Theta(1)	0,032552	0,0262
SILVER_R-FTSE100_R	Theta(2)	0,941242	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
SILVER_R-NIKKEI_R	Theta(1)	0,083427	0,0002
SILVER_R-NIKKEI_R	Theta(2)	0,862257	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
SILVER_R-SP500_R	Theta(1)	0,061175	0,0050
SILVER-R-SP500_R	Theta(2)	0,864954	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
WTI_R-DAX_R	Theta(1)	0,078660	0,0001
WTI_R-DAX_R	Theta(2)	0,876851	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
WTI_R-FTSE100_R	Theta(1)	0,035288	0,0248
WTI_R-FTSE100_R	Theta(2)	0,957321	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
WTI_R-NIKKEI_R	Theta(1)	0,065068	0,0075
WTI_R-NIKKEI_R	Theta(2)	0,864627	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			
WTI_R-SP500_R	Theta(1)	0,050411	0,0021
WTI_R-SP500_R	Theta(2)	0,938262	0,0000
STABILITY CONDITION: Theta (1) + Theta (2) < 1 is met			

5.5 DCC MODELS

Based on the above parameters is possible to build different models:

1) $Q_{i,j,t} = c_{i,j} + 0,065661\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.911633\ Q_{i,j,t-1}$

Equation 1 BRENT_R – DAX_R DCC

2) $Q_{i,j,t} = c_{i,j} + 0.036784\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.955200\ Q_{i,j,t-1}$

Equation 2 BRENT_R – FTSE100_R DCC

3) $Q_{i,j,t} = c_{i,j} + 0.088671\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.834204\ Q_{i,j,t-1}$

Equation 3 BRENT_R – NIKKEI_R DCC

4) $Q_{i,j,t} = c_{i,j} + 0.052812\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.937725\ Q_{i,j,t-1}$

Equation 4 BRENT_R – SP500_R DCC

5) $Q_{i,j,t} = c_{i,j} + 0.057868\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.901174\ Q_{i,j,t-1}$

Equation 5 GOLD_R-DAX_R DCC

6) $Q_{i,j,t} = c_{i,j} + 0.025875\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.926091\ Q_{i,j,t-1}$

Equation 6 GOLD_R-FTSE100_R DCC

7) $Q_{i,j,t} = c_{i,j} + 0.007241\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 1.037751\ Q_{i,j,t-1}$

Equation 7 GOLD_R-NIKKEI_R DCC

8) $Q_{i,j,t} = c_{i,j} + 0.050797\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.895809\ Q_{i,j,t-1}$

Equation 8 GOLD_R-SP500_R DCC

9) $Q_{i,j,t} = c_{i,j} + 0.047128\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.903350\ Q_{i,j,t-1}$

Equation 9 SILVER_R-DAX_R DCC

10) $Q_{i,j,t} = c_{i,j} + 0.032552\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.941242\ Q_{i,j,t-1}$

Equation 10 SILVER_R-FTSE100_R DCC

11) $Q_{i,j,t} = c_{i,j} + 0.083427\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.862257\ Q_{i,j,t-1}$

Equation 11 SILVER_R-NIKKEI _R DCC

12) $Q_{i,j,t} = c_{i,j} + 0.061175\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.864954\ Q_{i,j,t-1}$

Equation 12 SILVER_R-SP500 _R DCC

13) $Q_{i,j,t} = c_{i,j} + 0.078660\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.876851\ Q_{i,j,t-1}$

Equation 13 WTI_R-DAX_R DCC

$$14)\ Q_{i,j,t} = c_{i,j} + 0.035288\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.957321\ Q_{i,j,t-1}$$

Equation 14 WTI_R-FTSE100_R DCC

$$15)\ Q_{i,j,t} = c_{i,j} + 0.065068\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.864627\ Q_{i,j,t-1}$$

Equation 15 WTI_R-NIKKEI_R DCC

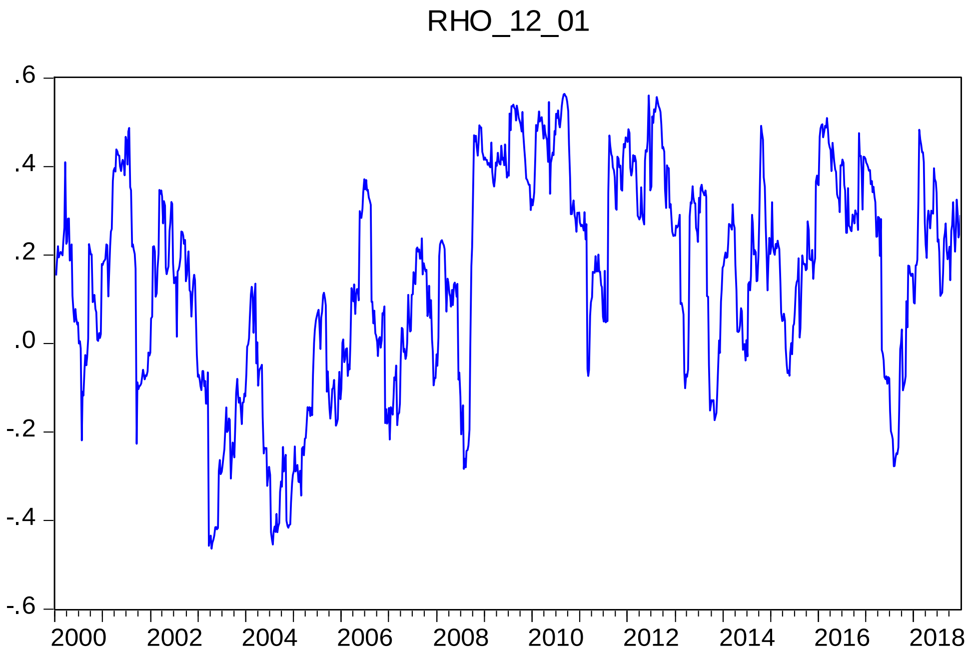
$$16)\ Q_{i,j,t} = c_{i,j} + 0.050411\ \varepsilon_{i,t-1}\ \varepsilon_{j,t-1} + 0.938262\ Q_{i,j,t-1}$$

Equation 16 WTI_R-SP500_R DCC

As Bampinas, Ladopoulos & Panagiotidis (2018) mentioned in their paper, the conditional variance has to be stationary and the estimators of the GARCH(1,1) models has to be significant in order to have significant DCC GARCH(1,1) results. Also, the stability condition of the model Theta (1) + Theta (2) < 1 has to be met. We can observe that almost all thetas are significant. The theta1 and 2 in equation 7 are not significant, the stability condition is not met and this dcc analysis is false. However, all though theta 1 in equation 6 and theta 1 in equation 9 are not significant, the stability condition is met, so we do not encounter a problem in the results.

