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The influence of biofuels, economic and financial factors on daily returns of commodity futures prices

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Abstract

Biofuels production has experienced rapid growth worldwide as one of several strategies to promote green energy economies. Indeed, climate change mitigation and energy security have been frequent rationales behind biofuel policies, but biofuels production could generate negative impacts, such as additional demand for feedstocks, and therefore for land on which to grow them, with a consequent increase in food commodity price. In this context, this paper examines the effect of biofuels and other economic and financial factors on daily returns of a group of commodity futures prices using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models in univariate and multivariate settings. The results show that a complex of drivers are relevant in explaining commodity futures returns; more precisely, the Standard and Poor's (S&P) 500 positively affects commodity markets, while the US/Euro exchange rate brings about a decline in commodity returns. It turns out, in addition, that energy market returns are significant in explaining commodity returns on a daily basis, while monetary liquidity does not. Finally, the GARCH model has shown that current variance is influenced more by its past values than by the previous day's shocks, and there is high persistence, meaning that variance slowly decays and prompts a sluggish "revert to the mean." The multivariate BEKK framework confirms the results of the univariate setting.

Keywords: futures returns, biofuels, univariate and multivariate GARCH

JEL classification: C58, G15, Q14, Q43

1. Introduction

Over recent years, the production of biofuels has surged significantly, pushed by concerns about climate change, the possibility of fossil fuel scarcity, the need to improve the security of energy supply, and government incentives. In particular, the need to reduce dependency on fossil fuel energy has increased after high price swings registered in many producing countries due to several factors including unstable geopolitics, natural disasters, and financial speculations. Biofuels (e.g., ethanol and biodiesel) would facilitate lessening CO2 emissions and contribute to general rural development. Nevertheless, until new technologies are well developed[1], using food to produce biofuels might squeeze the already tight supplies of arable land and water on a global level, and would drive food prices even higher (Mercer-Blackman et al. 2007).

From 2006 to 2012, worldwide ethanol production has more than doubled and biodiesel production has increased more than three-fold (see appendix). Ethanol is an alcohol product usually produced from corn, sugar, wheat, sorghum, potatoes, and biomass such as cornstalks and vegetable waste. When combined with gasoline, it increases octane levels while also promoting more complete fuel burning which reduces harmful tailpipe emissions such as carbon monoxide and hydrocarbons. U.S. ethanol production is primarily fuelled by corn, while in Europe, ethanol is made from wheat and sugar beets, and in Brazil, the ethanol industry relies mainly on sugarcane[2]. Biodiesel is a domestic, renewable fuel for diesel engines derived from natural oils such as soybean oil, rapeseed oil, and palm oil. The biodiesel market is primarily driven by rapeseed oil in Europe; by soybeans in the U.S. and Brazil, and by palm oil in Malaysia (Ravindrana et al., 2011; USDA, 2013). Ethanol production is mainly concentrated in the United States and Brazil, while biodiesel production is mainly centered in Europe (see appendix).

[1] First-generation biofuels are derived from food and feed crops through the process of fermentation. Advanced or second-generation technologies convert ligno-cellulosic material (including woody crops and forest and agricultural residues) into biofuel. These offer the possibility of utilizing biomass, which is less directly competitive for food and feed, and are also capable of yielding a much higher energy return. However, there is no large-scale production of second-generation biofuels, mainly because of their high production costs (Natahelov et al., 2013).

[2] Sugar can be derived from both sugar cane and sugar beets, the latter being more costly to produce. Most sugar cane comes from countries with warm climates. Sugar beets are grown in regions with cooler climates. Of all the sugar produced, almost 80% is processed from sugar cane.

As the production of biofuel derived from cereal, sugar, and oil seeds rises, producers of this feedstock experience an increased demand for their commodities, which in turns leads to price increases. An additional issue is the volume of planting area that could be diverted from producing other crops to producing those crops used for biofuel production. For instance, high corn prices in 2006 stimulated U.S. farmers to intensify corn planting by 18 per cent in 2007 reducing the areas devoted to soybean and wheat production. This decline led to a sharp rise in soybean and wheat prices (Ecofys, 2008).

The evidence linking biofuels to rising food prices and volatility cannot be ignored and should be investigated in more detail. In this context, the present study examines the impact of biofuels on corn, rapeseed, soybean, soybean oil, sugar and wheat futures returns, i.e. changes in the log prices, using GARCH family models and controlling for financial and economic factors, such as the Standard & Poor’s 500, crude oil, the U.S. dollar/euro exchange rate, and monetary variables.

The study contributes to the existent literature in several ways. First, a systematic assessment of the impact of biofuels and other drivers on commodity futures prices on a daily basis is missing, with the exception of the study by Sariannidis (2010), which confines his analysis to the case of sugar. Indeed, most of the existing studies examine the link between energy and agricultural markets, disregarding other control variables. These studies use econometric or simulation models to explain price interdependencies, their transmission between markets, and volatility spillovers in order to establish a causal hierarchy between energy and agricultural goods. The present study broadens the perspective as it gauges the influence of different drivers on futures returns. This study includes two measures of “monetary liquidity” to evaluate how monetary policy - and specifically the liquidity generated by the world’s main central banks - affect price changes. The importance of “global liquidity” for food and commodity prices has been highlighted and analyzed by Belke et al. (2013). Furthermore, the analysis first explores the dynamics of commodity returns in a univariate framework then extends the focus to a multivariate setting using a trivariate BEKK parameterization where energy - distinguished in oil and ethanol - and agricultural markets are examined simultaneously. This can be viewed as a robustness check of the univariate framework and as a test for the presence of cross-market spillovers in the mean equation. A final important contribution is the use of futures daily returns to allow for a finer investigation of price changes. Most of the existing studies are based on more aggregated observations; Gardebroek and Hernandez (2013), and Wu and Li (2013), for instance, used weekly data.

The remainder of the study is organized as follows: Section 2 reviews the existent literature on the topic, Section 3 depicts the dataset and the descriptive statistics, Section 4 presents the empirical analysis and discusses the results, and Section 5 concludes.

2. Literature review

The integration between energy and agricultural markets has attracted increasing attention in recent years. Indeed, several studies have investigated both the direct link between oil and food commodity prices (e.g. Harri et al. 2009; Nazlioglu and Soytas, 2011) and the relationship between biofuel and agricultural price variability. This is because energy costs have traditionally influenced agricultural markets through input channels on the supply side, and the expansion of biofuel production has stimulated the demand side of the commodity market, thus affecting prices (Chen et al., 2010).

The empirical literature offers contrasting results regarding the existence of interdependencies between energy and agricultural markets. Zhang et al. (2009) explored the relationship between the price levels (volatility) of corn, soybeans, oil and ethanol in the U.S., and found no spillovers from ethanol price volatility to corn and soybean price volatility. They further found no long-run relationships between energy and agricultural price levels. Conversely, the studies by Harri and Darren (2009), Du et al. (2011) and Wu and al. (2011) revealed a linkage between oil price and corn price after the introduction of the Energy Policy Act in the U.S. in 2005. These studies, however, have not taken into account ethanol prices explicitly, despite their indication that the inter-linkages between the energy and agricultural markets are due to ethanol production. Trujillo-Barrera et al. (2012) extended Wu and al.'s model (2011) to specifically account for the impact of ethanol on corn, and have identified the presence of volatility spillovers from the crude oil futures markets to ethanol and corn futures markets. The study by Serra et al. (2011) assesses volatility interactions within the Brazilian ethanol markets, and found important volatility spillovers across markets that flow in multiple directions. The results of Balcombe and Rapsomanikis (2008), also on the Brazilian case, suggest that oil prices are the main long-run drivers of ethanol and sugar prices and that the causal chain runs directly from oil prices to sugar, rather than through the ethanol market. This indicates that sugar prices Granger-cause ethanol prices but not vice versa, and thus producers appear to utilize information on oil and sugar prices before making decisions on how much ethanol and sugar to produce. Gardebroek and Hernandez (2013) performed an analysis of the dynamics and cross dynamics of weekly spot price volatility across crude oil, ethanol and corn prices in the U.S. and do not find important spillover from energy to agricultural spot markets. Wu and Li (2013) analyzed the price volatility spillovers among China's crude oil, corn and fuel ethanol markets and find a higher interaction among crude oil, corn, and fuel ethanol markets, after September 2008. They indicate that there exist unidirectional spillover effects from the crude oil market to the corn and fuel ethanol markets, and double-directional spillovers between the corn market and the fuel ethanol market. However, the spillover effects from the corn and fuel ethanol markets to the crude oil market are not significant.

The literature that identifies a rising linkage between agricultural prices and biofuels can be distinguished into two main groups according to the empirical methodology adopted in analysis.

A first group of studies has investigated the dynamic linkages between biofuels and food commodities using statistical and time series techniques. The influence of biofuels on food prices varies considerably. In particular, as highlighted in Table 1, the change in food price ascribed to biofuels ranges from 10% to 75%. These differences can be due to the different countries under investigation, the typology of food and fuel taken into account, the selected time dimension, and the adopted methodology.

Table 1 Selected studies based on econometric-statistic methodologies

Author	Change in food price ascribed to biofuels	Period of investigation	Methodology
Mitchell (2008)	+70-75% food prices	2002-2008	Statistical analysis
Kind et al. (2009)	+10–15% food prices	2007-2008	Time series analysis
Baier et al. (2009)	+27% corn, +21% soybean, +12% sugar	2006-2008	Interactive spreadsheet
Sariannidis (2010)	+0.68% in sugar price returns	2002-2009	Econometric approach

Source: Own elaborations

Among others, Kind et al. (2009) found that the growing use of corn for ethanol accounted for about 10–15% of the increase in food prices over the period of April 2007 to April 2008. Mitchell (2008) found that the increase in internationally traded food prices from January 2002 to June 2008 was caused by a confluence of factors, but the most significant driver was the large increase in biofuels production from grains and oilseeds in the U.S. and EU. The latter - together with the related consequences of low grain stocks, large land use shifts, speculative activity and export bans - accounted for a 70-75% increase in food commodities prices. Baier et al. (2009) estimated that the increase in worldwide biofuels production pushed up corn, soybean and sugar prices by 27, 21 and 12 percentage points respectively. Sariannidis (2010) estimated that a 10% increase in the demand for biofuels led to a 0.7% rise in sugar price returns.

A second group of studies is based on simulation models, partial equilibrium or computable general equilibrium models that evaluate the projected impact of the introduction of given biofuel trade or policy scenario on food prices and produced quantities.

Table 2 Selected studies based on simulation models

Author	Projected change in food price ascribed to biofuels	Methodology
Rosegrant (2008)	+ 39% corn real prices, +22% wheat real prices +21% rice real prices	IMPACT model a partial equilibrium modeling
Saunders et al. (2009)	The RFS policy will lead to higher corn prices, by 8-15%	Applied Lincoln Trade and Environment Model which is a non-spatial, partial equilibrium model
Elobeid and Tokgoz (2006)	+ 58% corn price (*$/bushel*) + 20% wheat price (*$/bushel*) -5% soybean price (*$/bushel*)	A multi-commodity, multi-country system of integrated commodity models
Ignaciuk and Dellink (2006)	+5% agricultural price	General equilibrium model

Source: Own elaborations

For instance, Rosegrant (2008) adopted a partial equilibrium model to examine 1) the food price evolution with and without high biofuel demand, 2) the impact of a freeze on biofuel production from all crops at 2007 levels and 3) the impact of a moratorium on biofuel production after 2007. He found that the increased biofuel demand during 2000-2007 has accounted for 30 percent of the increase in weighted average grain prices. If biofuel production was frozen at 2007 levels for all countries and for all crops used as feedstock, corn prices were projected to decline by 14 percent by 2015. If biofuel demand from food crops was abolished after 2007, prices of key food crops would drop more significantly— for instance by 20 percent for corn. Saunders et al. (2009) applied a partial equilibrium model of international agricultural trade to analyze the impact of the renewable fuel standard (RFS) policy of the United States on the agricultural sector in New Zealand. The authors found that the renewable fuel standard policy has a significant impact on corn prices, but a small effect on livestock prices and production. Elobeid and Tokgoz (2006) developed a multi-commodity, multi-country system of integrated commodity models to determine the impact of ethanol production on food prices and found that, as the U.S. ethanol industry expands, corn price and wheat price will rise by 58% and 20% respectively, while soybean price will decrease by 5%. Ignaciuk and Dellink (2006) adopted a general equilibrium model to gauge the impact of multi-product crops in response to climate policies and found that the competition between agriculture and biomass for scarce land will decrease the production of agricultural products at most by 5% and increase the price of agricultural goods by 5%.

