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Matthias Bernhardt

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Dynamic Volatility Behaviour in Agricultural Commodity Markets - Evidence from VIRF Analysis and Spillover Index Calculations

Matthias Bernhardt

November 10, 2017

This paper provides an empirical analysis of volatility time structures in agricultural markets (sugar, wheat, soybeans and coffee) for a time period from 2008 to 2016. The time period covers at least three food crises which make the analysis interesting for both researches and policy makers. In order to investigate the behaviour of agricultural market's volatility after a shock, I calculated the volatility impulse response function based on a VAR(1) BEKK(1,1)-in-mean model. The result indicates that extreme weather events do have large impact on volatility. Furthermore, with the application of the spillover index, it is possible to calculate the quantity of volatility spillovers across time. There is evidence for a high news sensitiveness in certain agricultural products and a dominant position of wheat and soybeans.

Keywords: Agricultural commodity spot markets, BEKK in mean, Volatility Impulse Response, Spillover Index, generalized forecast error variance decomposition, VAR

1 Introduction

Food markets are one of the most important global markets because of their interrelation not only to other markets like energy markets, precious commodities, or stock markets, but also to

political and social events.

The literature provides many studies about the connection between food markets and non food markets. A well investigated field is the link between agricultural markets and energy markets. Fernandez-Perez et al. (2016) detected unidirectional effects from agricultural commodities on ethanol and from crude oil on agricultural commodities. Similar results are reported by Mensi et al. (2014), Onour and Sergi (2016), as well as Al-Maadid et al. (2016). Linkages between food markets and stock markets were found by Al-Maadid et al. (2016), Baldi et al. (2016), and Tadesse et al. (2014), whereas Kang et al. (2017) proves the empirical connection between crude oil, gold, and agricultural commodities.

Rising food prices since 2008 and price peaks in 2011 and 2012, respectively, are the reasons for an increased interest in research. Many studies come to the point that higher food prices are the result of shifts in demand and supply factors. One of the reasons with respect to demand are high energy prices and a high demand for biofuel which corresponds to empirical studies in terms of return linkages. Another issue is the continuing growth of the world's population. On the supply side, one can observe declining grain stocks and lower investments from 2007 to 2014 (Trujillo-Barrera et al. (2012), Tadesse et al. (2014)). Additionally, climate change and extreme weather events have an immense influence. For example, due to a very dry summer in the US, Europe, Russia and Ukraine in 2012, global prices for soybeans and wheat soared to new peaks. However, ignoring the source of price peaks and recognizing just the fact of high food prices, developing countries suffer the most from rising food prices, since poor people need to spend more of their disposable income for food. This implicates that they have to reduce spendings for health and education. According to the Food Security Information Network (2017) more than 100 million people were facing the danger of food insecurity in 2016. This is mostly the result of the high number of conflicts in Africa and the Middle East (e.g. the Arabic Spring) being the biggest food importers in the world. Bellemare (2015) reports a connection between food price increases and social unrest for the period from 1990 to 2011. One can see immediately that turmoils in agricultural markets can cause political and social instability as documented by the United Nations (2011), Lagi et al. (2011), Arezki and Brückner (2011), Kalkuhl et al. (2016), and can have extensive consequences.

Although, Bellemare (2015) does not find an interaction between riots and food price volatility, food price volatility is an issue, which needs to be considered in any respect. Volatility is a factor, which causes uncertainty within markets and for market participants. On the producer

side, high uncertainty can be responsible for higher producer's risk management costs and these cost adjustments may affect market prices. Moreover, price uncertainty could have an impact on both investment decisions and capacity utilization. Apergis and Rezitis (2011) explored the relation between food price volatility and macroeconomic variables in Greece within a GARCH-X framework. They found evidence for welfare losses for both consumers and suppliers due to rising uncertainty in future prices.

For this reason, it is very important to know exactly how agricultural markets are interconnected in terms of their volatility. All in all, there is little known about volatility behaviour of agricultural markets in a dynamic context and to the best of my knowledge this is the first paper that investigates volatility in food markets without considering non food markets with modern time series tools introduced in the next section.

In order to contribute to the existing literature, this paper investigates the important topic of volatility dynamics in food markets since the crisis in 2008. To detect volatility dynamics, I adopted two approaches. The first one is the volatility impulse response analysis provided by Hafner and Herwartz (2006), which is based on the multivariate GARCH methodology. The novel of this method is the analysis of the conditional variance instead of the conditional mean as suggested by Koop et al. (1996). This analysis allows to visualize the behaviour of the conditional volatility after a historical shock.

The second method is the spillover index framework introduced by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012). This framework is based on the forecast error analysis of vector autoregressive models using a generalized forecast error variance decomposition developed by Koop et al. (1996) and Pesaran and Shin (1998). With this index it is possible to calculate volatility spillovers both received by a commodity from others and given to others in a certain time period.

The rest of the paper is organized as follows: Section two explains both the data and the methodology in detail. The main part represents the discussion of the empirical findings in part 3. The paper ends with a conclusion in section 4.

2 Data and Methodology

2.1 Data

The data set of interest contains daily spot prices of S&P-GSCI sugar, S&P-GSCI wheat, S&P-GSCI soybeans, and S&P-GSCI coffee. The prices are obtained from Thomson Reuters Datastream. Each S&P-GSCI commodity index is a widely used benchmark. With this commodity selection, I can capture a wide range of major agricultural commodities to explore how different classifications¹ of agricultural markets are interrelated. Daily data from 01.01.2008 to 31.12.2016 are used for the analysis.

In order to guarantee stationarity, I used log-returns r_t , computed as

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \cdot 100 \quad (1)$$

for this analysis whereas P_t denotes the daily spot price at time t . Figure 1 shows both the spot prices of each commodity and its return series from 01.01.2008 to 31.12.2016. Table 1 presents descriptive statistics (panel A) of the time series as well as univariate time series tests (panel B). As shown in table 1, the data set contains dependencies in the second moments (LB^2) and also highly significant ARCH effects ($ARCH - LM$).

2.2 Methodology

2.2.1 Multivariate GARCH models

Since its introduction by Bollerslev (1986) GARCH models became very popular within empirical capital market research. With its multivariate extensions it is possible to estimate interdependencies between markets. The general multivariate GARCH(p,q) model is defined as

$$r_t = \mu_t + \varepsilon_t \quad (2)$$

$$\varepsilon_t = \Sigma_t^{\frac{1}{2}} \eta_t, \quad \eta_t \sim i.i.d.(0, I_k) \quad (3)$$

$$vech(\Sigma_t) = C^* + \sum_{i=1}^q A_i^* \cdot vech(\varepsilon_{t-i} \varepsilon_{t-i}') + \sum_{j=1}^p B_j^* \cdot vech(\Sigma_{t-j}). \quad (4)$$

¹ Wheat is classified as grains, sugar and coffee as softs, and soybeans as oilseeds. Moreover, wheat, sugar and soybeans can be integrated as basic food and coffee as luxury food.



