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Volatility transmission in agricultural futures markets ☆

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ABSTRACT

After the huge rise and fall of agricultural commodity spot and futures prices between 2007 and 2008, the potential reasons for and the impact of the strong rise in volatility provoked an intensive debate in the media as well as in the academic literature. However, owing to the increasing interdependence of global markets, an isolated examination of single futures markets does not seem to be appropriate. Therefore, the aim of this study is to investigate the volatility spillover between various agricultural futures markets from a new perspective. To do this, we use data for the prices of first nearby futures contracts for corn, cotton, and wheat and estimate GARCH-in-mean VAR models in the tradition of Elder (2003). Our results provide evidence in favor of an existing short-run volatility transmission process in agricultural futures markets.

1. Introduction and literature overview

Since agricultural commodity prices began to exhibit large swings between 2007 and 2008, the evolution of these has attracted considerable attention in the media and in academia. The FAO (Food and Agriculture Organization of the United Nations), which held a ministerial meeting on food price volatility on October 16, 2012 in Rome concerning this development, expects the increase in volatility to continue in the medium-term. This pattern does not appear solely in cash markets, but also in futures markets for agricultural products (Beckmann and Czudaj, forthcoming). To mention just one example, the price of the first nearby futures contract of soft red wheat traded at the Chicago Board of Trade (CBOT) increased by almost 200% from April 2007 to March 2008 and had decreased by 63% by December 2008 (see Fig. 1). Other agricultural commodity prices experienced a similar pattern. Thus, the role of futures markets is also discussed controversially when it comes to whether the potential engagement of speculative capital introduces volatility and price movements unrelated to demand and supply effects such as changes in the world population, economic growth or agricultural production (Piesse and Thirtle, 2009; Wright, 2011). Generally speaking, futures markets can offer the possibility of gaining arbitrage revenues and thus exhibit speculation, while they may also form the mechanism by which new information is incorporated into prices if markets are efficient. These markets allow for the transfer of risk from commercial traders, who are exposed to futures price movements, to non-commercial traders, who are frequently labeled speculators and take short (long) futures positions in the hope of yielding a capital gain from the fall (rise) in prices.

Against this background, this paper analyzes the futures markets of agricultural commodities from a new perspective. While previous studies have mostly examined either futures or spot markets separately or the link between them, we focus on spillover effects between various futures markets. The question of spillover effects is important for several reasons: firstly, general causality patterns can be identified. Secondly, co-movements of futures markets are a crucial issue for both investors and policymakers: on the one hand, the possibility of cross-market hedging can be affected. On the other hand, co-movements or cross-sectional volatility might be a result of a systematic influence stemming from a particular group of participants. However, it is worth mentioning that a direct evaluation of speculative pressure is beyond the scope of this study. As outlined further below, it is hard to judge whether speculation has the predominate role in increasing volatility. Nevertheless, it is important to shed some light on the general discussion regarding this issue in the following in order to put our findings in a general context.

An implication of standard theory is that futures prices should follow a random walk with price innovations introducing new information and

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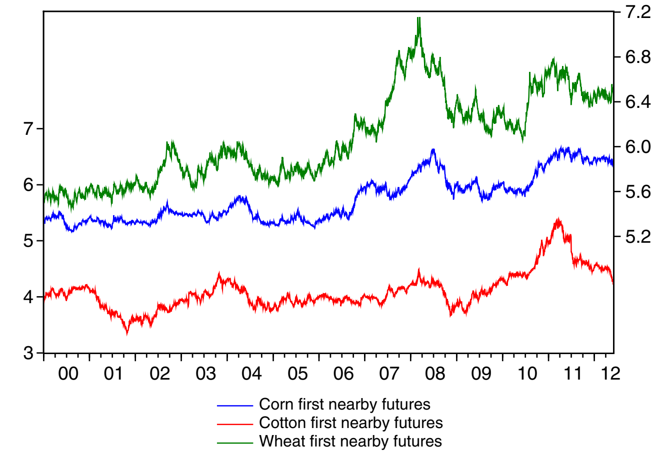

