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This paper provides insights into agricultural commodity markets in terms of return and volatility spillover effects. To replicate a broad agricultural market, grain products, softs and oilseeds are taken into account, including daily spot prices for sugar, wheat, soybeans and coffee over the period 2008-2016. The study shows the importance of both asymmetry and risk in spot return's volatility and spot returns itself, respectively. During the study the VAR(1)-GARCH-ABEKK(1,1)-in-mean model emerged as the best model to capture the special characteristics of spot market returns. The study provides evidence of return and volatility linkages between agricultural commodities. Based on the model results optimal dynamic portfolio weights and dynamic hedge ratios are calculated.

Keywords: Agricultural commodity spot markets, VAR-ABEKK-in-mean, optimal asset allocation, optimal hedge ratios

1 Introduction

In agricultural commodity markets one can observe sharp price changes and an increased volatility in recent years. Sumner (2009) and Headey (2011) reported that prices for the most important products tripled between 2005 and 2008 and reached unprecedented price levels price levels. Another example for turmoils in agricultural markets is the food crisis in 2011. Price movements on agricultural markets are due to shifts in demand and supply. On the demand side, population growth, increasing affluence and the use of grains as fuel exert have influences on prices.

According to The State of Agricultural Commodity Markets (2015), the world's population will increase by 34 % to 9.1 billion people up to 2050. Since not only population but also urbanization will increase, people will become richer in the upcoming years and therefore a shift in demand for agricultural products is expected. Headey (2011) determined the demand for biofuels as an entirely new demand source, which also affects food prices. On the supply side, geopolitical and climate-related changes are decisive. For example, heat waves are responsible for failure of crops and result in excess demand. Additionally, other markets influence the prices of agricultural commodity markets, e.g. energy markets. High oil prices affect food prices in both direct and indirect ways, as found in the literature (see Onour and Sergi (2016) or Birur et al. (2008)).
On the one hand, however, much is known about the linkage of agricultural and non agricultural markets, on the other hand, it is crucial to know exactly how agricultural markets are interacting with each other, particularly with regard to "feeding the world" and "food crisis". This paper amplifies the literature by investigating the internal return and volatility structure of major agricultural commodities after the financial crisis with a special spot on the influence of uncertainty (in terms of volatility) on spot price returns. This study provides a return and volatility analysis for spot prices of four major agricultural products: wheat, sugar, soybeans and coffee. Based on a multivariate model for conditional heteroscedasticity, optimal hedge ratios and portfolio weights are calculated as well. To examine how uncertainty affects agricultural spot prices, an unrestricted full VAR-ABEKK-in-mean model is appropriate.
The paper is structured as follows: Section 2 gives a review of recent literature relating to agricultural commodity markets. Section 3 describes the data and model used for this approach. Section 4 shows and handles the empirical findings, followed by a conclusion.

2 Literature Review

The literature provides a great amount of investigations of the interrelationship of agricultural, energy or precious commodities and stocks. Kang et al. (2017) studied dynamic spillover effects such as crude oil, gold, silver and agricultural commodities (corn, wheat and rice) for a period from 2002 to 2016 by using a DECO-GARCH model[1] and spillover index. They found that agricultural commodities are net receivers of spillover effects and concluded that return and

[1] DECO stands for dynamic equicorrelation and is a special case of the DCC (dynamic conditional correlation) model. The model is able to overcome the limitation of DCC, namely the computational and presentational disadvantages.

volatility spillovers in these markets are more distinctive in times of financial crises.
Among others, Mensi et al. (2014) explained the dynamics of return and volatility across energy and cereal spot market returns between 2000 and 2013. They showed with both a VAR-DCC-GARCH model and a VAR-BEKK-GARCH model, how WTI, Brent, gasoline, heating oil, barley, corn, sorghum and wheat are interrelated. In their analysis, they built pairs of cereal markets and energy markets in a bivariate context. Similar to Kang et al. (2017) they found a rising tendency of dynamic conditional correlation during the financial crisis in 2007 for all commodity returns (except gasoline and sorghum). Onour and Sergi (2016) investigated volatility spillover effects between wheat, corn, crude oil and fertilizers with monthly data (1992 to 2011). With a MGARCH-VECH specification the authors pointed out that firstly corn price volatility transmits to wheat price volatility and secondly the volatility of the investigated agricultural commodities are both influenced by crude oil. Al-Maadid et al. (2016) also found empirical significant linkages in terms of return and volatility between agricultural commodities (corn, soybeans, coffee, cocoa, sugar and wheat) and energy (crude oil and ethanol) in a bivariate VAR-GARCH-BEKK framework. They also controlled for parameter shifts by including dummy variables and, based on this specification, observed that disturbances in the world economy affect the linkage between agricultural and energy markets.
Baldi et al. (2016) considered agricultural commodities and stock markets. They used weekly data in a wide range from 1970 to 2015 of the S&P500 Index, S&P Agricultural Index, Grain Index and Corn Index. Their study resulted in an increasing connection of these markets in terms of increasing volatility spillovers after the crisis in 2008.

Common to all introduced articels is their lack of investigation of the pure agricultural commodity market, and their focus on the interrelation of agricultural commodities and other asset classes. Even less authors deal with the very relationship of agricultural commodity markets.
Lahiani et al. (2013) investigated spillover effects within four major agricultural commodities (wheat, cotton, corn and sugar). Their main findings included a significant return and volatility spillover across the markets for wheat, cotton, sugar and corn. The authors devided the commodities into three levels of news-sensitiveness and concluded that sugar is the most news-sensitive. They also highlighted that the corn transmits its variance shock to all other explored markets. Hernandez et al. (2014) discovered the volatility dynamics for corn, wheat and soybeans across major agricultural exchanges in the US, Europe and Asia. They focused on different closing times of the exchanges and concluded a high interrelation between the markets. Moreover,

the exchange in the United States plays a major role in terms of spillover effects on the other markets.

With a SVAR model allowing for GARCH-in-mean errors, Beckmann and Czudaj (2014) examined futures markets of corn, cotton and soft red wheat from 2000 to 2012. They observed (short-run) volatility spillover effects in each market. Nevertheless, they recognized an influence of volatility of returns of corn futures on returns itself, of cotton and wheat futures. According to the authors, this is an indication for potential speculation in one market, affecting agricultural markets. Also Hernandez et al. (2014) engaged in exploring volatility transmissions in major agricultural futures markets in the US, Europe and Asia. They examined the interrelationships of futures markets of corn, wheat and soybeans[2] . To generate a hypothesis, they used daily closing data of commodity futures contracts traded at each market for a time period from 2005 until 2009. As a special case, they dealt with asynchronous trading times and used different multivariate GARCH models for their investigation[3] . Their work provides interesting insights into the dynamics of different markets of the same commodity. They found that the United States play a major role in terms of volatility spillover effects and concluded an overall important status of the USA in global agricultural markets. From a structural point of view, Chen and Weng (2017) also explored dynamic links between markets of soybeans, wheat and corn in the USA and China. They argued with the importance of the consideration of an asymmetric error distribution and therefore choose a skew Student t distribution as the underlying distribution. They estimated a VAR-BEKK-GARCH model and considered daily futures prices from 2005 to 2014. The results are in line with Hernandez et al. (2014), consolidating the assumption that the US market is taking lead.

