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What drives food price volatility? Evidence based on a generalized VAR approach applied to the food, financial and energy markets

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Abstract

The aim of this study is to investigate sources of food prices volatility. The analysis uses daily series for volatility of corn, soybean, wheat, rice, US dollar, crude oil, and SP500 futures spanning the period January 4, 2000 to April 1, 2017. The authors employ the generalized vector autoregressive framework in rolling sample approach in order to capture the time-varying nature of volatility spillovers. The results reveal that: volatility spillovers measures change over time; most of the volatility spillovers are observed within the two groups of markets: food markets and "non-food" markets; corn market is net volatility transmitter.

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Keywords Volatility spillovers; food markets; financial and energy markets; generalized VAR; lasso estimation

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1 Introduction

The 2007–2008 and 2010–2011 surges in food prices were not concentrated in a market for a single agricultural commodity but resulted from developments in the whole range of markets for commodities grown in different places. That is why supply-side factors could not have been the only reason for the price co-movement. Alternative explanations for food price upsurges have been put forward in the literature and include e.g.: financial speculation in commodity futures markets, global economic growth (increased demand), trade restrictions, macroeconomic shocks to money supply, the US exchange rate movements (Abbott et al., 2009, 2011; Gilbert, 2010; Roache, 2010), competition for land (Harvey and Pilgrim, 2011), countries' aggressive stockpiling policies, and tightening relations between food prices and energy prices.

In the literature two reasons of food price volatility are investigated most frequently.[1] The first one is "finacialization" of commodity markets which results from the development of future market trading. Deregulation of commodity markets, initiated in the beginning of the 21st century, induced an increase in the inflow of capital to commodity futures (Christoffersen et al., 2014). Crucial for co-movement of commodity futures is the large inflow of commodity index investment (Tang and Xiong, 2012). The prices that underlie agricultural commodity indices are more strongly correlated with the oil price than those commodities that are not included in the indices. The increase of correlation between futures prices of agricultural commodities and oil after 2004, as observed by Tang and Xiong (2012), stemmed from significant index investments which started to flow into commodity markets. The second most frequently investigated reason of increased food price volatility concerns the relation between food and energy prices. The relation is bidirectional. On the one hand, modern food production requires more and more energy, e.g. to power agricultural machinery, to heat greenhouses, to power irrigation systems, to produce fertilizers etc. On the other hand, some agricultural products are used as a source of energy (biofuels). In the United States corn is used as the main feedstock to produce ethanol. This has resulted in tighter competition for the cultivated area: the area used for biofuels (corn) production increased, as fuel ethanol production grew eight-fold from 233 trillion Btu in 2000 to 1,938 trillion Btu in 2014 (https://www.eia.gov), and the land on which it was grown could not be used for other crops.

The objective of the paper is to identify the main sources of food price volatility. Apart from developments in related food markets, the likely sources of food price volatility can include fluctuation in the US stock, energy and foreign exchange markets. We focus on the food prices volatility in the 21st century, i.e. the period when many developing economies – and among them food exporters – have built tighter links with the world economy. Moreover, this period is of particular interest because it has witnessed both tranquil times and financial turbulence, as the Great Moderation was disrupted by the global financial crisis in the late 2000s.

[1] Another important reason, not covered in the study, include: supply variation and storage capacity (see, Tadasse et al., 2016; Chatterjee, 2018).

The study is based on daily series for volatility of futures prices of corn, soybean, wheat,[2] rice, the US dollar, crude oil and the SP500 spanning the period January 4, 2000–April 1, 2017. We base our analysis on forecast-error variance (FEV) decompositions obtained within a generalized vector autoregressive (VAR) framework, as proposed by Diebold and Yilmaz (2012). This framework allows us to estimate total, net, directional and pairwise volatility spillovers for markets considered. The generalized VAR is also used to obtain the impulse response functions that can be considered a complementary description of how price volatility in the US stock, energy and foreign exchange markets affects food price volatility. Both a whole-sample approach and a rolling-sample approach are used in order to capture the time-varying nature of volatility spillovers. Bearing in mind that the number of parameters to be estimated in comparison to the number of observations is large, we use lasso estimation methods in a single iteration.

The Diebold-Yilmaz approach is not the only possible approach to study relations among volatility of different markets. MGARCH models are the most popular alternative. There are two differences between these two approaches. First, in MGARCH models, it is possible to analyse conditional correlation as well as make inferences about pairwise relations between markets. Second, MGARCH models are typically heavily parametrized with number of parameters growing very fast with each additional variable. In consequence, computational difficulties in high dimensional cases grow equally fast. Even though more parsimonious parametrizations of MGARCH models are possible, they typically require stringent restrictions on the model structure. Hence, two dimensional models (VAR-GARCH or different MGARCH) were used to study volatility spillovers between food markets and SP500 (Mensi et al., 2013) and between oil markets and food markets (Mensi et al., 2014). The advantage of the Diebold-Yilmaz approach is that models including more variables can be used and such a feature can be critical. For example, the omitted variable bias is less likely and there are no serious numerical difficulties when estimating VAR models. Moreover, the FEV decomposition obtained within the Diebold-Yilmaz approach, summarised in the connectedness table, has a quite natural interpretation and in fact conveys different, in comparison to MGARCH models, kind of information (for example it is possible to compare volatility transmitted and received).

Our study is not the first one which examines the role of the stock and energy markets as drivers of food markets volatility (see, e.g., Diebold and Yilmaz, 2012; Chevallier and Ielpo, 2013; Jebabli et al., 2014; Awartani et al., 2016; Grosche and Heckelei, 2016). The advantage of our approach, however, is that it is among the most general ones.

Our contribution to the literature is visible in three aspects. First, we use a relatively large number of markets: the set we analyse in our study includes volatility of four main crops produced in the United States, which helps understand interrelations between them and volatility of the US stock, energy and foreign exchange markets. Second, we apply lasso estimation techniques and compare the results with those obtained with the ordinary least squares (OLS). The advantages of the lasso-based approach over the OLS-based approach

[2] Christoffersen et al. (2014) show that corn, soybean, and wheat are among the most heavily traded commodity futures. In the period 2004–2013 there were more than 60 million transactions of soybeans and more than 34 million for corn.

become evident when the number of regressors is large.[3] What is more, the lasso-based approach seems to be more sensitive to differences in the evolution of the total volatility spillover index in turbulent and tranquil times. Third, apart from using the spillover indices, we extend the analysis by applying such tools as forecast error variance decompositions and generalized impulse responses in order to uncover the direction and strength of volatility transmission. To illustrate the responses of food markets to different impulses we construct the heat plots.

Our findings include four novel results. First, we find that volatility spillovers are observed mostly within the group of food markets and within the group of other markets and much less between these groups. Second, the susceptibility of food markets to volatility spillovers from "non-food" markets, i.e. the stock, energy and foreign exchange markets, is larger during crisis periods. Third, the market for corn seems to be the most important source of volatility within food markets, as it is found to be the net volatility transmitter in most of the analysed subperiods. One may conjecture that the reason for this is that a large part of corn output is used to produce biofuels, and that there is an indirect relation between the food and energy markets. Fourth, the price of rice is detached from the developments in other markets, i.e. the sources of its volatility can hardly be found outside the market for rice.

The paper consists of the following sections. Section 2 presents the most important findings of the studies investigating volatility spillovers between the agricultural commodity, energy and financial markets. Section 3 describes the methodological approach, Section 4 presents the data, and Section 5 reports and comments on the empirical results. The paper ends with the conclusions.

2 Literature review

The two main methodological approaches are employed in the studies devoted to the issue of shocks transmission and volatility spillovers between energy markets, agricultural commodity markets (food markets) and financial markets (stock market). The first one, more frequently used, is based on different specifications of multivariate GARCH models (see, e.g., Zhang et al., 2009; Serra et al., 2011; Trujillo-Barrera et al., 2012; Gardebroek and Hernandez, 2013; Creti et al., 2013; Mensi et al., 2014; Abdelradi and Serra, 2015a, b; Cabrera and Schulz, 2016; Hegerty, 2016; Silvennoinen and Thorp, 2013, 2016). The second one applies the measures of volatility spillover proposed by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) (see, e.g., Antonakakis et al., 2016; Batten, et al. 2015; Chevallier and Ielpo, 2013; Jebabli et al., 2014; Magkonis, and Tsouknidis, 2017; Awartani et al., 2016; Grosche and Heckelei, 2016; and Kang et al., 2017).

Three main strands can be identified in the literature on the sources of food prices volatility. The first one focuses on relations between energy prices (including biofuel prices) volatility and

[3] The issue is particularly important for large VAR models, when effectiveness of estimators seems to be crucial. It is well known, that when a number of parameters in the model is large in comparison to the number of observations, the variance of OLS estimator increases (see Greene, 2003, p. 49).

food prices volatility. The second one examines volatility spillovers between financial markets and commodity markets including both food and energy markets.[4] The third one considers relations between volatility within the food markets.

The results obtained within the first strand of literature suggest that in general volatility is transmitted from food markets to energy markets. Zhang et al. (2009) study price transmissions and volatility spillovers between weekly U.S. ethanol, corn, soybean, gasoline and oil prices and notice volatility transmissions from agricultural commodity prices to energy prices. In contrast, Trujillo-Barrera et al. (2012) show volatility transmission from crude oil to corn and ethanol markets and from corn market to ethanol market. Gardebroek and Hernandez (2013) show significant volatility spillovers from corn to ethanol prices but not in the opposite direction. Mensi et al. (2014) investigate volatility spillovers across international energy (i.e. WTI, Brent, heating, and gasoline) and cereal commodity markets (i.e. corn, barley, sorghum and wheat,) and find that the correlations between the energy and cereal commodity futures evolve through time and are highly volatile, particularly since the subprime mortgage crisis. Serra et al. (2011) analyse Brazilian agricultural markets and confirm that ethanol price volatility is affected by shocks in the oil and sugar markets. Cabrera and Schulz (2016) find no volatility transmission between food, energy and biodiesel markets in Germany. Abderladi and Serra (2015b) consider food and biofuel prices in Spain and find bidirectional and asymmetric volatility spillovers between biodiesel and refined sunflower oil prices. Tadasse et al. (2014) show that energy prices can trigger food price spikes and volatility.