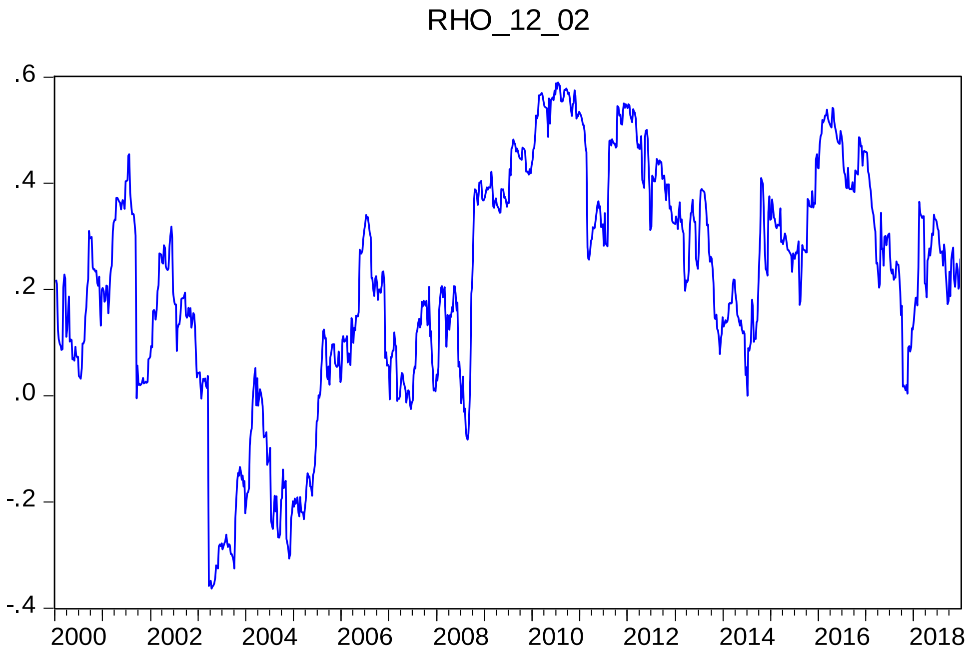
5.6 DCC GRAPHS

Figure 1 BRENT_R –DAX_R DCC



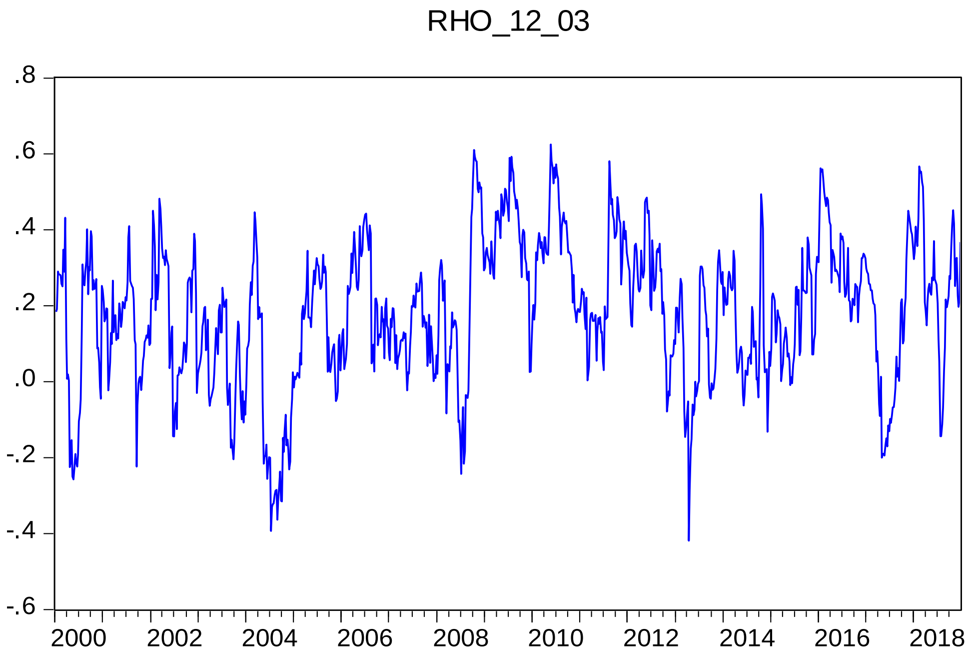
We notice that, the correlation started to be negative during the dot-com bubble and it took its minimum value -0.4 during 2003-2004. Then an upward trend was noticed until 2008 and the financial crisis, which caused a new negative correlation. After the 2007-2009 shock we can observe a positive correlation, which might be occurred by the financialization of the market.

