Volatility spillovers between food, energy, US dollar, and equity markets. Evidence from Diebold-Yilmaz's approach

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Abstract

The causes of the surges in food prices in 2007 and 2012 are still a controversial issue. Literature offers their plausible explanations, which include e.g. financialization, depreciation of US dollars, or the tighter connection between the food market and the energy market (biofuels).

The aim of the study is to investigate volatility spillovers between food, energy, US dollar and equity markets. The analysis uses daily series of volatility of corn, soybean, wheat, rice, US dollar, crude oil, and SP500 futures covering the period from January 4, 2000 to December 30, 2016. We base our analysis on forecast-error variance decompositions in a generalized vector autoregressive framework, which are invariant to the ordering of variables, as proposed by Diebold and Yilmaz (2012). The data are studied in rolling subsamples, since the evolution of relationships is expected. Taking into account a large number of parameters in the models in single iterations, lasso estimation methods are used. The results of the study reveal that both total and directional volatility spillovers change in time. Most volatility transmissions are observed among the same category of instruments, i.e. the financial instrument group or the agricultural commodity group. Corn is the most important agricultural commodity, as it transmits vast volatility to other instruments in the food market.

Keywords: *volatility spillovers, agricultural commodity, lasso, financial markets*

JEL Classification:

1 Introduction

Volatility of food prices has a number of negative consequences. On a macro level, it influences public finances and the balance of trade for countries that are exporters or importers of food, while in developing countries it influences the level of inflation. At the micro level, it is an obstacle for food manufacturers, increasing the risk and the credit costs. Rising food prices have dramatic consequences for the poor in developing countries, as they spend a substantial part of their income (even 2/3 of disposable income) on food.

The recent food price surges (2008 and 2010-2011) covered many kinds of agricultural commodities grown in different places. That is why supply problems could not be the only reason for price co-movement. A set of factors that determine food price upsurges includes

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financial speculation in commodity futures markets, global economic growth (increased demand), trade restrictions, macroeconomic shocks to money supply, exchange rates (in relations to US dollars) (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.

The food-energy-price nexus stems from several areas. First, modern food production requires more and more energy (to power agricultural machinery, to heat greenhouses, to power irrigation systems, for fertilizers, etc.). Second, food is also used as energy (biofuels). It the US, corn is used as the main feedstock to produce ethanol, which has another serious consequence connected with the competition for the harvested area: the area used for biofuels (corn) production increased, as fuel ethanol production grew eight-fold between 2000 and 2014 (from 233 trillion Btu in 2000 to 1 938 trillion Btu in 2014, EIA), and could not be used for other crops. Additionally, the links between oil and agricultural prices are connected with index investments. The instruments which are listed in agricultural commodity indexes are more strongly correlated with oil than the ones not listed in the indexes. The increase of the correlation between futures prices of agricultural commodities and oil after 2004, as observed by Tang and Xiong (2012), resulted from significant index investments which started to flow into commodity markets.

The aim of the paper is to analyse volatility spillovers between food prices, energy prices, the equity market and exchange rates, and to identify which of them are the main contributors to food price volatility in the last decades.

The study is based on daily series of volatility of futures price of corn, wheat, soyabean, rice, US dollar, crude oil and SP500 covering the period from January 4, 2000 to December 28, 2016. We base our analysis on forecast-error variance decompositions in a generalized vector autoregressive framework, as proposed by Diebold and Yilmaz (2012). This framework allows us to estimate total, net and directional volatility spillovers for each instrument. We also analyse forecast error variance decomposition of food prices in order to indicate the main contributors to food price volatility. The data are studied in rolling subsamples, since the evolution of relationships is expected. Taking into account a large number of parameters in the models in comparison to the number of observations, lasso estimation methods are used in single iterations.

Our study is not the first one which examines the role of financial instruments and energy prices as drivers of food prices (see: Diebold and Yilmaz, 2012; Chevallier and Ielpo, 2013; Jebabli et al., 2014; Awartani et al., 2016; Grosche and Heckelei, 2016). But we think that our approach is the most general. Two aspects differentiate our paper from other papers. First, we use a large number of instruments: the set we analyse in our study includes four main crops in the US, which helps understand the interrelations between them and different areas of financial markets. Second, we apply lasso estimation techniques, which allows us to use generous parametrization of VAR models with a relatively large number of lags. As a result, volatility spillovers could be observed in the extended horizon, which distinguishes our paper from previous studies.