The results obtained in the second strand of literature reveal, in general, limited volatility transmission between food markets and financial markets (see, e.g., Silvennoinen and Thorp 2013; Chevallier and Ielpo 2013; Awartani et al. 2016), which, however, changes over time. Volatility transmission increases during turbulent periods. Creti et al. (2013), Mensi et al. (2013), Silvennoinen and Thorp (2013), Diebold and Yilmaz (2012) show the strongest relationship between financial markets and food markets volatility during the global financial crisis. Jebabli et al. (2014) find that during the global financial crisis stock markets are a net transmitter of volatility shocks while a crude oil market is its net receiver. A stronger impact of financial market on food markets after the global financial crises is reported by Baldi et al. (2016). Kang et al. (2017) examine spillover effects among six commodity futures markets (gold, silver, WTI, corn, wheat, and rice) and find that both gold and silver are net volatility transmitters to other commodity markets, while the remaining four commodity futures (i.e. WTI, corn, wheat, and rice) are net receivers of volatility during the recent financial crises. Grosche and Heckelei (2016) reveal the strongest volatility spillover within the agricultural commodities in comparison to other markets. A more important role of financial markets in the commodity price formation process is found in Tadasse et al. (2014) and Babalos and Balcilar (2017). Using the quantile analysis Tadasse et al. (2014) demonstrated, however, that "financial crisis and speculation do not necessarily trigger volatility, in contrast to price spikes" (Tadasse et al., 2016, p. 127). Babalos and Balcilar (2017) reported, based on causality-in-quantiles approach, a substantial evidence of predictability of the variance of commodities market returns and originating from financial market returns.

[4] In most cases, food markets are not treated separately, but are considered as one of the components of the commodity markets.

The third strand of literature is devoted to the analysis of volatility transmissions within the agricultural commodity markets and shows different roles of a particular commodity. Beckmann and Czudaj (2014) argue that potential speculation effects on the corn futures market may be contagious for the cotton and wheat futures markets. Gardebroek et al. (2016) reveal that the markets for wheat and corn are major sources of volatility that spills over the market for soybean. Hamadi et al. (2017) find significant bidirectional volatility spillovers between markets for corn, wheat, soybeans and soybean oil, although a stronger spillover effect is observed from soybeans and soybean oil markets to corn and wheat markets.

3 Methodology

Pesaran and Shin (1998), building on the work of Koop et al. (1996), introduced the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD) for unrestricted vector autoregressive (VAR) and cointegrated VAR models. Unlike the conventional IRF and FEV decomposition, their approach does not require orthogonalization of shocks and is invariant to the ordering of the variables in VAR models. Since it is rarely possible to justify one particular ordering of variables under consideration, the methods promising to circumvent this restriction are of great interest to the scientific community.

Diebold and Yilmaz (2009) introduced a volatility spillover measure based on the standard FEV decomposition and focused on total spillovers (from/to a particular market, to/from all other markets). Later Diebold and Yilmaz (2012), building on the work of Pesaran and Shin (1998), used the GFEVD to introduce a spillover measure which is invariant to the variable ordering.

This study employs both the spillover indices as introduced by Diebold and Yilmaz (2012) and the GIRF analysis of Pesaran and Shin (1998). The spillover indices are constructed by performing a rolling-window generalized forecast error variance decompositions. This approach enables us to identify time-varying patterns. While the static GFEVD classifies the variables of the study into transmitters and receivers, the dynamic GFEVD may identify episodes when the role of transmitters and receivers of spillovers is interrupted or even reversed. The GIRFs are also calculated within the rolling-window approach.

It is assumed that volatility is fixed within periods (in this case days), but can vary across periods. Following Alizadeh et al. (2002), daily high and low prices are used to estimate volatility.[5] The proxy we use is the logarithm of the difference between the highest and lowest log price:[6]

$$range_t = ln\Big(ln\big(max(y_t)\big) - ln\big(min(y_t)\big)\Big), \tag{1}$$

where *t* refers to a particular moment (day).

[5] It seems to be the most common choice, however, there are some studies, e.g. Yarovaya et al. (2016), which use other proxy of volatility.

[6] The formula is related to a volatility proxy used by Demirer et al. (2018). The both formulas differ only by a constant value, and the correlation coefficient between the two measures is one.

Our empirical strategy includes inference both from the whole sample and from the rolling windows. Each time, we repeat the following steps.

In the first step, the conventional VAR model is estimated. It takes the following form:[7]

$$y_t = \sum_{i=1}^{q} B_i y_{t-i} + \varepsilon_t \tag{2}$$

where y_t is an $N \times 1$ vector of endogenous variables (vector of log ranges of prices), B_i are $N \times N$ autoregressive coefficient matrices, and $\varepsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. All VARs are estimated using the lasso regression proposed by Tibshirani (1996). The lasso is a shrinkage method for a linear regression. It minimizes the sum of squared errors, with a bound on the sum of the absolute values of individual regression coefficients. Particularly in the rolling-window approach estimation degrees of freedom are substantially limited, so the application of pruning and shrinkage is quite appealing (Diebold and Yilmaz, 2015).

In the second step, total and directional spillover indices are obtained by generalized forecast error variance decompositions of the moving average representation of the VAR model. Variance decompositions allow for parsing forecast error variances of each variable into parts which are attributable to various system shocks. They allow for assessing the fraction of the *H*-step-ahead error variance in forecasting one variable that is due to shocks to another variable. The moving average representation of the VAR is:

$$y_t = \sum_{j=1}^{\infty} A_j \varepsilon_{t-j}, \tag{3}$$

where the $N \times N$ coefficient matrices A_j obey the recursion of form $A_j = B_1 A_{j-1} + B_2 A_{j-2} + \cdots + B_p A_{j-p}$, with A_0 being the $N \times N$ identity matrix and $A_j = 0$ for $j < 0$. The *H*-step-ahead generalized forecast error variance decomposition invariant to the variable ordering is defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{4}$$

for $i, j = 1,2, \ldots, N$, where Σ is the covariance matrix for the error vector ε, σ_{jj} is the *j*-th diagonal element of Σ, and e_i is the selection vector with one as the *i*-th element and zeros otherwise. $\Theta(\mathrm{H})$ is an $N \times N$ matrix, with elements $\theta_{ij}(H)$, where each entry gives the contribution of variable *j* to the forecast error variance of variable *i*. The rows of $\Theta(\mathrm{H})$ need to be normalized, as under the generalized decomposition they do not sum to one. After normalization of $\Theta(\mathrm{H})$, the total spillover index is:

$$TS(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} 100\%. \tag{5}$$

[7] Equations (2) and (3) include intercepts.

The index represents the average contribution of spillovers of volatility shocks across all the markets considered to the total forecast error variance.

Directional spillovers received by market *i* from all other markets *j* are defined as:

$$DS_{i\leftarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} 100\% \tag{6}$$

Analogously, directional volatility spillovers transmitted by market *i* to all other markets *j* are defined as:

$$DS_{i\rightarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ji}(H)}{N} 100\% \tag{7}$$

The difference between directional volatility spillovers transmitted by market *i* to all other markets j ($DS_{i\rightarrow j}(H)$) and directional spillovers received by market *i* from all other markets *j* ($DS_{i\leftarrow j}(H)$) is defined as net volatility spillovers of market *i*.

In the third step, GIRFs are calculated. An impulse response function depicts the time profile of the effect of shocks on the expected future values of variable in a dynamic system. The scaled generalized impulse response function is calculated as $\frac{A_n \Sigma e_j}{\sqrt{\sigma_{jj}}}$, and measures the effect of one standard error shock to the *j*-th VAR equation at time t on expected values of *y* at time $t+n$. In this equation Σ is the variance matrix of the error vector ε, σ_{jj} is the *j*-th diagonal element of Σ, and e_j is the selection vector, with one as the *j*-th element and zeros otherwise.

The GIRFs are calculated for a predefined time point ($n = 1$).[8] In order to visualize GIRF results, the R package 'superheat 0.1' for generating extendable and customizable heatmaps developed by Barter and Yu (2017) is used.

4 Data

We examine the volatility spillovers between the US stock, energy, foreign exchange markets and food markets using daily data spanning the period from January 4, 2000 to April 1, 2017, which yields 4239 observations. In particular, we examine the S&P 500 index futures contract traded on the CME (SP500), the WTI crude oil futures contract traded on the NYMEX (WTI), the US dollar index futures contract traded on the ICE (USD), and the corn, soybean, wheat and rough rice futures contract traded on the CBOT (CORN, SOYBEAN, WHEAT, RICE). Following Tang and Xiong (2012), the US dollar index (USD) is used as a control variable, because it has an impact on the interaction between agricultural and energy commodities. The data are obtained from Bloomberg. Following Diebold and Yilmaz (2012), we calculate the log range volatility proxy (Eq. 1). Next we use the linear regression as the standard tool for doing seasonal monthly adjustments of the series. The models estimated with the daily data take the form: $range_t = \alpha + \sum_{i=1}^{11} \beta_i D_{it} + \varepsilon_t$, where: D_{it} are binary variables equalling 1 if "*it*" is the

[8] The responses for lager n are irrelevant.

given month and zero otherwise. The residuals ε_t express the seasonal adjustment of monthly data and are used as daily volatility proxy in all further calculations.[9]

Table 1 presents the summary statistics of the log range volatility and Figure 1 depicts seven series of log range volatility in the period between January 4, 2000 and April 1, 2017. Table 1 reveals that volatility of USD and RICE is not normally distributed.[10] In the first case, the violation of normality assumption results from large values observed in 2001 and 2003 (see Figure 1). In the second case, outliers can be observed in the period after 2008.