Figure 2 BRENT_R –FTSE100_R DCC



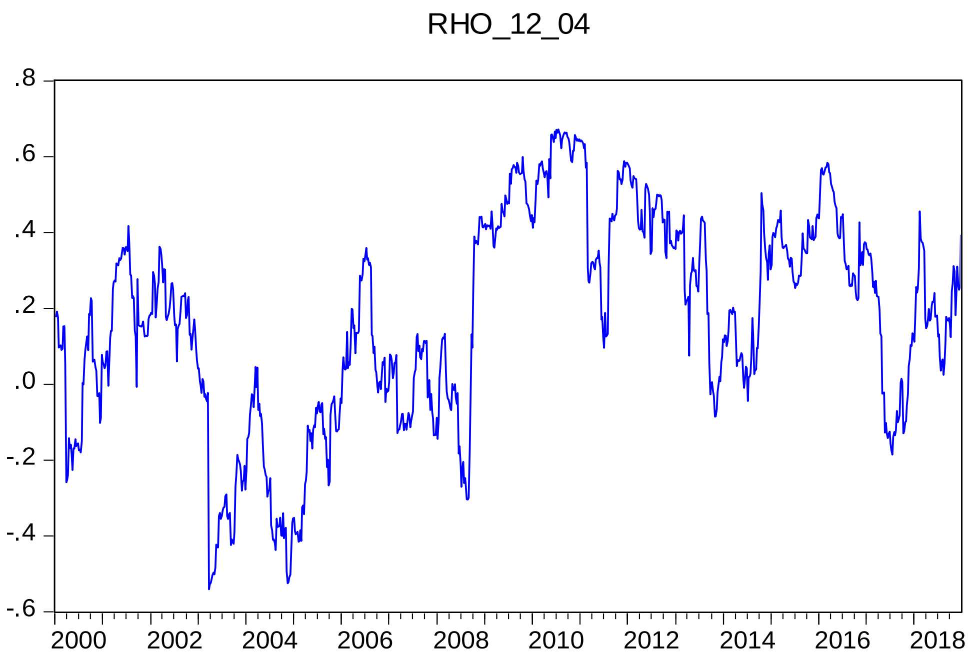
We notice that, the correlation started to be negative during 2003-2004. Then had an upward trend until 2008 and the financial crisis, which caused a new negative correlation. After the 2007-2009 shock we can observe a positive correlation ,which might be occurred by the financialization of the market.

Figure 3 BRENT_R –NIKKEI_R DCC



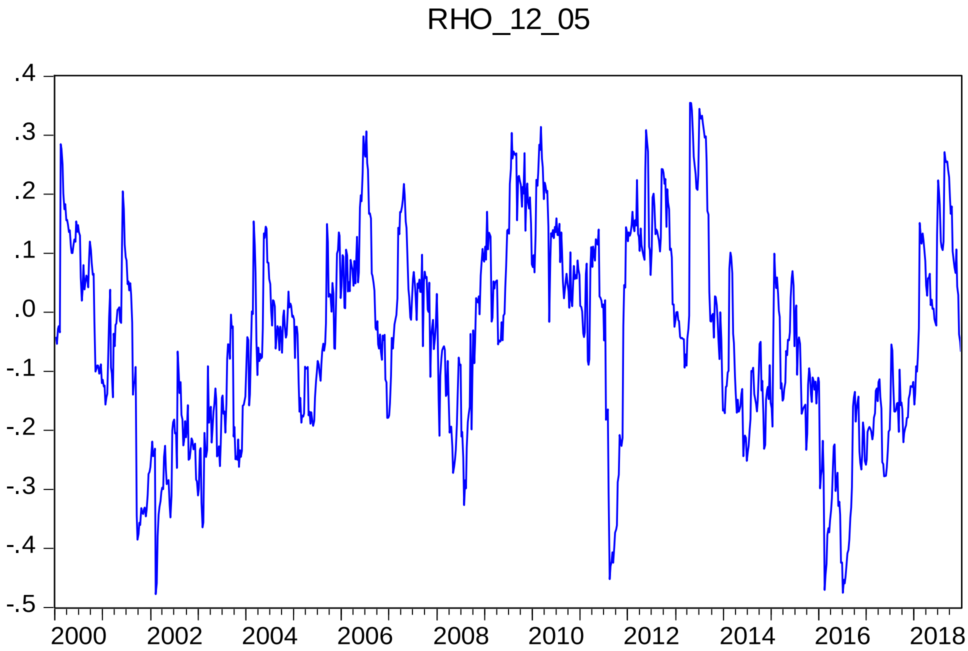
We notice that, the correlation started to be negative during the dot-com bubble and continued until 2004, after that we can see an upward trend until the financial crisis , which brought back negative correlation. After the 2007-2009 shock we can observe a positive correlation, which might be occurred by the financialization of the market.

Figure 4 BRENT_R –SP500_R DCC



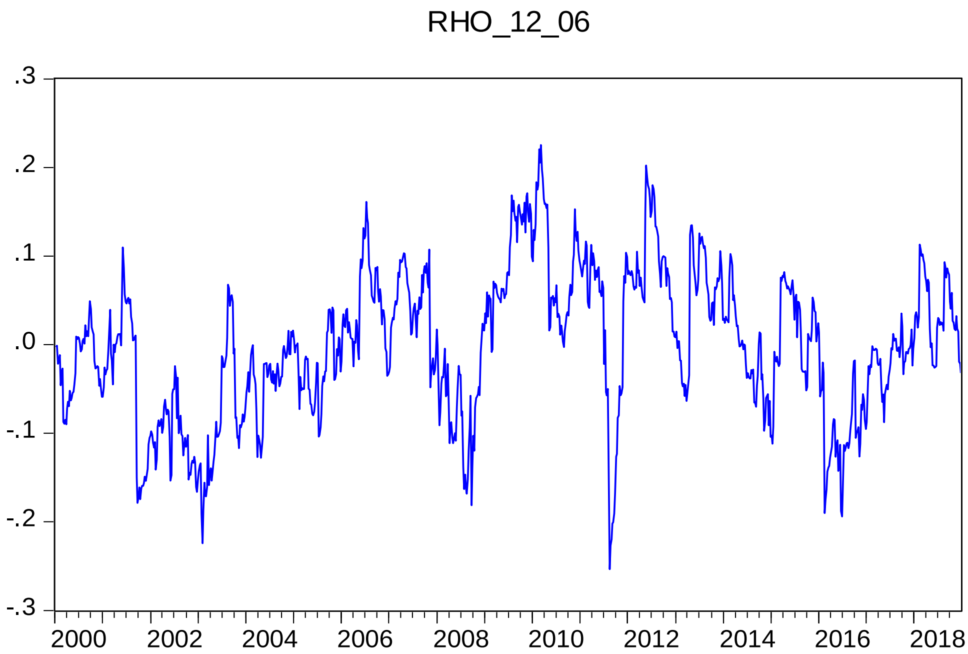
We notice, that the correlation started to be negative during the dot-com bubble, and continued through until 2004. Then the financial crisis changed the correlation, but after 2008 we have positive correlation.