2 Methodology

Diebold and Yilmaz (2009) introduce a volatility spillover measure based on forecast error variance decompositions (FEVD) from vector autoregressions (VARs). The Diebold and Yilmaz (2009) framework relies on the Cholesky-factor identification of VARs, and thus the resulting variance decompositions can be, and usually are, dependent on variable ordering. A spillover measure which is invariant to ordering should be preferred. Diebold and Yilmaz (2012) use a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering. This is especially important since it is rarely possible to justify one particular ordering of the variables under consideration. Additionally, Diebold and Yilmaz's (2012) approach allows for examining directional spillovers (from/to a particular market). Our study employs volatility spillover indexes as introduced by Diebold and Yilmaz (2012). The spillover indexes are constructed by performing a rolling-window forecast error variance decompositions. This methodology allows for identifying time-varying patterns. While the static FEVDs classify the variables of the study into transmitters and receivers, the dynamic FEVDs may identify episodes when the role of transmitters and receivers of spillovers is interrupted or even reversed .

During the first step, VARs are estimated using the lasso regression (see Tibshirani, 1996). The lasso is a shrinkage method for linear regression; it minimizes the sum of squared errors, with a bound on the sum of the absolute values of the individual regression coefficients. Particularly in the rolling-sample, estimated degrees of freedom are substantially limited, so the incorporation of pruning and shrinkage is appealing (Diebold and Yilmaz, 2015).

During the second step, the total and directional spillover indexes are obtained by the generalized forecast error variance decompositions of the moving average representation of the VAR model. Variance decompositions allow for parsing the 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 caused by shocks from another variable.

It is assumed that volatility is fixed within periods (in our case, days) but variable across periods. Then, following Alizadeh et al. (2002), daily high and low prices are used to estimate daily volatility. Volatility proxy is defined as the logarithm of the difference between the future's highest and lowest log price. According to Alizadeh et al. (2002), the log range is better as a volatility proxy than log absolute or squared returns as it is more efficient and the distribution of the log range is closer to normality. This is particularly appealing as the generalized variance decomposition requires normality.

3 Data and empirical results

Data

The analysis of volatility spillovers is conducted using daily data from the period between January 4, 2000 and December 30, 2016, which yields 4225 observations. 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), the corn, soybean, wheat and rough rice futures contract traded on the CBOT. The prices and values of index data are obtained from Bloomberg. Next, following Diebold and Yilmaz (2012), we calculate the range volatility proxy that is described in Alizadeh et al. (2002).

The table of the full-sample return spillovers

We have calculated the table of volatility spillovers with the full sample and report the results of average volatility spillovers in Table 1. Its *ij*th entry denotes the estimated contributions to the forecast error variance of market *i* coming from innovations to market *j*. Therefore, the off-diagonal column sums (labeled 'to others') or row sums (labeled 'from others'), are the “to” and “from” directional spillovers, and the “from minus to” differences are the net directional volatility spillovers. The last row in Table 1 represents the contribution to volatilities of all markets from this particular market (equity, energy, exchange rate and food). Similarly, the last column in the table represents the contribution to volatilities of the particular market from all markets. The table of return spillovers may be viewed as the “input–output” decomposition of the total return spillover index.

As Table 1 demonstrates, the contribution of the corn market to other markets equals 35.3%, the impact of the other markets on the corn market equals 31.4%, and the net spillover index of the corn market equals 3.9%. If we analyse only the food market, we find that the contribution of the corn, soybean, wheat and rice markets to other food markets equals respectively: 33.5%, 21.6%, 22.9%, and 1.7%, and the impact of other food markets on the corn soybean, wheat and rice markets equals respectively: 30.2%, 23.8%, 24.1%, and 1.6%. The net spillover index of the corn, soybean, wheat and rice markets equals respectively: 3.3%, -2.2%, -1,2% and 0.1%. It can be observed that the food market (corn, soybean, wheat) and financial instruments (SP500, USD, WTI) produce two separate clusters. The volatility transmission inside each of the clusters is significantly larger then between pairs of instruments from separate clusters. Rice is specific in this respect, as it seems to belong neither to "food" (which is surprising) nor "financial instruments" (which is natural). The different rice category can result from unique conditions required for rice production, which makes the problem of competitions for land invalid, as no other crop can be grown on the same land that is used for rice.