Etienne et al. (2016) examined volatility spillover effects and dynamic conditional correlations between corn, soybean meal and DDGS[4] between 2000 and 2016 with weekly data and a trivariate VECM-MGARCH model[5] . They detected high interrelationships between the markets in price and volatility dynamics. Especially, they found a stronger dynamic correlation between DDGS and corn between 2006 and 2012 which is consistent with the literature. Furthermore, they uncovered strong unidirectional spillovers from corn and soybean meal prices into DDGS,

[2] The relation of the commodities, e.g. wheat, between USA, Europe and Asia. Finally, three trivariate models for three commodities and three markets have been estimated.

[3] A diagonal BEKK-GARCH model, a full BEKK-GARCH model, a Constant Conditional Correlation (CCC) model and a Dynamic Conditional Correlation (DCC) model. Furthermore, they assumed in each case a multivariate Student t distribution of the error terms.

[4] DDGS stands for distiller dried grains with solubles of 10 % moisture and is a co-product of ethanol productions

[5] They estimated both a DCC-GARCH and a BEKK-GARCH specification

whereas they observed both-sided volatility spillovers between corn and soybean meal.

However, the existing literature mainly take into consideration the agricultural futures markets and volatility spillover between different assets and agricultural commodities. With this paper, I want to contribute by analyzing four major agricultural spot prices between 2008 and 2016 with an asymmetric VAR-GARCH-BEKK-in-mean specification, which is flexible enough to deal with spillover effects in returns and volatility. Moreover, the model specification measures the variance-covariance matrix directly and it is also possible to measure how risk affects spot price returns in agricultural markets.

3 Data and Methodology

3.1 Data

The markets of interest are sugar, wheat, soybeans and coffee. The choice of these markets is driven by the aim to represent the whole width of major agricultural commodity classifications. For example, Thomson Reuters categorize agriculture commodities in grains (containing wheat), softs (sugar and coffee) and oilseeds (soybeans)[6] . In this case the luxury food coffee will be considered additionally to the basic foods sugar corn and soybeans. Adding the luxury food determines whether there is a potential relationship between the prices of basic foods and luxury foods.

For the spot market analysis, I use S&P-GSCI commodity indices, which are widely used benchmarks. All data are denoted in US Dollar to avoid exchange rate effects. The data are obtained from Thomson Reuters Datastream. Table 1 gives an overview of the data and data source.

commodity	Datastream RIC	period	observations
S&P GSCI Sugar spot price	GSSBSPT	01.01.2008 - 21.12.16	2348
S&P GSCI Wheat spot price	SGWTSPT	01.01.2008 - 21.12.16	2348
S&P GSCI Soybeansnspot price	GSSOSPT	01.01.2008 - 21.12.16	2348
S&P GSCI Coffee spot price	GSKCSPT	01.01.2008 - 21.12.16	2348

Table 1: Overview data

To guarantee stationarity (see ADF test in table 3) in the following analysis, each return series

[6] Additionally there are biofuels (e.g. ethanol and biodiesel), livestock and dairy, fertilizer and forestry

is computed as log-return r_t as follows

$$r_t = ln\Big(\frac{P_t}{P_{t-1}}\Big) \cdot 100 \tag{1}$$

where P_t denotes the closing price at time t.

Figure 1 plots the spot prices and log returns of sugar, wheat, soybeans and coffee, respectively.

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

A first look suggests that the commodities behave differently but they all had a strong increase during 2011. Also, they seem to be quite volatile (particularly sugar and wheat), which is confirmed by the standard deviation in table 2, summarizing the descriptive statistics. As expected, the mean of each series is close to zero and all commodity returns exhibit a positive excess kurtosis. The log returns of sugar and soybeans are negatively skewed, whereas the relative price changes of wheat and coffee are positively skewed.

Moreover, agricultural commodities manifest the typical characteristics of financial time series. Table 3 shows well-established time series tests. The Ljung-Box statistics indicate no serial correlation in returns (except for wheat) but dependencies in the second moment. The ARCH-

	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

Table 2: Descriptive Statistics

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

Table 3: Preliminary tests for the four return series. The Jarque Bera statistic tests 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.

LM test of R. Engle (1982) states conditional heteroscedasticity in the data.

3.2 Methodology

Univariate GARCH models

The financial literature provides a huge amount of studies about ARCH and GARCH models since its introduction by R. Engle (1982) and Bollerslev (1986), respectively. These models have become a very important tool in the analysis of behaviour of time series volatility. For this paper, a univariate AR(1)-GARCH(1,1)-in-mean model and a univariate AR(1)-EGARCH(1,1)-in-mean model has been estimated.

On the one hand, the conditional mean is described by an autoregressive process. One could argue that the return at time t depends not only on an autoregressive part, but on its standard deviation (risk) at time t, as well. To consider that assumption, R. F. Engle et al. (1987)

introduced the GARCH-in-mean model.

$$r_t = \mu + \phi \cdot r_{t-1} + \psi \cdot \sigma_t + \varepsilon_t, \quad \varepsilon_t | I_{t-1} \sim (0, \sigma_t^2) \tag{2}$$

$$\varepsilon_t = \nu_t \cdot \sigma_t, \quad \nu_t \sim (0,1) \tag{3}$$

$$\sigma_t^2 = w + a \cdot \varepsilon_{t-1}^2 + b \cdot \sigma_{t-1}^2 \tag{4}$$

r_t is the return at time t and ϕ is an autoregressive parameter, which measures the influence of the own past returns. The parameter ψ is the risk premium, an investor wants to be compensated for. ε_t is a random variable with $\varepsilon_t | I_{t-1} \sim (0, \sigma_t^2)$ and can be interpreted as a market shock or unexpected return. I_t is the information set, which contains all information available at time t. Equation 4 is the conditional variance with w as a constant and a measures the ARCH effect, that is the influence of a market shock on the conditional volatility[7] , whereas b measures the GARCH effect of the time series and can be interpreted as the persistence of the conditional volatility[8] .

Black (1976) was the first one to recognize the negative correlation of stock returns and stock stock returns' volatility. This phenomenon is called leverage effect. An implication of the leverage effect is that decreasing stock prices tend to higher volatility, whereas increasing stock prices tend to a lower volatility. In other words, volatility reacts asymmetric to returns. Christie (1982) as well as Nelson (1991) already noted this result and described, given a similar magnitude, the different impacts of positive and negative returns. In time series where the leverage effect is observable, the GARCH model is not appropriate because it captures only a symmetric reaction. Nelson (1991) published an approach capable of handling the asymmetry. For this purpose, I use the definition of an EGARCH model given in (Xekalaki & Degiannakis, 2010, p. 43)

$$ln(\sigma_t^2) = w + a \cdot (\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}})) + c \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + b \cdot ln(\sigma_{t-1}^2) \tag{5}$$

Equation 5 describes another specification of the conditional variance, which can be substituted in (4). The parameter c measures the magnitude of asymmetry. The expectation of the standardized error term, $E(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}})$, depends on the assumed underlying distribution. For a normal distribution, the expectation $E(\cdot)$ turns to $\sqrt{\frac{2}{\pi}}$.

[7] Relatively high values correspond with high sensibility to market movements.
[8] Relatively high values can be interpreted as a slow decline of volatility after a shock.