5 Empirical results and discussion

Empirical strategy applied in the study consist of several steps. First, the volatility spillover table for the entire sample is estimated. Next, rolling windows analysis is carried out. The aggregated volatility spillover measures ("from", "to", "net") for each market are estimated. The aim of this step is to find markets that are net volatility transmitters or net volatility receivers in different windows. Then, the analysis moves on to the issue of sources of food prices volatility. Thus, some measures depicted in volatility spillover tables, which estimate the amount of volatility transmitted to food markets (from the stock, energy and foreign exchange markets, and food markets as well) are calculated. In particular, contributors to forecast error variance of

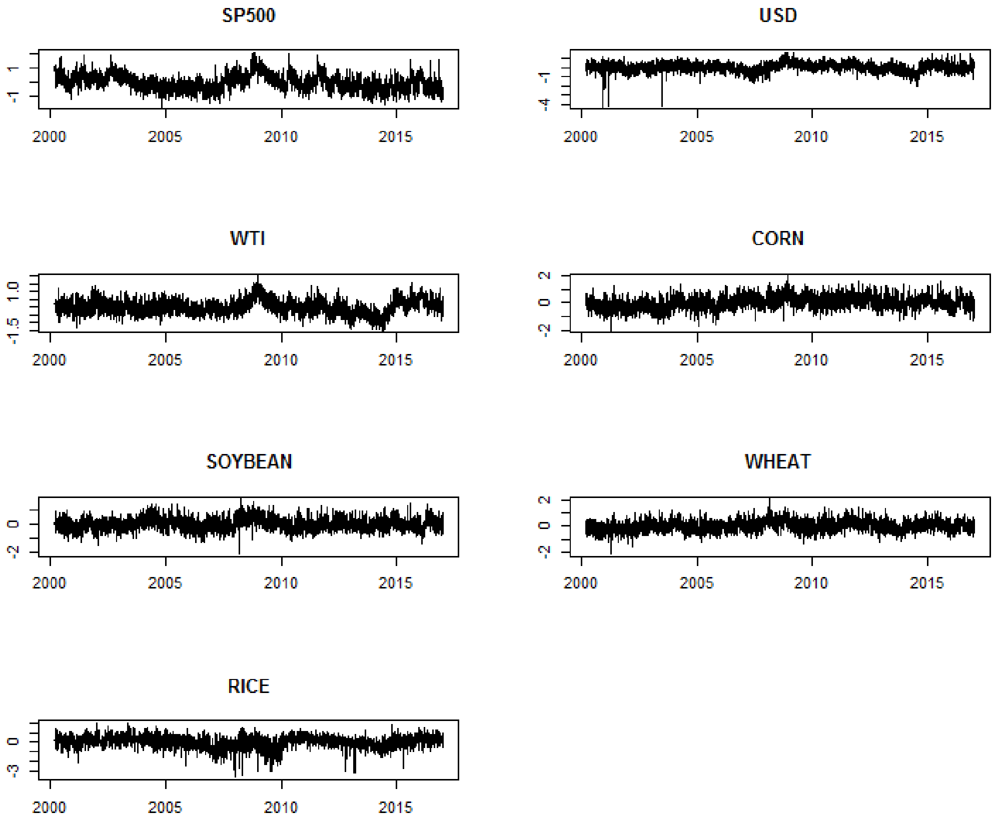
Table 1: Descriptive statistics of log range volatility for seven assets

	SP500	**WTI**	**USD**	**CORN**	**SOYBEAN**	**WHEAT**	**RICE**
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	-0.020	-0.018	0.012	-0.009	-0.018	-0.014	0.046
Max	2.137	2.004	1.665	1.957	1.723	2.022	2.003
Min	-1.758	-1.497	-4.306	-2.012	-2.078	-2.125	-3.701
Std. dev.	0.590	0.483	0.511	0.473	0.430	0.421	0.618
Skewness	0.328	0.204	-0.766	0.089	0.231	0.174	-0.828
Kurtosis	3.085	3.151	8.131	3.248	3.246	3.266	5.316

[9] We checked two other specifications. First, we augmented the seasonal adjustment to include daily seasonality. Second, we used raw data, that is without any correction for seasonality. Regardless of seasonal adjustment adopted the evolution of total volatility spillover index is quite similar. The correlation between all the indices is very high, above 0.95. Daily seasonal effects are insignificant for the food markets, with the exception of rice market on which Monday effect is significant. For "non-food" markets, except for SP500, some daily seasonal effects are found. Overall, the results obtained for these alternative specifications are quite similar to those obtained under the baseline specification and are available upon request.

[10] The null of normality was tested with Jarque-Bera test and rejected for volatility of all the series. The approach adopted in the study, i.e. rolling window regressions, requires normality of residuals assumption, which is difficult to verify since the number of windows is large and the problem of multiple comparison arises. Because of this two reasons normality assumption is usually ignored (see e.g. Diebold Yilmaz, 2009, 2012).

Figure 1: Seasonally adjusted series of log range volatility: January 4, 2000–April 1, 2017



food prices volatility are determined. Finally, the responses of food prices volatility to different shocks are studied within the VAR models with five lags that are estimated in rolling samples of 250 daily observations (about one year). The parameters of the models are estimated using the lasso method. The results obtained for the OLS-based approach are presented in the Appendix.

5.1 The full-sample results

We calculate the connectedness table based on variance decomposition for the full sample using the lasso estimation. The results are reported in Table 2. Its *ij*-th entry denotes the estimated contributions to the forecast error variance of market *i* coming from innovations in market *j*. Therefore, the off-diagonal column sums (labeled "to others") and row sums (labeled "from others") are the "to" and "from" directional spillovers, respectively, and the "to minus from" differences are net directional volatility spillovers. The penultimate row in Table 2 reports the contribution of a volatility shock in a particular market to volatility observed in all other markets (stock, energy, foreign exchange and food). The volatility spillovers from all other markets to volatility in a given market is tabulated in the last column. The table of volatility spillovers may be viewed as the "input–output" decomposition of the total volatility spillover index.

Table 2: The direction of implied volatility spillovers (the lasso method)

	SP500	USD	WTI	CORN	SOYBEAN	WHEAT	RICE	From Others
SP500	89.4	4.8	3.9	0.6	0.4	0.6	0.3	10.6
USD	5.9	87.6	3.8	0.8	1.0	0.5	0.5	12.4
WTI	5.8	4.0	87.4	0.6	0.8	0.7	0.7	12.6
CORN	0.5	0.7	0.6	68.0	14.1	15.6	0.5	32.0
SOYBEAN	0.7	1.0	0.8	15.7	74.5	6.9	0.5	25.5
WHEAT	0.6	0.7	0.6	16.3	6.4	74.8	0.6	25.2
RICE	0.1	1.0	0.5	0.6	0.5	0.6	96.7	3.3
To Others	13.7	12.1	10.1	34.5	23.3	24.8	3.1	17.4
Net spillovers	3.1	-0.3	-2.5	2.5	-2.2	-0.4	-0.2	

Note: Total spillover index, 17.4%, is calculated as in Diebold and Yilmaz (2012).

As Table 2 demonstrates, the percentage of other markets in the US stock market (SP500) forecast error variance decomposition is 10.6%. At the same time, the US stock market (SP500) transmits about 13.7% of volatility to other markets. The difference between the amount of volatility transmitted to other markets and the amount of volatility received by the stock market is 3.1%, which means that the stock market is a net volatility transmitter. It is worth noting that the stock market transmits only 1.9% of volatility to food markets and 11.7% to other markets and receives only 1.9% of volatility from food markets and 8.7% from other markets. This means that the connectedness between the stock market and food markets is more or less the same in both directions and weak if not negligible.

Similar calculations for the energy market (WTI) and the foreign exchange market (USD) reveal that both markets are net volatility receivers with indices –0.3% and –2,5% respectively. The contribution of the energy market to the food markets volatility and "non-food" markets volatility is 2.5% and 7.7%, respectively, and the energy market receives 2.8% of volatility from the food markets and 9.8% from other markets. Similarly, the contribution of the foreign exchange market to food markets volatility and other markets volatility is 3.4% and 8.8%, respectively, while the foreign exchange market receives 2.8% of volatility from the food markets and 9.7% from other markets.

Therefore, we may conclude that there exists some volatility spillovers from the stock, energy and foreign exchange markets to these markets, but not to the food (corn, soybean, wheat and rice) markets. We find that volatility spillovers between the stock, energy and foreign exchange markets and food markets are weak. Such a weak impact of the energy market on the food markets is also found by Awartani et al. (2016).

When the food markets are taken into account, the corn market seems to be the most important, as it is the net volatility transmitter with net volatility spillover index 2.5%. The corn market transmits as much as 34.5% of volatility to other markets, however, most of this volatility (about 32.6%) is transmitted to other food markets (mainly the soybean and wheat markets). The corn market is also the main receiver of volatility (32%) which comes from the food markets (30.2%). Other food markets are net volatility receivers: the net volatility index is

–2.2%, –0.4% and –0.2% for the soybean, wheat, and rice markets, respectively. The rice market is specific in this respect, because it transmits about 3.1% of volatility to other markets and receives also only 3.3% of volatility from other markets. So, the rice market seems to belong neither to the food markets (which is surprising) nor to the “non-food” markets (which is natural). The different nature of the rice market can result from unique conditions required for rice production, which makes the problem of competition for land invalid, as no other crop can be grown on the same land that is used for rice.

In order to check if our results are robust, we calculate the connectedness table based on variance decomposition for the full sample using the OLS estimation. The results of the direction of implied volatility spillovers are presented in Table 1A in the Appendix. The comparison of the two methods applied reveals that in the case of the lasso method there is less volatility transmission in the system. What is common for both approaches is that the same two markets – the stock and corn markets – are the only net volatility transmitters and the market for rice remains separated from the other markets.

As another robustness check we analyse the connectedness table estimated for the system extended by adding the VIX index, following Basak and Pavlova (2016). The results are reported in Table 2A in the Appendix. The results of the direction of implied volatility spillovers show that only the connectedness of the stock market (SP500) with other market changes since volatility spillovers to that market are dominated by volatility of the VIX. The stock market receives 33.4% of volatility to other markets, out of which 27.7% spills over from the VIX. At the same time, the stock market transmits 11.0% of volatility to other markets. So, in this case the stock market becomes the net volatility receiver (–22.3%) and the VIX becomes the net volatility transmitter to all markets in the system (29.5%). The remaining elements of the connectedness table do not change significantly.