Figure 1: Spot prices and log-returns of sugar, wheat, soybeans and coffee

Equation 2 describes the conditional mean. r_t is a $(k \times 1)$ vector with log returns. μ_t could be either a vector of constants or a time series system (e.g. a VAR). ε_t is the $(k \times 1)$ error vector, whereas $\varepsilon_t | I_{t-1} \sim i.i.d.(0, \Sigma_t)$ with $I_{t-1} = (\varepsilon_{t-1}, \varepsilon_{t-2}, \dots)$ is the information set up to time $t - 1$ containing all available information.

Equation 4 describes the conditional variance. $\Sigma_t = Cov(\varepsilon_t | I_{t-1})$ is the $(k \times k)$ conditional variance covariance matrix.

The $vech()$ operator stacks the lower part of a $(k \times k)$ matrix into a $k' = k(k + 1)/2$ dimensional vector. C^* is a $(k' \times 1)$ parameter vector with constants, A^* and B^* are parameter matrices with $(k')^2$ parameters. Finally, q is the order of the ARCH effect and p is the order of the GARCH effect.

A special case of equation 4 is the BEKK representation of Engle and Kroner (1995). The BEKK

Panel A: Descriptive statistics				
	Sugar	Wheat	Soybeans	Coffee
mean	0.025	-0.033	-0.008	0.0003
std. deviation	2.118	2.082	1.589	1.990
exc. kurtosis	2.346	3.085	2.191	1.867
skewness	-0.273	0.149	-0.244	0.069
min	-12.367	-9.795	-7.338	-11.249
max	8.557	15.597	6.432	10.853

Panel B: Univariate time series tests							
	JB	ADF	$LB(6)$	$LB(12)$	$LB^2(6)$	$LB^2(12)$	ARCH-LM
sugar	570.01 (0.000)	-12.31 (0.000)	9.98 (0.125)	14.17 (0.194)	159.49 (0.000)	195.47 (0.000)	118.52 (0.000)
wheat	942.81 (0.000)	-13.04 (0.000)	12.75 (0.047)	24.57 (0.017)	217.59 (0.000)	301.59 (0.000)	148.38 (0.000)
soybeans	494.90 (0.000)	-12.68 (0.000)	7.29 (0.295)	10.58 (0.565)	320.56 (0.000)	588.49 (0.000)	252.42 (0.000)
coffee	344.33 (0.000)	-13.13 (0.000)	10.26 (0.114)	15.23 (0.229)	43.36 (0.000)	137.70 (0.000)	89.96 (0.000)

Table 1: Descriptive statistics and preliminary tests for the four return series. The Jarque Bera (JB) statistics tests the normality of the data. ADF is the Augmented Dickey Fuller test for stationarity and LB stands for Ljung-Box test for autocorrelation. LB^2 tests autocorrelation in squared returns. Values in parenthesis are p values.

model is defined as

$$\Sigma_t = C'C + \sum_{i=1}^m A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{j=1}^s B_j' \Sigma_{t-j} B_j \quad (5)$$

C is a $(k \times k)$ lower triangular matrix with constants and A and B are now $(k \times k)$ parameter matrices. Note, that with matrix algebra it is possible to calculate A^* or B^* , respectively, given matrix A and B^2 .

$$\begin{aligned} A^* &= E_k(A' \otimes A') D_k \\ B^* &= E_k(B' \otimes B') D_k \end{aligned} \quad (6)$$

E_k denotes the elimination matrix, D_k denotes the duplication matrix³ and \otimes is the Kronecker product.

For this research, I estimated a VAR(1)-BEKK(1,1)-in-mean model with $k=4$ time series, which

² For more detail on the required matrix algebra see Harville (2005], c1997)

³ The elimination matrix is the matrix where the equation $vech(A) = E_k vec(A)$ holds. The duplication matrix is the matrix where the equation $vec(A) = D_k vech(A)$ holds.

can be quantified as

$$r_t = \mu + \phi \cdot r_{t-1} + \Psi \cdot \sqrt{\text{diag}\Sigma_t} + \varepsilon_t \quad (7)$$

$$\Sigma_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'\Sigma_{t-1}B \quad (8)$$

In concrete terms this means that the conditional mean follows a VAR(1)-in-mean process with r_t as a (4×1) vector with log returns and μ as a (4×1) vector of constants. ϕ is the autoregressive parameter matrix with (4×4) entries, whereas Ψ (also a (4×4) matrix) measures the effects of the conditional volatility on returns and can be interpreted as a risk premium.

Assuming that ε_t is following a Student-t distribution⁴ the conditional likelihood function is given as

$$L(\Theta) = \sum_{t=1}^T l_t \quad (9)$$

$$l_t = \ln\left(\Gamma\left(\frac{\nu+k}{2}\right)\right) - \frac{k}{2} \cdot \ln(\pi \cdot (\nu-2)) - \ln\left(\Gamma\left(\frac{\nu}{2}\right)\right) - \frac{1}{2} \cdot \ln(\det(\Sigma_t)) - \frac{\nu+k}{2} \cdot \ln\left(\left(1 + \varepsilon'_t \Sigma_t^{-1} \varepsilon_t\right) \cdot \frac{1}{\nu+2}\right). \quad (10)$$

Θ is a parameter vector containing all parameters that need to be estimated.

2.2.2 Volatility impulse response functions

As stated in Hafner and Herwartz (2006), the fact that the residual vector ε_t is simultaneously correlated, the error vector can not be assumed to be received from independent sources. That means that a change in one component of ε can not be regarded without considering a change in another component. For this reason we need to orthogonalize the components. In order to ensure orthogonally residuals, I decomposed the residual vector ε_t as

$$\varepsilon_t = P_t \xi_t, \quad (11)$$

⁴ In the context of VIRF analysis, Hafner and Herwartz (2006) have shown that it is necessary that ε_t is non Gaussian.