Partial equilibrium or computable general equilibrium models show several shortcomings. First of all, they generate the long-term price impacts of specific shocks, but do not capture short-term price dynamics that are significantly more pronounced (Mitchell, 2008; Serra and Zilberman, 2013). Additionally, PA and GCE are based on too many restrictive assumptions (Pfuderer et al., 2010). The following analysis investigates the drivers of a set of food commodities with the objective of disentangling some factors behind the daily log futures returns.

3. Descriptive analysis

3.1 Data

To estimate the effect of energy prices, economic and financial variables on commodity futures price returns, daily trading data from 16 May 2005 to 19 June 2013, a total of 2041 observations, have been collected from the Bloomberg database. The series start in May 2005, since ethanol futures trading was newly introduced at the Chicago Board of Trade in that period.

Specifically, the daily synchronous closing futures prices of the main food commodities used to produce the first generation of biofuels have been considered as a dependent variable. They comprise corn, rapeseed, soybeans, soybean oil, sugar, and wheat.

For corn, No. 2 Yellow futures traded at the Chicago Board of Trade have been considered. Corn price is quoted in US cents per bushel. The contract months for the Chicago Board of Trade corn futures are March, May, July, September and December. The Bloomberg ticker for the CBOT one-month generic corn futures contract is C 1 <Commodity>. Rapeseed prices are first generic futures prices traded at LIFFE-Paris, which operates the MATIF (Marché à Terme International de France) and which is the most important stock exchange for rapeseed worldwide (Busse et al., 2010). Rapeseed futures are traded on EURONEXT. The Bloomberg ticker for the CBOT one month generic rapeseed futures contract is IJ1

<Commodity>. Soybean and soybean oil futures are traded mainly on the Chicago Board of Trade (CBOT) the Dalian Commodity Exchange in China, and the Tokyo Grain Exchange (TGE). The soybean price is quoted in US cents per pound. The Bloomberg ticker for the CBOT one month generic soybean futures contract is S 1 <Commodity>. The Bloomberg ticker for the CBOT one month generic soybean oil futures contract is BO1 <Commodity>. The most actively traded sugar futures contract is the No. 11 (world) sugar contract on the New York Board of Trade (NYBOT). The sugar price is quoted in US cents per pound. The Bloomberg ticker for the one month generic futures sugar contract is SB1 <Commodity>. The wheat price is quoted in US cents per bushel. The Bloomberg ticker for the one month generic futures wheat contract is W 1 <Commodity>.

The independent variables include energy, economic, and financial factors. In particular, energy factors are distinguished in oil and biofuels. Oil affects commodity prices and returns mainly through the supply side: a rise in oil prices exerts an upward pressure on input costs such as fertilizers, irrigation, and transportation costs, which in turn lead to a decline in profitability and production, with a consequent rise in commodity prices. Biofuels, stimulated by higher crude oil prices and facilitated by indirect or direct subsidies and mandates, impact commodity prices through the demand side. This is because the demand for corn, soybeans and other grains increases in order to produce more biofuels, and this results in higher prices of these grains. The demand for biofuels has been further facilitated by (indirect or direct) subsidies and biofuel mandates.

For oil, data consist of time series of daily futures prices of West Texas Intermediate (WTI), also known as Texas Light Sweet, which is a type of crude oil used as a benchmark in oil pricing and the underlying commodity of the New York Mercantile Exchange's (NYMEX) oil futures contracts. As proxy for the price of biofuels, ethanol futures prices have been considered. Ethanol futures are traded primarily on the Chicago Board of Trade (CBOT) in U.S. gallons[3]. The Bloomberg ticker for one month generic denatured fuel ethanol contract traded on the CBOT is DL1 <Commodity>. Biodiesel futures are not considered in the analysis due to lack of data. Specifically, generic 1st biodiesel with Bloomberg tickers ZQS1 Comdty

[3] In April 2007, Brazil launched a futures contract for anhydrous ethanol on the Brazilian Mercantile and Futures Exchange. The Bloomberg ticker is AFA1 <Commodity>, however the series does not have data for 2010-2012, and therefore was not included in the analysis.

and BLB1 Comdty are available staring from 4 January 2012 and 20 May 2009 respectively. The alternative option to consider biofuel spot price was not possible as data referring to Germany Aggregate consumer biodiesel (BIOCEUGE ATPU FOL Index) are available only on a weekly basis.

The financial and the macroeconomic side of the economy is proxied by the S&P500, the dollar/euro exchange rate, and 'monetary liquidity' measures, namely the outstanding open market operation by the ECB and the lending rate by the Fed[4]. The Standard and Poor's 500 composite index comprises the 500 largest U.S. firms and is a benchmark indicator of overall U.S. stock market conditions. Put differently, the S&P 500 Index is the widely followed financial indicator of the U.S. stock market and the global economy. The euro/dollar exchange rate has been considered since international food prices are denominated in U.S. dollars. Therefore, a change in the dollar exchange rate can modify the demand and supply for agricultural commodities and thus change their prices. This is because consumers purchase food using local currency. The declining U.S. dollar during this period reduced the cost of commodities such as oil and grains to consumers paying in foreign currency. The reduced cost resulted in increased demand and upward pressure on prices. The U.S. dollar depreciated 35% against the euro from January 2002 to June 2008.

A central bank influences the money supply in the economy, injecting or reducing monetary liquidity in the system. The central bank implements monetary policy mainly through three channels: by conducting open market operations, by changing the discount/interest rate, or by modifying the required reserves. Open market operations typically involve the purchase or sale of Treasury securities. By buying and selling government securities, the bank affects the aggregate level of balances available in the banking system, and thus impacts the interest rate. Therefore, two alternative proxies of monetary liquidity have been considered in order to evaluate how it affects the commodity market: the outstanding open market operations implemented by the ECB and the lending rate by the FED. The data on the outstanding open market operations contain information on the historical liquidity conditions in the euro area (i.e. the Eurosystem's supply of and the credit institution's demand for liquidity in euro). It's worthwhile noting that the federal New York permanent

[4] The monetary aggregate M2 has been not considered since it is available only at a weekly frequency.

open market operations are not considered because the series from Bloomberg are not disaggregated at a fine level (POMOTPOM Index).

The surge in outstanding open market operations (MRO+LTRO) increases excess liquidity (defined as open market operations recourse to the marginal lending facility autonomous liquidity factors reserve requirements) in the economy. The Federal Bank's rate on the FEDL01 Index (the U.S. Federal Funds Rate) is a daily overnight volume weighted average that is calculated the day after closing for the previous day. The overnight rate is the rate at which banks, members of the Federal Reserve System, lend money to the maximum duration of 24 hours via overnight deposits. Put differently, banks are required to hold a certain amount of capital in reserve: 10% of the deposits they hold at the end of each day. Some banks at the end of the day have surpluses, others do not meet reserve requirements. The federal funds rate is the rate at which the banks in deficit borrow from those with a surplus[5]. This rate gives an idea of the liquidity: a high rate means that there is little liquidity in the interbank market.

Due to different holidays across exchanges, those days for which we have available information for all exchanges have been included in the estimations.

Detailed data specifications and tickers and are reported in Table 9, Appendix.

3.2 Descriptive statistics

Daily continuous compounded returns for the selected variables are calculated as $R_t=\ln(P_t/P_{t-1})$ where R_t are the daily returns, P_t is the closing futures price of the day, t is time, and ln is the natural logarithm.

Descriptive summary statistics for log-returns of the considered variables are reported in Table 3. The latter provides information on the mean return values, their minimum and maximum values, and the dispersion of returns with respect to the mean. The average daily

[5] The effective federal funds rate that the borrowing institution pays to the lending institution is determined between the two banks. This implies that the effective federal funds rate is essentially determined by the market, but is influenced by the Federal Reserve through open market operations to reach the federal fund's "target rate" – its desired overnight borrowing rate. Thus, the Fed Funds Rate is a market rate between depositor banks, only indirectly "set" by the Fed.

returns for the food commodities futures ranges between 0.03% of rapeseed to 0.06% of corn; these returns are higher than S&P returns and exchange rate. In detail, the average daily returns in corn are roughly 1.5 times higher than returns in oil and 3 times higher than the stock market. Higher average returns are connected with greater risk exposure in futures markets. The gap between the maximum and minimum returns gives evidence of the high variability in price changes. The daily standard deviation confirms the high level of volatility in the commodity markets and points also to the highest risk of the futures returns. Specifically, volatility is 2% for corn, sugar, and wheat, 1.8% for soybeans, and 1.6% for soybean oil and rapeseed.

Table 3 further reveals that commodity returns exhibit the typical phenomena of financial time series, namely leptokurtosis, asymmetry, and volatility clustering. Leptokurtosis implies that the distribution of stock returns is not normal, but exhibits fat-tails. In a normally distributed series, kurtosis is 3 and skewness is 0. Kurtosis coefficients less than or greater than 3 suggest flatness and peakedness in the returns data, respectively. The food commodity futures distributions, then, are all peaked relative to normal. Form the economic point of view, leptokurtosis indicates that high probabilities for extreme values are more frequent than the normal law predict in a series. For the soybean market returns, the values of excess kurtosis are much higher than those of the other commodity markets. This implies that the soybean market is much more prone to extreme movements than the other commodities.

Positive or negative skewness indicates asymmetry in the series. For a symmetric distribution, like the normal, the median is the average and so the skewness is zero. Asymmetry, also known as leverage effects, suggests that a decrease in returns is followed by an upsurge in volatility greater than the volatility caused by a rise in returns. This implies that prices tend to depart more from their average trend in a bust than in a boom due to a higher perceived uncertainty (Fama, 1965; Black, 1976). Aggregate returns for corn, ethanol, rapeseeds, soybeans, soybean oil and sugar, as well as the S&P 500 and the exchange rate are negatively skewed and thus have a long left tail. This implies that there is a propensity to generate negative returns with greater probability than suggested by a symmetric distribution. Conversely, positively skewed distributions, such as returns for wheat and oil, indicate that there is a greater than normal probability of big positive returns.

Similarly to kurtosis and skewness, the Jarque-Bera test rejects normality at the 5% level for all distributions, which could be due to partly to the presence of extreme observations. In case of a normal distribution, the J-B is 0.

Volatility clustering occurs when large changes in returns are followed by further large changes, of either sign, and small changes in returns are followed by periods of small changes. Put differently, the current level of volatility tends to be positively correlated with its level during the immediate previous periods. The daily returns show that volatility occurs in bursts, as highlighted in Chart 1.

Correlation analysis (Table 4) reveals positive correlation between ethanol prices and commodity returns and between commodity returns and oil returns. The open market operations are negatively correlated to food returns, while S&P and the lending rate, with the exception of sugar, are positively correlated. The correlation between oil and ethanol price during the considered time frame is 0.31.

All the correlations between the S&P 500 and the commodity log returns are below 0.3, indicating low co-movements of asset returns. The highest correlation is between the S&P 500 and the soybean oil returns. The correlation of returns between that of the main commodity futures and energy futures, in particular oil, is somewhat higher.