It can be observed, however, that the food markets (the corn, soybean and wheat markets) and the “non-food” markets (the stock, energy and foreign exchange markets) constitute two separate clusters. The volatility transmission within such clusters is significantly larger than between clusters.

5.2 The rolling windows results

Total volatility spillover index

Many changes took place in the food markets during the sample period, i.e. between 2000 and 2017. Some of them affected the relations studied gradually, e.g. the increase in capital mobility, the rising importance of electronic trading and hedge funds, and a shift in the distribution of crops related to increased production of biofuels, while other changes, like surges in food prices in 2007–2008 and 2010–2011, exerted a sudden impact on the markets. This suggests that a dynamic approach should be used to analyse the relations. Following Diebold and Yilmaz (2012), we estimate our models using a rolling-window approach. Each window includes 250 days, approximately the number of working days in a calendar year. The underlying VAR model, estimated using the lasso method, has five lags, and the forecasting horizon is 10 days.

Figure 2: Dynamic total implied volatility spillover index for seven markets (the lasso method)

Notes: This figure shows the total volatility spillover index over the sample period January 4, 2000 to April 1, 2017 estimated with a rolling window of 250 days and calculated from the forecast error variance decompositions on 10-step-ahead forecasts. The starting date of a window is on the horizontal axis.

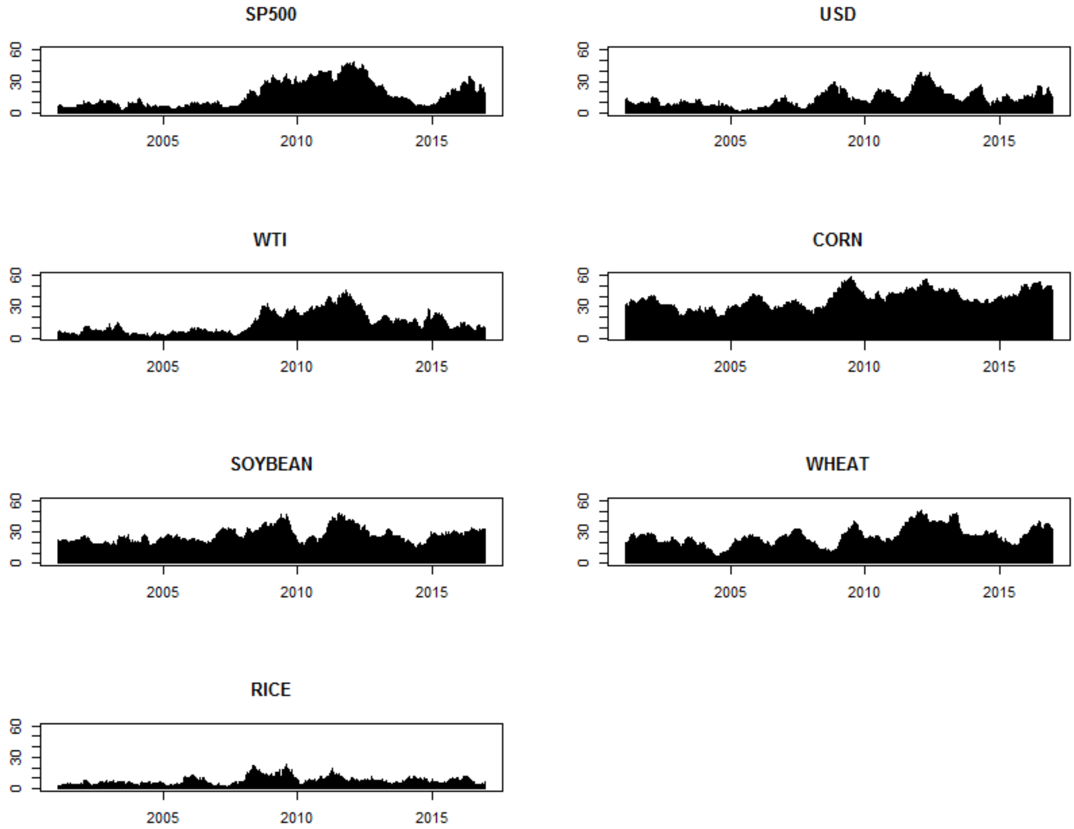
We divide the sample period into subperiods in order to assess the evolution of the total volatility spillover index. The results obtained by the lasso method are presented in Figure 2. The index is about 14% for the initial subperiods. The minimum values (about 8%) are obtained in subperiods starting in the third quarter of 2003. In the subsequent windows the total volatility spillover index increases substantially. For the period from 2007 to 2009, the values exceed 25%. The largest volatility spillover index, almost 38%, is observed in the windows beginning in the first quarter of 2011, which coincide with crises in the food market. Then, the total volatility index decreases to about 20% in 2015, and next rises to about 26% in 2016. In the Appendix in Figure 1A the total volatility spillover index obtained with the lasso method is compared with the one estimated with the OLS method. Two conclusions can be drawn from this comparison. First, the total spillover index estimated with the OLS is larger (its value ranges from 17% to 43%) than the one obtained with the lasso method. Second, the difference between the two indices decreases during turmoil periods. This observation implies that lasso estimation is more appropriate to distinguish normal from extreme market conditions.

Gross and net volatility spillovers

Figure 3 illustrates the directional volatility spillovers from a given market to other markets which are calculated using the lasso method (corresponding to the "to others" row in Table 2).[11]

[11] In order to compare the results of the lasso method with the results of the OLS method, Figure 2A in the Appendix shows the directional volatility spillovers from each of the seven markets to others which are calculated using the OLS method.

Figure 3: Directional volatility spillovers "to others" for seven markets (the lasso method)



The results presented reveal different patterns of volatility transmitted by the food markets and the stock, energy and foreign exchange markets (SP500, WTI, USD). The volatility spillovers from the food markets to other markets display a cyclical behaviour. There are subperiods in which more (in comparison to other subperiods) volatility is transmitted (e.g. windows covering 2009, 2011 or 2016) and subperiods in which less volatility is transmitted (2004, 2010, 2015). The rice market is specific, as it transmits much less volatility than any other market. In the case of the stock, energy and foreign exchange markets the situation is quite different. In the initial subperiods (up to 2007) little volatility is transmitted to other markets. Then, the volatility transmission increases significantly. Finally, for windows beginning in 2014 the amount of volatility transmitted decreases.

Figure 4 presents the directional volatility spillovers from the other markets to a given market which are calculated using the lasso method (corresponding to the "from others" columnin Table 2).[12] In general, the results are quite similar to those reported in Figure 3. Once again, there is a clear distinction between patterns of volatility received by the food markets (the corn, soybean and wheat markets) and the "non-food" markets (SP500, WTI, USD). What is

[12] Figure 3A in the Appendix illustrates the directional volatility spillovers from other markets to a given market which are calculated using the OLS method.

Figure 4: Directional volatility spillovers "from others" for seven markets (the lasso method)

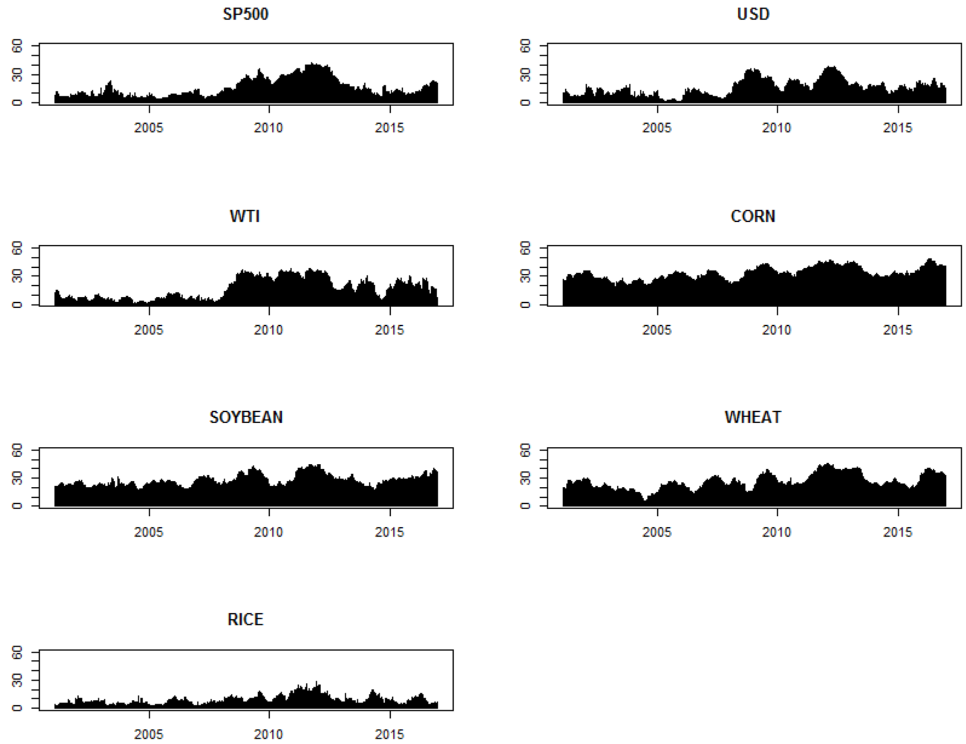
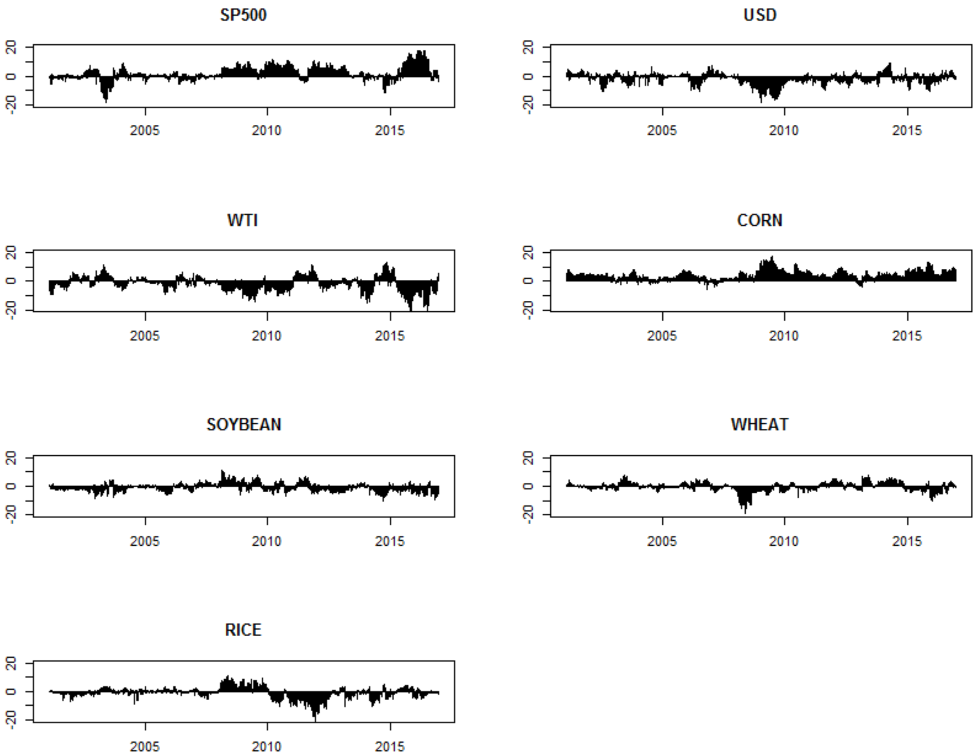