	SP500	**WTI**	**USD**	**Corn**	**Soybean**	**Wheat**	**Rice**	**From Others**
SP500	89.3	3.9	4.8	0.7	0.5	0.6	0.3	10.8
WTI	5.9	87.6	4.3	0.4	0.7	0.6	0.5	12.4
USD	6.0	3.8	87.8	0.7	0.8	0.4	0.5	12.2
Corn	0.4	0.3	0.5	68.6	14.5	15.3	0.4	31.4
Soybean	0.6	0.6	0.8	16.3	74.2	7.0	0.5	25.8
Wheat	0.7	0.6	0.7	16.7	6.6	73.9	0.8	26.1
Rice	0.2	0.4	0.9	0.5	0.5	0.6	96.9	3.1
To Others	13.8	9.6	12.0	35.3	23.6	24.5	3.0	x
Net spillovers	3.0	-2.8	-0.2	3.9	-2.2	-1.6	-6.1	x

Table 1. The direction of implied volatility spillovers.

Rolling test results

Next, we compute net volatility spillovers in a rolling window, as advised by Diebold and Yilmaz (2012). We use rolling subperiods of 250 days. The underlying VAR model has five lags, and the forecasting horizon is equal to 10 days. Net volatility spillovers estimated between the financial market and the food market are presented in Fig. 1. In every case there are short periods when food predominates (is the net transmitter, positive values in Fig. 1) over financial instruments, and short periods of opposite relations (food is the net receiver, negative values).

Also the volume of net volatility spillovers is usually low. All this suggests that relations between volatilities in the financial market represented by equity, exchange rate and oil prices and food market are not very strong, thus the results may not be reliable. Our results in this respect are similar to the ones obtained in studies by Diebold and Yilmaz, 2012; Chevallier and Ielpo, 2013; Jebabli et al., 2014; Awartani et al., 2016; Grosche and Heckelei, 2016.

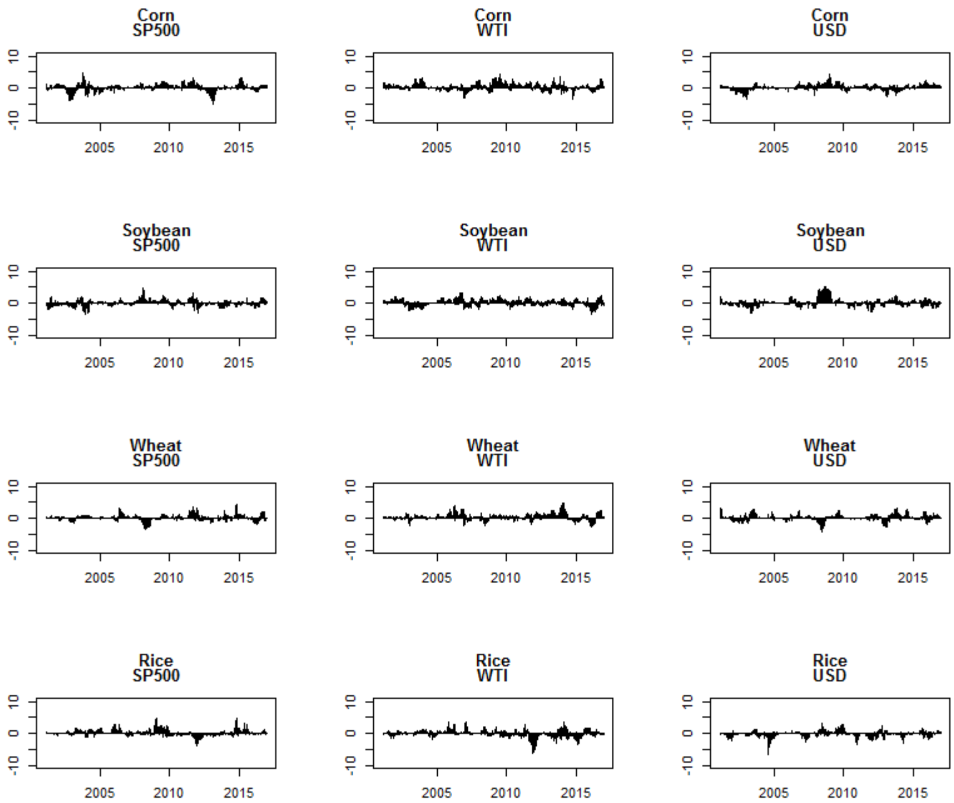

Fig. 1. Net volatility spillovers between the financial market and the food market.