with $P_t P_t' = \Sigma_t$, and ξ_t is a i.i.d. random vector. To identify $\xi_t = P^{-1} \varepsilon_t$, Hafner and Herwartz (2006) recommend using a Jordan decomposition⁵ to obtain the symmetric matrix $\Sigma_t^{\frac{1}{2}}$ with

$$\Sigma_t^{\frac{1}{2}} = \Gamma_t \Lambda_t^{\frac{1}{2}} \Gamma_t', \quad (12)$$

whereas $\Lambda_t = \text{diag}(\lambda_{t,1}, \dots, \lambda_{t,k})$ is a matrix with Eigenvalues of Σ_t on its main diagonal and $\Gamma_t = (\gamma_{t,1}, \dots, \gamma_{t,k})'$ is the matrix which contains the corresponding Eigenvectors $\gamma_{t,i}$. Knowing that $\Sigma_t = \Sigma_t^{\frac{1}{2}} \Sigma_t^{\frac{1}{2}}$ we can set $P_t = \Sigma_t^{\frac{1}{2}}$ and calculate

$$\xi_t = \Sigma_t^{-\frac{1}{2}} \varepsilon_t \quad (13)$$

Hafner and Herwartz (2006) developed the volatility impulse response framework based on the VEC representation of MGARCH models. As an implication, the VIRF approach is applicable for all multivariate GARCH models, which have a VEC representation⁶. Hafner and Herwartz (2006) defined the volatility impulse response function as the difference in expectation between the variance conditioned on a historical shock and the information set up to time $t - 1$, and the variance conditioned only on the information set. Mathematically this relationship can be described as

$$V_t(\xi_0) = E[\text{vech}(\Sigma_t) | \xi_0, I_{t-1}] - E[\text{vech}(\Sigma_t) | I_{t-1}] \quad (14)$$

In order to obtain an explicit expression for equation 14 the authors used the fact that a MGARCH(p,q) model can be rewritten as a VARMA(max(p,q), q) model and a VARMA(max(p,q), q) model, in turn, as a VMA(∞) model. With some matrix algebra Hafner and Herwartz (2006) obtained

$$\begin{aligned} V_1(\xi_0) &= A^* \cdot (\text{vech}(\Sigma_0^{\frac{1}{2}} \xi_0 \xi_0' \Sigma_0^{\frac{1}{2}})) - \text{vech}(\Sigma_0) \\ &= A^* D_N^+(\Sigma_0^{\frac{1}{2}} \otimes \Sigma_0^{\frac{1}{2}}) D_N \text{vech}(\xi_0 \xi_0' - I_N) \end{aligned} \quad (15)$$

⁵ In linear models it is common to use a Cholesky decomposition, but in this case with high frequency data some assumptions to obtain independent shocks are hardly available. See Hafner and Herwartz (2006) for more details.

⁶ For example, a DCC-GARCH model does not have a VEC representation.

and for $t > 2$

$$\begin{aligned} V_t(\xi_0) &= (A^* + B^*)^{t-1} A * D_N^+(\Sigma_0^{\frac{1}{2}} \otimes \Sigma_0^{\frac{1}{2}}) D_N vech(\xi_0 \xi_0' - I_N) \\ &= (A^* + B^*) V_{t-1}(\xi_0) \end{aligned} \quad (16)$$

ξ_0 is a specific historical shock and Σ_0 its corresponding variance covariance matrix.

2.2.3 Spillover index

Within the spillover index framework developed by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012), it is possible to detect spillovers between markets based on forecast error variance decomposition in vector autoregressive models (VAR). A VAR(p) model is defined as

$$\mathbf{r}_t = \boldsymbol{\phi}_0 + \boldsymbol{\phi}_1 \mathbf{r}_{t-1} + \dots + \boldsymbol{\phi}_p \mathbf{r}_{t-p} + \boldsymbol{\varepsilon}_t = \boldsymbol{\phi}_0 + \sum_{i=1}^p \boldsymbol{\phi}_i \mathbf{r}_{t-i} + \boldsymbol{\varepsilon}_t \quad (17)$$

and its corresponding VMA(∞) representation is

$$\mathbf{r}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \boldsymbol{\psi}_i \boldsymbol{\varepsilon}_t \quad (18)$$

The VMA matrices $\boldsymbol{\psi}_i$ can be computed recursively by $\sum_{j=1}^i \boldsymbol{\psi}_{i-j} \boldsymbol{\phi}_j$ with $\boldsymbol{\psi}_0$ equaling the identity matrix and $\boldsymbol{\phi}_j = 0$ for $j > p$ (see Lütkepohl (2007)).

The forecast error variance decomposition (FEVD) is a tool used to analyse an estimated VAR model. One can interpret the FEVD by the contribution of variable i to the H -step ahead forecast error of variable j , but the calculation of FEVD depends on the variable ordering. In order to avoid this problem, Koop et al. (1996) and Pesaran and Shin (1998) provided a generalization that is independent from variable ordering. The generalized forecast error variance decomposition (gFEVD) can be computed as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \boldsymbol{\psi}_h \boldsymbol{\Sigma} e_j)^2}{\sum_{h=0}^{H-1} (e_i' \boldsymbol{\psi}_h \boldsymbol{\Sigma} \boldsymbol{\psi}_h' e_i)} \quad (19)$$

θ_{ij} is the ij -th entry in the $(k \times k)$ FEVD matrix and depends on the forecast horizon H . $e = (0..1..0)'$ is a $(k \times 1)$ selection vector with 1 at the i -th (j -th) entry and zero otherwise. $\boldsymbol{\Sigma}$ is the variance covariance matrix of the errors obtained from the estimated VAR model and σ_{jj} is the jj -th standard deviation. Each entry in θ gives the contribution of variable j to the forecast error variance of variable i . It is easy to recognize that off-diagonal elements express spillover effects.

Since the row sum of θ does not equal 1, we standardized each entry by the row sum as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^k \theta_{ij}(H)} \quad (20)$$

Diebold and Yilmaz (2012) constructed their total spillover index S as

$$S(H) = \frac{\sum_{i,j=1, i \neq j}^k \tilde{\theta}_{ij}(H)}{k} \cdot 100 \quad (21)$$

The total spillover index is a measurement for the amount of spillovers across the investigated markets. But it is still unclear in which direction these spillovers take place. Solving this dubiety, one can compute directional spillovers, which enables us to make a statement about how much spillovers a market received from/transmitted to other markets.

$$S_{i.}(H) = \frac{\sum_{j=1, j \neq i}^k \tilde{\theta}_{ij}(H)}{k} \cdot 100 \quad (22)$$

$$S_{.i}(H) = \frac{\sum_{j=1, j \neq i}^k \tilde{\theta}_{ji}(H)}{k} \cdot 100. \quad (23)$$

$S_{i.}(H)$ is the directional spillover received by market i from all other markets j and $S_{.i}(H)$ is the directional spillover transmitted by market i to all other markets j . Finally, subtracting equation 23 from 22 we derive net spillover effects from market i to all other markets j .

3 Empirical Findings

3.1 Estimation results from the VAR(1)-BEKK(1,1) in mean model

The historical shock analysed in the next subsection is based on a VAR(1)-BEKK(1,1)-in-mean model with t distributed error terms. Compared to Hafner and Herwartz (2006) who prewhitened their return series by estimating univariate GARCH models and used the residuals as input data for the BEKK model, I estimated the mean and variance equation simultaneously. Table 2 reports the estimation result for the model. All Eigenvalues are less but very close to one⁷ indicating a high persistence in commodity's volatility.