Figure 5: Net volatility spillovers, seven markets (the lasso method)



more, the periods in which the largest amount of volatility is received by particular markets are similar to the ones obtained when the volatility is transmitted. Once more, the rice market receives much less volatility than other markets.

Figure 5 presents net volatility spillovers (estimated using the lasso method) across markets corresponding to the difference between the amount of volatility transmitted by a single market and the amount of volatility received by this market.[13] The results indicate that in the case of the stock, energy and foreign exchange markets, there are numerous subperiods in which a particular market is the net volatility transmitter in the system and numerous subperiods in which the same market is the net volatility receiver. Thus, it is not easy to indicate a single market that dominates other markets in terms of volatility. When food markets alone are taken into account, the situation is slightly different as the corn market is the net volatility transmitter for the entire period. In the case of other food markets, there are again periods in which a particular market is the net volatility transmitter and the net volatility receiver.

Sources of food prices volatility

The net volatility spillovers between pairs of markets in which one element belongs to the stock, energy and foreign exchange markets and the second element belongs to the food markets are estimated. The results are presented in Figure 6.[14] In each case there are short periods when the food market dominates over other markets, i.e. it is the net volatility transmitter (negative values in Figure 6), and short periods of the opposite relation, i.e. the food market is the net receiver of volatility (positive values in Figure 6). The volume of net volatility spillovers, however, is low for most subperiods. This suggests that the relations between volatility in the stock, energy and foreign exchange markets and volatility in the food markets are not very strong. In this respect our results are similar to those reported in many other studies (see, e.g., Diebold and Yilmaz, 2012; Chevallier and Ielpo, 2013; Jebabli et al., 2014; Awartani et al., 2016; Grosche and Heckelei, 2016). Moreover, this finding is in line with Irvin (2013), Aulerich et al. (2014) and Etienne et al. (2014) who found that the process of financialization did not contribute to an incidence of food prices bubbles.

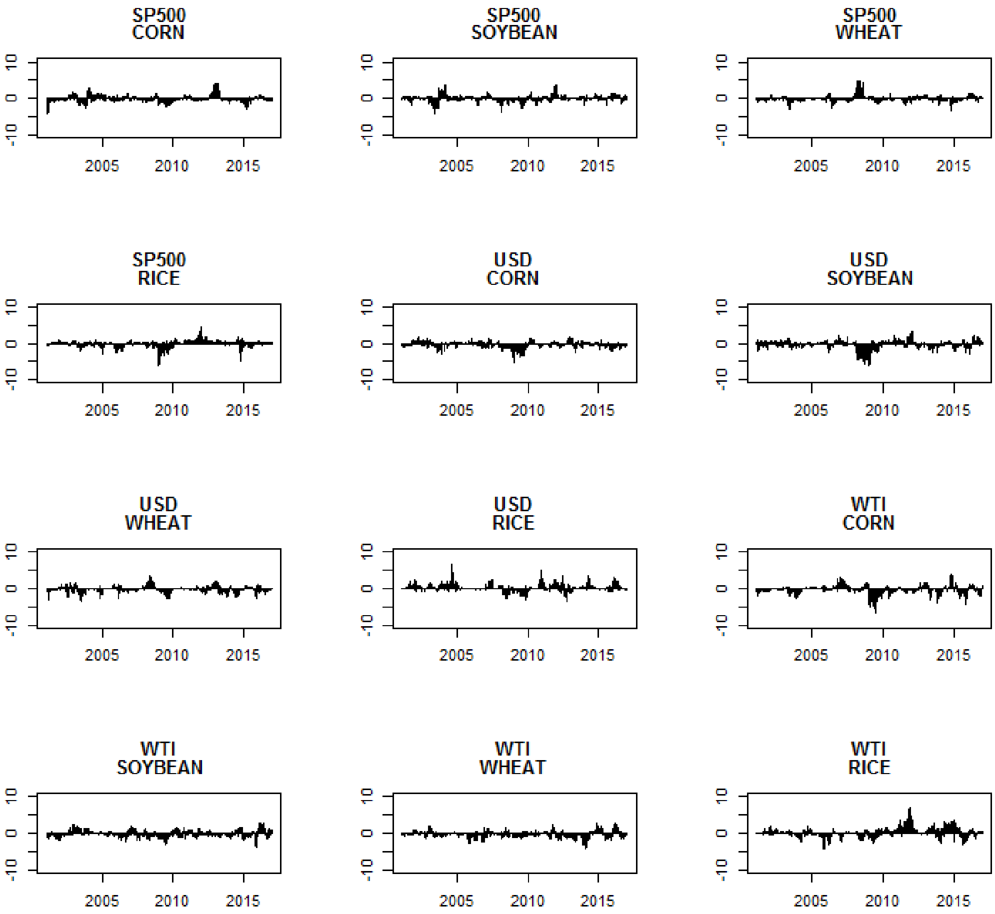
Net volatility spillovers within the food markets are presented in Figure 7.15 The corn market is the net volatility transmitter to the soybean and wheat markets. In this case the net volatility spillovers are positive and almost always above 1%. In many subperiods they are even stronger, above 4%. The corn market is also a net volatility transmitter to the rice market, although the index is on average smaller, less than 1%. The patterns of the net pairwise connectedness obtained for the remaining pairs are less clear-cut. There are many subperiods in which a particular food market is the net volatility transmitter and many in which the same

[13] Figure 4A in the Appendix presents the rolling net volatility spillovers of the seven markets obtained with the OLS method.

[14] Figure 5A in the Appendix shows the pairwise net volatility spillovers between the US stock (SP500), energy (WTI) and foreign exchange (USD) markets and the food market obtained with the OLS method.

[15] Figure 6A in the Appendix illustrates net volatility spillovers within the food market obtained with the OLS method.

Figure 6: Pairwise net volatility spillovers from the US stock (SP500), energy (WTI) and foreign exchange (USD) markets to the food markets (the lasso method)

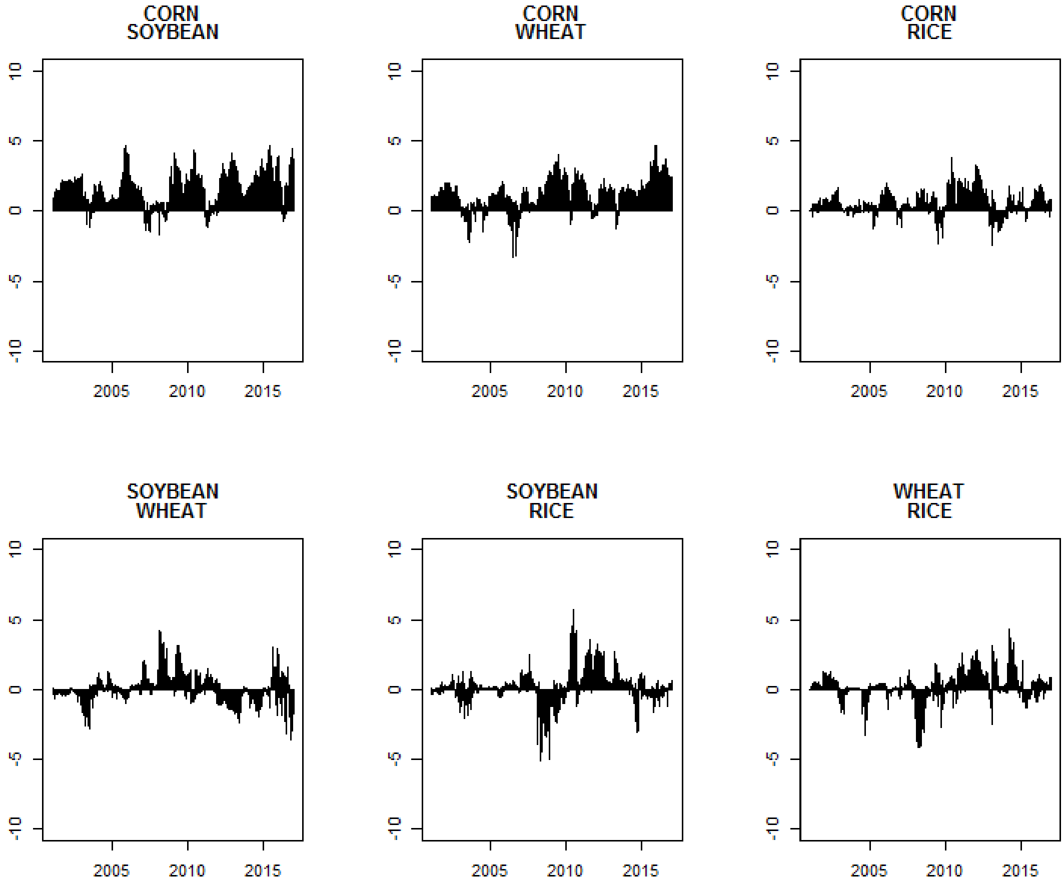


market is the net volatility receiver. For example, the soybean market transmits more volatility to the wheat market in the period 2007–2011, while in the period 2012–2014 in most subperiods the relation is opposite. Both the soybean and wheat markets are net volatility receivers from the market for rice in 2009, when skyrocketing of the price of rice is observed. In the remaining subperiods the rice market is the net volatility receiver.