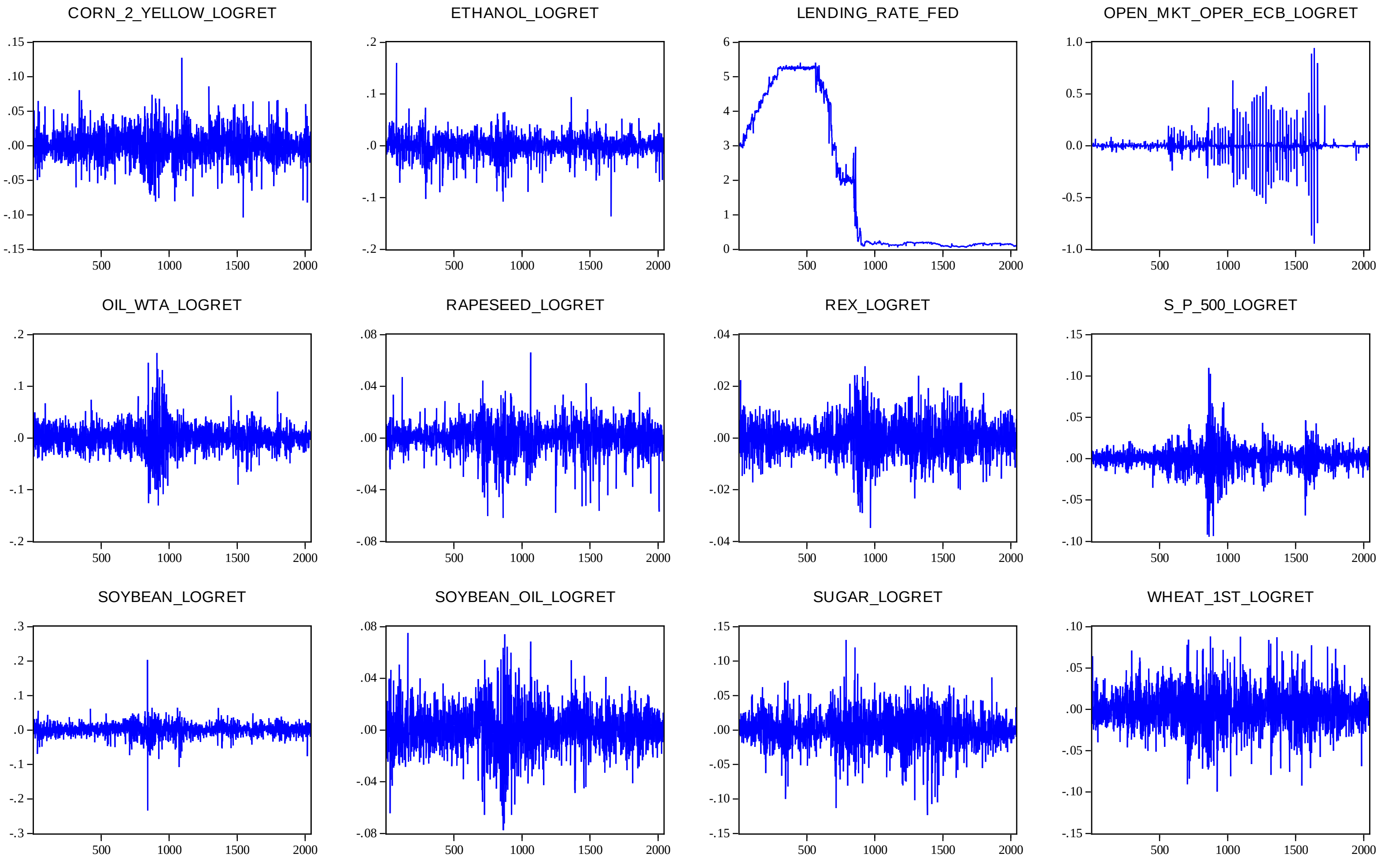
Table 3 Descriptive statistics log returns

	CORN_2_YELLOW_LOGRET	ETHANOL_LOGRET	LENDING_RATE_FED	OPEN_MKT_OPER_ECB_LOGRET	OIL_WTA_LOGRET	RAPESEED_LOGRET	REX_LOGRET	S_P_500_LOGRET	SOYBEAN_LOGRET	SOYBEAN_OIL_LOGRET	SUGAR_LOGRET	WHEAT_1ST_LOGRET
Mean	0.000585	0.000375	1.829456	0.000314	0.000346	0.000334	-2.47E-05	0.000170	0.000432	0.000388	0.000349	0.000410
Median	0.000000	0.000853	0.200000	0.000000	0.001014	0.000909	-0.000132	0.000801	0.001288	0.000225	0.000000	0.000000
Maximum	0.127571	0.160343	5.410000	0.943345	0.164097	0.066101	0.027743	0.109572	0.203209	0.075046	0.130620	0.087943
Minimum	-0.104088	-0.136507	0.040000	-0.945550	-0.130654	-0.061844	-0.034831	-0.094695	-0.234109	-0.077680	-0.123658	-0.099728
Std. Dev.	0.021396	0.019817	2.110809	0.084447	0.024221	0.011615	0.006592	0.013898	0.018523	0.016205	0.023544	0.023253
Skewness	-0.001196	-0.474272	0.635103	0.379786	0.126076	-0.705601	-0.009755	-0.310151	-0.807063	-0.046416	-0.251013	0.024658
Kurtosis	4.908043	8.849193	1.626734	48.79397	8.237004	6.931694	4.721155	12.70831	24.07320	5.482205	5.805366	4.414348
Jarque-Bera	309.4538	2984.587	297.5850	178301.5	2336.632	1483.225	251.8343	8044.064	37968.24	524.4465	690.3793	170.2390
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.192677	0.764666	3733.920	0.640905	0.706532	0.681732	-0.050302	0.347177	0.882030	0.790875	0.711540	0.836629
Sum Sq. Dev.	0.933396	0.800720	9089.253	14.54074	1.196168	0.275055	0.088613	0.393854	0.699592	0.535421	1.130263	1.102522
Observations	2040	2040	2041	2040	2040	2040	2040	2040	2040	2040	2040	2040

Table 4 Correlation, Included observations 2040

Correlation	CORN_2_YELLOW_LOGRET	ETHANOL_LOGRET	LENDING_RATE_FED	OPEN_MKT_OPER_ECB_LOGRET	OIL_WTA_LOGRET	RAPESEED_LOGRET	REX_LOGRET	S_P_500_LOGRET	SOYBEAN_LOGRET	SOYBEAN_OIL_LOGRET	SUGAR_LOGRET	WHEAT_1ST_LOGRET
CORN_2_YELLOW_LOGRET	1.000000											
ETHANOL_LOGRET	0.477128	1.000000										
LENDING_RATE_FED	0.021125	0.001201	1.000000									
OPEN_MKT_OPER_ECB_LOGRET	-0.030374	-0.004318	0.003141	1.000000								
OIL_WTA_LOGRET	0.309830	0.312517	0.011685	-0.018506	1.000000							
RAPESEED_LOGRET	0.368353	0.318281	0.034520	-0.020459	0.338098	1.000000						
REX_LOGRET	-0.227702	-0.196279	-0.022688	0.015536	-0.326152	-0.118725	1.000000					
S_P_500_LOGRET	0.164910	0.136081	-0.010529	-0.016338	0.334110	0.154930	-0.350642	1.000000				
SOYBEAN_LOGRET	0.582217	0.338295	0.017107	-0.037047	0.374721	0.485498	-0.235275	0.200732	1.000000			
SOYBEAN_OIL_LOGRET	0.544030	0.384659	0.030810	-0.040818	0.502919	0.548374	-0.286030	0.273851	0.734982	1.000000		
SUGAR_LOGRET	0.255326	0.207644	-0.005097	-0.025662	0.259582	0.216546	-0.159390	0.153400	0.249688	0.268358	1.000000	
WHEAT_1ST_LOGRET	0.659800	0.391250	0.032759	-0.047865	0.281826	0.379820	-0.196061	0.175574	0.440705	0.474824	0.226739	1.000000

Chart 1 Daily returns



4. Empirical analysis

4.1 Model specification

The GARCH family of statistical processes is adopted in order to investigate the nonlinear relationships between variables. Indeed, this class of models allows us to capture the relevant features of the data, namely the high non-normality of price returns, volatility clustering and lack of constant variance of errors. In addition, family GARCH models works better when data are sampled daily rather than at a lower frequency. Engle (1982) introduced the first autoregressive conditional Heteroskedasticity (ARCH) model which allows the conditional variance to change over time as a function of past innovations (or disturbance). Bollerslev (1986) generalized the ARCH model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of innovations. This extension is known as the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH). The ARCH and GARCH models explain time series behavior by allowing the conditional variance to evolve dynamically over time and respond to previous price changes.

The GARCH (1,1) model has the following form:

$$R_t \left| \Omega_{t-1} = \alpha + \beta' X_t + \varepsilon_t \right. \quad (1)$$

$$\varepsilon_t \left| \Omega_{t-1} \approx iid \ \mathrm{N}(0, \sigma_t^2) \right. \quad (2)$$

$$\sigma_t^2 = \gamma_0 + \delta_1 \sigma_{t-1}^2 + \mu_1 \varepsilon_{t-1}^2 \quad (3)$$

Equation 1 is called the conditional mean equation and depicts the first moment of the process. Specifically, conditional on the information available up to time t-1[6], the commodity price returns at time t (R_t) are a function of a drift coefficient (α) that denotes the average returns, a set of independent economic and financial variables (X_t), with the associated coefficients to be estimated βs, and an error term (ε_t). Equation 2 indicates that the error term is assumed to be independently and identically normally distributed with zero mean and conditional variance σ^2_t conditioned by the information set Ω_{t-1}. Equation 3 is the conditional variance equation and describes the second moment of the process. It indicates

[6] "Unconditional" describes situations where one has no information.

that the value of the conditional variance scaling parameter σ^2_t depends on a) the long-term average value (γ_0); b) the past values of the variance itself, which are captured by lagged σ^2_t term $(\delta_1 \sigma^2_{t-1})$; and c) the lagged squared residual term $(\mu_1 \varepsilon^2_{t-1})$, which denotes the past values of shocks or news. This implies that the larger the shocks, the greater the volatility in the series. Put differently, the coefficient δ_1 represents the GARCH effect and μ_1 represents the ARCH effect, or short run persistence of shocks to returns. The sum of the ARCH and GARCH coefficients ($\mu_1 + \delta_1$) measures the persistence of the contribution of shocks to returns to long-run persistence and indicates persistence in volatility clustering. The sum ($\mu_1 + \delta_1$) varies from 0 to 1. The nearer it is to 1 the more persistent the volatility clustering. When using the GARCH approach the conditional standard deviation is the measure of volatility, and is given by the square root of each of the fitted values of σ^2_t (equation 3). Unlike the volatility in the absence of the ARCH effect (where it remains constant for the entire period and can hence be presented by a single value), the conditional standard deviation varies over time.

While GARCH models consider non-linearity in the conditional mean equation and are able to capture volatility clustering and leptokurtosis, they fail to model the leverage effect since their distribution is symmetric. Put differently, GARCH models assume that negative and positive shocks of equal magnitude have identical impact on the conditional variance, i.e. they enforce a symmetric response of variance to positive and negative innovations. This arises since the conditional variance in the GARCH model is a function of the magnitudes of the lagged residuals and not their signs (indeed by squaring the lagged error in GARCH the sign is lost). Since the positive and negative shocks on conditional volatility can be asymmetric (leverage effect), variants of the GARCH model have been developed to capture asymmetry. Some of the models include the Exponential GARCH (EGARCH), originally proposed by Nelson (1991); the Threshold GARCH (TGARCH) model by Zakoian (1994); the GJR-GARCH by Glosten, Jagannathan, and Runkle (1993); and the Asymmetric Power ARCH (APARCH) by Ding, Granger and Engle (1993)[7]. In the following analysis, a GARCH model will be tested against three specifications of EGARCH models, which can characterize asymmetric responses to shocks. The EGARCH specification is given by:

[7] See Tim Bollerslev (2009) for an extensive reference guide to the long list of ARCH-GARCH family models.

$$\ln \sigma_t^2 = \gamma_0 + \delta_1 \sigma_{t-1}^2 + \mu_1 \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} \right] + \gamma_1 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \quad (4)$$

Where the coefficient δ_1 represents the GARCH effect, μ_1 represents the ARCH effect and γ_1 is the asymmetry term. When the asymmetry coefficient is negative, then negative shocks tend to produce higher volatility in the immediate future than positive shocks. The opposite would be true if γ_1 were positive.

4.2 Empirical results

In the first step, the presence of ARCH effects, as described in Engle (1982), were tested for each food commodity return estimating an ARMA model via OLS (Table 5). Then the ARCH test on residuals was performed to check for the presence of autoregressive conditional heteroskedasticity. Table 5 shows that the AR(1) coefficients and the MA(1) coefficients are significant and there are resilient ARCH effects (the values of the heteroskedasticity test statistic for all the samples reject the null of homoskedasticity) that point to the fact that the volatility in the prices of these crops is time varying. Therefore an ARCH-GARCH approach can be used.

Table 5 Testing for Arch Effects

	CORN_2_YELLOW_LOGRET	RAPESEED_LOGRET	SOYBEAN_LOGRET	SOYBEAN_OIL_LOGRET	SUGAR_LOGRET	WHEAT_1ST_LOGRET
C	0.0006	0.0004	0.0005	0.0004	0.0003	0.0004
	(0.2303)	(0.2030)	(0.2781)	(0.2832)	(0.5155)	(0.4391)
AR(1)	-0.505	-0.974***	0.803***	-0.718**	0.751*	0.682*
	(0.1152)	(0.0000)	(0.0000)	(0.0357)	(0.0904)	(0.0714)
MA(1)	0.548*	0.967***	-0.823***	0.736**	-0.761*	-0.695*
	(0.0776)	(0.0000)	(0.0000)	(0.0269)	(0.0815)	(0.0616)
			Heteroskedasticity Test: ARCH on residuals			
F-statistic	12.188	27.043	144.280	52.407	15.994	16.917
Prob. F(5,2028)	0.0000˜	0.0000˜	0.0000˜	0.0000˜	0.0000˜	0.0000˜
Obs*R-squared	59.336	127.136	533.690	232.738	77.167	81.437
Prob. Chi-Square(5)	0.0000˜	0.0000˜	0.0000˜	0.0000˜	0.0000˜	0.0000˜

Note: Dependent variable: Commodity log returns (LOGRET), i.e. log changes in price. *p-values are in brackets* Method: Least Squares. The test for the presence of ARCH in the residuals is computed by regressing the squared residuals on a constant and p lags set to 5, since trading days are considered. ˜ Reject null hypothesis of no ARCH effect at 1 percent level of significance, indicating time-varying volatility

Five models have been implemented under maximum likelihood (ML) estimation[8]: two traditional GARCH and three EGARCH specifications to account for leverage effects. The commodity variables (log returns of futures prices) are the dependent variables in the models. The exogenous variables include ethanol log returns, oil log returns, exchange rate log returns, S&P 500 log returns, log open market operations and Fed funds in their first difference[9]. The total number of daily observations is 2041.