Residual diagnostics are based on calculations recommended in (Tsay, 2014, pp.401, 402). The rank based test for autocorrelation in the standardized residuals overcomes the weakness of

⁷ The Eigenvalues are available upon request

the portmanteau statistic when there are extreme returns in the data. For the same reason, the robust test cuts the upper 5% of the data and uses this data to perform a multivariate Ljung-Box statistic⁸ to test the standardized residuals for ARCH effects. The diagnostic results validate the model choice and we can continue with the analysis of a historical shock.

3.2 Analysis of a historical shock with volatility impulse response functions

3.2.1 The impact of tornado outbreaks on food markets' volatility

Volatility impulse response functions depend on a historical shock. In this paper, I investigated the impact of a historical weather shock on the volatility of agricultural markets.

The United States are one of the most important wheat and soybeans producers in the world, where the plants extend to the Midwest and Midwest/North-East⁹. It is a well-known fact that agricultural commodities are affected by extreme weather conditions like heat waves or tornados. The National Centers for Environmental Information provide a detailed documentation for weather events in the United States. Between June 3 and 11, 2008, the US suffered from a series of tornado outbreaks over central and southern states, which wreaked damage costs about two billion US Dollars. The tornado area covered both the large wheat and soybeans fields¹⁰. The shock date $t = 0$ is June 11, 2008 where the whole impact of the tornado outbreak is fully transmitted to agricultural commodity markets. For this date, the estimated residual vector is $\varepsilon = (7.976586 \ 6.939327 \ 4.623891 \ -0.604250)'$ and $\xi = (3.188965 \ 2.345994 \ 1.894313 \ -1.951129)'$. Figure 2 plots the VIR function for each conditional variance. It is notable that the pattern and size are different for the expected change in volatility.

Although the tornados did not harm sugar production directly, the effect on the conditional volatility of sugar is relatively high, but dies out fast (compared to wheat and soybeans). This result underlines the information sensitiveness of sugar as also reported in Lahiani et al. (2013). As expected, the response of conditional volatility of soybeans and wheat after the impulse is very high and very persistent. Beside the fact that these two commodities were affected directly by the tornados, one possible additional explanation for the strong impact of the shock and very long persistence until the shock canceled out could be the low and declining ending inventory

⁸ $Q_k^*(m) = T^2 \cdot \sum_{i=1}^m (T-i)^{-1} \text{vec}(\hat{\rho}_i)' (\hat{\rho}_0^{-1} \otimes \hat{\rho}_0^{-1}) \text{vec}(\hat{\rho}_i)$ and $Q_k^*(m) \sim \chi_{k^2 m}^2$. T is the sample size and k the dimension of the system. $\hat{\rho}_j$ is the correlation matrix of the error matrix with lag j . Note, that $Q_k^*(m)$ is asymptotically equivalent to the multivariate generalization of the Lagrange multiplier test.

⁹ For example, the largest producer of wheat are the states Kansas, North Dakota, Texas, and Oklahoma

¹⁰ Among others, the affected states were Kansas, Nebraska, Missouri, Iowa, Illinois

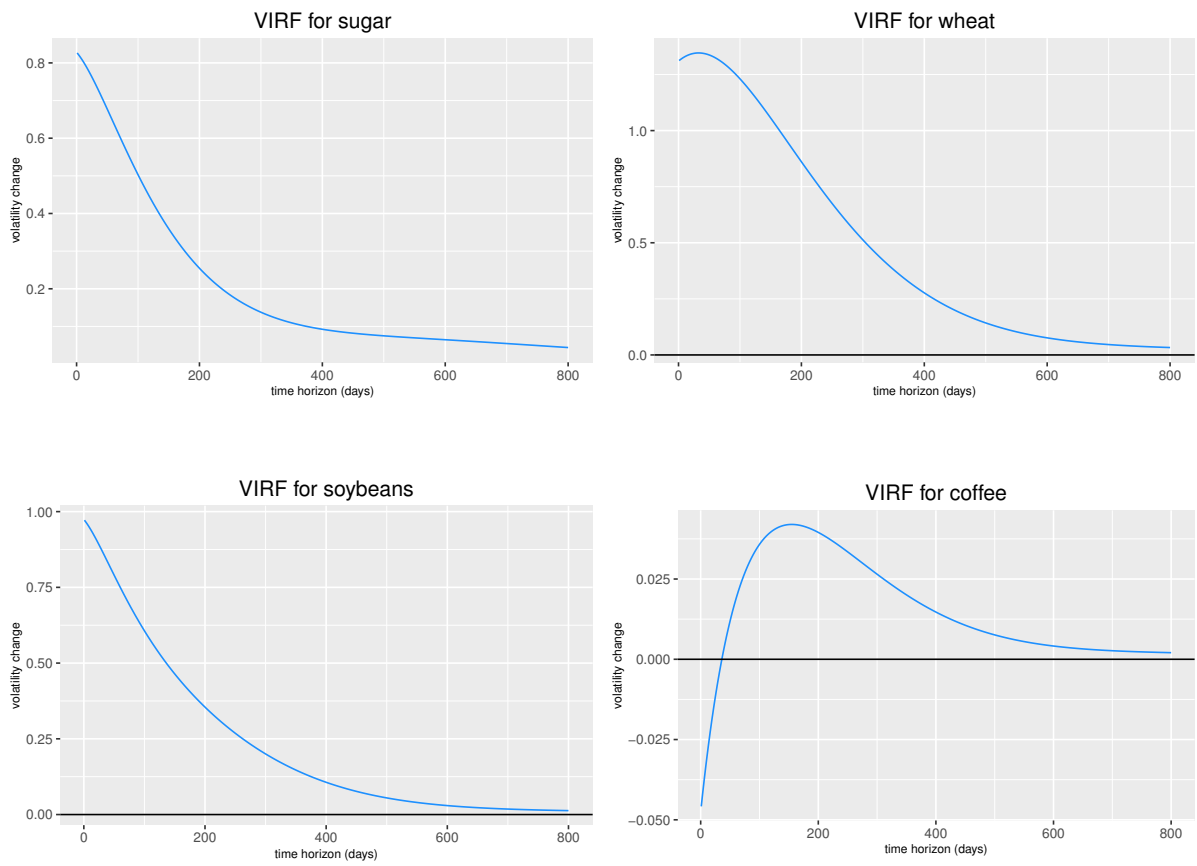


Figure 2: Volatility Impulse Response functions for a historical weather shock on June 11, 2008

levels for wheat and soybeans around the period when the shock occurred¹¹. Last but not least, the change in volatility of coffee is not much affected by the shock. The size of the response indicates that there is no (strong) connection between coffee and the other markets.