Multivariate GARCH models

To detect spillover effects in returns and volatility of financial time series, multivariate GARCH models are appropriate. In this study, I use the VAR(1)-GARCH-BEKK(1,1)-in-mean specification[9]

$$\boldsymbol{r_t} = \boldsymbol{\mu} + \Phi \boldsymbol{r_{t-1}} + \boldsymbol{\Psi}\sqrt{\boldsymbol{diag(H_t)}} + \boldsymbol{\varepsilon_t} \tag{6}$$

$$\boldsymbol{\varepsilon_t}|I_{t-1} \sim (0, \boldsymbol{H_t}) \tag{7}$$

$$\boldsymbol{H_t} = \boldsymbol{CC'} + \boldsymbol{A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A} + \boldsymbol{B'H_{t-1}B} \tag{8}$$

Equation (6) describes the conditional mean. Here, $\boldsymbol{r_t}$ is a (px1) vector of returns at time t. $\boldsymbol{\mu}$ is a (px1) vector with constants and Φ with $\phi_{ij} \in \Phi$ is a (pxp) matrix, which measures return spillover effects. ϕ_{ii} measures the influence of the own past of each return series. The off-diagonal elements $\phi_{ij}, \quad i \neq j$ can be interpreted as the spillover effects in returns; this means if return of series i at time t is influenced by the return of series j at time t-1.

$$\boldsymbol{r_t} = \begin{pmatrix} r_{1,t} \\ r_{2,t} \\ r_{3,t} \\ r_{4,t} \end{pmatrix}, \quad \boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \end{pmatrix}, \quad \boldsymbol{\Phi} = \begin{pmatrix} \phi_{11} & \phi_{12} & \phi_{13} & \phi_{14} \\ \phi_{21} & \phi_{22} & \phi_{23} & \phi_{24} \\ \phi_{31} & \phi_{32} & \phi_{33} & \phi_{34} \\ \phi_{41} & \phi_{42} & \phi_{43} & \phi_{44} \end{pmatrix}, \quad \boldsymbol{\Psi} = \begin{pmatrix} \psi_{11} & \psi_{12} & \psi_{13} & \psi_{14} \\ \psi_{21} & \psi_{22} & \psi_{23} & \psi_{24} \\ \psi_{31} & \psi_{32} & \psi_{33} & \psi_{34} \\ \psi_{41} & \psi_{42} & \psi_{43} & \psi_{44} \end{pmatrix}$$

$$\sqrt{diag(\boldsymbol{H_t})} = \begin{pmatrix} \sqrt{h_{11,t}} \\ \sqrt{h_{22,t}} \\ \sqrt{h_{33,t}} \\ \sqrt{h_{44,t}} \end{pmatrix}$$

With equation (8) the conditional variance can be computed. $\boldsymbol{H_t}$ is the conditional variance-covariance matrix at time t with $h_{ij} \in \boldsymbol{H_t}$. The diagonal elements are the conditional variances of each series. The off-diagonal elements are covariances between series i and series j. $a_{ij} \in \boldsymbol{A}$ and $b_{ij} \in \boldsymbol{B}$ are (pxp) parameter matrices. The elements of both matrices denote cross market effects for $i \neq j$ and own effects for $i = j$. $\boldsymbol{C}$ is lower triangular matrix with constants.

To deal with asymmetry Grier et al. (2004) introduced a GARCH-BEKK model with consider-

[9] BEKK stands for the names of the developers of the model, namely Yoshi Baba, Robert Engle, Dennis Kraft and Ken Kroner). The model itself was published by R. F. Engle and Kroner (1995).

ation of asymmetry. The so-called GARCH-ABEKK model can be written as follows

$$\boldsymbol{H_t} = \boldsymbol{CC'} + \boldsymbol{A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A} + \boldsymbol{B'H_{t-1}B} + \boldsymbol{D'\zeta_{t-1}\zeta_{t-1}{}'D} \tag{9}$$

where $\boldsymbol{G}$ is a (pxp) parameter matrix, which measures the effects of asymmetry. $\boldsymbol{\zeta_t}$ is a (px1) vector and corresponds to $\boldsymbol{\varepsilon_t}$ if $\boldsymbol{\varepsilon_t}$ is negative or zero otherwise.

$$\boldsymbol{H_t} = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} & h_{14,t} \\ h_{21,t} & h_{22,t} & h_{23,t} & h_{24,t} \\ h_{31,t} & h_{32,t} & h_{33,t} & h_{34,t} \\ h_{41,t} & h_{42,t} & h_{43,t} & h_{44,t} \end{pmatrix}, \quad \boldsymbol{C} = \begin{pmatrix} c_{11} & 0 & 0 & 0 \\ c_{21} & c_{22} & 0 & 0 \\ c_{31} & c_{32} & c_{33} & 0 \\ c_{41} & c_{42} & c_{43} & c_{44} \end{pmatrix}, \quad \boldsymbol{A} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix}$$

$$\boldsymbol{B} = \begin{pmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{pmatrix}, \quad \boldsymbol{D} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & d_{14} \\ d_{21} & d_{22} & d_{23} & d_{24} \\ d_{31} & d_{32} & d_{33} & d_{34} \\ d_{41} & d_{42} & d_{43} & d_{44} \end{pmatrix}, \quad \boldsymbol{\zeta_t} = \begin{pmatrix} \zeta_{1,t} \\ \zeta_{2,t} \\ \zeta_{3,t} \\ \zeta_{4,t} \end{pmatrix}$$

Estimation and numerical procedure

To estimate all models, I use the maximum likelihood approach. Assuming normal error terms, the (conditional) log likelihood function is maximized so that the probability to achieve the true parameters is maximized. The multivariate normal distribution has the form

$$L(x) = \frac{1}{\sqrt{(2\pi)^p \cdot det(H)}} \cdot exp(-0.5 \cdot (x-\mu)' H^{-1} (x-\mu)) \tag{10}$$

Assuming that the error vector has zero mean and a time-varying variance-covariance the (conditional) log likelihood function of the joint distribution L is the sum of all log likelihood functions of (conditional) distributions.

$$L(\theta) = \sum_{t=1}^{T} L_t(\theta), \qquad L_t(\theta) = -0.5 \cdot p \cdot log(2\pi) - 0.5 \cdot log(det(H_t)) - 0.5 \cdot \varepsilon_t' H_t^{-1} \varepsilon_t \tag{11}$$

θ represents the parameter vector, which contains all parameters to be estimated. T is the sample size, p is the dimension of the system and equal to the number of time series.

Because of both, the large number of parameters to estimate and the highly non-linear structure of the Log-Likelihood function, the choice of initial values is elementary. To find the optimal values, which maximize the Log-Likelihood function, I carry out a two-step estimation procedure. To reach better starting values, in a first step I use the Nelder-Mead algorithm, which is a gradient-less method. For the first estimation, I take the estimated parameters from the univariate cases as initial values in the main diagonals in the variance equation. All other elements are set to zero.

For the main optimization process, I use the estimates from step one as starting values for the second estimation, where the BHHH algorithm is applied. All models are programmed in the statistical software R. Within the program code, I use the maxLik package provided by Henningsten and Toomet (2011) to compute the numerical parts.