Figure 5 GOLD_R –DAX_R DCC



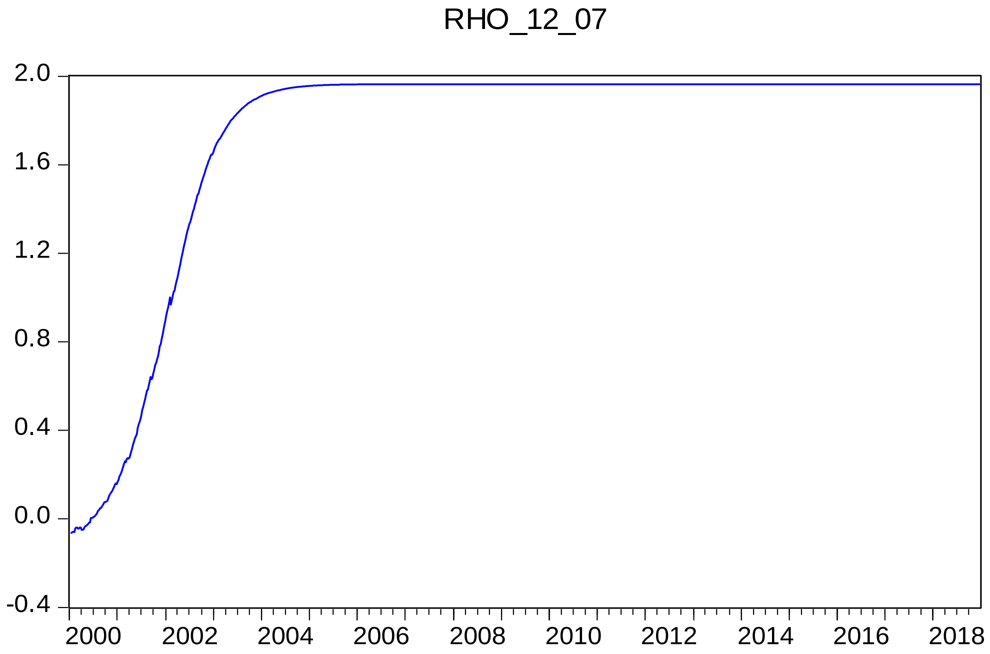
We can observe that the correlation has a negative trend. During the two shocks it took its minimum values, thus we have an evidence of the safe heaven hypothesis of gold.

Figure 6 GOLD_R –FTSE100_R DCC



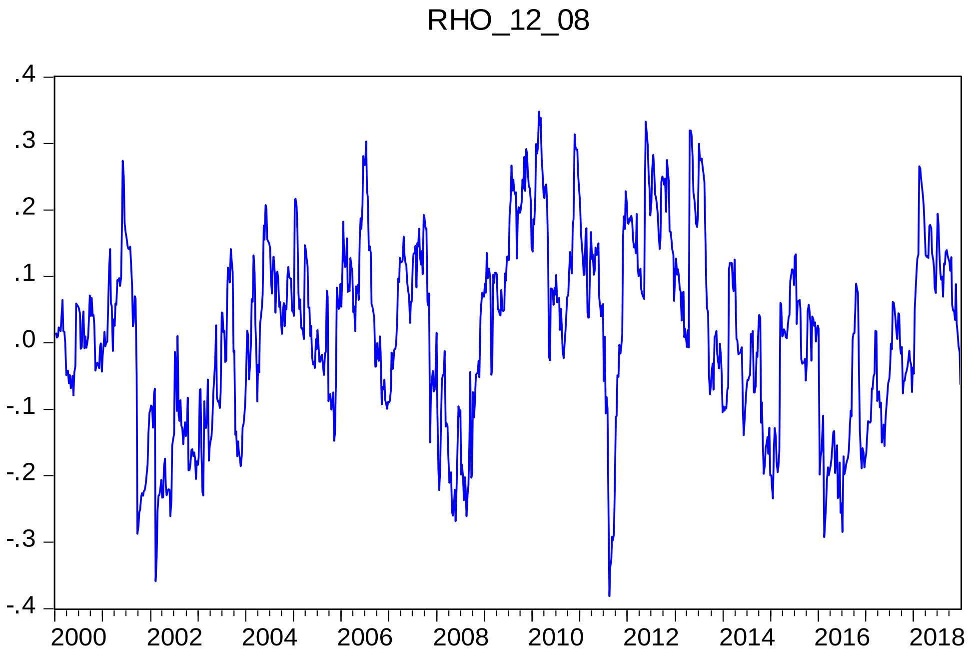
We can observe that the correlation has a negative trend. During the two shocks it took negative values, thus we have an evidence of the safe heaven hypothesis of gold.