To analyse the effects of the tornado outbreaks on average, I calculated average responses¹² based on shocks up to seven days before and after June 2, 2008 (one day before the first tornado was observed), as shown in Figure 3. On average, in the time period before the tornado series started shocks had even a negative influence on sugar and wheat markets and are characterized by a low persistence. During the shock period, on average, one can observe an increasing volatility in each market. Except for coffee, the shape and impact on conditional volatility changed dramatically. This comparison makes clear, how strong the tornado outbreak influenced the food markets' conditional volatility.

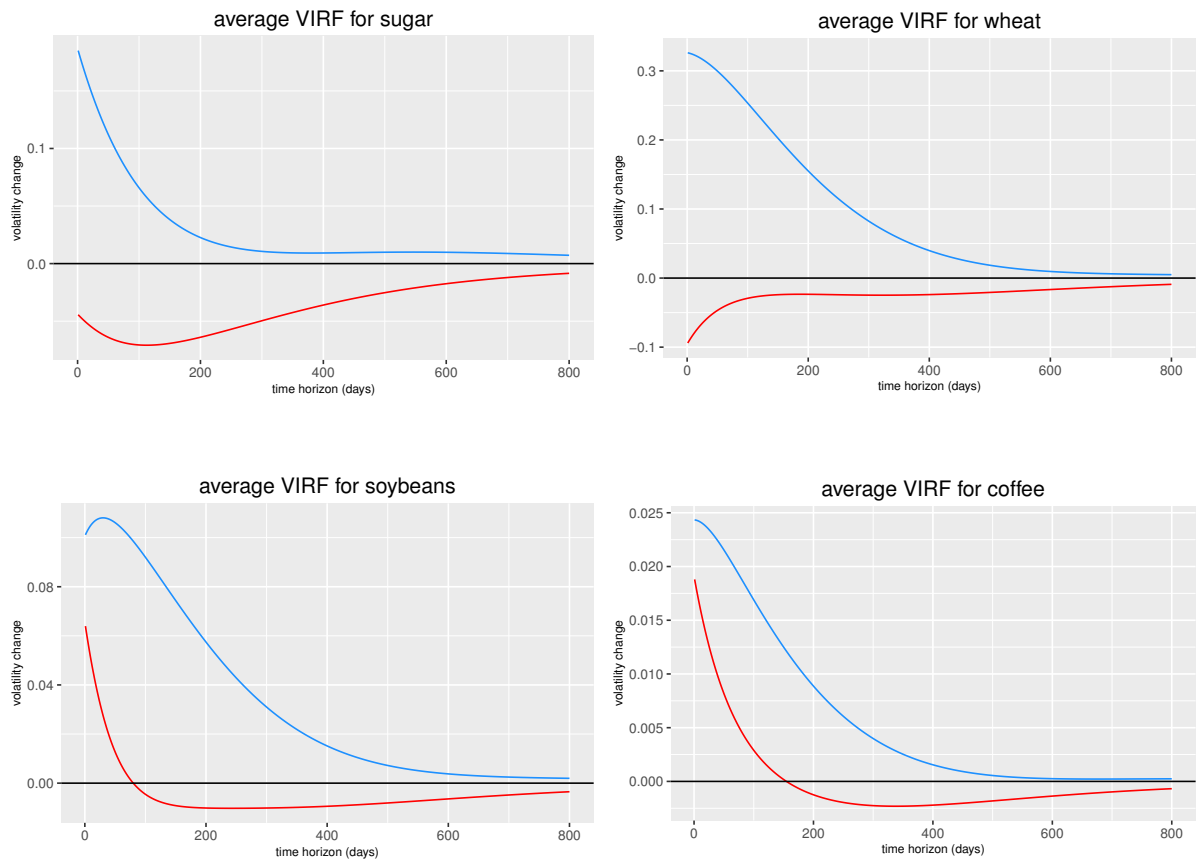


Figure 3: Average Volatility Impulse Response functions for seven days before (red line) and after (blue line) June 2, 2008

¹¹Data from AMIS (Agricultural Market Information System): <http://statistics.amis-outlook.org/data/index.html>

¹²calculated as mean of the function values evaluated at time t .

3.2.2 Distribution of Volatility Impulse Response functions

In this section, I treated shocks as random and therefore volatility impulse response functions are also random. Hafner and Herwartz (2006) have shown in their work that the VIRF distribution is non Gaussian and asymmetric. To investigate the distributions of each VIRF in this case, I simulated 20,000 realizations of a random shock ξ_0 taken from an independent and standardized Student-t distribution¹³ and then calculated volatility impulse response values based on the estimates from the VAR(1)-BEKK(1,1) in mean model. The variance covariance is obtained at the shock date mentioned above. Afterwards, the densities are computed by kernel density estimation.

With this hypothetical experiment, one can shock the current conditional variance without knowing the size of the shock and can forecast the change in volatility.

Figure 4 and figure 5 plots the VIRF distribution for a time horizon of 30 and 60 days, respectively.

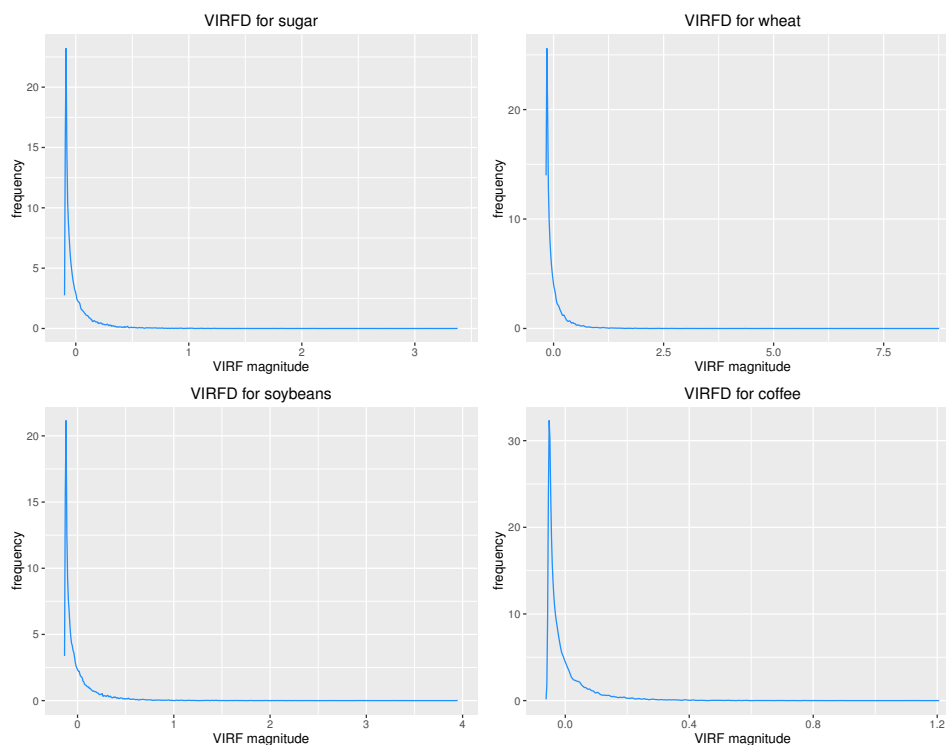


Figure 4: Distribution of the Volatility Impulse Response function with 20,000 realizations of a standardized Student-t distribution and a time horizon of 30 days.