4 Empirical Findings and Discussion

4.1 Interdependencies in agricultural markets

As a first step, both an univariate AR(1)-GARCH(1,1)-in-mean model (Panel A in table 4) and an AR(1)-EGARCH(1,1)-in-mean model (Panel B in table 4) have been estimated. Looking at each univariate return series, both own past and own volatility do not play a role when modelling the conditional mean. Except for the negative autoregressive parameter for wheat (-0.0392) neither the autoregressive part nor the in-mean part is significantly different from zero. Conditional variance offers a different perspective in both model specifications. The influence of a market shock on the conditional volatility (measured in the parameter a) is statistically highly significant, whereas the coefficients vary in magnitude. The conditional volatility of soybeans is most news-sensitive ($a = 0.1429$), followed by wheat ($a = 0.0143$) compared to the other commodities. Nevertheless, all parameters show a positive sign indicating that positive (negative) market shocks influence conditional volatility in a positive (negative) way.

The coefficient b is close to one in each case, indicating a relatively high persistence after a volatility shock. That means when one commodity is hit by a volatility shock, conditional volatility decays slowly, concluding that each commodity holds typical time series characteristics. It is a common fact that the leverage effect in stock returns is negative (expressed as negative values for γ). This is not true for agricultural commodities. For the spot returns of sugar, wheat and coffee, the estimates are significantly different from zero and positive.

To check whether the models capture the data characteristics in an appropriate manner, the residual diagnostics of the standardized residuals[10] in table 4 indicate an acceptable fit. The unconditional first and second moment of the standardized residual is zero and one, respectively. Furthermore, no time series show significant autocorrelation (see Ljung-Box statistics) and no conditional heteroscedasticity (see Lagrange-Multiplier test for ARCH effects).

[10]calculated as $\frac{\varepsilon_t}{\sigma_t}$

	Panel A: AR(1)-GARCH(1,1)-in-mean				Panel B: AR(1)-EGARCH(1,1)-in-mean			
cond. mean	$r_t = \mu + \phi \cdot r_{t-1} + \psi \cdot \sigma_t + \varepsilon_t$				$r_t = \mu + \phi \cdot r_{t-1} + \psi \cdot \sigma_t + \varepsilon_t$			
	sugar	wheat	soybeans	coffee	sugar	wheat	soybeans	coffee
μ	-0.1523	-0.1550	0.1175	0.0097	-0.1259	-0.1612	0.1304	0.3628
	(0.204)	(0.227)	(0.271)	(0.976)	(0.299)	(0.182)	(0.205)	(0.224)
ϕ	0.0244	-0.0340	0.0161	-0.0276	0.022	**-0.0392**	0.0169	-0.0280
	(0.254)	(0.110)	(0.486)	(0.197)	(0.287)	(0.064)	(0.4347)	(0.186)
ψ	0.0825	0.0505	-0.079	-0.0155	0.073	0.0537	-0.0785	-0.1846
	(0.217)	(0.487)	(0.414)	(0.927)	(0.288)	(0.432)	(0.301)	0.238
cond. variance	$\sigma_t^2 = \omega + a \cdot \varepsilon_{t-1}^2 + b \cdot \sigma_{t-1}^2$				$ln(\sigma_t^2) = w + a \cdot (\frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}} - E(\frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}})) + c \cdot \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + b \cdot ln(\sigma_{t-1}^2)$			
ω	**0.0050**	**0.0225**	**0.0282**	**0.0817**	**0.0036**	**0.0143**	**0.0165**	**0.0423**
	(0.074)	(0.000)	(0.000)	(0.000)	(0.013)	(0.004)	(0.00)	(0.00)
a	**0.0208**	**0.0512**	**0.0617**	**0.0315**	**0.0410**	**0.117**	**0.1429**	**0.0746**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.00)	(0.00)	(0.00)	(0.00)
b	**0.9778**	**0.9446**	**0.9273**	**0.9478**	**0.9983**	**0.9919**	**0.9869**	**0.9712**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.00)	(0.00)	(0.00)	(0.00)
γ					**0.0089**	**0.0254**	-0.0026	**0.0404**
					(0.087)	(0.01)	(0.80)	(0.00)
Log Likelihood	-4903.09	-4862.20	-4215.04	-4895.43	-4903.42	-4857.62	-4215.01	-4891.03
Residual diagnostic								
mean	0.004580	0.012427	-0.003049	0.010901	0.000523	0.013522	-0.011762	-0.001548
sd	0.999931	0.999666	1.000548	1.000468	1.000027	0.999879	0.999918	0.999989
LB(12)	0.043201	0.030213	0.216261	0.380479	0.012411	0.006732	0.233851	0.107183
	(0.835)	(0.862)	(0.642)	(0.537)	(0.911)	(0.935)	(0.629)	(0.743)
ARCH LM	10.64369	6.452859	13.15504	13.84739	12.69984	5.892210	14.17322	12.361450
	(0.560)	(0.892)	(0.359)	(0.311)	(0.391)	(0.921)	(0.90)	(0.417)

Table 4: Estimation results of an AR(1)-GARCH(1,1)-in-mean model (Panel A) and AR(1)-EGARCH(1,1)-in-mean model (Panel B). Values in parenthesis are p values.

For a deeper insight into the interdependencies of returns and volatility of agricultural commodities, the use of multivariate GARCH models is appropriate. To check return spillover effects, the conditional mean equation corresponds to a VAR construction. To find the optimal lag length, I calculated three information criteria (AIC, HQ, SC). Each criterion suggests a VAR(1) model for the conditional mean.

For the variance equation, I tested several specifications, beginning with the simplest form, a BEKK representation. Both with and without consideration of asymmetry in the variance equation all models behave poorly when examining residual diagnostics. So far, the best model is a VAR(1)-ABEKK(1,1)-in-mean model. Table 5 demonstrates the estimation results.

Starting with analyzing the results of the **conditional mean** equation, keep in mind that the columns of all matrices in table 5 represent the markets in the following chronological order: sugar, wheat, soybeans, coffee. The entry ij can be translated as the influence of commodity j on commodity i. For example, we assumed $i = 2$ and $j = 3$ is the influence of soybeans on wheat.

I detect return spillover effects (matrix Φ) from wheat (-0.0395) and soybeans (0.0511) to sugar in a unidirectional way. This means, that higher returns in the wheat (soybeans) spot market lead to lowering (increasing) the returns in the sugar spot market. Furthermore, return spillovers from coffee (0.0334) to wheat and from soybeans to coffee (0.0616) are observed. Soybeans exhibit the highest return spillover effects (0.0511, 0.0616) compared to the other commodities and have in both cases a positive influence. By contrast, soybeans are not affected by other commodities. Sugar returns are not only affected by price changes in wheat and soybeans, but also indirectly by coffee due to the fact that wheat is influenced by coffee and influences sugar. Taking it together, sugar reacts very sensitive to return changes in other markets.