The results are reported in Tables 10-15 in the Appendix. The first part of each table sketches the outcomes for the mean equation and the second part highlights the variance equation. The five models reveal that energy returns (ethanol and oil) exert an upward pressure on the considered commodities futures returns. This could be due to the effects of higher expected input costs such as fertilizers, pesticides and fuels on commodity futures returns, and to the fact that the production of grains, oils and seeds becomes competitive in the energy sector as feedstock for the production of biofuels. In addition, energy futures, which make up the larger part of the commodity futures portfolio, may dominate investors' behavior, and expectations for increasing energy prices may trigger increases in investments in all commodities. This might transmit upward movements in oil and ethanol prices to food commodities, increasing the correlation across all commodity futures and providing another link between the energy and food markets. The findings show that the stock market (S&P 500) also positively affects the commodity market. The exchange rate enters the equations with the expected negative sign. This can be explained by the fact that the volatility of the U.S. dollar/euro weakens the confidence in commodities markets, creating an unstable environment for investments. The monetary variables entering the models show a positive sign for the open market operations and a negative sign for the fed interest rate.

Although the coefficients among the five models do not vary that much, on the basis of the information criteria method (minimum values), the maximum likelihood method (maximum values), and the significance of the asymmetric coefficients, the baseline specification is the EGARCH model 3 for all commodities excluding soybeans and soybean oil, for which the

[8] The method works by finding the most likely values of the parameters given the actual data. More specifically, a log-likelihood function is formed and the values of the parameters that maximise it are sought (Brooks, 2008).

[9] In GARCH models the series need to be stationary to stabilize the variance. Therefore, when the logs of the changes of the series were not used, the series have been differenced, as in the case of liquidity measures.

baseline specification is the GARCH model 1. The baseline results of the mean equations are summarized in Table 6, the baseline for the variance equations are in Table 7.

Table 6 Baseline mean equations for commodity returns

Variables	Corn EGARCH Model 3	Rapeseed EGARCH Model 3	Soybean GARCH Model 1	Soybean oil GARCH Model 1	Sugar EGARCH Model 3	Wheat EGARCH Model 3
	Mean equation	Mean equation	Mean equation	Mean equation	Mean equation	Mean equation
Ethanol_logret	0.607***	0.111***	0.198***	0.175***	0.106***	0.398***
	(0.013)	(0.009)	(0.013)	(0.012)	(0.021)	(0.017)
Oil_wta_logret	0.078***	0.106***	0.174***	0.247***	0.157***	0.111***
	(0.017)	(0.008)	(0.014)	(0.012)	(0.021)	(0.018)
Rex_logret	-0.219***	-0.052*	-0.202***	-0.189***	-0.197***	-0.255***
	(0.058)	(0.029)	(0.049)	(0.043)	(0.073)	(0.069)
S&P_500_logret	0.034	0.028*	0.048*	0.074***	0.101***	0.091***
	(0.029)	(0.016)	(0.026)	(0.022)	(0.037)	(0.032)
Monetary liquidity	--	--	--	--	--	--

In detail, the baseline specifications reveal that ethanol returns have a larger impact on corn (0.6) and wheat (0.4) and less impact on other commodities. This implies that a 1% increase in biofuels returns is associated with 0.6% and 0.4% increases in corn and wheat returns respectively. Ethanol is the variable that exerts the most influential role among other variables on corn and wheat futures returns. In any case, one should mention that there are multiple and complex interactions between factors, and drivers influence each other through various linkages and feedback loops. For instance, the link between energy and non-energy commodities is much more complex and broad, with a number of additional dimensions. These dimensions include high energy intensity of most agricultural commodities, transmission elasticities that may change overtime and likely spillover-effects from crude oil to non-energy markets through investment fund activity. The oil variable positively impacts commodity futures returns. Its influence ranges between 0.078 for corn and 0.247 for soybean oil. This result testifies that energy and agricultural prices have become increasingly interwoven, in line with Tang and Xiong (2012) and Chen et al. (2010).

The exchange rate variable enters the equation with a negative sign and it is significant for all considered commodities. In particular, a 1% U.S. dollar appreciation leads to a decrease in commodity futures prices, with a consequent drop in returns ranging between 0.052 and 0.255%. Wheat is the commodity futures that is most influenced by exchange rate movements, while rapeseed is the less influenced. The S&P 500 returns are generally positive and significant meaning that the movements in stock markets returns put an upward pressure on agricultural commodity futures returns. The variable is not significant only for corn. The highest market's reaction to the S&P 500 price change is observed in the sugar market, followed by the wheat and soybean oil markets, with estimated coefficients of 0.101, 0.091 and 0.074, respectively. The value for the impact of S&P returns on wheat returns is similar to that (0.0981) computed by Mensi et al. (2013).

It is valuable noting that the baseline equations do not include any monetary liquidity measures (table 6). It has been argued that the loose monetary policies pursued by the world's main central banks in response to the global financial crisis and the subsequent recession in advanced countries have led to a surge of global liquidity with a consequent increase in commodity prices/returns (Belke at al. 2013). The results of this analysis highlight that monetary liquidity does not influence commodity futures returns on a daily basis (Tables 10-15, appendix). The coefficients of liquidity, in fact, although they have the expected signs, are not significant. This however does not imply that a positive long-run relation between global liquidity and the development of food commodity prices returns could not exist. Generally, monetary policy does not have an immediate effect on the economy, therefore it appears realistic that monetary liquidity does not trigger commodity returns on a daily basis. The effects of monetary policy on prices occur with significant lags, which are unforeseeable in their duration. This result is confirmed if different measures of liquidity are used. Indeed, it turns out that both open market operations and the federal effective funds rate do not influence futures returns. In short, an increase in monetary liquidity does not have an immediate impact on the commodity markets.

Turning to the variance equations of the baseline models (Table 7), the coefficients on both the lagged squared residuals (ARCH term) and lagged conditional variance terms (GARCH term) in the conditional variance equation are highly statistically significant. The effect of “news” (unexpected shocks) on commodity markets at time $t - 1$ impacts current returns to a different extent, with a higher impact on rapeseed (0.343) and a lesser effect on soybean oil (0.068). The GARCH term ($\delta 1$) has a coefficient of 0.99 for corn and sugar and 0.95 for wheat, and a smaller value of 0.81 for soybeans, which implies that 99%, 95% and 81% of a variance shock remains the next day, suggesting the presence of volatility clustering in the daily returns. The persistence parameters ($\delta + \mu$) are very large for all commodities, suggesting that shocks to the conditional variance will be highly persistent and that the variance moves slowly through time, so that volatility takes a long time to die out following a shock. It is worthwhile mentioning that since the ARCH term + GARCH term <1 for all commodities, the second moment and log moment conditions are satisfied in all markets, and this is a sufficient condition for consistency and asymptotic normality of the ML-ARCH-Marquardt estimator.

The asymmetry coefficient c(8) in models 3, 4, and 5 is significant for all commodities, with the exception of soybeans and soybean oil. This implies that there are leverage effects for corn, rapeseed, sugar, and wheat, but not for soybeans and soybean oil. This different feature is reflected in the structure of the selected baseline models. In more detail, the variance equations of the baseline models reported in Table 7 show that the asymmetry coefficients are significant and negative for corn and rapeseed, and positive for sugar and wheat. When the coefficient is negative, then negative shocks tend to produce higher volatility in the immediate future than positive shocks, i.e. the variance goes up more after negative news than after good news. The opposite would be true if γ_1 were positive: when the asymmetric coefficient is larger than zero, then positive innovations are more destabilizing than negative innovations.

Table 7 Baseline variance equations for commodity returns

Variables	Corn EGARCH Model 3	Rapeseed EGARCH Model 3	Soybean GARCH Model 1	Soybean oil GARCH Model 1	Sugar EGARCH Model 3	Wheat EGARCH Model 3
	variance equation	variance equation	variance equation	variance equation	variance equation	variance equation
Constant	-0.157***	-1.467***	1.35E-05***	3.51E-06***	-0.117***	-0.488***
γ_0	(0.025)	(0.157)	(2.21E-06)	(1.11E-06)	(0.019)	(0.103)
Arch term	0.103***	0.343***	0.143***	0.068***	0.091***	0.146***
$\mu_1\left[\frac{\lvert\varepsilon_{t-1}\rvert}{\sqrt{\sigma_{t-1}^2}}\right]^{(a)}$, $\mu_1\varepsilon_{t-1}^{2\ (b)}$	(0.011)	(0.023)	(0.010)	(0.010)	(0.010)	(0.023)
Garch term	0.990***	0.868***	0.812***	0.912***	0.994***	0.952***
$\delta_1\sigma_{t-1}^2$	(0.003)	(0.016)	(0.017)	(0.013)	(0.002)	(0.012)
Asymmetry coef	-0.040***	-0.064***			0.019***	0.054***
$\gamma_1\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}$	(0.006)	(0.012)			(0.006)	(0.012)

(a) EGARCH (b) GARCH

Some diagnostic tests were performed for all the models[10]. They reveal that there is absence of serial correlation among the standardized residuals as highlighted by the correlogram and Ljung Box Q Statistic. Furthermore, the ARCH-LM test reveals that there are no ARCH remaining effects, confirming the strength of the adopted models. Only the property of normality is not met; however, this is a common feature of several financial series.

4.3 A multivariate extension

The models described thus far are models of single markets. When examining several markets or several assets in the same market, one can ask “does the volatility of one influence the volatility of another?” In particular, the volatility of an individual market or asset could be influenced by the volatility of other markets or assets. This implies that one should estimate the correlations and covariances between individual assets in order to

[10] The residual analysis is not reported for reasons of space, but is available upon request.

understand if there is a link between the magnitude of correlations and the magnitude of variances and how correlations propagate between different markets.

Thus an empirical extension of the models has been carried out to estimate agricultural commodity, oil, and ethanol markets simultaneously and to evaluate their likely interdependency and the presence of spillovers in the mean and/or the variance equations. To this purpose, a multivariate GARCH model with dynamic covariances and conditional correlation, the BEKK parameterization[11] (Baba, Engle, Kraft, and Kroner, 1990), has been adopted. This type of model has been shown to be more useful in studying cross-market volatility spillover effects than univariate models, which are likely to occur with increasing market integration.

In each equation, the returns of each food commodity, oil and ethanol are regressed on macroeconomics and financial controls, on the lagged dependent variable and on the lagged returns of the other energy and non-energy commodities.

The diagonal BEKK parameterization (Engle and Kroner, 1995) of the conditional variance-covariance matrix H_t is given by:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

The matrices A, B, and C possess the dimension (nxn); C is a 3x3 matrix of the constant, A is a matrix containing "*a*" elements that measure the degree of innovation from market i to market j, and B shows the persistence in the conditional volatility. In the present model A and B are diagonal matrices. The resulting variance and covariance equations for N=3 (commodity, oil and ethanol) are*:*

$$h_{11} = c_{11} + a_{11}^2\varepsilon_1^2 + b_{11}^2 h_1^2 \quad (5)$$

$$h_{21} = c_{21} + a_{11}a_{22}\varepsilon_1\varepsilon_2 + b_{11}b_{22}h_1h_2 \quad (6)$$

$$h_{31} = c_{31} + a_{11}a_{33}\varepsilon_1\varepsilon_3 + b_{11}b_{33}h_1h_3 \quad (7)$$

[11] Other multivariate GARCH models are the CCC (constant conditional correlation) and DCC (dynamic conditional correlation) models. For an extensive survey of multivariate GARCH models, see Bauwens et al. (2006).

$$h_{22} = c_{22} + a_{22}^2 \varepsilon_2^2 + b_{22}^2 h_2^2 \quad (8)$$

$$h_{32} = c_{32} + a_{22} a_{33} \varepsilon_2 \varepsilon_3 + b_{22} b_{33} h_2 h_3 \quad (9)$$

$$h_{33} = c_{33} + a_{33}^2 \varepsilon_3^2 + b_{33}^2 h_3^2 \quad (10)$$

The results of the estimations for the mean and variance equations are reported in Tables 13-18 in the appendix. The coefficients C(2), C(3), and C(4) in the mean equations capture own and cross-markets dependence for the agricultural commodities, i.e. the dependence of food commodity returns on its lagged value (C(2)), and the dependence of food commodity returns on the lagged returns in the ethanol and oil markets (C(3) and C(4)). In the same way, the two groups of coefficients C(9)-C(10)-C(11), and C(16)-C(17)-C(18) in the mean equations capture own and cross-markets dependence for ethanol and oil markets, respectively.