Net volatility spillovers obtained for the food market are presented in Fig. 2. Corn is the net volatility transmitter to soybean and wheat. In this case net volatility spillovers are positive for most subperiods, their volume usually exceeds 1%, and in many subperiods even reaches 4 or 5%. Corn is also the volatility transmitter to rice. However, the net volatility index is smaller (less than 1%) in comparison to previously described corn-soybean relations. The patterns of the net pairwise connectedness of the net volatility index obtained for remaining pairs are not so clear. There are many subperiods in which a particular food is the net volatility transmitter, and a lot of subperiods in which the same instrument is the net volatility receiver. For example, soybean transmits more volatility to wheat in the period 2007-2011, while in the period 2011 – 2014 in most windows the relations are opposite.

A common factor in relations between soybean and rice and wheat and rice is that in windows covering 2009 (in 2009 rice prices surge to a record level, and rice transmits more volatility to both soybean and wheat then receives from them. But in the remaining superiods rice is the net volatility receiver).

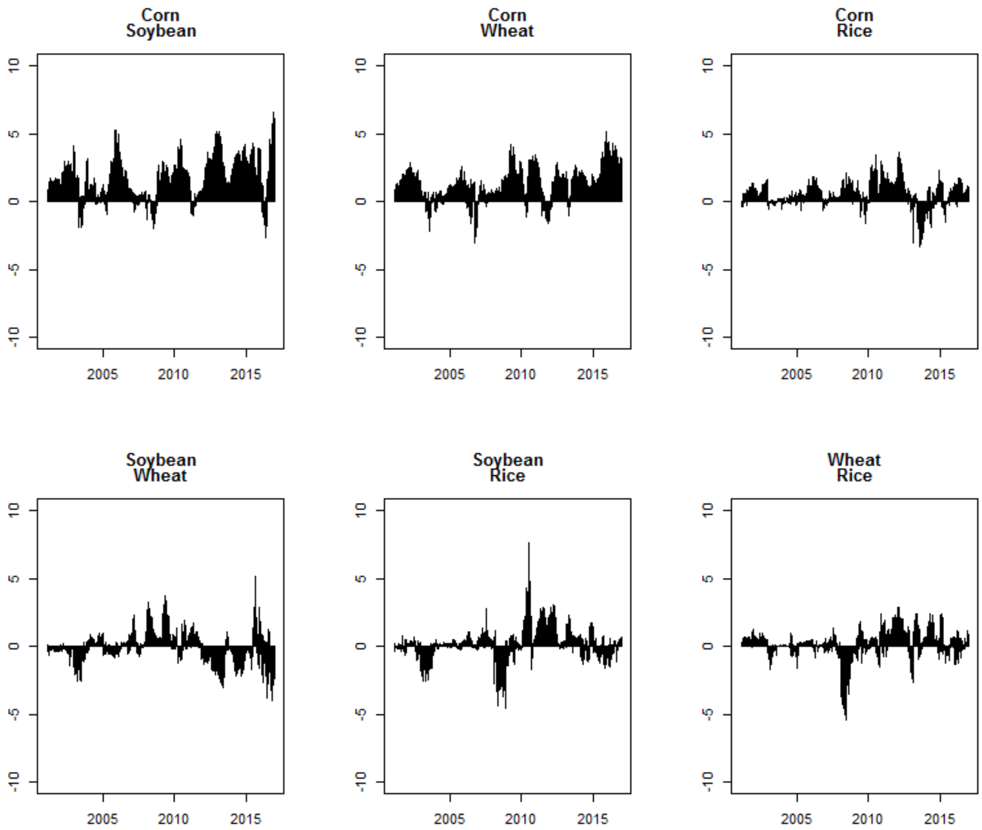

Fig. 2. Net volatility spillovers in the food market.

The results of forecast error variance decompositions obtained for each food are presented in Fig. 3. Different colours represent the share of volatility that comes from different markets. It can be noticed that for each food the greatest share of FEVD comes from its own, specific source. To be more precise, at least 50% FEVD for wheat around the year 2012 and 80% FEVD for rice result from own shocks.

In case of corn, a large proportion (about 20%, and in 2016 between 35% and 40%) of the forecast error variance (FEV) depends on volatility of soybean and wheat. What is worth noticing, soybean seems to be responsible for a similar proportion of FEV for corn in every subperiod, but the importance of wheat varies. The share of wheat in FEVD for corn varies between several percent in the subperiods covering 2005 and 2009 and about 20% between

2011-2014. The role of rice in the FEVD for corn, as well as financial instruments, is negligible.