Matrix Ψ considers the effects of risk (measured as conditional standard deviation) on returns. Surprisingly, risk does not play an important role in describing commodity's return (in terms of significant influence). However, soybeans are most affected by risk. On the one hand, own past conditional volatility influences the return series negatively (-0.2318). Higher conditional volatility in the market for soybeans leads to decreasing soybeans returns. On the other hand, rising conditional volatility of wheat results in increasing returns of soybeans (0.2217). Lastly, conditional volatility of sugar affects coffee (0.1961). The spillover effects behave as expected,

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

$$\boldsymbol{\mu} = \begin{pmatrix} -0.2712 \\ (0.249) \\ -0.1593 \\ (0.410) \\ 0.0831 \\ (0.746) \\ -0.2689 \\ (0.386) \end{pmatrix} \qquad \boldsymbol{\Phi} = \begin{pmatrix} 0.0149 & \mathbf{-0.0395} & \mathbf{0.0511} & 0.0201 \\ (0.492) & (0.091) & (0.080) & (0.288) \\ 0.0234 & -0.0297 & -0.0065 & \mathbf{0.0334} \\ (0.237) & (0.204) & (0.820) & (0.077) \\ 0.0193 & -0.0124 & 0.0227 & 0.0221 \\ (0.171) & (0.452) & (0.344) & (0.122) \\ 0.0266 & 0.0100 & \mathbf{0.0616} & \mathbf{-0.0432} \\ (0.166) & (0.652) & (0.032) & (0.047) \end{pmatrix}$$

$$\boldsymbol{\Psi} = \begin{pmatrix} 0.0364 & 0.0040 & 0.1234 & 0.0095 \\ (0.798) & (0.977) & (0.326) & (0.938) \\ -0.0286 & 0.1145 & -0.0596 & 0.0068 \\ (0.786) & (0.445) & (0.654) & (0.943) \\ -0.0599 & \mathbf{0.2217} & \mathbf{-0.2318} & -0.0291 \\ (0.542) & (0.035) & (0.032) & (0.811) \\ \mathbf{0.1961} & -0.0397 & -0.0491 & 0.0070 \\ (0.088) & (0.764) & (0.679) & (0.968) \end{pmatrix}$$

conditional variance	$\boldsymbol{H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\zeta_{t-1}\zeta'_{t-1}D}$

$$\boldsymbol{C} = \begin{pmatrix} \mathbf{0.1162} & & & \\ (0.000) & & & \\ \mathbf{-0.1079} & \mathbf{0.1261} & & \\ (0.060) & (0.004) & & \\ 0.0329 & 0.0393 & \mathbf{0.1939} & \\ (0.564) & (0.568) & (0.000) & \\ \mathbf{0.1867} & \mathbf{0.1619} & -0.0083 & 0.0004 \\ (0.000) & (0.003) & (0.915) & (0.997) \end{pmatrix} \qquad \boldsymbol{A} = \begin{pmatrix} \mathbf{0.0812} & \mathbf{0.0806} & 0.0204 & 0.0069 \\ (0.000) & (0.000) & (0.122) & (0.587) \\ \mathbf{-0.0382} & \mathbf{0.1948} & \mathbf{-0.0303} & -0.0123 \\ (0.028) & (0.000) & (0.038) & (0.464) \\ \mathbf{0.040} & -0.0269 & \mathbf{0.2022} & 0.0328 \\ (0.055) & (0.292) & (0.000) & (0.104) \\ 0.0169 & 0.0003 & -0.0002 & \mathbf{0.1323} \\ (0.166) & (0.985) & (0.988) & (0.000) \end{pmatrix}$$

$$\boldsymbol{B} = \begin{pmatrix} \mathbf{0.9879} & -0.0027 & \mathbf{-0.0051} & -0.0026 \\ (0.000) & (0.549) & (0.050) & (0.279) \\ \mathbf{0.0162} & \mathbf{0.9735} & \mathbf{0.0166} & 0.0070 \\ (0.005) & (0.000) & (0.006) & (0.178) \\ \mathbf{-0.0142} & -0.0022 & \mathbf{0.9529} & -0.0085 \\ (0.031) & (0.793) & (0.000) & (0.170) \\ \mathbf{-0.0058} & -0.0046 & -0.0013 & \mathbf{0.9816} \\ (0.032) & (0.500) & (0.782) & (0.000) \end{pmatrix} \qquad \boldsymbol{D} = \begin{pmatrix} \mathbf{-0.1575} & 0.0266 & \mathbf{-0.0518} & -0.0232 \\ (0.000) & (0.434) & (0.029) & (0.239) \\ \mathbf{0.1384} & \mathbf{0.1796} & \mathbf{0.0524} & \mathbf{0.0811} \\ (0.000) & (0.000) & (0.071) & (0.003) \\ 0.0242 & \mathbf{0.0699} & \mathbf{0.1663} & -0.0007 \\ (0.420) & (0.065) & (0.000) & (0.983) \\ 0.0322 & \mathbf{-0.0641} & 0.0198 & -0.045 \\ (0.165) & (0.0899) & (0.541) & (0.146) \end{pmatrix}$$

Log Likelihood -18232.05

Table 5: Estimation result of a VAR(1)-ABEKK(1,1)-in-mean model for agricultural spot returns. The values in parenthesis are p values

that is higher conditional standard deviation leads to higher commodity returns.

All in all, returns of the chosen commodities seem not to be much affected by each other, but neglecting the mean specifications lead to misspecification of the model, which is also convinced by residual diagnostic in table 6 and preliminary estimations of different specifications. The reason for that could be unusual risk factors as the weather, which is a dominant and influential factor in agricultural commodity markets. Weather is a non-economical measure for risk and hence not easy to estimate. But it is a fact that, as a risk factor, it is present and appears not directly in coefficients but rather in misspecification if risk is ignored.

Next, the **conditional variance** equation is regarded and I start the analysis with matrix **A** which measures the effects of market shocks or unexpected news to the conditional variance. As expected, all diagonal elements are positive and significantly different from zero, implying that the own past of each commodity has an influence on the actual conditional variance. The off-diagonal entries a_{ij} represent spillover effects in terms of market shocks from market i to market j.

It stands out immediately that coffee is less important. Conditional volatility of coffee is neither influenced by, nor influences other markets through unexpected shocks. In wheat, quite the opposite is to be discovered. It negatively affects conditional variance of sugar and soybeans ($a_{21} = -0.0382$, $a_{23} = -0.0303$). Additionally, wheat and sugar are in a bidirectional relationship, because both a_{12} and a_{21} are significantly different from zero but interestingly with diverse signs. A shock in the wheat market shows a negative impact on the conditional variance of sugar whereas a shock in the sugar market influences the conditional variance of wheat in a positive way. Lastly, shocks in soybeans affect the sugar market ($a_{31} = 0.040$). The conclusion for matrix A is that wheat plays a dominate role. It impacts conditional variance of all basic food markets and can be thought of a major commodity. Furthermore, sugar is very news-sensitive, because conditional variances are affected by shocks in both wheat and soybeans markets. The last finding is in line with literature, e.g. Lahiani et al. (2013) recognized this fact as well.

Matrix **B** measures the effect of lagged conditional variance. Here, all coefficients b_{ii} specify the persistence of a (own) volatility shock and exhibit values close to one. This indicates a high persistence of own conditional volatility shocks in each market. Again, the off-diagonal entries in B offer spillover effects from market i to market j.