Specifically, the BEKK model for corn-ethanol and oil points to a linkage between the agriculture and energy markets; indeed in the last period ethanol (C(3)) and oil (C(4)) returns are statistically significant in explaining current corn returns in the first moment of the process. Conversely, last period corn returns do not explain current ethanol (C9) and oil (C16) returns. This means that there are mean spillovers going from energy markets to corn markets, but not vice-versa. This confirms the validity of the results obtained in the univariate setting. The same results are found for wheat, sugar, and soybeans, where the mean equations reveal that current returns are influenced by the lagged returns in oil and ethanol markets. For soybean oil and rapeseed the results point to a weak significance or no significance of past ethanol in explaining returns. This would suggest that the univariate model can have a caveat due to the fact that the proxy for biofuels (ethanol price changes) is not so precise for oilseed commodities, for which it would be better to use biodiesel prices. An interesting aspect that emerges is that past oil and ethanol returns negatively impact current commodity futures returns, while when considering synchronous timing, as in the univariate case, the current oil and ethanol returns positively impact current commodity futures returns. This points to a sort of J-curve behavior of the effect of price change variations on commodity returns, probably due to the fact that when there is not time idiosyncrasy, an increase in oil and ethanol returns would further increase the demand for these financial products because investors are attracted by higher returns with a consequent drop in the demand for futures contracts in agricultural markets. When instead all markets are considered with synchronous time, the effect of increase in oil and ethanol returns translated to an increase in returns for the agricultural market, too. This is indeed a typical phenomenon in the financial markets: when there is good news there is an overreaction in the affected market, with a partial correction in the following period.

As regards the other exogenous variables, the S&P is always significant and positively linked to commodity markets with the highest impact on sugar, wheat and soybean oil; the exchange rate is always significant and negatively linked to commodity markets, while monetary liquidity is not significant. These results also corroborate the univariate framework.

Turning to the variance-covariance matrix, in the diagonal BEKK it is possible to identify own volatility spillover (A1) reflected by lagged innovations on the current conditional returns, and own volatility persistence (B1) in each markets, i.e. the dependence of volatility in market i on its own past volatility. It emerges that the variance of returns in each market are more influenced by their own lagged values (B1) rather than by “old news” (A1), which is reflected by lagged innovations. In particular, “old news” or past shocks affect more oil markets, while the corn market exhibits the highest own volatility persistence. For the other commodities the past conditional variances affect the current level of conditional variances, as well. Indeed, the GARCH effect (B1) can be interpreted as long term persistence and ARCH effect (A1) as short-term persistence; thus own volatility long-run persistence is larger than short-run persistence.

In sum, energy and agricultural markets seems to be interrelated at a mean level with spillovers going from energy to commodity markets.

5. Conclusions

Biofuels production has rapidly increased worldwide as one of several strategies to make economies “greener”. The increase in biofuels production, mainly reliant on first-generation technologies, has increased demand for food commodities, and has pushed prices up. This study examined the role of energy factors, namely biofuels and oil, financial factors, and macroeconomic factors on daily commodity futures price returns. Since many relationships in futures markets are non-linear a GARCH approach in an univariate and multivariate framework was adopted. This allowed us to better capture the relevant features of the data, namely leptokurtosis, volatility clustering, and non-constant variance of the errors. Family GARCH models work better when data are sampled daily rather than at a lower frequency.

The results reveal that a complex of factors contributes to movements in daily futures returns including energy factors, macroeconomic variables, and stock market, which require a complex response at the international level. The significance of the Standard & Poor’s 500 illustrates the magnified effect of stock market returns on commodity price returns, which is more pronounced for sugar, wheat and soybean oil markets. The evolution in commodity and stock in the same direction reduces their potential substitutability in portfolios and risk diversification for investors. An increase in exchange rate returns has a curbing effect on all commodity futures returns. The results of this analysis further highlight that monetary liquidity does not influence commodity returns on a daily basis. This, however, does not imply that a positive long-run relationship between global liquidity and the development of food commodity price returns could not exist. Generally, monetary policy does not have an immediate effect on the economy, therefore it appears realistic that monetary liquidity does not trigger commodity returns immediately but with lags.

It emerges that the past variance (δ_1) has a greater influence on current variance than past innovations (μ_1), and that the sum of the coefficients on the lagged squared error and lagged conditional variance is very close to unity. This implies that shocks to conditional variance will be highly persistent and therefore the variance reverts or “decays” toward its long-run average very slowly.

The results further reveal that the leverage effects γ are negative and significant at a 5% significance level for corn and rapeseed, which means that good news generates less volatility than bad news for these commodity markets, while the contrary happens for wheat and sugar.

The multivariate model supports the findings of the univariate setting and provides evidence of mean spillovers in the price returns across energy and agricultural markets. Both lagged oil and ethanol returns have a significant influence on corn, wheat, sugar and soybeans. This implies that energy markets can influence price changes, and thus increase volatility in agricultural markets. This would indicate that biofuel policies should be carefully monitored and in some cases changed to avoid unnecessary first-generation subsidization. It would be appropriate to ameliorate technology to move toward second-generation biofuels and offer incentives to use food wastes.

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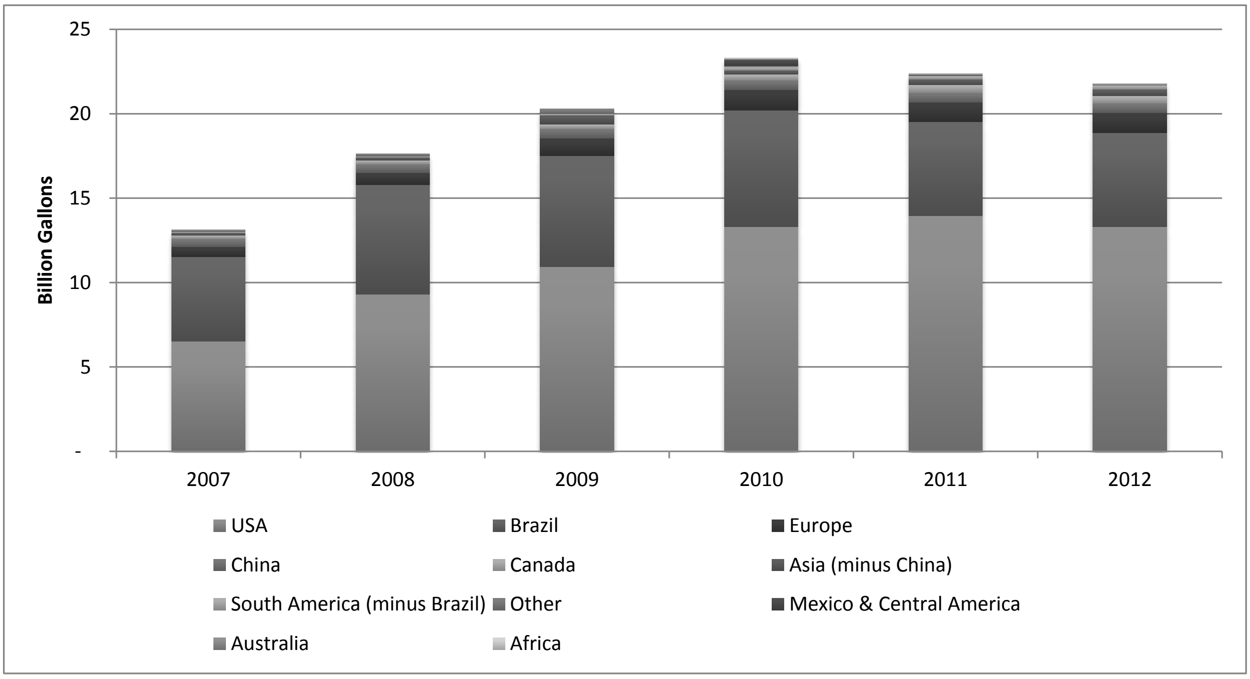
Appendix

Table 8 Ethanol and biodiesel production, 2006-2012

Year	World Ethanol Fuel Production	World Biodiesel Production
	(Million Liters)	(Million Gallons)
2006	39252	1710
2007	49625	2775
2008	66075	4132
2009	73088	4699
2010	85047	4893
2011	84501	5651
2012	85088	5670

Source: *F.O. Licht and Worldwatch*

Chart 2 Global Ethanol Production by Country and Year



Source: Elaborations on www.afdc.energy.gov/data/

Table 9 Dataset

Commodity	Exchange	Bloomberg Ticker
Generic 1st Corn No. 2 Yellow futures, US$	Chicago Board of Trade (CBOT)	C 1 Comdty
Generic 1st Rapeseed, €	LIFFE Paris	IJ1 Comdty
Generic 1st Soybean No. 2 Yellow futures, US$	Chicago Board of Trade (CBOT)	S 1 Comdty
Generic 1st Soybean oil, US$	Chicago Board of Trade (CBOT)	BO1 Comdty
Generic 1st Sugar No. 11 futures, US$	Intercontinental Exchange (ICE)	SB1 Comdty
Generic 1st Wheat futures, US$	Chicago Board of Trade (CBOT)	W 1 Comdty
Generic 1st Ethanol, cme futures, US$	Chicago Board of Trade (CBOT)	DL1 Comdty
Generic 1st WTI Crude Oil futures, US$	New York Mercantile Exchange NYMEX	CL1 Comdty
Standard & Poor's 500	Chicago Mercantile Exchange	SPX Index
Dollar Euro exchange rate	FOREX Price of 1 USD in EUR	USDEUR Curncy
Dollar Jen exchange rate	FOREX Price of 1 USD in Jen	USDJPY Curncy
Outstanding open market operations ECB	Open market	ECBLEFAC Index
Federal fund rate (overnight interest rate)	Open market	FEDL01 Index

Note: Generic 1st Corn No. 2 Yellow futures= corn is quoted in U.S. cents per bushel
Generic 1st Rapeseed futures= rapeseed is quoted in euro and euro cents per tonne
Generic 1st Soybean No. 2 Yellow futures= soybean is quoted in U.S. cents per pound
Generic 1st Soybean oil futures= soybean oil is quoted in U.S. cents per pound
Generic 1st Sugar No. 11 futures= sugar is quoted in U.S. cents per pound
Generic 1st Wheat futures= wheat is quoted in US cents per bushel
Generic 1st Ethanol, cme futures = ethanol is quoted in U.S. dollars and cents per gallon
Generic 1st WTI Crude Oil futures= crude oil is quoted in U.S. dollars per barrel, WTI crude oil generic one month futures contracts.
Rapeseed prices have been converted in US$.

Table 10 Estimations for Corn returns

Variables	Model 1 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 2 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 3 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 4 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 5 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution	
	Mean equation		Mean equation		Mean equation		Mean equation		Mean equation	
Ethanol_logret	0.569*** (0.012)		0.568*** (0.011)		0.607*** (0.013)		0.609*** (0.014)		0.608*** (0.013)	
Oil_wta_logret	0.093*** (0.018)		0.092*** (0.018)		0.078*** (0.017)		0.075*** (0.017)		0.077*** (0.017)	
Rex_logret	-0.243*** (0.061)		-0.245*** (0.062)		-0.219*** (0.058)		-0.222*** (0.058)		-0.222*** (0.058)	
S&P_500_logret	0.036 (0.028)		0.038 (0.029)		0.034 (0.029)		0.040 (0.029)		0.034 (0.029)	
D_Open_mkt_oper_log			-				0.004 (0.004)		-	
D_lending_rate_fed			-0.003 (0.005)				-		-0.002 (0.005)	
	Variance Equation		Variance Equation		Variance Equation		Variance Equation		Variance Equation	
	C	4.34E-06*** (1.04E-06)	C	4.76E-06*** (1.11 E-06)	C(6)	-0.157*** (0.025)	C(6)	-0.161*** (0.025)	C(6)	-0.160*** (0.026)
	resid(-1)^2	0.048*** (0.006)	resid(-1)^2	0.051*** (0.006)	C(7)	0.103*** (0.011)	C(7)	0.106*** (0.011)	C(7)	0.104*** (0.011)
	garch(-1)	0.940*** (0.007)	garch(-1)	0.937*** (0.007)	C(8)	-0.040*** (0.006)	C(8)	-0.042*** (0.006)	C(8)	-0.041*** (0.006)
					C(9)	0.990*** (0.003)	C(9)	0.989*** (0.003)	C(9)	0.989*** (0.003)
N. of obs	2040		2035		2040		2035		2035	
R-squared	0.253		0.254		0.244		0.245		0.244	
S.E. of regression	0.018		0.018		0.019		0.019		0.019	
Log likelihood	5328.65		5317.04		5345.19		5334.29		5334.13	
Durbin-Watson	1.892		1.892		1.889		1.889		1.891	
Akaike info crit.	-5.217		-5.217		-5.232		-5.233		-5.233	
Schwarz criterion	-5.198		-5.195		-5.210		-5.208		-5.209	
Convergence	31 iterations		29 iterations		25 iterations		27 iterations		31 iterations	

Note: Estimation method: *ML - ARCH (Marquardt) - Normal distribution. Dependent variable:* CORN_2_YELLOW_LOGRET. *Std-error are in brackets. ***p<0.01, **p<0.05, *p<0.10. Models 3-4-5:* LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8) *RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1)).
D(·) is the differentiation operator.