Fig. 1. Logarithms of different agricultural futures price series.

mostly uninformed traders or speculators trying to follow informed market participants. In this vein, a suggestive distinction between informed and uninformed traders is that informed traders will trigger a return to a fundamental value through trading if uninformed traders have previously moved a market away from its fundamental value (Gilbert, 2010a). With regard to agricultural markets, a related argument is that a limited number of traders, who previously supported investment and stabilized futures prices, were generally engaged before the group of futures investors or futures speculators, who regard agricultural futures as an asset, entered the market (Gilbert, 2010a). A popular line of reasoning is that these actors have no intention of selling in the real market, with their purchasing potential introducing volatility as well as upward or downward pressure or speculative bubbles on prices (Pace et al., 2008). In this context, Masters (2008), Masters and White (2008), and Gensler (2009) argue that extensive buy-side pressure from index funds has recently created a speculative bubble in commodity prices, with the consequence that prices heavily exceeded their fundamental values at the highest level.[2]

However, despite this popular line of reasoning, there is little clear-cut evidence that speculative trading affects the prices and volatility of commodities (Brunetti et al., 2011). The U.S. Commodity Futures Trading Commission (CFTC) argues that the percentage level of speculation in agricultural commodity markets has remained relatively constant as prices have risen (CFTC, 2008). Testing the hypothesis of an impact from speculation provided by Masters (2008) and Masters and White (2008), Irwin et al. (2009), Irwin and Sanders (2011, 2012), Sanders and Irwin (2010, 2011a, 2011b), and Bohl et al. (2013) also conclude that index investors have no impact on agricultural futures prices. On the other hand, futures price volatility should be positively influenced by the volume traded, according to various theoretical models which rely on traders with asymmetric information (Copeland, 1976; Epps and Epps, 1976) or divergent beliefs (Harris and Raviv, 1993; Shalen, 1993). Empirically, this pattern has been confirmed by previous studies which have found that increased trading volume is accompanied by increased futures price volatility, measured by absolute or squared returns (Chen and Lin, 2004; Ciner, 2002; Clark, 1973; Cornell, 1981; Kocagil and Shachmurove, 1998; Moosa and Silvapulle, 2000; Wang and Yau, 2000). However, since futures trading in commodity markets is conducted by both hedgers and speculators, we cannot simply conclude which type of trader affects futures price volatility (Bohl et al., 2013).

As mentioned above, we are interested in the role of volatility in agricultural futures, and one strand of the literature argues that a causal link exists between volatility and speculation. However, no enhancing influence of speculators is found by Brorsen and Irwin (1987) for six agricultural commodities and copper (1978–1984) or by Irwin and Yoshimaru (1999) for 23 agricultural, energy, and metal commodities (1988–1989). Both studies cover periods prior to the intensive financialization process of raw material markets. Focusing on the latter, the same result is obtained by Bryant et al. (2006) for three agricultural commodities, crude oil, and gold (1995–2003); Haigh et al. (2007) for crude oil and natural gas (2003–2004); and Brunetti et al. (2011) for corn, crude oil, and natural gas (2005–2009). By contrast, analyzing prices for corn, gold, and soybeans (1983–1990), Chang et al. (1997) detect that the positive effect of speculators' trading volume on volatility is much stronger than that of other traders. Finally, drawing on nine agricultural, energy, and metal commodities (1994), Irwin and Holt (2004) also conclude that speculative trading increases futures price volatility, but explain this relationship by valuable private information instead of noise trading. Cooke and Robles (2009) focus on international prices of corn, wheat, rice, and soybeans (2002–2009) and show that the observed change in food prices may be explained by financial activity in futures markets and different proxies for speculation.[3]

Detached from any reasoning about speculation, one sensible argument is that the complexity of agricultural futures markets has increased significantly for producers in recent times. In this vein, it is not surprising that an increasing number of empirical studies have put those markets under closer scrutiny. From a general perspective, analyzing the relationship between spot and futures prices for commodities to evaluate the price discovery role of futures markets, which may help reduce uncertainty, is a well-established research subject (Hernandez and Torero, 2010). It is often stated that, under the joint assumption of risk neutrality and rationality, the current futures price should be an unbiased estimator of the expected future spot price if changes in futures prices are uncorrelated with changes in other asset prices (Beckmann and Czudaj, 2013, forthcoming).