Figure 7 GOLD_R –NIKKEI_R DCC UNSTABLE



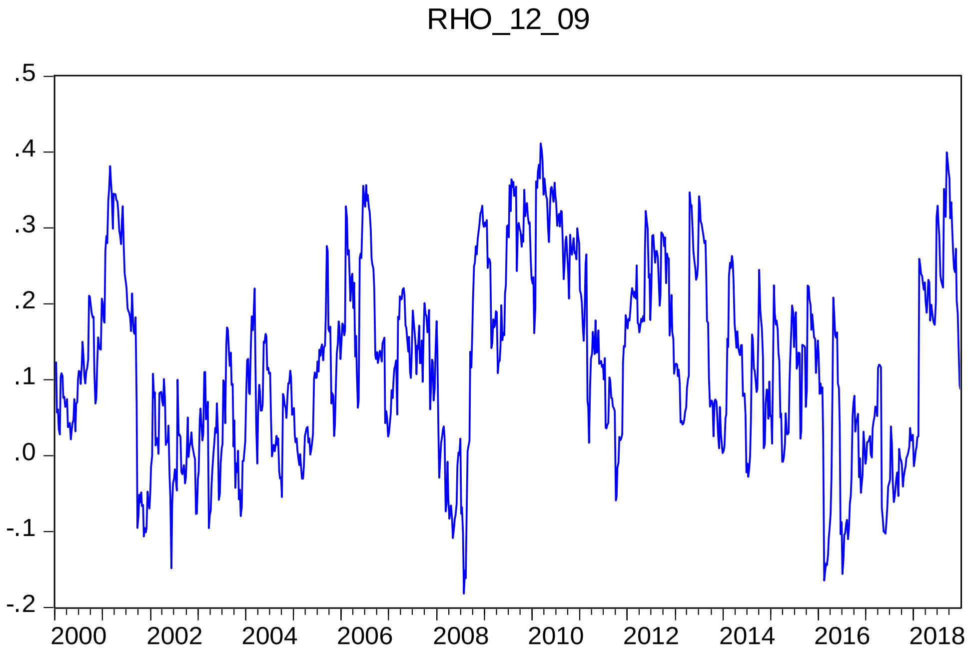
The stability condition of our analysis is not met.

Figure 8 GOLD_R –SP500_R DCC



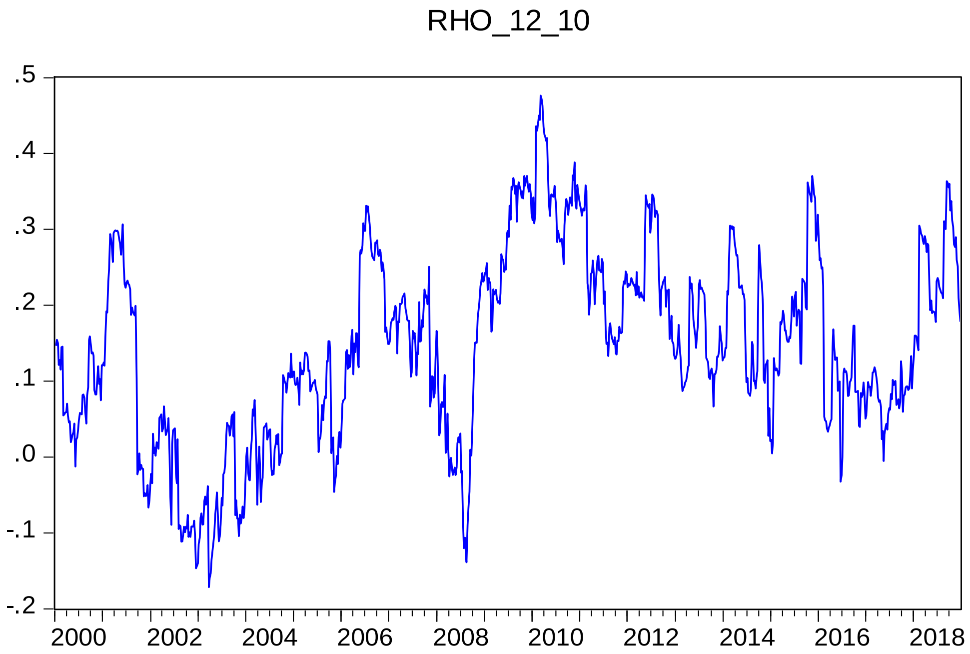
We can observe that the correlation has a negative trend. During the two shocks it took negative values, thus we have an evidence of the safe heaven hypothesis of gold.

Figure 9 SILVER_R –DAX_R DCC



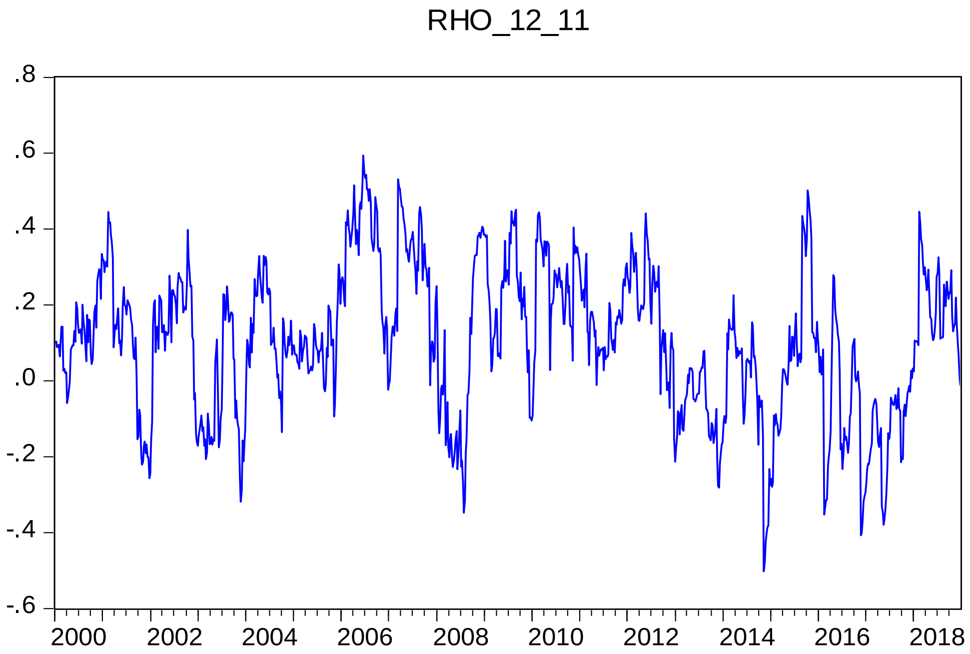
We can observe that the correlation has a negative trend. During the two shocks it took negative values, thus we have an evidence of the safe heaven hypothesis of silver.