Table 11 Estimations for Rapeseed returns

Variables	Model 1 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 2 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 3 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 4 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 5 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution	
	Mean equation		Mean equation		Mean equation		Mean equation		Mean equation	
Ethanol_logret	0.111*** (0.009)		0.112*** (0.009)		0.111*** (0.009)		0.111*** (0.009)		0.110*** (0.009)	
Oil_wta_logret	0.108*** (0.008)		0.108*** (0.009)		0.106*** (0.008)		0.108*** (0.009)		0.108*** (0.008)	
Rex_logret	-0.146*** (0.034)		-0.044 (0.031)		-0.052* (0.029)		- 0.056* (0.030)		-0.054* (0.029)	
S&P_500_logret	0.085*** (0.016)		0.028* (0.016)		0.028* (0.016)		0.029* (0.016)		0.027* (0.016)	
D_Open_mkt_oper_log			-				0.001 (0.002)		-	
D_Lending_rate_fed			-0.0004 (0.003)				-		-0.0002 (0.003)	
	Variance Equation		Variance Equation		Variance Equation		Variance Equation		Variance Equation	
	C	1.15E-05*** (1.46E-06)	C	1.13E-05*** (1.43E-06)	C(6)	-1.467*** (0.157)	C(6)	-1.445*** (0.157)	C(6)	-1.455*** (0.153)
	resid(-1)^2	0.179*** (0.017)	resid(-1)^2	0.173*** (0.016)	C(7)	0.343*** (0.023)	C(7)	0.339*** (0.023)	C(7)	0.341*** (0.023)
	garch(-1)	0.730*** (0.021)	garch(-1)	0.739*** (0.021)	C(8)	-0.064*** (0.012)	C(8)	-0.064*** (0.011)	C(8)	-0.064*** (0.012)
					C(9)	0.868*** (0.016)	C(9)	0.870*** (0.016)	C(9)	0.869*** (0.016)
N. of obs	2040		2035		2040		2035		2035	
R-squared	0.120		0.162		0.112		0.161		0.161	
S.E. of regression	0.011		0.011		0.011		0.011		0.011	
Log likelihood	6505.18		6478.03		6513.52		6496.54		6496.34	
Durbin-Watson	1.713		1.699		1.700		1.699		1.699	
Akaike info crit.	-6.374		-6.359		-6.378		-6.375		-6.376	
Schwarz criterion	-6.354		-6.337		-6.356		-6.351		-6.351	
Convergence	14 iterations		14 iterations		15 iterations		23 iterations		16 iterations	

Note: Estimation method: *ML - ARCH (Marquardt) - Normal distribution. Dependent variable:* RAPESEED_LOGRET. *Std-error are in brackets. ***p<0.01, **p<0.05, *p<0.10. Model 3,*4, 5: LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8) *RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1)). D(·) is the differentiation operator.

Table 12 Estimations for Soybean returns

Variables	Model 1 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 2 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 3 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 4 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 5 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution	
	Mean equation		Mean equation		Mean equation		Mean equation		Mean equation	
Ethanol_logret	0.198*** (0.013)		0.198*** (0.013)		0.197*** (0.013)		0.197*** (0.013)		0.198*** (0.013)	
Oil_wta_logret	0.174*** (0.014)		0.174*** (0.014)		0.164*** (0.014)		0.167*** (0.014)		0.166*** (0.014)	
Rex_logret	-0.202*** (0.049)		-0.195*** (0.048)		-0.199*** (0.048)		-0.205* (0.047)		-0.196*** (0.047)	
S&P_500_logret	0.048* (0.026)		0.051* (0.026)		0.044* (0.025)		0.040* (0.025)		0.045* (0.025)	
D_Open_mkt_oper_log			-				0.004 (0.003)		-	
D_Lending_rate_fed			-0.008 (0.005)				-		-0.009* (0.005)	
	Variance Equation		Variance Equation		Variance Equation		Variance Equation		Variance Equation	
	C	1.35E-05*** (2.21E-06)	C	1.34E-05*** (2.20E-06)	C(6)	-0.524*** (0.075)	C(6)	-0.540*** (0.076)	C(6)	-0.550*** (0.078)
	resid(-1)^2	0.143*** (0.010)	resid(-1)^2	0.142*** (0.010)	C(7)	0.255*** (0.014)	C(7)	0.258*** (0.014)	C(7)	0.260*** (0.014)
	garch(-1)	0.812*** (0.017)	garch(-1)	0.813*** (0.017)	C(8)	0.007 (0.011)	C(8)	0.007 (0.011)	C(8)	0.007 (0.011)
					C(9)	0.961*** (0.008)	C(9)	0.959*** (0.008)	C(9)	0.958*** (0.008)
N. of obs	2040		2035		2040		2035		2035	
R-squared	0.203		0.206		0.201		0.202		0.204	
S.E. of regression	0.017		0.016		0.017		0.017		0.016	
Log likelihood	5707.66		5694.89		5710.29		5696.27		5697.84	
Durbin-Watson	2.006		2.011		2.007		2.000		2.012	
Akaike info crit.	-5.589		-5.589		-5.590		-5.589		-5.591	
Schwarz criterion	-5.569		-5.566		-5.568		-5.565		-5.566	
Convergence	26 iterations		32 iterations		46 iterations		67 iterations		58 iterations	

Note: Estimation method: *ML - ARCH (Marquardt) - Normal distribution. Dependent variable:* SOYBEAN_LOGRET. *Std-error are in brackets. ***p<0.01, **p<0.05, *p<0.10. Models 3-4-5:* LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8) *RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1)).
D(·) is the differentiation operator.

Table 13 Estimations for Soybean oil returns

Variables	Model 1 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 2 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 3 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 4 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 5 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution	
	Mean equation		Mean equation		Mean equation		Mean equation		Mean equation	
Ethanol_logret	0.175*** (0.012)		0.175*** (0.012)		0.173*** (0.012)		0.173*** (0.012)		0.171*** (0.012)	
Oil_wta_logret	0.247*** (0.012)		0.246*** (0.012)		0.250*** (0.012)		0.250*** (0.012)		0.250*** (0.012)	
Rex_logret	-0.189*** (0.043)		-0.189*** (0.043)		-0.190*** (0.042)		-0.194*** (0.042)		-0.189*** (0.043)	
S&P_500_logret	0.074*** (0.022)		0.075*** (0.022)		0.079*** (0.22)		0.077*** (0.022)		0.080*** (0.023)	
D_Open_mkt_oper_log			-				0.004 (0.003)		-	
D_Lending_rate_fed			-0.003 (8.98E-05)				-		-0.002 (0.003)	
	Variance Equation		Variance Equation		Variance Equation		Variance Equation		Variance Equation	
	C	3.51E-06*** (1.11E-06)	C	3.26E-06*** (1.05E-06)	C(6)	-0.306*** (0.075)	C(6)	-0.293*** (0.068)	C(6)	-0.289*** (0.065)
	resid(-1)^2	0.068*** (0.010)	resid(-1)^2	0.065*** (0.009)	C(7)	0.151*** (0.014)	C(7)	0.148*** (0.018)	C(7)	0.147*** (0.018)
	garch(-1)	0.912*** (0.013)	garch(-1)	0.916*** (0.012)	C(8)	-0.005 (0.011)	C(8)	-0.004 (0.010)	C(8)	-0.005 (0.010)
					C(9)	0.978*** (0.008)	C(9)	0.980*** (0.007)	C(9)	0.980*** (0.006)
N. of obs	2040		2035		2040		2035		2035	
R-squared	0.325		0.326		0.326		0.325		0.326	
S.E. of regres.	0.013		0.013		0.013		0.013		0.013	
Log likelihood	6030.13		6016.23		6029.62		6016.19		6015.71	
Durbin-Watson	1.941		1.940		1.942		1.939		1.942	
Akaike info cr.	-5.905		-5.905		-5.903		-5.903		-5.903	
Schwarz cr.	-5.885		-5.883		-5.881		-5.879		-5.878	
Convergence	12 iterations		14 iterations		12 iterations		15 iterations		15iterations	

Note: Estimation method: *ML - ARCH (Marquardt) - Normal distribution. Dependent variable:* SOYBEAN_OIL_LOGRET. *Std-error are in brackets. ***p<0.01, **p<0.05, *p<0.10. Models 3-4-5:* LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8) *RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1)). D(·) is the differentiation operator.

Table 14 Estimations for Sugar returns

Variables	Model 1 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 2 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 3 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 4 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 5 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution	
	Mean equation		Mean equation		Mean equation		Mean equation		Mean equation	
Ethanol_logret	0.100*** (0.022)		0.100*** (0.022)		0.106*** (0.021)		0.104*** (0.021)		0.104*** (0.021)	
Oil_wta_logret	0.161*** (0.021)		0.165*** (0.021)		0.157*** (0.021)		0.161*** (0.021)		0.161*** (0.021)	
Rex_logret	-0.205*** (0.072)		-0.201*** (0.071)		-0.197*** (0.073)		-0.196*** (0.073)		-0.196*** (0.071)	
S&P_500_logret	0.097** (0.039)		0.093** (0.039)		0.101*** (0.037)		0.097*** (0.037)		0.097*** (0.037)	
D_Open_mkt_oper_log			-				0.0002 (0.006)		-	
D_Lending_rate_fed			-0.001 (0.005)				-		-0.001 (0.005)	
	Variance Equation		Variance Equation		Variance Equation		Variance Equation		Variance Equation	
	C	2.47E-06*** (8.22E-07)	C	2.75E-06*** (8.22E-07)	C(6)	-0.117*** (0.019)	C(6)	-0.124*** (0.020)	C(6)	-0.123*** (0.020)
	resid(-1)^2	0.041*** (0.005)	resid(-1)^2	0.041*** (0.005)	C(7)	0.091*** (0.010)	C(7)	0.093*** (0.011)	C(7)	0.092*** (0.011)
	garch(-1)	0.955*** (0.005)	garch(-1)	0.955*** (0.005)	C(8)	0.019*** (0.006)	C(8)	0.020*** (0.006)	C(8)	0.020*** (0.006)
					C(9)	0.994*** (0.002)	C(9)	0.993*** (0.002)	C(9)	0.993*** (0.002)
N. of obs	2040		2035		2040		2035		2035	
R-squared	0.100		0.100		0.100		0.100		0.100	
S.E. of regression	0.022		0.022		0.023		0.022		0.022	
Log likelihood	4986.05		4971.05		4992.97		4978.17		4978.19	
Durbin-Watson	2.007		2.007		2.008		2.007		2.008	
Akaike info crit.	-4.881		-4.878		-4.887		-4.884		-4.884	
Schwarz criterion	-4.862		-4.856		-4.865		-4.859		-4.859	
Convergence	14 iterations		15 iterations		13 iterations		13 iterations		15 iterations	

Note: Estimation method: *ML - ARCH (Marquardt) - Normal distribution. Dependent variable:* SUGAR_LOGRET. *Std-error are in brackets. ***p<0.01, **p<0.05, *p<0.10. Models 3-4-5:* LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8) *RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1)).
D(·) is the differentiation operator.