More related to our research topic, volatility spillover effects are about to become a popular line of research. In an early study, Buguk et al. (2003) examine the price volatility spillover in U.S. catfish markets based on monthly data running from 1980 to 2000. They conduct a univariate exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model and conclude that a strong volatility spillover from feeding material to catfish prices can be observed. More recently, Von Ledebur et al. (2009) analyze by means of a multivariate GARCH whether and to what extent the volatility of agricultural commodity prices at different market places were transferred during the dramatic price changes of 2008. They use a daily sample period from March 27, 2007 to March 5, 2008 and argue in favor of an operating volatility transmission.

In this vein, the aim of the present study is to analyze the volatility spillover between different agricultural futures markets from a new perspective. In so doing, we use data for prices of first nearby futures contracts for corn, cotton, and wheat and estimate a GARCH-in-mean VAR model in the tradition of Elder (2003). Although we are not able to measure the influence of speculation directly, this may provide some insight into the issue if we follow the literature, which assumes a causality

[2] More specifically, Gutierrez (2013) has actually tested the hypothesis of a speculative bubble in agricultural commodity markets and has identified explosive processes and collapsing bubbles for the prices of wheat, corn, and rough rice, while the evidence appears to be weak in the case of prices for soybeans. From a policy point of view, Von Braun and Torero (2008, 2009) have suggested the specification of a price band which would be a signal (threat) to speculators on food markets in the sense that a market assessment based on virtual reserve is likely to occur when futures prices exceed the upper limit of this band.

[3] However, Irwin et al. (2009) state that the hypothesis of a speculative bubble in commodity markets does not withstand close scrutiny, and provide four main reasons for this: firstly, they point out that arguments in favor of a speculative bubble are often conceptually flawed and reflect fundamental and basic misunderstandings of the functioning of commodity futures markets. Secondly, they see a number of facts related to the situation in commodity markets that appear to be inconsistent with the existence of a speculative bubble in commodity prices. Thirdly, in their view, statistical evidence suggests that neither position for any group in commodity futures markets, including long-only index funds, actually triggers futures price changes. Finally, they emphasize that there is a historical pattern of attacks upon speculation during periods of high volatility.

Table 1
Descriptive statistics.

Commodity	Mean	Median	Max	Min	Std. dev.	Skewness	Kurtosis	JB (p-val.)	Obs.
Corn	0.00	0.00	0.10	−0.10	0.02	0.18	5.55	884.39 (0.00)	3240
Cotton	0.00	0.00	0.17	−0.27	0.02	−0.51	15.57	21,481.52 (0.00)	3240
Wheat	0.00	0.00	0.13	−0.10	0.02	0.22	5.39	798.33 (0.00)	3240

Note: The sample period covers each working day from January 3, 2000 to June 1, 2012. Each series is taken as return. JB denotes the Jarque–Bera test statistic.

Table 2
Bivariate cointegration tests.

Commodity pair	Trace stat. [Lags]	τ-stat. [Lags] (p-value)	ϕ-stat. [Lags] (t-Max-stat.)	$\phi(M)$-stat. [Lags] (t-Max(M)-stat.)
Corn–Cotton				
H_0: $r = 0$ vs. H_1: $r \geq 1$	10.21	−2.09 [0]	2.73 [2]	2.98 [2]
H_0: $r \leq 1$ vs. H_1: $r \geq 2$	2.18 [2]	(0.48)	(−1.08)	(−0.84)
Corn–Wheat				
H_0: $r = 0$ vs. H_1: $r \geq 1$	17.65	−2.76 [1]	3.84 [2]	4.31 [2]
H_0: $r \leq 1$ vs. H_1: $r \geq 2$	3.82 [2]	(0.18)	(−1.51)	(−1.06)
Cotton–Wheat				
H_0: $r = 0$ vs. H_1: $r \geq 1$	9.41	−2.27 [0]	2.65 [2]	2.60 [2]
H_0: $r \leq 1$ vs. H_1: $r \geq 2$	3.17 [2]	(0.39)	(−1.52)	(−1.55)