As in the analysis of unexpected shocks it seems that, in terms of volatility shocks, sugar is also very news-sensitive, since each market influences conditional volatility of sugar ($b_{21} = 0.0162$, $b_{31} = -0.0142$, $b_{41} = -0.0058$). Sugar and soybeans are the only commodities where a bidirectional linkage is observable. Similar to unexpected market shocks, wheat plays a major role again

when considering volatility shocks. The significant coefficients b_{21} and b_{24} implicate positive impact of volatility shocks in the wheat market on conditional variance of sugar and soybeans.
Matrix $\mathbf{D}$ estimates asymmetric responses, that is negative price shocks end in more price volatility compared to a positive shock with the same magnitude. Except for coffee, all commodities reach asymmetry (coefficients d_{ii} are significantly different from zero). Note, that significant asymmetric effects are only observable for commodities with both significant d_{ij} and significant a_{ij}. I also observe cross price asymmetric behaviour where wheat plays a major role. A negative shock in the wheat market is responsible for higher conditional volatility in sugar spot prices as well as soybeans spot prices (d_{21} and d_{23} in combination with significant a_{21} and a_{23}). An interesting fact is the magnitude a asmmytric effect coming from wheat. It affects the conditional volatility of sugar much more than the conditional volatility of soybeans what is, again, another indicator for the news sensitiveness of sugar.
The overall result of the spillover analysis shows, that the basic food commodities sugar, wheat and soybeans are strongly linked. Coffee as a luxury food, however, takes a stand-alone position in this analysis, indicating that basic food products and luxury food products are not linked. Above all, this result is comprehensible comparing the world wide production of each commodity. According to the United States Department of Agriculture the average annual world wide production of wheat is 740 million tons, whereas the world wide annual production of coffee is only 154 million tons, what explains the importance of wheat in the world economy hence the finding that wheat transmits shocks to the other investigated basic food commodities.

4.2 Residual Diagnostics and specification tests

To check if the estimated model is adequate, standardized residuals are investigated. Figure 2 shows the standardized residuals for each agricultural commodity, calculated as $H_t^{-\frac{1}{2}}\varepsilon_t$, and table 6 shows residual diagnostic tests for standardized residuals. Panel A demonstrates univariate diagnostics for each series. The Ljung-Box (LB) statistics is statistically not different from zero (including 8 and 12 lags), suggesting that there is no more autocorrelation in the standardized error terms. Except for standardized residuals of coffee, all commodities exhibit no ARCH effects.
The second part of panel A in table 6 deals with multivariate diagnostic tests. Here, I calculated a multivariate version of the Ljung-Box-test and the Li-McLeod-test to test autocorrelation for all commodities simultaneously. The test statistics indicate that there is no significant joint

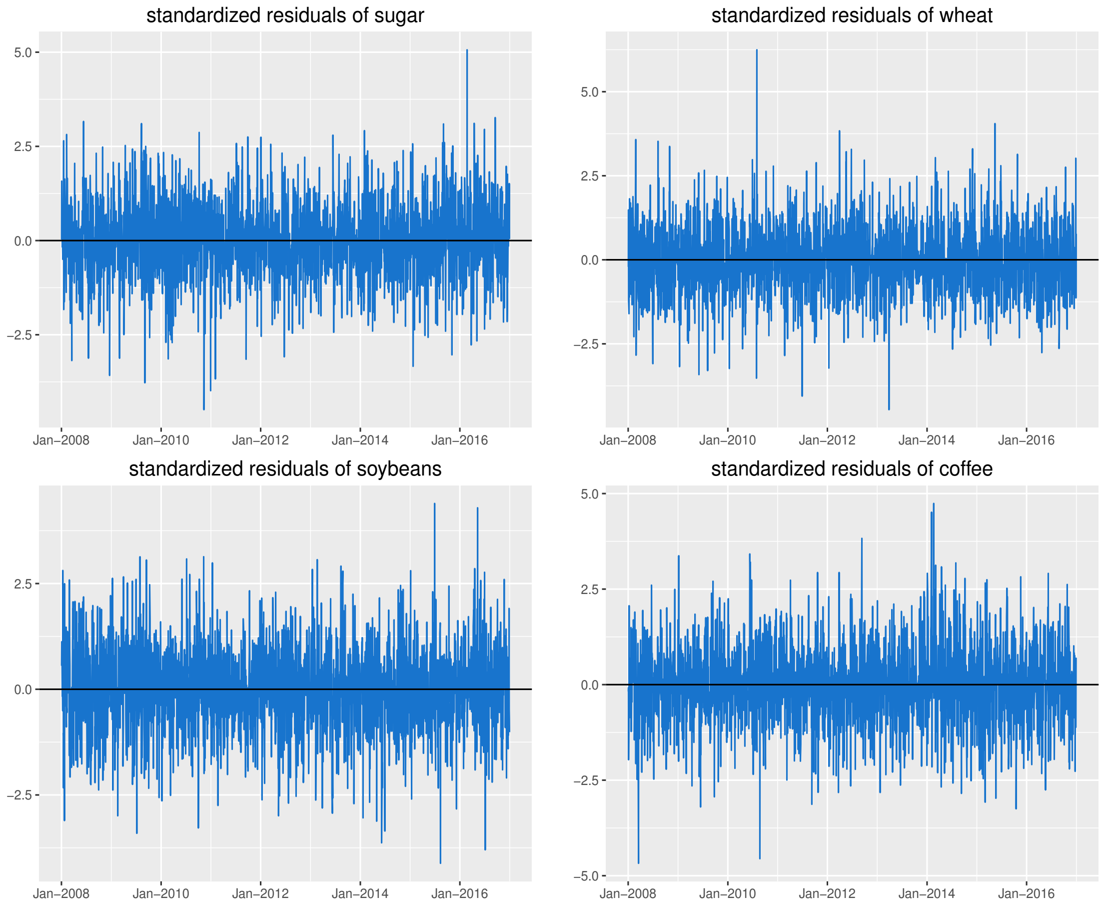

Figure 2: Standardized Residuals

autocorrelation. To test for conditional heteroscedasticity in the standardized residuals I perform a multivariate ARCH test and its robust specification[11] as documented in (Tsay, 2014, pp. 401-405). Although coffee shows heteroscedasticity in the standardized residuals, the hypothesis that there is heteroscedasticity in all series contemporaneous is rejected.

With regard to both different models estimated[12] and residual diagnostics I conclude that a VAR(1)-GARCH-ABEKK(1,1)-in-mean model represents the investigated agricultural commodities best.

Panel B of table 6 illustrates three specification tests: no VAR effects in the conditional mean, no GARCH-in-mean effects and no asymmetry. All tests[13] reject the null hypothesis that particular coefficients are zero simultaneously. Besides the results from the residual diagnostics the executed specification tests support that the model choice is adequate.

[11] The robust modification of the Ljung-Box-statistic is to trim away the upper 5 % tail. With this approach one can reduce the effects of potential heavy tails in the error terms.

[12] As already described I started the investigation with the simplest model, e.g. a BEKK specification. I compared both residual diagnostics and log likelihood values. All models behaved poorly when doing goodness of fit tests. I also modeled a VARMA(1,1)-GARCH-ABEKK(1,1)-in-mean model but with no improvement.

[13] For each Null I performed likelihood ratio (LR) tests.