Table 15 Estimations for Wheat returns

Variables	Model 1 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 2 Garch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 3 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 4 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution		Model 5 EGarch(1,1) Method: ML - ARCH (Marquardt) - Normal distribution	
	Mean equation		Mean equation		Mean equation		Mean equation		Mean equation	
Ethanol_logret	0.408*** (0.018)		0.408*** (0.018)		0.398*** (0.017)		0.395*** (0.017)		0.394*** (0.017)	
Oil_wta_logret	0.114*** (0.019)		0.111*** (0.019)		0.111*** (0.018)		0.109*** (0.018)		0.111*** (0.018)	
Rex_logret	-0.260*** (0.069)		-0.255*** (0.069)		-0.255*** (0.069)		-0.247*** (0.069)		-0.249*** (0.069)	
S&P_500_logret	0.093*** (0.033)		0.097*** (0.032)		0.091*** (0.032)		0.096*** (0.033)		0.090*** (0.032)	
D_open_mkt_oper_log			-				0.002 (0.005)		-	
D_Lending_rate_fed			-0.005 (0.006)				-		-0.003 (0.005)	
	Variance Equation		Variance Equation		Variance Equation		Variance Equation		Variance Equation	
	C	2.15E-05*** (6.13E-06)	C	2.13E-05*** (6.00E-06)	C(6)	-0.488*** (0.103)	C(6)	-0.486*** (0.102)	C(6)	-0.492*** (0.103)
	resid(-1)^2	0.077*** (0.012)	resid(-1)^2	0.078*** (0.012)	C(7)	0.146*** (0.023)	C(7)	0.146*** (0.023)	C(7)	0.147*** (0.023)
	garch(-1)	0.874*** (0.005)	garch(-1)	0.874*** (0.022)	C(8)	0.054*** (0.012)	C(8)	0.054*** (0.011)	C(8)	0.055*** (0.012)
					C(9)	0.952*** (0.012)	C(9)	0.952*** (0.012)	C(9)	0.952*** (0.012)
N. of obs	2040		2035		2040		2035		2035	
R-squared	0.190		0.190		0.191		0.189		0.191	
S.E. of regression	0.021		0.021		0.021		0.021		0.021	
Log likelihood	5059.16		5051.31		5068.86		5060.65		5060.81	
Durbin-Watson	1.965		1.965		1.967		1.967		1.968	
Akaike info crit.	-4.953		-4.957		-4.962		-4.965		-4.965	
Schwarz criterion	-4.934		-4.934		-4.940		-4.939		-4.940	
Convergence	10 iterations		12 iterations		13 iterations		13 iterations		14 iterations	

Note: Estimation method: *ML - ARCH (Marquardt) - Normal distribution. Dependent variable:* WHEAT_1ST_LOGRET. *Std-error are in brackets. ***p<0.01, **p<0.05, *p<0.10. Models 3-4-5:* LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8) *RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1)). D(·) is the differentiation operator.

Table 16 Diagonal BEKK: Estimations for Corn-Ethanol-Oil returns

	Specification[1] 1			Specification[2] 2		
Mean Eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
C(1)	0.001	0.000	0.019	0.001	0.0004	0.021
C(2)	0.072	0.020	0.000	0.073	0.0197	0.000
C(3)	-0.038	0.016	0.020	-0.037	0.0165	0.026
C(4)	-0.063	0.017	0.000	-0.063	0.0165	0.000
C(5)	-0.424	0.071	0.000	-0.423	0.0710	0.000
C(6)	0.163	0.034	0.000	0.160	0.0346	0.000
C(7)	0.006	0.004	0.196	-0.008	0.0055	0.169
C(8)	0.000	0.000	0.261	0.000	0.0003	0.244
C(9)	0.029	0.018	0.113	0.030	0.0181	0.099
C(10)	0.053	0.021	0.011	0.053	0.0208	0.011
C(11)	-0.035	0.014	0.013	-0.035	0.0139	0.011
C(12)	-0.230	0.057	0.000	-0.230	0.0572	0.000
C(13)	0.152	0.029	0.000	0.150	0.0299	0.000
C(14)	0.005	0.003	0.076	0.002	0.0037	0.664
C(15)	0.001	0.000	0.043	0.001	0.0004	0.041
C(16)	0.025	0.019	0.192	0.025	0.0189	0.186
C(17)	-0.013	0.020	0.511	-0.013	0.0201	0.504
C(18)	-0.014	0.018	0.440	-0.014	0.0183	0.458
C(19)	-0.698	0.060	0.000	-0.698	0.0599	0.000
C(20)	0.471	0.031	0.000	0.470	0.0305	0.000
C(21)	0.004	0.004	0.282	-0.002	0.0044	0.648
Variance Eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
M(1,1)	7.94E-06	1.47E-06	0.0000	7.89E-06	1.45E-06	0.0000
M(1,2)	5.84E-06	6.74E-07	0.0000	5.73E-06	6.74E-07	0.0000
M(1,3)	1.45E-06	6.38E-07	0.0226	1.46E-06	6.30E-07	0.0201
M(2,2)	9.15E-06	9.25E-07	0.0000	8.85E-06	1.01E-06	0.0000
M(2,3)	2.37E-06	6.66E-07	0.0004	2.34E-06	6.55E-07	0.0003
M(3,3)	1.10E-05	1.92E-06	0.0000	1.10E-05	1.91E-06	0.0000
A1(1,1)	0.241	0.012	0.0000	0.239	0.012	0.0000
A1(2,2)	0.274	0.009	0.0000	0.272	0.009	0.0000
A1(3,3)	0.281	0.011	0.0000	0.280	0.011	0.0000
B1(1,1)	0.965	0.003	0.0000	0.965	0.003	0.0000
B1(2,2)	0.953	0.003	0.0000	0.954	0.003	0.0000
B1(3,3)	0.947	0.005	0.0000	0.948	0.004	0.0000

[1] System of Equations:

CORN_2_YELLOW_LOGRET = C(1) + C(2)*CORN_2_YELLOW_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-2) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET+ C(6)*S_P_500_LOGRET + C(7)*D_lending_rate_fed

ETHANOL_LOGRET = C(8) + C(9)*CORN_2_YELLOW_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET+ C(13)*S_P_500_LOGRET + C(14)*D_lending_rate_fed

OIL_WTA_LOGRET = C(15) + C(16)*CORN_2_YELLOW_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET+ C(20)*S_P_500_LOGRET + C(21)*D_lending_rate_fed

[2] CORN_2_YELLOW_LOGRET = C(1) + C(2)*CORN_2_YELLOW_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-2) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_open_ecb_log

ETHANOL_LOGRET = C(8) + C(9)*CORN_2_YELLOW_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET + C(14)*D_open_ecb_log

OIL_WTA_LOGRET = C(15) + C(16)*CORN_2_YELLOW_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET + C(21)*D_open_ecb_log

Table 17 Diagonal BEKK: Estimations for Rapeseed-Ethanol-Oil returns

	Specification[1] 1			Specification[2] 2		
Mean eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
C(1)	0.000	0.000	0.0352	0.000	0.000	0.0394
C(2)	0.168	0.022	0.0000	0.167	0.022	0.0000
C(3)	0.013	0.010	0.1906	0.014	0.010	0.1658
C(4)	0.007	0.010	0.4641	0.008	0.010	0.4252
C(5)	-0.062	0.033	0.0614	-0.065	0.033	0.0507
C(6)	0.101	0.016	0.0000	0.099	0.016	0.0000
C(7)	0.005	0.002	0.0062	-0.002	0.003	0.5150
C(8)	0.000	0.000	0.4062	0.000	0.000	0.4107
C(9)	-0.002	0.035	0.9598	-0.001	0.035	0.9861
C(10)	0.066	0.023	0.0049	0.067	0.023	0.0043
C(11)	0.014	0.017	0.4170	0.015	0.017	0.3872
C(12)	-0.404	0.061	0.0000	-0.405	0.061	0.0000
C(13)	0.130	0.029	0.0000	0.127	0.029	0.0000
C(14)	0.005	0.003	0.1295	0.001	0.004	0.8255
C(15)	0.001	0.000	0.1616	0.001	0.000	0.1612
C(16)	-0.040	0.035	0.2552	-0.039	0.035	0.2676
C(17)	0.003	0.020	0.8979	0.002	0.020	0.9031
C(18)	0.001	0.020	0.9400	0.002	0.020	0.9081
C(19)	-0.744	0.061	0.0000	-0.745	0.061	0.0000
C(20)	0.474	0.032	0.0000	0.471	0.032	0.0000
C(21)	0.007	0.004	0.1174	-0.001	0.004	0.7361
Variance eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
M(1,1)	9.97E-06	1.10E-06	0.0000	1.01E-05	1.11E-06	0.0000
M(1,2)	7.54E-06	1.12E-06	0.0000	7.68E-06	1.13E-06	0.0000
M(1,3)	2.40E-06	6.11E-07	0.0001	2.45E-06	6.16E-07	0.0001
M(2,2)	6.11E-05	7.41E-06	0.0000	6.21E-05	7.49E-06	0.0000
M(2,3)	8.61E-06	1.76E-06	0.0000	8.78E-06	1.78E-06	0.0000
M(3,3)	4.94E-06	1.15E-06	0.0000	4.97E-06	1.15E-06	0.0000
A1(1,1)	3.51E-01	1.57E-02	0.0000	0.349	0.016	0.0000
A1(2,2)	0.357	0.016	0.0000	0.358	0.016	0.0000
A1(3,3)	0.215	0.011	0.0000	0.215	0.011	0.0000
B1(1,1)	0.895	0.008	0.0000	0.895	0.008	0.0000
B1(2,2)	0.844	0.016	0.0000	0.842	0.017	0.0000
B1(3,3)	0.970	0.003	0.0000	0.970	0.003	0.0000

1 RAPESEED_LOGRET = C(1) + C(2)*RAPESEED_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_lending_rate_fed

ETHANOL_LOGRET = C(8) + C(9)*RAPESEED_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1)+ C(11)*OIL_WTA_LOGRET(-1)+ C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET+C(14)*D_lending_rate_fed

OIL_WTA_LOGRET = C(15) + C(16)*RAPESEED_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET + C(21)*D_lending_rate_fed

2 RAPESEED_LOGRET = C(1) + C(2)*RAPESEED_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_open_ecb_log

ETHANOL_LOGRET = C(8) + C(9)*RAPESEED_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1)+ C(11)*OIL_WTA_LOGRET(-1)+ C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET+C(14)*D_open_ecb_log

OIL_WTA_LOGRET = C(15) + C(16)*RAPESEED_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET + C(21)*D_open_ecb_log

Table 18 Diagonal BEKK: Estimations for Soybeans-Ethanol-Oil returns

	Specification[1] 1			Specification[2] 2		
Mean eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
C(1)	0.001	0.000	0.0097	0.001	0.000	0.0235
C(2)	0.066	0.024	0.0056	0.061	0.023	0.0087
C(3)	-0.031	0.018	0.0879	-0.031	0.019	0.0936
C(4)	-0.044	0.014	0.0020	-0.043	0.015	0.0035
C(5)	-0.404	0.053	0.0000	-0.392	0.054	0.0000
C(6)	0.146	0.028	0.0000	0.148	0.029	0.0000
C(7)	0.002	0.003	0.5675	-0.003	0.004	0.4699
C(8)	0.000	0.000	0.3568	0.000	0.000	0.4379
C(9)	0.028	0.020	0.1523	0.030	0.019	0.1178
C(10)	0.051	0.023	0.0282	0.050	0.024	0.0333
C(11)	0.003	0.017	0.8813	0.003	0.017	0.8731
C(12)	-0.402	0.060	0.0000	-0.398	0.060	0.0000
C(13)	0.112	0.028	0.0001	0.109	0.029	0.0002
C(14)	0.005	0.003	0.0748	0.001	0.005	0.8357
C(15)	0.000	0.000	0.2307	0.000	0.000	0.2525
C(16)	-0.003	0.019	0.8592	-0.005	0.019	0.8114
C(17)	-0.014	0.021	0.5145	-0.013	0.021	0.5366
C(18)	0.007	0.020	0.7374	0.006	0.020	0.7463
C(19)	-0.745	0.060	0.0000	-0.744	0.060	0.0000
C(20)	0.466	0.032	0.0000	0.465	0.031	0.0000
C(21)	0.001	0.004	0.7571	-0.001	0.004	0.7673
Variance eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
M(1,1)	1.70E-05	2.07E-06	0.0000	1.17E-05	1.75E-06	0.0000
M(1,2)	1.07E-05	1.38E-06	0.0000	8.95E-06	1.22E-06	0.0000
M(1,3)	2.95E-06	7.57E-07	0.0001	1.91E-06	6.16E-07	0.0020
M(2,2)	5.02E-05	5.40E-06	0.0000	4.56E-05	4.97E-06	0.0000
M(2,3)	7.44E-06	1.52E-06	0.0000	6.62E-06	1.38E-06	0.0000
M(3,3)	5.80E-06	1.24E-06	0.0000	5.12E-06	1.15E-06	0.0000
A1(1,1)	0.330	0.013	0.0000	0.297	0.013	0.0000
A1(2,2)	0.367	0.016	0.0000	0.353	0.015	0.0000
A1(3,3)	0.224	0.011	0.0000	0.219	0.011	0.0000
B1(1,1)	0.915	0.007	0.0000	0.934	0.006	0.0000
B1(2,2)	0.859	0.013	0.0000	0.871	0.012	0.0000
B1(3,3)	0.967	0.003	0.0000	0.969	0.003	0.0000