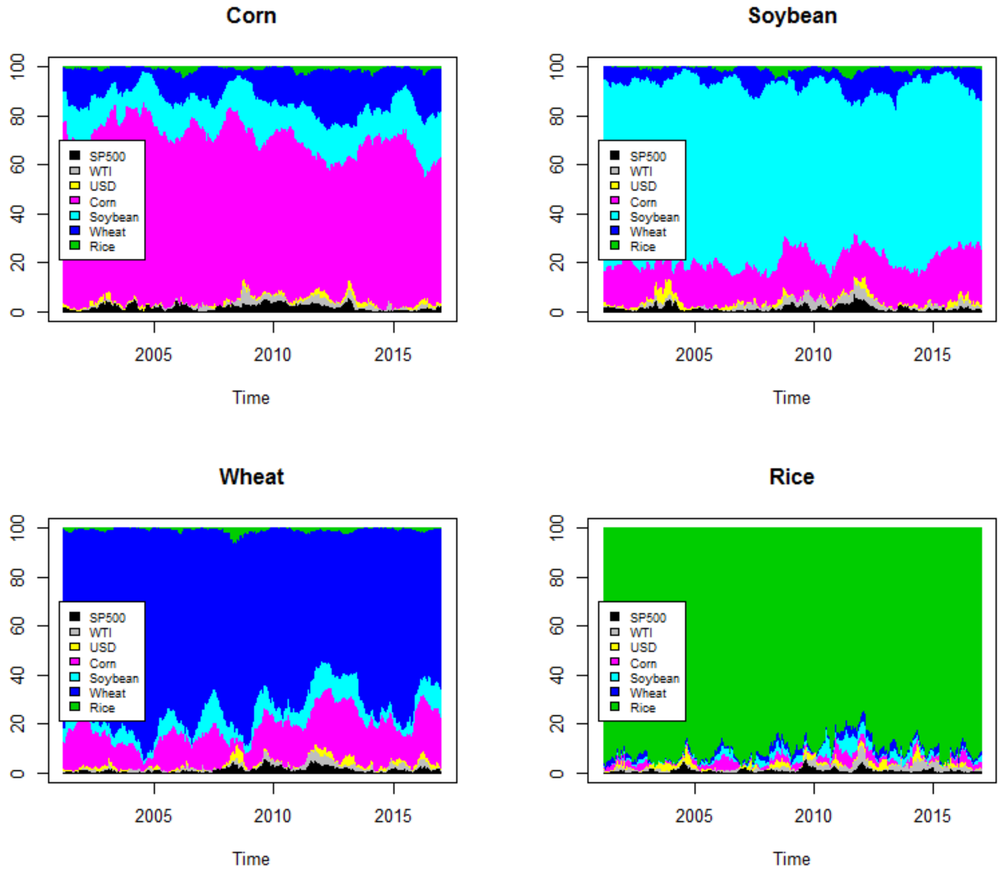

Fig. 3. The forecast error variance decompositions (FEVD) for food.

In case of FEVD for soybean and wheat, apart from the importance of their own FEV, the second most important factor is corn. The share of corn in FEV exceeds 20% in many subperiods. The third most important factor is wheat for soybean and soybean for wheat. The share of one of these agricultural commodities in FEV of the other ranges from 4 to 10%. Again, the role of financial instruments is not significant. FEVD obtained for rice demonstrates that no instrument transmits significant portions of volatility to rice. It is worth mentioning that around 2011 FEVD for rice depends on others factors in about 20%.

Conclusion

The objective of the study is to examine volatility spillovers for the food market and the financial market. Our main findings can be summarized in the following way.

Most volatility transmissions are observed among the same categories of instruments. We identify two groups which are interrelated in terms of volatility spillovers, i.e. the financial group (including equity, crude oil and US dollar exchange rates) and the food group (including corn, soybean and wheat). The food group transmits much more volatility within elements than the financial group (which can result from heterogeneity of the financial group). Rice volatility seems not to depend on other instruments and does not transmit volatility to other markets, with the exception of one episode, i.e. 2009, when rice reaches record values and significantly influences volatility of soybean and rice.

The sources of FEV for foods vary for different foods and for different supberiods. Corn, however, seems to be the most important agricultural commodity, as it transmits vast volatility to other instruments in the food group. Corn is the net volatility transmitter for soybean and wheat and is the second most important source of FEV for these two foods, representing up to 20% of FEV. On the one hand, the results demonstrate that the role of financial security in creating the food market volatility is limited. In particular, volatility of energy prices is insignificant for food prices. On the other hand, corn emerges as the most important commodity in the food market, as it is the net volatility transmitter to soybean and wheat. Since the share of corn production used for biofuels (ethanol) rises significantly during the analysed period, one can speculate that the relations between energy and agricultural commodities increase indirectly.

Acknowledgements

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