I found a highly skewed distribution in each case. It follows that there is a low probability to face a large positive influence of a shock. Rather the probability of a small positive or negative

¹³with the estimated degrees of freedom $\nu = 8.363003$.

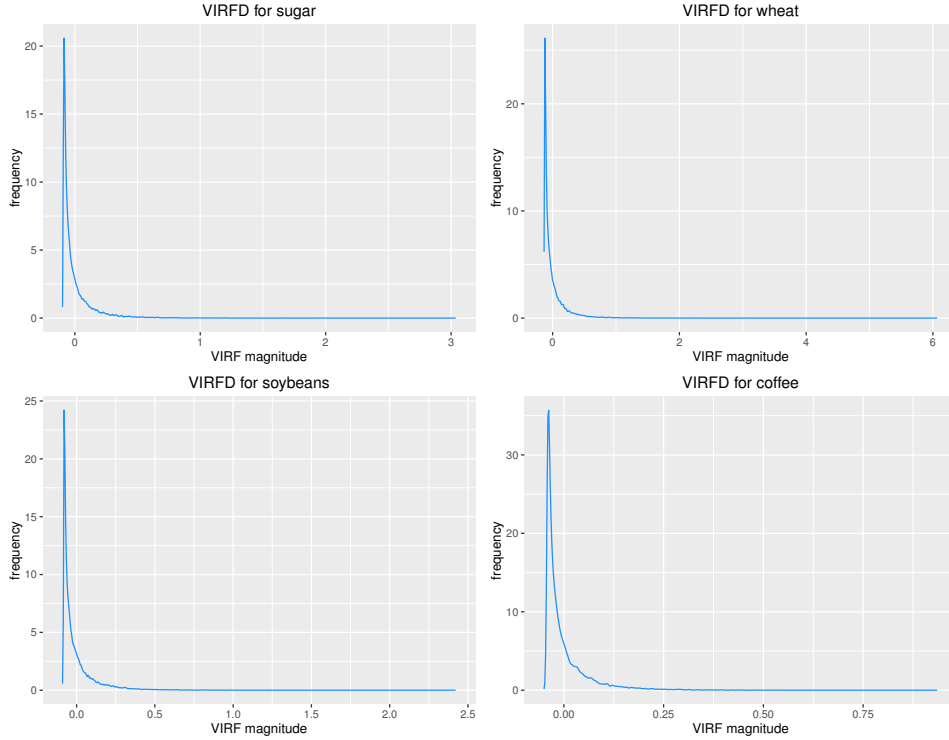


Figure 5: Distribution of the Volatility Impulse Response function with 20,000 realizations of a standardized Student-t distribution and a time horizon of 60 days.

impact is very high. It is also notable that the distribution of the VIR function becomes more and more centered as the time horizon rises (from 30 days in figure 4 to 60 days in figure 5), what can be translated as a successive dampening of the influence of the initial random shock.

3.3 Dynamic volatility spillovers measured by the spillover index

The next part of the empirical analysis deals with the spillover index, where I analysed time dependent volatility spillover effects. The literature approximates the latent variable volatility in different ways using either open, closing, high and low (OCHL) prices or intraday data (tick data). Since OCHL data and intraday data are not available, I used the estimated conditional volatility from the applied VAR(1)-BEKK(1,1) in mean model instead. The analysis is based on a VAR(2)¹⁴ model and the spillover index is calculated with a 10-step ahead generalized forecast error variance decomposition. In order to show the time effects of volatility transmissions, I used a 200-day-window for the rolling window analysis. To test the robustness of the results, I calculated the index with various n-step ahead forecast horizons and time windows with no difference in the pattern of the plot.

¹⁴as suggested by AIC, BIC and SIC

Figure 6 plots the result of equation 21 in a rolling window framework. It can be seen that up to the middle of 2009, total volatility spillovers rose from an already high level to a maximum of about 50 % of total spillovers between the markets due to the consequences of the crisis in 2007/2008. These findings are in line with the results of Kang et al. (2017), Tadesse et al. (2014), and Trujillo-Barrera et al. (2012). The next maximum was reached in 2011 caused by the food price crisis. With about 40 % of total spillover effects in volatility, this event causes the second highest value in the sample. Further, a sharp increase of the index is observable in 2012. The reason for this increase could be the very hot and dry summer in US and Europe. It is interesting that total volatility spillovers decreased since this peak continuously. The reason for this decrease could be increasing inventory levels in recent years. All in all, the model finds primarily strong volatility spillovers in times of a crisis.

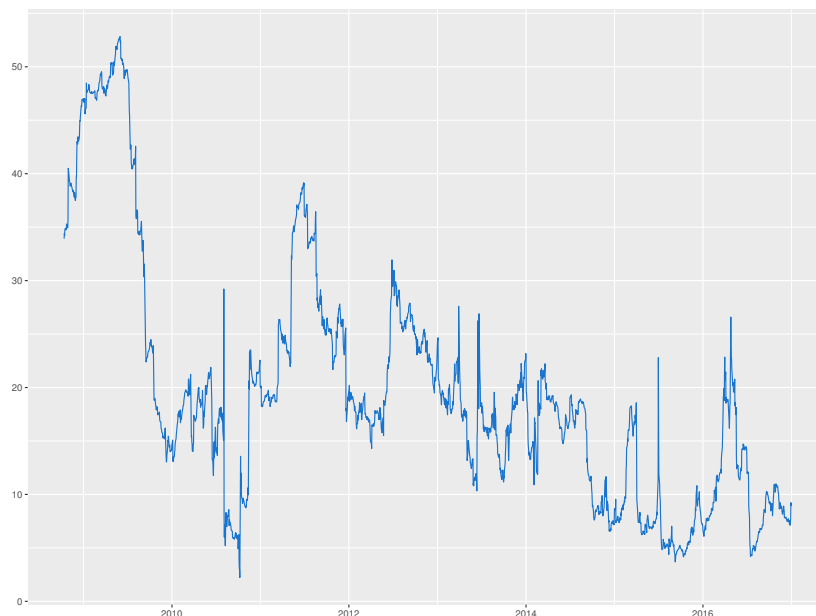


Figure 6: Overall Spillovers. Spillover Index estimated by a rolling window estimation with a window size of 200 days, based on a 10 step ahead generalized forecast error variance decomposition

Next, I took a closer look at the spillover components. Figure 7 shows directional spillovers in volatility from market i to all other markets considered¹⁵. Sugar spills volatility to other markets primarily at the beginning of the sample with a sharp decrease by 2010. During the food crisis in 2011, the index rose again.