1 SOYBEAN_LOGRET = C(1) + C(2)*SOYBEAN_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_lending_rate_fed

ETHANOL_LOGRET = C(8) + C(9)*SOYBEAN_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET+ C(13)*S_P_500_LOGRET + C(14)*D_lending_rate_fed

OIL_WTA_LOGRET = C(15) + C(16)*SOYBEAN_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET+ C(20)*S_P_500_LOGRET + C(21)*D_lending_rate_fed

2 SOYBEAN_LOGRET = C(1) + C(2)*SOYBEAN_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_open_ecb_log

ETHANOL_LOGRET = C(8) + C(9)*SOYBEAN_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET+ C(13)*S_P_500_LOGRET + C(14)*D_open_ecb_log

OIL_WTA_LOGRET = C(15) + C(16)*SOYBEAN_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET+ C(20)*S_P_500_LOGRET + C(21)*D_open_ecb_log

Table 19 Diagonal BEKK: Estimations for Soybean oil-Ethanol-Oil returns

	Specification1 1			Specification2 2		
Mean eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
C(1)	0.001	0.000	0.0314	0.001	0.000	0.0338
C(2)	0.034	0.023	0.1507	0.036	0.024	0.1277
C(3)	-0.028	0.017	0.0999	-0.028	0.017	0.0958
C(4)	-0.001	0.015	0.9496	-0.001	0.015	0.9430
C(5)	-0.391	0.048	0.0000	-0.390	0.048	0.0000
C(6)	0.217	0.025	0.0000	0.215	0.025	0.0000
C(7)	0.003	0.003	0.2188	-0.004	0.003	0.2146
C(8)	0.000	0.000	0.3808	0.000	0.000	0.3743
C(9)	-0.006	0.028	0.8391	-0.006	0.028	0.8381
C(10)	0.053	0.023	0.0213	0.053	0.023	0.0199
C(11)	0.011	0.019	0.5688	0.011	0.019	0.5667
C(12)	-0.367	0.064	0.0000	-0.367	0.064	0.0000
C(13)	0.112	0.030	0.0002	0.110	0.030	0.0003
C(14)	0.005	0.003	0.1230	0.003	0.004	0.5119
C(15)	0.001	0.000	0.1676	0.001	0.000	0.1632
C(16)	-0.012	0.027	0.6671	-0.011	0.027	0.6870
C(17)	-0.008	0.020	0.7040	-0.008	0.020	0.7087
C(18)	0.012	0.021	0.5629	0.013	0.021	0.5596
C(19)	-0.728	0.060	0.0000	-0.729	0.060	0.0000
C(20)	0.464	0.032	0.0000	0.463	0.031	0.0000
C(21)	0.003	0.004	0.4551	-0.002	0.004	0.7247
Variance eq	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
M(1,1)	2.87E-06	7.22E-07	0.0001	2.84E-06	7.22E-07	0.0001
M(1,2)	2.49E-06	4.08E-07	0.0000	2.41E-06	4.00E-07	0.0000
M(1,3)	1.68E-06	4.14E-07	0.0001	1.68E-06	4.14E-07	0.0001
M(2,2)	1.34E-05	1.60E-06	0.0000	1.29E-05	1.62E-06	0.0000
M(2,3)	2.42E-06	6.64E-07	0.0003	2.36E-06	6.47E-07	0.0003
M(3,3)	6.83E-06	1.50E-06	0.0000	6.83E-06	1.51E-06	0.0000
A1(1,1)	0.196	0.011	0.0000	0.195	0.011	0.0000
A1(2,2)	0.226	0.010	0.0000	0.222	0.010	0.0000
A1(3,3)	0.255	0.011	0.0000	0.256	0.011	0.0000
B1(1,1)	0.974	0.003	0.0000	0.974	0.003	0.0000
B1(2,2)	0.956	0.004	0.0000	0.958	0.004	0.0000
B1(3,3)	0.959	0.004	0.0000	0.959	0.004	0.0000

1 SOYBEAN_OIL_LOGRET = C(1) + C(2)*SOYBEAN_OIL_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_lending_rate_fed

ETHANOL_LOGRET = C(8) + C(9)*SOYBEAN_OIL_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET+ C(14)*D_lending_rate_fed

OIL_WTA_LOGRET = C(15) + C(16)*SOYBEAN_OIL_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET + C(21)*D_lending_rate_fed

2 SOYBEAN_OIL_LOGRET = C(1) + C(2)*SOYBEAN_OIL_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_open_ecb_log

ETHANOL_LOGRET = C(8) + C(9)*SOYBEAN_OIL_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET+ C(14)*D_open_ecb_log

OIL_WTA_LOGRET = C(15) + C(16)*SOYBEAN_OIL_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET + C(21)*D_open_ecb_log

Table 20 Diagonal BEKK: Estimations for Sugar-Ethanol-Oil returns

	Specification[1] 1			Specification[2] 2		
	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
C(1)	0.000	0.000	0.5809	0.000	0.000	0.5903
C(2)	0.011	0.021	0.6043	0.010	0.021	0.6207
C(3)	0.041	0.021	0.0512	0.041	0.021	0.0494
C(4)	-0.021	0.021	0.3105	-0.021	0.021	0.3055
C(5)	-0.330	0.073	0.0000	-0.332	0.073	0.0000
C(6)	0.184	0.041	0.0000	0.181	0.041	0.0000
C(7)	0.004	0.004	0.2531	-0.008	0.006	0.1674
C(8)	0.000	0.000	0.3568	0.000	0.000	0.3591
C(9)	0.055	0.015	0.0002	0.054	0.014	0.0002
C(10)	0.050	0.024	0.0383	0.050	0.024	0.0353
C(11)	0.010	0.017	0.5608	0.010	0.017	0.5411
C(12)	-0.383	0.063	0.0000	-0.385	0.063	0.0000
C(13)	0.126	0.030	0.0000	0.124	0.030	0.0000
C(14)	0.004	0.003	0.2113	0.000	0.004	0.9593
C(15)	0.001	0.000	0.1568	0.001	0.000	0.1555
C(16)	0.028	0.016	0.0897	0.027	0.016	0.0940
C(17)	-0.009	0.020	0.6434	-0.009	0.020	0.6440
C(18)	0.005	0.019	0.8097	0.005	0.020	0.7981
C(19)	-0.737	0.060	0.0000	-0.738	0.060	0.0000
C(20)	0.465	0.031	0.0000	0.463	0.031	0.0000
C(21)	0.004	0.004	0.3133	-0.003	0.004	0.4764
	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
M(1,1)	3.42E-06	8.03E-07	0.0000	3.43E-06	8.07E-07	0.0000
M(1,2)	5.39E-06	1.47E-06	0.0003	5.49E-06	1.48E-06	0.0002
M(1,3)	1.39E-06	5.44E-07	0.0108	1.37E-06	5.42E-07	0.0115
M(2,2)	5.79E-05	7.30E-06	0.0000	5.87E-05	7.30E-06	0.0000
M(2,3)	7.95E-06	1.73E-06	0.0000	8.08E-06	1.74E-06	0.0000
M(3,3)	9.10E-06	1.82E-06	0.0000	9.00E-06	1.81E-06	0.0000
A1(1,1)	0.176	0.011	0.0000	0.177	0.011	0.0000
A1(2,2)	0.352	0.016	0.0000	0.353	0.016	0.0000
A1(3,3)	0.272	0.013	0.0000	0.271	0.013	0.0000
B1(1,1)	0.981	0.002	0.0000	0.981	0.002	0.0000
B1(2,2)	0.850	0.016	0.0000	0.849	0.016	0.0000
B1(3,3)	0.951	0.005	0.0000	0.951	0.005	0.0000

1 SUGAR_LOGRET = C(1) + C(2)*SUGAR_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_lending_rate_fed

ETHANOL_LOGRET = C(8) + C(9)*SUGAR_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET + C(14)*D_lending_rate_fed

OIL_WTA_LOGRET = C(15) + C(16)*SUGAR_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET + C(21)*D_lending_rate_fed

2 SUGAR_LOGRET = C(1) + C(2)*SUGAR_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_open_ecb_log

ETHANOL_LOGRET = C(8) + C(9)*SUGAR_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET + C(14)*D_open_ecb_log

OIL_WTA_LOGRET = C(15) + C(16)*SUGAR_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET + C(21)*D_open_ecb_log

Table 21 Diagonal BEKK: Estimations for Wheat-Ethanol-Oil returns

	Specification[1] 1			Specification[2] 2		
	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
C(1)	0.000	0.000	0.2567	0.000	0.000	0.2527
C(2)	0.014	0.024	0.5704	0.015	0.024	0.5419
C(3)	-0.045	0.025	0.0737	-0.046	0.025	0.0683
C(4)	-0.027	0.021	0.1942	-0.029	0.021	0.1772
C(5)	-0.411	0.077	0.0000	-0.408	0.076	0.0000
C(6)	0.191	0.037	0.0000	0.188	0.037	0.0000
C(7)	0.006	0.005	0.2409	-0.009	0.005	0.0613
C(8)	0.000	0.000	0.2140	0.000	0.000	0.2101
C(9)	-0.002	0.019	0.9072	-0.002	0.019	0.9056
C(10)	0.069	0.024	0.0038	0.069	0.024	0.0037
C(11)	-0.004	0.017	0.7927	-0.005	0.017	0.7854
C(12)	-0.305	0.061	0.0000	-0.305	0.061	0.0000
C(13)	0.122	0.030	0.0001	0.121	0.031	0.0001
C(14)	0.002	0.003	0.4820	0.001	0.004	0.8662
C(15)	0.001	0.000	0.1171	0.001	0.000	0.1162
C(16)	0.021	0.017	0.2381	0.021	0.018	0.2341
C(17)	-0.019	0.021	0.3701	-0.019	0.021	0.3797
C(18)	-0.004	0.019	0.8201	-0.004	0.019	0.8345
C(19)	-0.731	0.062	0.0000	-0.731	0.062	0.0000
C(20)	0.465	0.032	0.0000	0.465	0.032	0.0000
C(21)	0.002	0.004	0.5954	-0.002	0.004	0.6422
	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
M(1,1)	1.98E-05	2.64E-06	0.0000	1.95E-05	2.59E-06	0.0000
M(1,2)	7.72E-06	8.22E-07	0.0000	7.61E-06	8.11E-07	0.0000
M(1,3)	1.35E-06	6.58E-07	0.0402	1.33E-06	6.49E-07	0.0404
M(2,2)	1.40E-05	1.56E-06	0.0000	1.37E-05	1.62E-06	0.0000
M(2,3)	2.29E-06	6.56E-07	0.0005	2.27E-06	6.50E-07	0.0005
M(3,3)	6.50E-06	1.42E-06	0.0000	6.46E-06	1.41E-06	0.0000
A1(1,1)	0.249	0.014	0.0000	0.247	0.014	0.0000
A1(2,2)	0.260	0.011	0.0000	0.259	0.010	0.0000
A1(3,3)	0.252	0.011	0.0000	0.252	0.011	0.0000
B1(1,1)	0.950	0.005	0.0000	0.951	0.005	0.0000
B1(2,2)	0.948	0.004	0.0000	0.948	0.004	0.0000
B1(3,3)	0.960	0.004	0.0000	0.960	0.004	0.0000

1 WHEAT_1ST_LOGRET = C(1) + C(2)*WHEAT_1ST_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)*REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_lending_rate_fed

ETHANOL_LOGRET = C(8) + C(9)*WHEAT_1ST_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)*REX_LOGRET + C(13)*S_P_500_LOGRET+ C(14)*D_lending_rate_fed

OIL_WTA_LOGRET = C(15) + C(16)*WHEAT_1ST_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)*REX_LOGRET + C(20)*S_P_500_LOGRET+ C(21)*D_lending_rate_fed

2 WHEAT_1ST_LOGRET = C(1) + C(2)*WHEAT_1ST_LOGRET(-1) + C(3)*ETHANOL_LOGRET(-1) + C(4)*OIL_WTA_LOGRET(-1) + C(5)* REX_LOGRET + C(6)*S_P_500_LOGRET + C(7)*D_open_ecb_log

ETHANOL_LOGRET = C(8) + C(9)*WHEAT_1ST_LOGRET(-1) + C(10)*ETHANOL_LOGRET(-1) + C(11)*OIL_WTA_LOGRET(-1) + C(12)* REX_LOGRET + C(13)* S_P_500_LOGRET + C(14)*D_open_ecb_log

OIL_WTA_LOGRET = C(15) + C(16)*WHEAT_1ST_LOGRET(-1) + C(17)*ETHANOL_LOGRET(-1) + C(18)*OIL_WTA_LOGRET(-1) + C(19)* REX_LOGRET + C(20)* S_P_500_LOGRET + C(21)*D_open_ecb_log