Figure 10 SILVER_R –FTSE100_R DCC



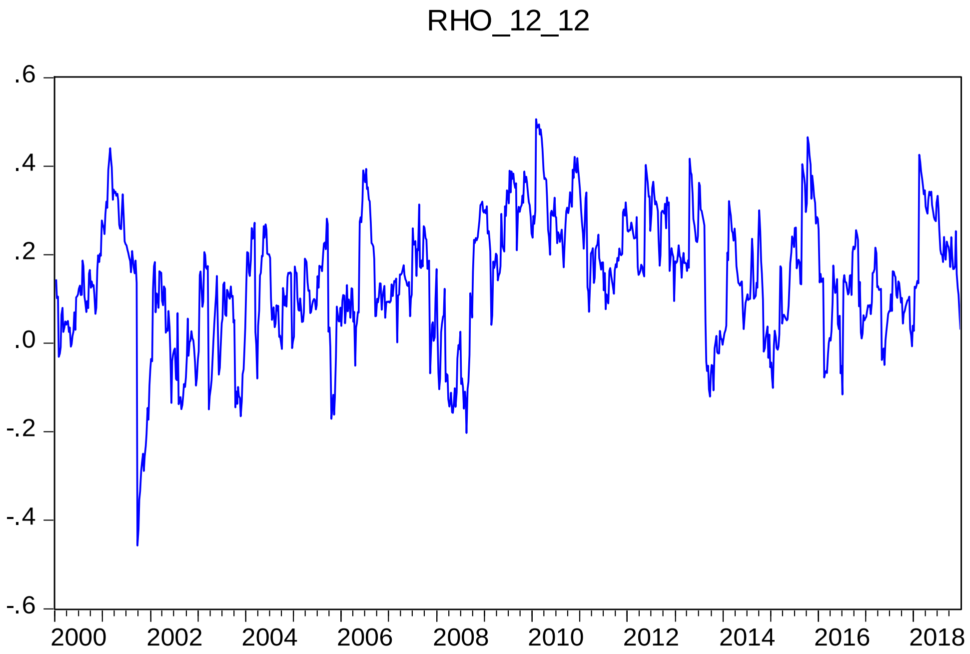
We can observe that the correlation has a negative trend. During the two shocks it took negative values , thus we have an evidence of the safe heaven hypothesis of silver. After 2008 we can see a positive correlation, which proves the financialization of the market.

Figure 11 SILVER_R –NIKKEI_R DCC



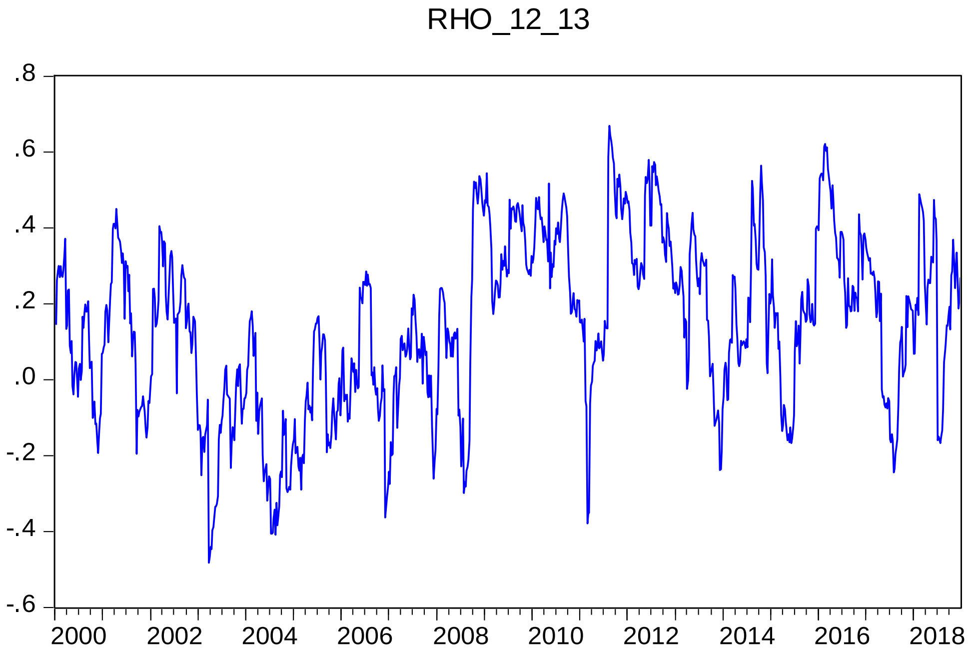
We can observe that the correlation has a negative trend. During the two shocks it took negative values, thus we have an evidence of the safe heaven hypothesis of silver.