The conditional volatility of wheat spot prices spill about 10 % to other markets after 2008.

¹⁵Note that the directional spillover FROM a market corresponds to equation 22. The time varying directional spillovers is calculated also using a 200-day-window.

Starting with the food crisis in 2011, spillovers grew and reached a maximum in the middle of 2013 of about 20 %. In the beginning of 2014, a phase of rather low spillovers started. Especially during the food crisis wheat seems to be a major player in terms of volatility spillovers.

Soybeans spilled way more to other markets in the beginning of the observation period. After a rather relaxing period, the index started to increase in the context of the food crisis in 2011. All in all soybeans have a similar pattern and characteristics as wheat but it spills its conditional volatility much stronger.

Basically coffee does not play a major role in spilling volatility over to other markets. Except for 2008/09 and 2014/15 the index is very low, indicating that coffee is not interrelated to the other markets in the sample. The common characteristics of markets for sugar, wheat and

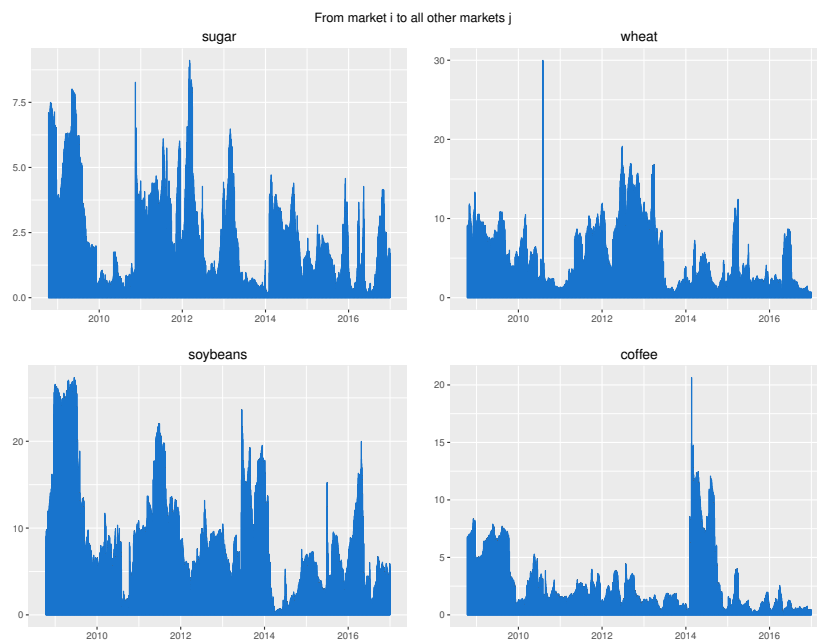


Figure 7: Directional spillovers from market i to all other markets

soybeans, is that the directional spillovers from market i to other markets rose dramatically in the end of 2010 and during 2011. That was the time period of the Arab Spring, which could be connected directly to those markets because of the importance of the involved countries in terms of food importer.

Turning now to the opposite case, where market i receives volatility shocks from all other markets. Again, sugar seems to be very sensitive regarding volatility shocks from other markets, especially in the time period from 2012 to 2015.

Wheat is characterized by sharp jumps again and again. The food crisis in 2011 is observable, where around 10 % of volatility shocks can be explained by other markets. This result may

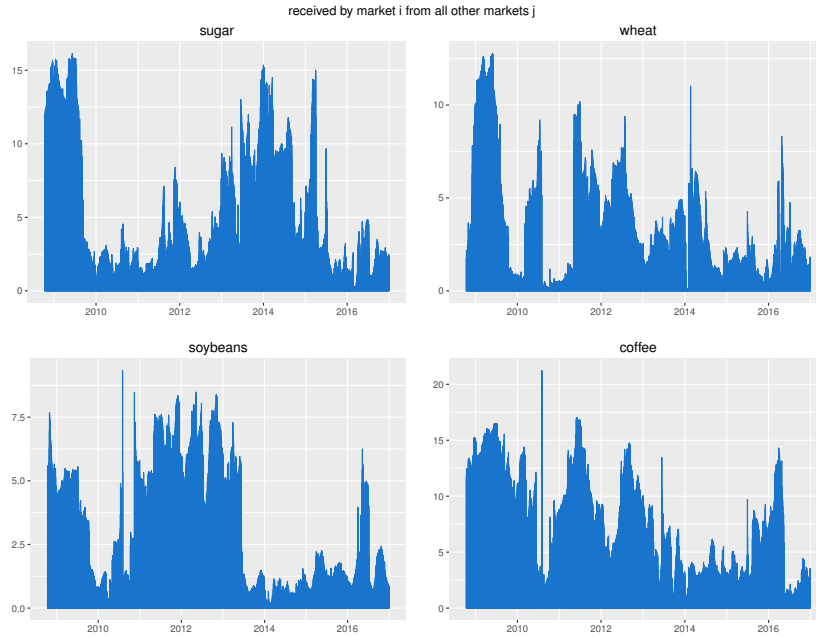


Figure 8: Directional spillovers from all other markets to market i

suggest that volatility of wheat is also quite news sensitive.

Soybeans' volatility was affected by the volatility of other markets between 2011 and 2012, but is much less affected in recent years. This effect could be explained by rising inventory levels as well.

Surprisingly, in the context of spillover index analysis, volatility of coffee seems to be much more affected as suggested so far. Lastly I calculated net spillovers to investigate if one certain market was a net volatility shock transmitter or a net volatility shock receiver. Net spillovers are calculated according to the difference of equation 23 and equation 22. Values above zero indicate that the commodity is a net receiver and vice versa.

Almost over the entire sample period, sugar spot acts as a net receiver of volatility shocks. Again, this is a sign for its news sensitiveness. Wheat and soybeans are mainly net transmitters of volatility shocks, as expected. The importance of these two commodities on world markets is also present in volatility transmissions. Just like sugar, coffee occurs mainly as a shock receiver. The results are not surprisingly, since it is obvious that both sugar and coffee price volatilities are influenced by the big player, namely soybeans and wheat, rather than vice versa.