The results of forecast error variance decompositions of each food market are presented in Figure 8.[16] Different colours represent the share of volatility that comes from different markets. It can be noticed that for each food market the greatest share of the FEV comes from its own, specific volatility shock. To be more precise, no less than 50% of the FEV of volatility in a given food market is accounted for by its own shocks.

[16] Figure 7A in the Appendix shows the forecast error variance decompositions of the food markets obtained with the OLS method.

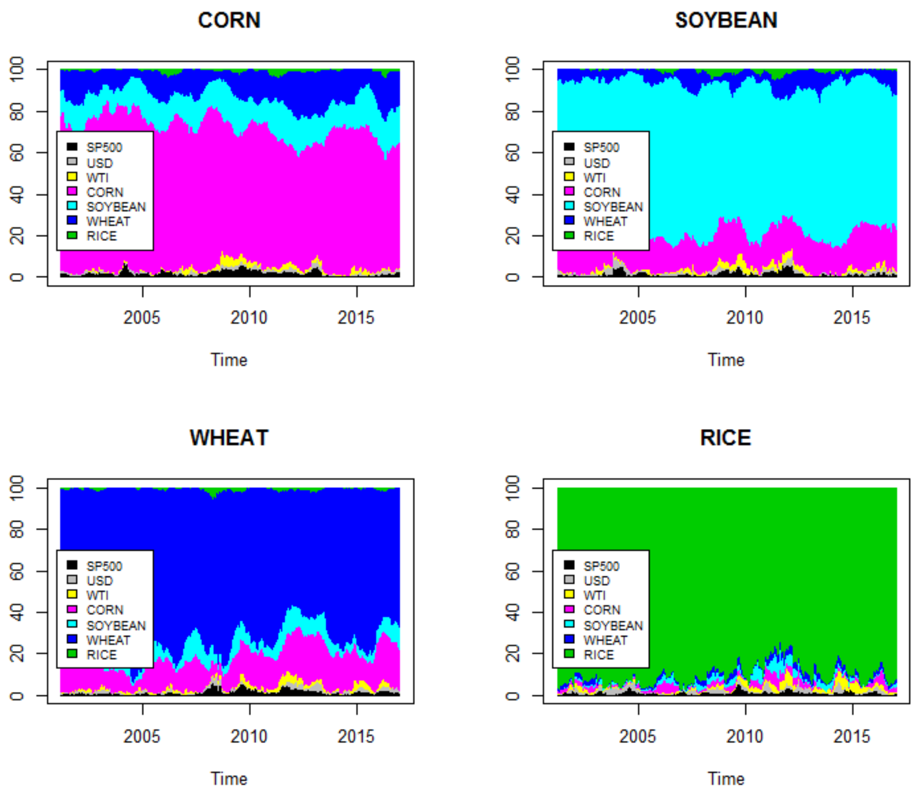
Figure 7: Pairwise net volatility spillovers within the food markets (the lasso method)



In the case of the corn market, a large proportion (about 20%, and in 2016 between 35% and 40%) of the FEV is accounted for by shocks specific to the soybean and wheat markets. It is worth noticing that the soybean market seems to be responsible for a similar proportion of the FEV of the corn market in every subperiod, whereas the importance of the wheat market changes over time. The share of the wheat market in the FEV decomposition of volatility in the corn market ranges between several per cent in the subperiods covering 2005 and 2009 and about 20% between 2011–2014. The contribution of the rice market to volatility in the corn market, as well as the stock, energy and foreign exchange markets (SP500, WTI, USD), is negligible.

In the case of the FEV decomposition of volatility in the soybean and wheat markets, apart from the importance of their own shocks, the second most important factor is volatility in the corn market. The share of the corn market in the FEV exceeds 20% in many subperiods. The third most important factor is the wheat market for the soybean market and the soybean market for the wheat market. The share of one of these agricultural commodities in the FEV of the other ranges from 4 to 10%. Again, the role of stock, energy and foreign exchange markets is not significant. The FEV decomposition of volatility in the rice market demonstrates that no market

Figure 8: Forecast error variance decompositions of the food markets (the lasso method)



transmits significant amount of volatility to the rice market. It is worth mentioning that around 2011 the FEV of volatility in the rice market is accounted for by other factors in about 20%.

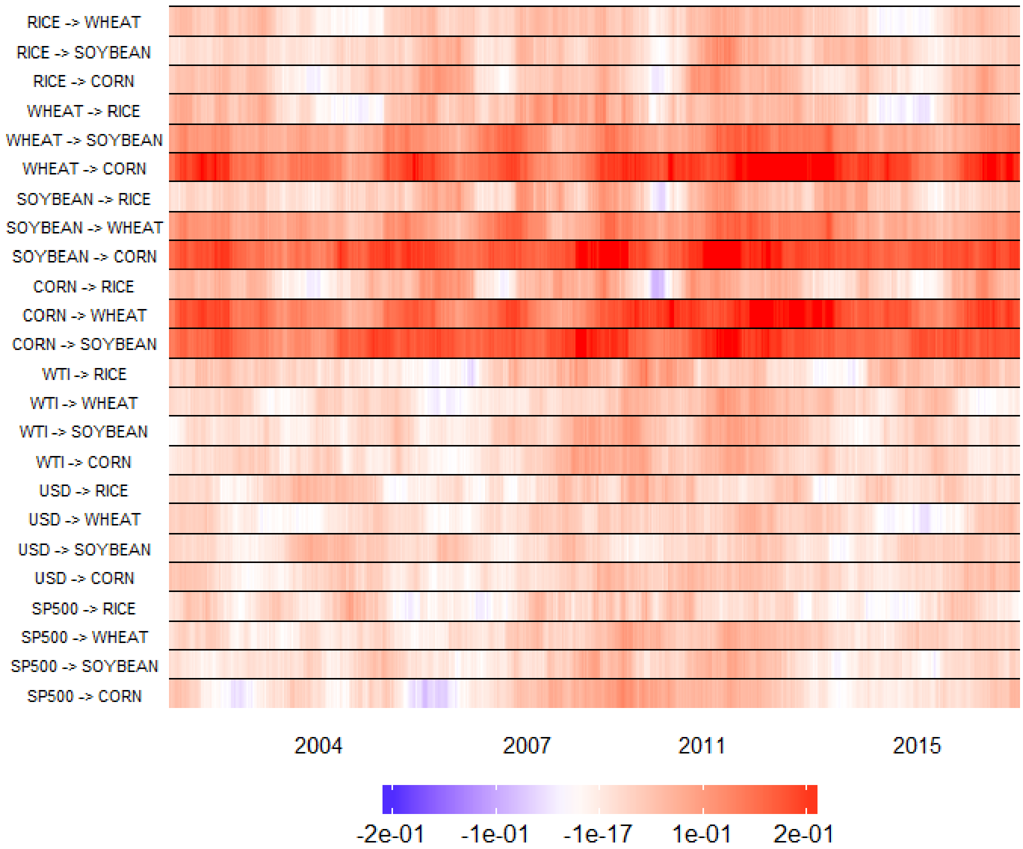
Apart from the volatility spillover indices, we intend to uncover the response of food volatility to shocks originating from the stock (SP500), energy (WTI) and foreign exchange (USD) markets and from the food markets. Thus, we calculate the generalized impulse response functions for all rolling windows and different horizons. Figure 9 presents, however, the response of food volatility to a one standard deviation shock at one-day horizon. The colours used represent the strength of response. The darker the blue colour, the more negative response of a variable is observed. On the other hand, the darker the red colour, the larger positive response of volatility to a shock received. The horizontal axis represents time. The response obtained for the first window (covering 250 observations from 2000) is depicted as the first on the left of the picture. The responses obtained in the last window (ending in April 2017) are on the right.

The results illustrated in Figure 9 can be summarized with three observations.[17] First, in most windows, food volatility increases as a result of shocks originating from other markets (warm colours dominate the heatplot). There are, however, subperiods in which the response of food volatility to other markets shocks are negligible or even negative (for example, the response of volatility in the corn market to the stock market (SP500) shock for windows

[17] Figure 8A in the Appendix illustrates the response of the food markets to shocks originating from other markets obtained with the OLS method. The results are similar to the ones reported in the main text.

covering 2006, or the response of volatility in any food market to the energy market (WTI) shocks in the same subperiod). Second, the strongest, positive response of volatility in food markets is observed for shocks generated on other food markets (the soybean and wheat markets response to the corn market shocks, or the corn market responses to the wheat or soybean markets shocks). The rice market seems to depend only weakly on other food shocks, as the response of the rice market to other shocks is moderate. Third, the strongest response of volatility in food markets to shocks originating from the stock, energy and foreign exchange markets appear between 2007 and 2012. It suggests that during the global financial crisis and food crises food volatility was more sensitive to information coming from other markets and the responses of volatility in the food markets were more significant.

Figure 9: Responses of the food markets to shocks originating from other markets (the lasso method)



6 Conclusion

The objective of the study is to examine volatility spillovers in the food markets and the "non-food" markets. Unlike in previous studies, we compare the volatility transmission within different food markets and between the food markets and the stock, energy and foreign exchange markets, which allows us to assess the importance of volatility in these markets in triggering volatility in the food markets. Our main findings can be summarized in the following way.