Figure 12 SILVER_R –SP500_R DCC



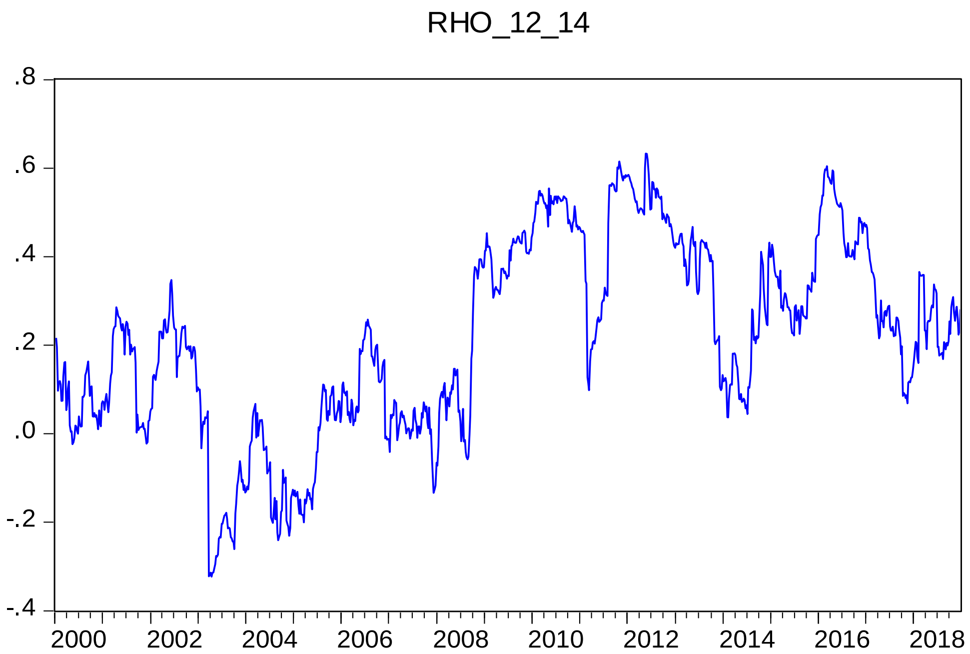
We can observe that the correlation has a negative trend. During the two shocks it took negative values, thus we have an evidence of the safe heaven hypothesis of silver.

Figure 13 WTI_R –DAX_R DCC



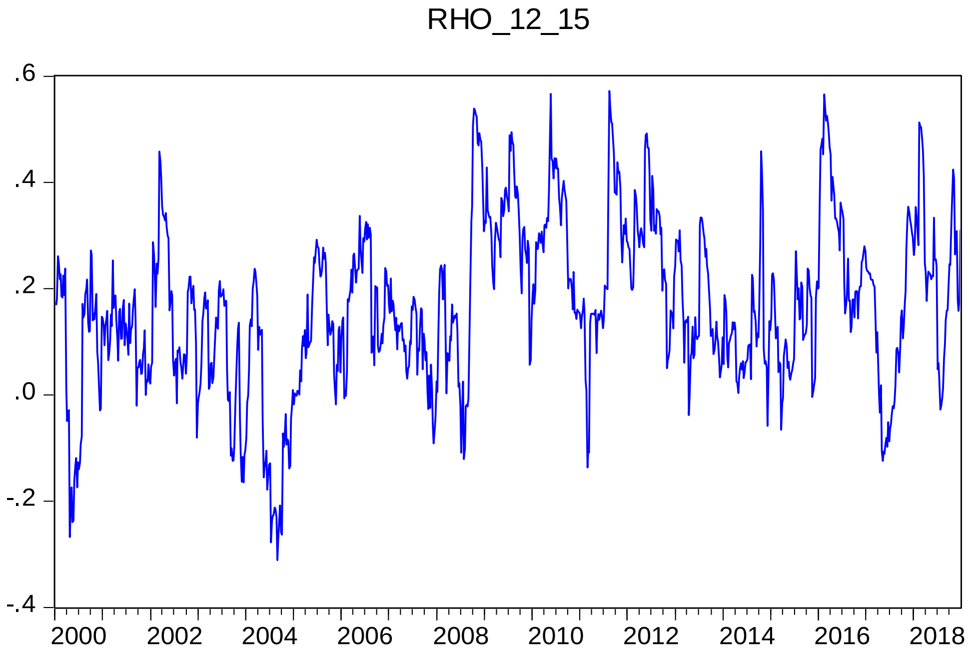
We notice that the correlation has a negative trend. During the two shocks it took negative values. After 2008 we have positive correlation but then the trend seems negative.

Figure 14 WTI_R –FTSE100_R DCC



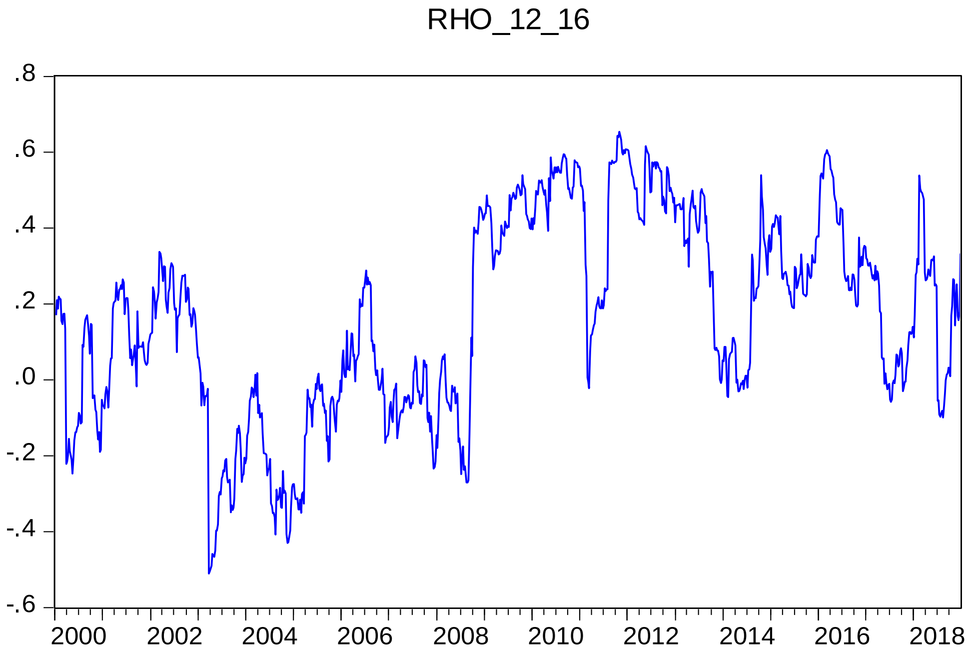
We notice that the correlation has a negative trend. During the two shocks it took negative values. After 2008 we have positive correlation, the cause of this change might be the financialization.

Figure 15 WTI_R –NIKKEI_R DCC



We notice that the correlation has a positive trend. Although, during the two shocks it took negative values.