Panel A: Residual diagnostic for standardized residuals				
univariate diagnostic	sugar	wheat	soybeans	coffee
mean	0.0052	0.0137	-0.0031	0.0066
	(0.8011)	(0.506)	(0.887)	(0.751)
sd	0.9981	0.9999	1.0002	0.9991
	(0.901)	(0.997)	(0.984)	(0.963)
LB(12)	8.6945	11.8105	11.6596	13.7207
	(0.729)	(0.461)	(0.473)	(0.319)
LB(8)	3.6374	9.8576	6.8315	4.2503
	(0.888)	(0.275)	(0.555)	(0.834)
ARCH(12)	12.9416	14.9708	7.5479	32.2128
	(0.373)	(0.243)	(0.819)	(0.001)
ARCH(8)	8.8749	12.1111	6.7654	19.8851
	(0.353)	(0.146)	(0.562)	(0.011)
multivariate diagnostic				
multivariate LB(12)	186.9100			
	(0.590)			
multivariate LB(8)	110.4000			
	(0.870)			
Li-McLeod(12)	186.8841			
	(0.591)			
Li-McLeod(8)	110.4174			
	(0.867)			
multivariate ARCH(12)	198.4609			
	(0.359)			
multivariate ARCH(8)	131.4232			
	(0.400)			
Robust Test (5%)	188.6387			
	(0.555)			
Panel B: Specification tests				
No VAR	30.153	H_0: all elements in Φ are zero		
	(0.017)			
No GARCH-in-mean	744.785	H_0: all elements in Ψ are zero		
	(0.000)			
No asymmetry	136.2267	H_0: all elements in D are zero		
	(0.000)			

Table 6: Residual diagnostics and specification tests. Values in parenthesis are p values. To test the H_0 for each specification test a likelihood ratio (LR) test was performed.

Because of the rejection of the null hypothesis for both VAR and in-mean effects, I conclude that risk plays an important role in modelling agricultural spot markets.

4.3 Conditional Correlation, Optimal Portfolio Weights and Hedge Ratios

Figure 4 plots the dynamic conditional correlations, computed as $\frac{h_{ij,t}}{h_{ii,t}, h_{jj,t}}$, where $i, j = 1, 2, 3, 4$ $i \neq j$ and sugar=1, wheat=2, soybeans=3, coffee=4. All commodities are positively correlated

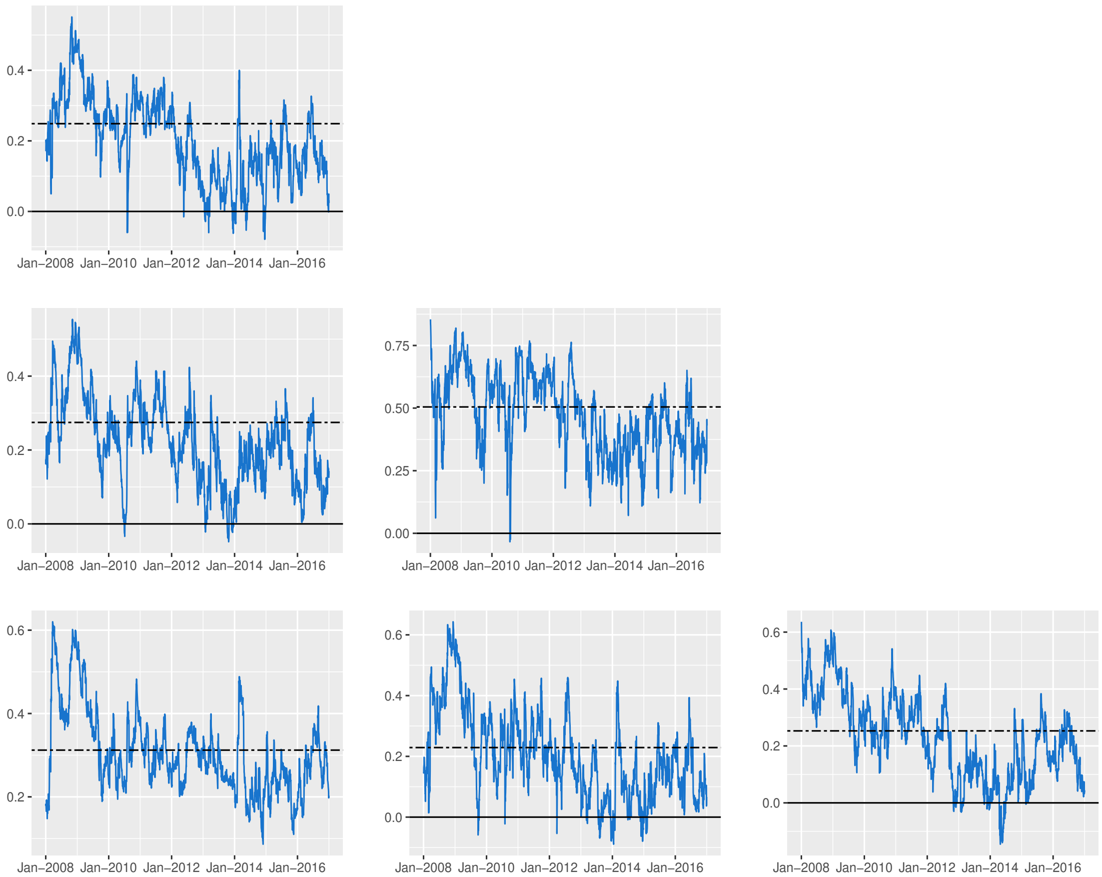

Figure 3: Dynamic correlation of the investigated commodities. Arrangement of the plots corresponding to $\begin{pmatrix} \rho_{21,t} & & \\ \rho_{31,t} & \rho_{32,t} & \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} \end{pmatrix}$, where 1 = sugar, 2 = wheat, 3 = soybenas, 4 = coffee. The dotted line represents the unconditional correlation.

over time. Since 2008, one can observe a sharp increase for all examined commodities with a peak in 2009. Since 2009, conditional correlations are lowering for all considered returns. With this result the study is in line with the existing literature. I can confirm, that the correlation is higher in times of market turmoils or crises. Interestingly, the conditional correlation (median) between wheat and soybeans is strongest ($\rho_{2,3}^{median} = 0.4765$), whereas the conditional correlation (median) between coffee and wheat is detected as the weakest ($\rho_{4,2}^{median} = 0.1854$), followed by sugar and wheat ($\rho_{1,2}^{median} = 0.1979$) and sugar and soybeans ($\rho_{1,3}^{median} = 0.2167$). The dynamic correlation (median) between soybeans and coffee or sugar and coffee is ($\rho_{3,4}^{median} = 0.2305$) and ($\rho_{1,4}^{median} = 0.2851$), respectively.

The results are in line with the spillover analysis.