The total volatility index has increased over time, which means that on average more volatility is transmitted between the markets. The largest values of the index are observed in two food crises (2008 and between 2011–2012). The results obtained for rolling directional spillover (from and to) reveal, however, a cyclical behaviour of the food markets and the increase of volatility spillover in the stock, energy and foreign exchange markets since 2007.

Most volatility transmissions are observed among the same categories of markets. We identify two groups which are interrelated in terms of volatility spillovers, i.e. the US stock, energy and foreign exchange markets and the food markets (including corn, soybean and wheat). A typical food market transmits much more volatility to other food markets than to other markets. This can result from dissimilarity of the stock, energy, foreign exchange markets. Volatility of the market for rice does not seem to depend on developments in other markets and is not transmitted to other markets, with the exception of one episode, i.e. 2009, when the price of rice reached a record high and the volatility shocks spilled over soybean and wheat markets.

The sources of the forecast error variance of food markets volatility vary for different food markets and for different subperiods. The corn market, however, seems to be the most important agricultural commodity, as it transmits a vast amount of volatility to other food markets. The corn market is the net volatility transmitter to the soybean and wheat markets and is the second most important source of volatility in these two markets, representing up to 20% of the FEV.

The results of the generalized impulse response functions suggest similar conclusions. The strongest response of food markets volatility results from shocks originating from another food market (with the exception of the rice market). Much smaller, but still a positive response of the food markets volatility to the shocks in the "non-food" markets can be observed. Finally, food markets volatility was more sensitive to shocks from different markets during the global financial crisis and surges in food prices.

The most general conclusion of the paper is that the role of the financial and energy markets in creating the food markets volatility is limited. In particular, volatility of energy prices appears to be insignificant for food prices. Interestingly, the corn market seems to be the most important food market, as it is the net volatility transmitter to the soybean, wheat and rice markets. Since the share of corn production used for biofuels (ethanol) has risen significantly during the analysed period, it can be concluded that the relations between energy and agricultural commodities markets have become tighter, although in an indirect way, i.e. via the market for corn.

There are two potential policy implications of the results obtained. First, financialization seems to have limited impact on food markets volatility. Therefore, the policy-oriented at maintaining low volatility of food markets can potentially be effective and is not undermined by financial volatility (transmission of volatility from financial markets to food markets is negligible). Second, since the corn market seems to be the most important source of volatility in food markets, policy should be focused on this market.

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Appendix

Table 1A: The direction of implied volatility spillovers (the OLS method).

	SP500	**USD**	**WTI**	**CORN**	**SOYBEAN**	**WHEAT**	**RICE**	**From Others**
SP500	89.4	4.7	3.9	0.6	0.4	0.6	0.3	10.6
USD	6.2	85.4	4.1	1.3	1.5	0.6	1.0	14.6
WTI	6.3	4.5	86.1	0.6	1.0	0.6	0.9	13.9
CORN	0.7	0.9	0.7	67.2	14.1	15.9	0.5	32.8
SOYBEAN	0.9	1.1	0.8	15.6	74.1	7.0	0.5	25.9
WHEAT	0.9	0.8	0.8	16.7	6.5	73.5	0.8	26.5
RICE	0.2	1.3	0.5	0.8	0.6	0.6	96.1	3.9
To Others	15.2	13.2	10.9	35.5	24.0	25.3	4.0	18.3
Net spillovers	4.7	-1.4	-3.1	2.8	-1.9	-1.2	0.1	

Table 2A: The direction of implied volatility spillovers, VIX included (the lasso method).

	SP500	**VIX**	**USD**	**WTI**	**CORN**	**SOYBEAN**	**WHEAT**	**RICE**	**From Others**
SP500	66.6	27.7	2.7	1.9	0.3	0.4	0.4	0.1	33.4
VIX	3.9	95.1	0.4	0.1	0.0	0.2	0.1	0.2	4.9
USD	3.2	1.9	88.0	3.2	1.0	1.5	0.4	0.8	12.0
WTI	2.6	3.1	3.6	88.0	0.5	1.0	0.6	0.7	12.0
CORN	0.3	0.5	0.7	0.5	67.5	14.1	15.8	0.6	32.5
SOYBEAN	0.6	0.4	0.9	0.7	15.5	74.5	6.9	0.5	25.5
WHEAT	0.4	0.5	0.6	0.6	16.6	6.5	74.0	0.7	26.0
RICE	0.0	0.4	1.1	0.4	0.8	0.6	0.6	96.1	3.9
To Others	11.0	34.4	9.9	7.4	34.7	24.2	24.8	3.6	18.8
Net spillovers	-22.3	29.5	-2.0	-4.6	2.3	-1.4	-1.2	-0.3	x

Figure 1A: Dynamic total implied volatility spillover index for seven asset classes (the lasso method and the OLS method)

Figure 2A: Directional volatility spillovers,TO seven markets (the OLS method)

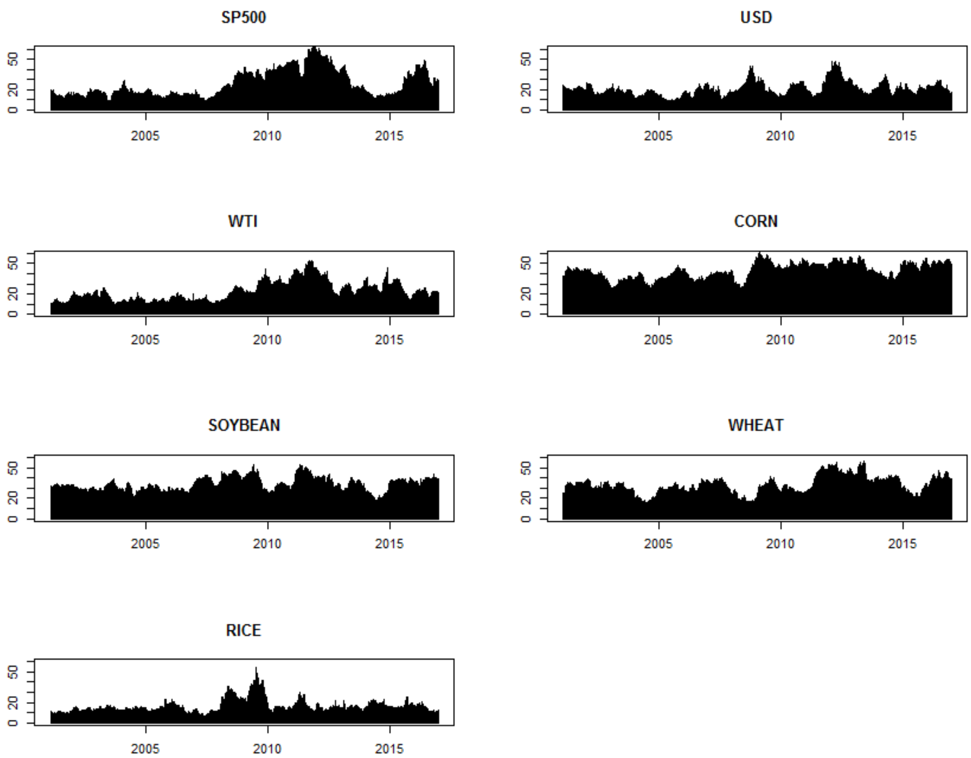


Figure 3A: Directional volatility spillovers, FROM seven markets (the OLS method)

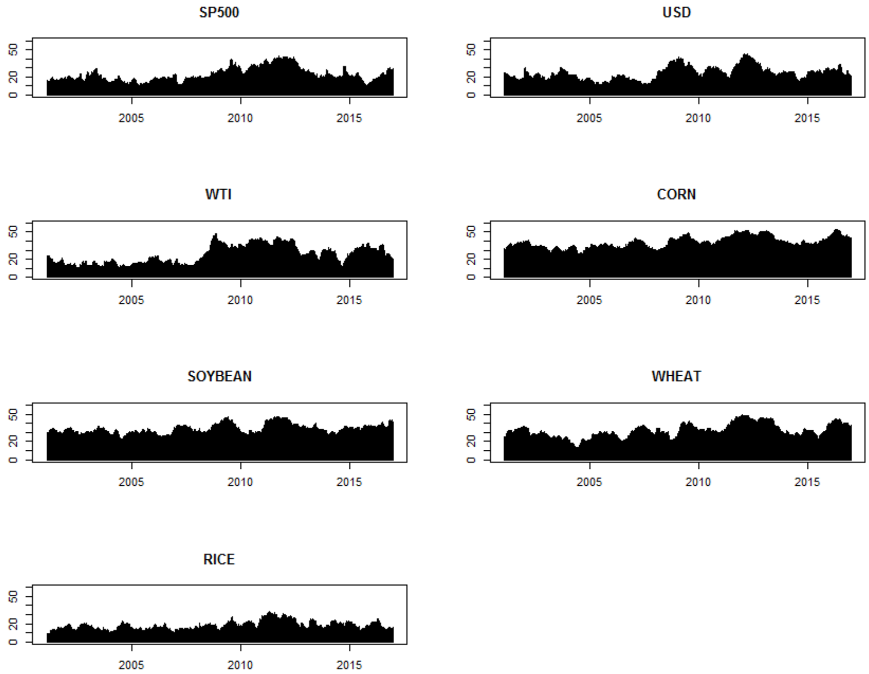


Figure 4A: Net volatility spillovers, seven markets (the OLS method)