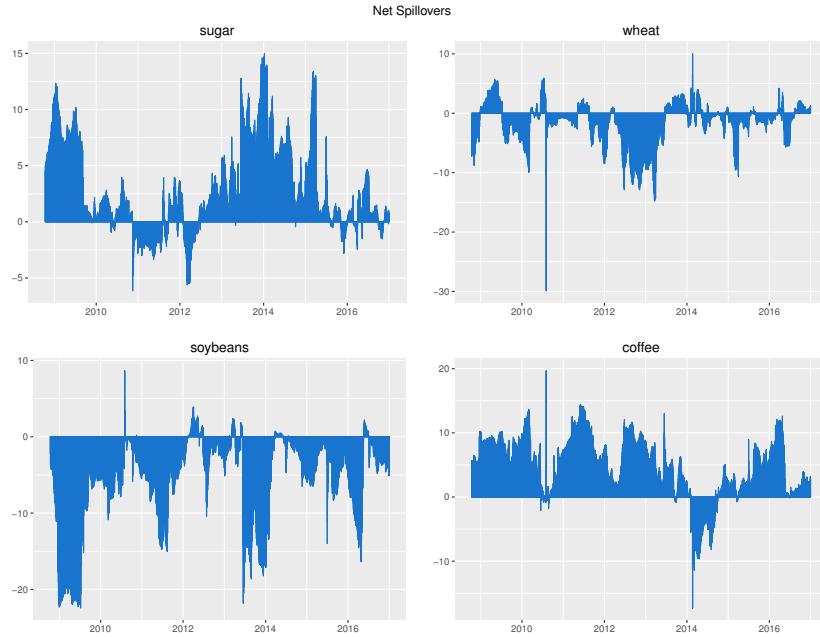


Figure 9: Net spillovers calculated as $S_{.i} - S_i$. from equation 23 and 22. Negative (positive) values indicate that the commodity is a net volatility transmitter (receiver).

4 Conclusion

This paper contributes to the existing literature of volatility behaviour and volatility transmissions in agricultural markets (sugar, wheat, soybeans, coffee) for a very recent time period from 2008 to 2016. First, the dynamic behaviour of conditional volatility after the tornado outbreak on June 11, 2008 in the USA is studied by using the VIRF framework developed by Hafner and Herwartz (2006) and secondly dynamic spillovers are calculated based on the spillover index constructed by Diebold and Yilmaz (2012).

Both application results lead to the statement that sugar's volatility is very news sensitive. However, the tornado outbreak caused a high and persistent positive change in conditional volatility of wheat and soybeans. The VIRF analysis also concludes that coffee is not very affected by this extreme weather event.

The amount of total volatility spillovers is being reduced since 2011. Nevertheless, food crisis in 2008/2009, 2011, and 2012 became visible through the model. In the context of volatility spillovers, directional spillovers are calculated as well. This analysis suggests that both wheat and soybeans are net volatility transmitters to the volatility of sugar and coffee.

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conditional mean $r_t = \mu + \Phi r_{t-1} + \Psi \sqrt{\text{diag}(H_t)} + \varepsilon_t$

$$\mu = \begin{pmatrix} -0.4011 \\ (0.178) \\ -0.1613 \\ (0.577) \\ 0.0803 \\ (0.756) \\ -0.2360 \\ (0.629) \end{pmatrix} \quad \Phi = \begin{pmatrix} -0.0081 & -0.0318 & 0.0428 & 0.0145 \\ (0.694) & (0.150) & (0.116) & (0.417) \\ 0.0110 & -0.0177 & -0.0277 & 0.0315 \\ (0.561) & (0.561) & (0.317) & (0.083) \\ 0.0067 & -0.0128 & 0.0178 & 0.0202 \\ (0.617) & (0.419) & (0.435) & (0.138) \\ 0.0219 & -0.0029 & 0.0709 & -0.0507 \\ (0.228) & (0.890) & (0.010) & (0.014) \end{pmatrix}$$

$$\Psi = \begin{pmatrix} 0.1355 & -0.0669 & 0.1899 & -0.0101 \\ (0.219) & (0.614) & (0.116) & (0.945) \\ 0.1260 & -0.0134 & -0.0970 & 0.0202 \\ (0.244) & (0.930) & (0.452) & (0.886) \\ 0.0382 & 0.0390 & -0.1060 & -0.0336 \\ (0.581) & (0.677) & (0.286) & (0.791) \\ 0.2130 & -0.0504 & -0.0139 & -0.0498 \\ (0.025) & (0.674) & (0.906) & (0.849) \end{pmatrix}$$

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

$$C = \begin{pmatrix} 0.0859 & 0.0276 & -0.0230 & 0.1251 \\ (0.004) & (0.708) & (0.781) & (0.152) \\ & 0.1743 & -0.0156 & 0.0368 \\ & (0.000) & (0.787) & (0.620) \\ & & 0.1872 & 0.0771 \\ & & (0.000) & (0.317) \\ & & & 0.1029 \\ & & & (0.242) \end{pmatrix} \quad A = \begin{pmatrix} 0.1231 & 0.0178 & 0.0172 & 0.0073 \\ (0.000) & (0.746) & (0.433) & (0.662) \\ -0.0073 & 0.1773 & -0.0159 & 0.0132 \\ (0.696) & (0.000) & (0.277) & (0.364) \\ 0.0062 & -0.0301 & 0.2295 & 0.0139 \\ (0.799) & (0.251) & (0.000) & (0.521) \\ 0.0002 & 0.0010 & -0.0007 & 0.1033 \\ (0.999) & (0.959) & (0.960) & (0.000) \end{pmatrix}$$

$$B = \begin{pmatrix} 0.9922 & 0.0017 & -0.0001 & -0.0002 \\ (0.000) & (0.861) & (0.974) & (0.995) \\ -0.0033 & 0.9784 & 0.0084 & -0.0017 \\ (0.612) & (0.000) & (0.115) & (0.645) \\ 0.0033 & 0.0080 & 0.9620 & -0.0024 \\ (0.680) & (0.297) & (0.000) & (0.695) \\ -0.0020 & -0.0025 & -0.0018 & 0.9900 \\ (0.527) & (0.606) & (0.683) & (0.000) \end{pmatrix}$$

$\nu = 8.3630$ (0.000)

Log Likelihood -18116.58

Diagnostics:

Rank based Test(8) 9.9677 0.267

Robustness(8) 123.5891 0.596

Rank based Test(12) 13.4835 0.335

Robustness(12) 187.4424 0.579

Table 2: Estimation result of a VAR(1)-BEKK(1,1)-in-mean model for agricultural spot returns.
The values in parenthesis are p values