With the knowledge of the behaviour of spillovers in agricultural spot markets, it is now possible to calculate optimal dynamic portfolio weights and optimal dynamic hedge ratios. Following

Portfolio	$med(w^*_{ij,t})$		$med(hr_{ij,t})$
sugar/wheat	0.49	wheat/sugar	0.19
sugar/soybeans	0.32	soybeans/sugar	0.15
sugar/coffee	0.48	sugar/coffee	0.29
wheat/soybeans	0.22	soybeans/wheat	0.35
wheat/coffee	0.49	wheat/coffee	0.18
soybeans/coffee	0.68	soybeans/coffee	0.17

Table 7: optimal portfolio weights and hedge ratios

the well-established approach of Kroner and Ng (1998), an investor can minimize the portfolio risk of a two-asset portfolio without reducing the portfolio's expected return. With a no-short constraint, the optimal time varying portfolio weights $w^*_{ij,t}$ for an optimal fully invested portfolio are

$$w^*_{ij,t} = \begin{cases} 0 & if \quad w_{ij,t} < 0 \\ w_{ij,t} & if \quad w_{ij,t} \in [0,1] \\ 1 & if \quad w_{ij,t} > 1 \end{cases} \quad w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2 \cdot h_{ij,t} + h_{jj,t}} \tag{12}$$

where $h_{ij,t}$ is the conditional covariance (for $i \neq j$) of commodity i and commodity j at time t, whereas h_{ii} is the conditional variance at time t. $w_{ij,t}$ is the weight of the i-th agricultural commodity in an one-dollar portfolio of a two-commodity portfolio with commodity i and commodity j at time t.

Kroner and Sultan (1993) introduced the beta hedge approach where the time-variant hedge ratios $hr_{ij,t}$ are based on conditional moments.

$$hr_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \tag{13}$$

With that approach one can detect how a one-dollar long position of commodity i should be hedged by a short position of $\$1 \cdot hr_{ij,t}$ in commodity j. Note, that effectiveness is reached when choosing the cheapest hedge ratio. Table 7 shows the median of optimal portfolio weights and hedge ratios in a two-asset portfolio.

First, considering optimal portfolio weights to minimize risk without reducing expected return. Sugar/wheat, sugar/coffee and wheat/coffee should be equal weighted over time[14] . Furthermore, in a sugar/soybeans portfolio, sugar should be underweighted with 33 % and in a wheat/soybeans

[14]Because of the fact that we calculated two-asset portfolios the weight of the denumerator in table 7 is $(1-w^*_{ij,t})$

portfolio, wheat should be weighted with 25 %. The overall result is that an investor should have been overweighted soybeans in all cases.

Next, we take into account optimal hedge ratios. For example, a one-dollar long position in wheat can be hedged (on average) by $\$1 \cdot 0.19 = \$0.19$ in shorting sugar. The most expensive portfolio to hedge is a soybeans/wheat portfolio (\$0.35). Each portfolio exhibits peaks of hedging ratios in 2008/2009, which means that a hedging position was most expensive during that time period. All portfolios have in common that the hedging ratios were declining after the crisis.

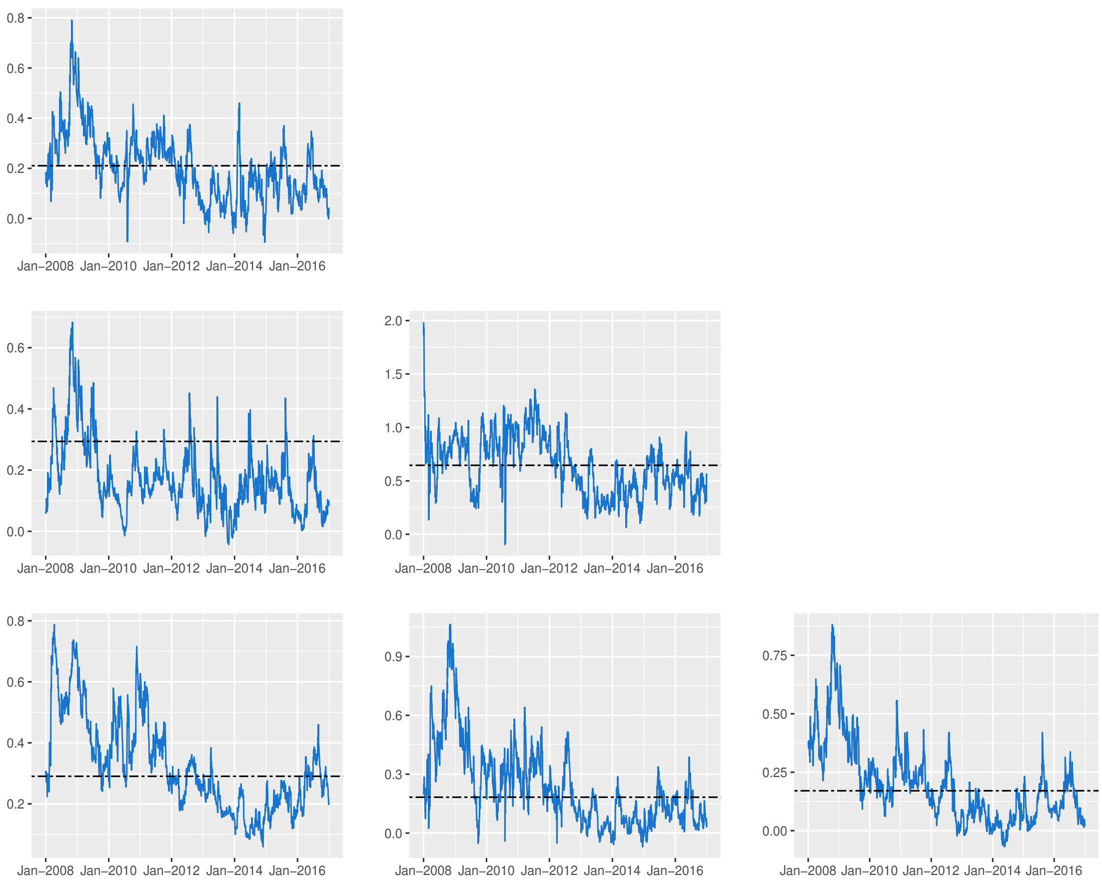

Figure 4: Optimal dynamic hedge ratios corresponding to $\begin{pmatrix} hr_{21,t} & & \\ hr_{31,t} & hr_{32,t} & \\ hr_{14,t} & hr_{24,t} & hr_{34,t} \end{pmatrix}$, where 1 = sugar, 2 = wheat, 3 = soybeans, 4 = coffee.

5 Conclusion

This study provides detailed insights into the empirical linkages of agricultural commodity spot markets. The paper engaged in return and volatility spillover effects of agricultural commodity markets between 2008 and 2016. For this purpose, daily spot returns of sugar, wheat, soybeans

and coffee have been used. After testing several models the author's choice is a VAR(1)-GARCH-ABEKK(1,1)-in-mean model which can capture the characteristics of spot returns best. All other tested models behave poorly in residual diagnostics. However, modelling these commodities seems to be difficult. During the estimation process, numerical problems arise again and again, suggesting a special state of agricultural commodities compared to classic assets like stocks.
Four major findings can be concluded. First, the results indicate that volatility and therefore risk plays an important role in agricultural spot markets with respect to the conditional mean as well as conditional volatility. Furthermore asymmetry must be taken into account. Second, wheat seems to play a major role in investigated spot markets, because a volatility shock in the wheat market is transferred to all other markets. Additionally, wheat spot returns are very sensitive for asymmetric responses. Third, conditional variance of sugar reacts very news-sensitive to both unexpected shocks and volatility shocks. Coffee in contrast is not affected by other market shocks. One can argue that coffee is a rather luxurious commodity and due to that not linked to the other markets. Lastly, conditional correlation between markets showed a peak after the crisis in 2008, but the strenghth of correlation was continously relaxxing and is found at a moderate level compared to 2008.

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