Figure 16 WTI_R –SP500_R DCC.



We notice that the correlation has a negative trend. During the two shocks it took negative values. After 2008 we have positive correlation, the cause of this change might be the financialization.

To sum up the two shocks changed the level of the correlation between commodity and equity markets. The investors tried to add commodities in their portfolios in order to lowered their loses from the downward trend of the equity market. The gold seemed to be the most popular option , because of the safe heaven hypothesis that was valid during that, troubled period.

5.7 DCC VS DUMMIES

TABLE 12

Dependent Variables	Constant Term	Bubble Dummy	Estate Dummy
RHO_12_01	0,148914 (Prob.=0,0000)	0,018441 (Prob.=0,4085)	-0,000715 (Prob.=0,9805)
RHO_12_02	0,222423 (Prob.=0,0000)	-0,024263 (Prob.=0,2299)	-0,039838 (Prob.=0,1333)
RHO_12_03	0,188335 (Prob.=0,0000)	-0,054246 (Prob.=0,0020)	-0,002280 (Prob.=0,9210)
RHO_12_04	0,182191 (Prob.=0,0000)	-0,046135 (Prob.=0,0737)	-0,109808 (Prob.=0,0012)
RHO_12_05	-0,027552 (Prob.=0,0000)	-0,072436 (Prob.=0,0000)	-0,046147 (Prob.=0,0244)
RHO_12_06	0,010380 (Prob.=0,0003)	-0,058266 (Prob.=0,0000)	-0,056061 (Prob.=0,0000)
RHO_12_08	0,038710 (Prob.=0,0000)	-0,087800 (Prob.=0,0000)	-0,124896 (Prob.=0,0000)
RHO_12_09	0,130726 (Prob.=0,0000)	-0,028426 (Prob.=0,0128)	-0,042047 (Prob.=0,0051)
RHO_12_10	0,161668 (Prob.=0,0000)	-0,080761 (Prob.=0,0000)	-0,079428 (Prob.=0,0000)
RHO_12_11	0,105080 (Prob.=0,0000)	0,023735 (Prob.=0,1911)	-0,043375 (Prob.=0,0690)
RHO_12_12	0,161987 (Prob.=0,0000)	-0,077245 (Prob.=0,0000)	-0,105515 (Prob.=0,0000)
RHO_12_13	0,140754 (Prob.=0,0000)	-0,001063 (Prob.=0,9603)	-0,003296 (Prob.=0,9064)
RHO_12_14	0,234371 (Prob.=0,0000)	-0,101900 (Prob.=0,0000)	-0,093033 (Prob.=0,0004)
RHO_12_15	0,173953 (Prob.=0,0000)	-0,068923 (Prob.=0,0000)	0,002113 (Prob.=0,9106)
RHO_12_16	0,185803 (Prob.=0,0000)	-0,093259 (Prob.=0,0001)	-0,127790 (Prob.=0,0001)

We ran the OLS estimation and we want to exploit the significance of our coefficients. We tested the H0 non-significant over the H1 significant , by using the probability. If probability is less than 0.05 then, we accept the H1 and reject the H0, otherwise we accept H0. The constant term is significant in all dynamic correlations. The bubble dummy estimators ,which referred to the dot-com-bubble are significant to almost every correlation except the RHO_12_01, RHO_12_02,RHO_12_04, RHO-12_11 and RHO_12_13.The estate dummy, which are referred to the financial crisis of 2007-2009 are significant to almost every correlation except the RHO_12_01, RHO-_12_02,RHO_12_03, RHO-12_11, RHO_12_12 and RHO_12_13.

From our estimation, it is noticeable that the two shocks have a negative impact in the dynamic correlation between the commodity and equity products. All the significant estimations of the dummies have a negative value, thus the correlation during the crisis tend to be negative, this is a fact that proves the theory.

6.DISCUSSION

In the beginning the commodities and the stocks were two separate assets for different kinds of investors. Moreover, stocks tend to have very high returns in the early 2000s and commodities were more stable, we can observe this by looking at all the figures in the data section. After the first shock occurred by the dot-com bubble the loses of the investors guided them to add commodities and equities in their portfolios in order to diversify their positions and lower their management risk. As the commodity investment began to be more and more popular, their returns started to increase and when the market healed from the first shock the investors had big profits, due to the negative correlation between the two financial products, as we can see from the DCC correlation results. All this changed suddenly, after the 2008 financial crisis, for the first time we observed a strong positive correlation between commodities and equities markets. This was the evidence, that we needed to support that, the shock was too strong, that created spillover effects to the commodity investing. That was also proof of the financialization of the economy. The prices of all the assets started to get higher and higher and then the collapse came with huge loses and the investors in order to take cover they invested in commodity market making the commodity prices very high. As Bampinas, Panagiotidis and Rouska (2018) mentioned in their paper the excess demand of noise traders for oil and gold reduced volatility, especially in the presence of a negative shocks, when there is an intense need for alternative investment vehicles or ‘safe havens’, this also proves the theory that commodity investing is more intense during the turmoil periods. Nowadays, the correlation tends to be negative again as the economy starts to recover from the financial crisis, but more research is needed in order to understand the patterns of the correlation between these two assets, mainly during the crisis period when the correlation tends to be negative.

7.CONCLUSION

Our analysis revealed that, the correlation between commodity and equity markets during the dot-com bubble and the financial crisis of 2007-2009 , was negative. This is the evidence that we needed to support that the investors could cover their loses during the crisis by investing into commodity products. In addition, the safe heaven hypothesis of gold was also valid, because this specific correlation had a continuous negative trend. On the other hand the financial crisis has changed the image of the market. Now we see that the correlation tends to be positive, due to the popularity of the commodity investing. This is the result from financialization in the economy. To sum up, we find that the commodity futures could be used as a hedge during the turmoil periods of the economy. However correlation is similar to a living organism, which always develops, therefore more investigation is needed, in order to have a clear perspective of the relationship between commodity and equity markets.

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