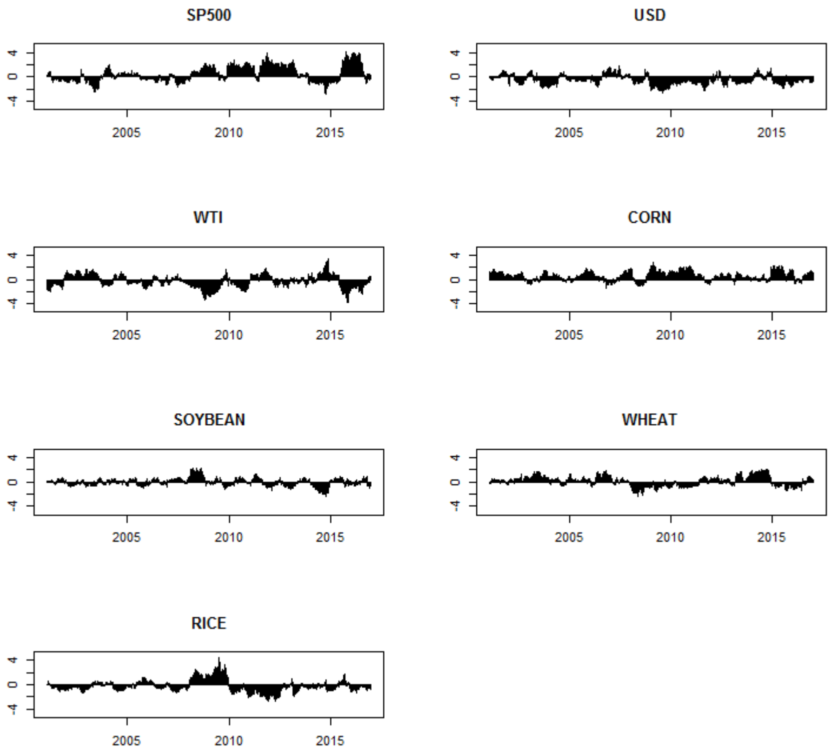


Figure 5A: Pairwise net volatility spillovers from the US stock (SP500), energy (WTI) and foreign exchange (USD) markets to the food markets (the OLS methods)

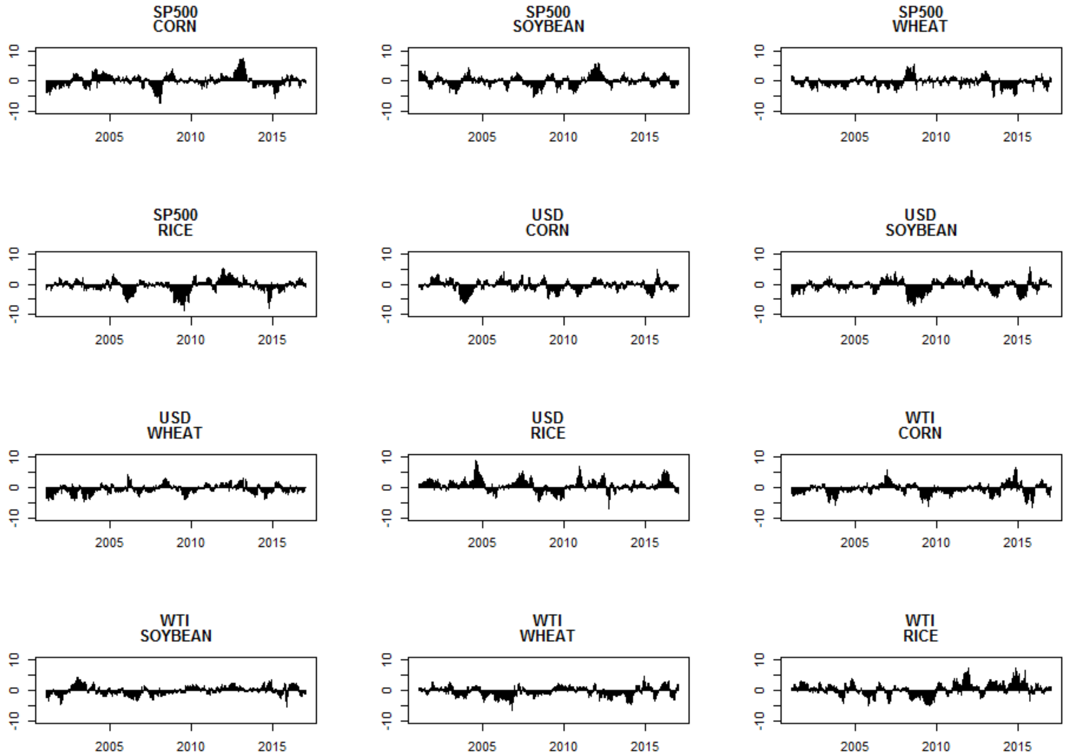


Figure 6A: Pairwise net volatility spillovers within the food markets (the OLS method)

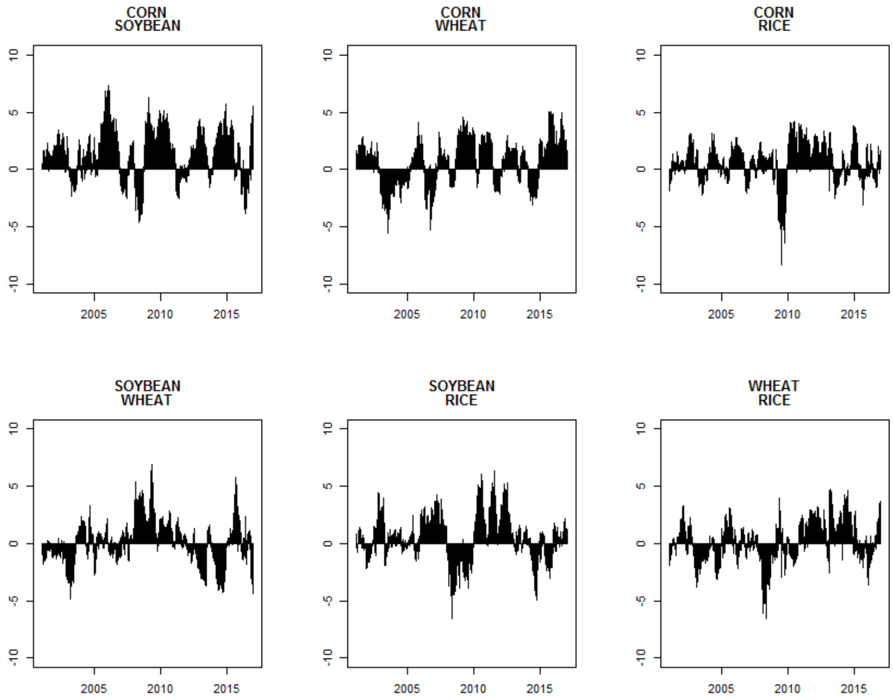


Figure 7A: The forecast error variance decompositions (FEVD) of the food markets (the OLS method)

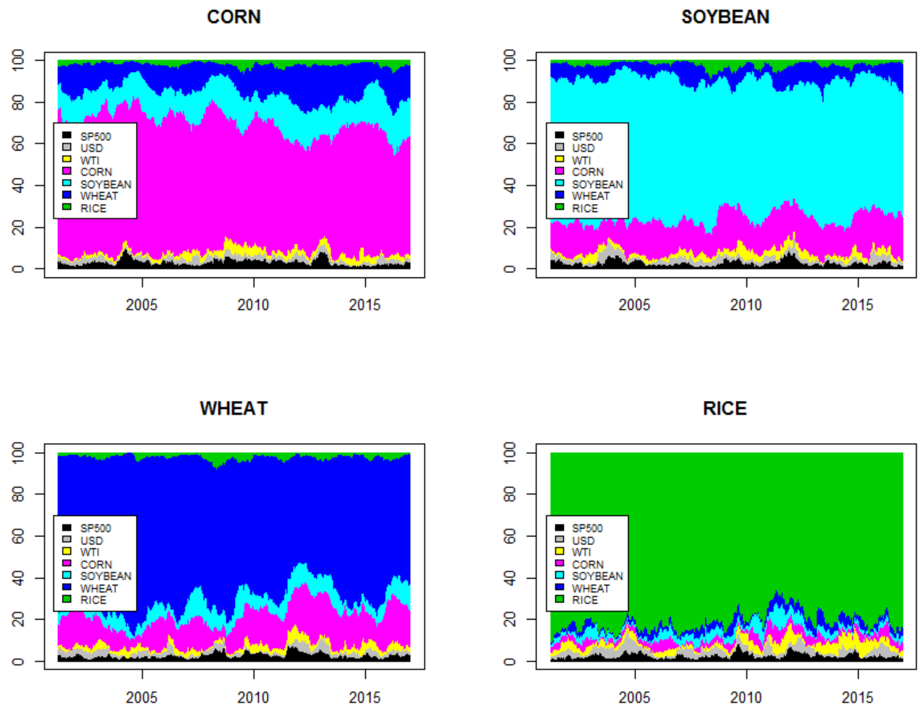
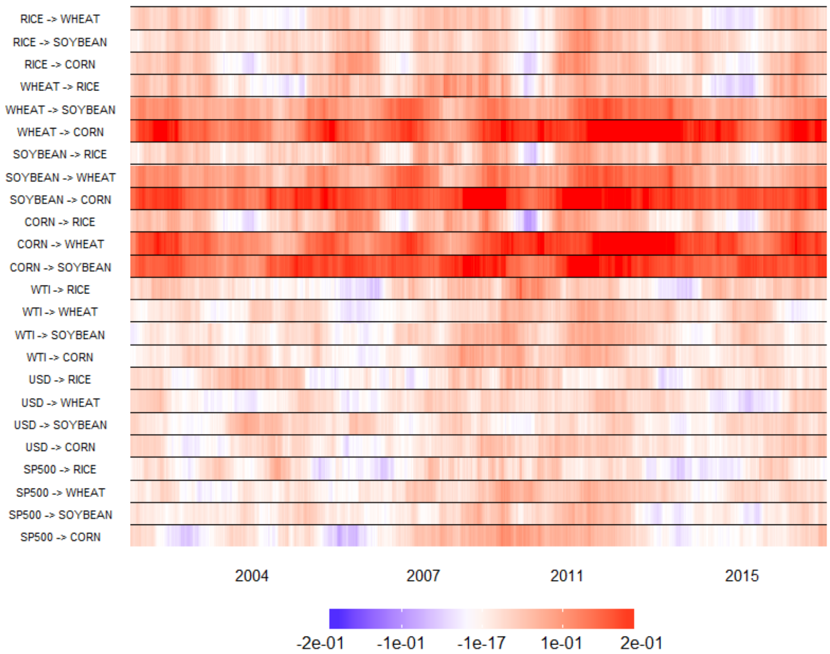


Figure 8A: The response of the food markets to shocks originating from other markets (the OLS method)



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The Editor

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