Note: * Statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. The constant is restricted to the cointegration relation, allowing for no linear trend, either in the data or in the cointegrating equation. The first two columns refer to the Johansen (1988, 1991) cointegration rank test. Critical values for testing H_0: $r = 0$ and H_0: $r \leq 1$ are taken from MacKinnon et al. (1999): 1% 25.08 and 12.76, 5% 20.26 and 9.16, 10% 17.98 and 7.56, respectively. The choice of the lag length is based on tests for autocorrelation. τ-stat. denotes the τ-statistic for the residual-based cointegration test proposed by Engle and Granger (1987) with MacKinnon (1996) p-values in parenthesis and ϕ-stat., t-Max-stat., $\phi(M)$-stat. as well as t-Max(M)-stat. refer to the residual-based (momentum) threshold cointegration test suggested by Enders and Siklos (2001). Each tests the null of no cointegration. For the (momentum) threshold cointegration test critical values are taken from Enders and Siklos (2001): (ϕ) 1% 7.81, 5% 5.79, 10% 4.88, (t-Max) 1% −2.51, 5% −2.10, 10% −1.90, ($\phi(M)$) 1% 8.40, 5% 6.28, 10% 5.32, (t-Max(M)) 1% −2.42, 5% −1.99, 10% −1.75. The lag length is chosen by minimizing the Schwarz information criterion. Maximum lag length has been set to 28.

between speculation and volatility. For instance, recent studies by Cooke and Robles (2009) and Gilbert (2010b) indicate that the observed change in food prices may be explained by financial activity in futures markets and various proxies for speculation. Their findings are supported by Von Braun and Tadesse (2012), who argue that speculation effects are stronger than demand- and supply-side shocks for short-term price spikes. In this vein, our cross-market framework enables us to gain some new insights. Spillover effects across markets may arise as a result of common stochastic trends, which in turn might result from various fundamental or non-fundamental global factors.

The remainder of this paper is organized as follows. The following section describes our data, provides a description of and motivation for our empirical framework, and presents our findings. Section 3 concludes.

2. Data, econometric methodology and results

2.1. Data

The sample period in our investigation runs from January 2000 to June 2012 in daily frequency. The choice of this time period is motivated by our attempt to analyze the most recent developments in agricultural futures markets. Von Ledebur et al. (2009) and Czudaj and Beckmann (2012) argue that commodity markets seem to have undergone a structural change around the turn of the millennium. Our study is based on futures prices of the first nearby contracts written on the following three agricultural commodities: yellow corn no. 2, cotton no. 2, and soft red wheat no. 2. This choice is motivated by the fact that these markets are among the world's largest agricultural futures markets by trading volume. Cotton is traded at the New York Board of Trade (NYBOT), corn and soft wheat at the Chicago Board of Trade (CBOT). All futures prices are taken from Thomson Reuters Datastream and are quoted in US-cents per bushel (corn and soft wheat) and pound (cotton), respectively.[4] More precisely, all nearby futures series are constructed by rolling over on the same day that the previous contract expires.[5] We take the return of each nearby futures series, i.e. the first difference of the natural logarithm, in the following and give the descriptive statistics in Table 1. These indicate that the returns for the first nearby futures contracts for corn and wheat exhibit excess skewness to a minor degree, while returns for cotton show a shortage in skewness and each series reveals an excess in kurtosis in comparison to a Gaussian. Thus, as is usually found in financial data, the Jarque–Bera (JB) test clearly rejects the null of normality in each case. This supports the typical finding that asset returns are non-Gaussian.

In an attempt to examine the short-run effects among agricultural futures markets, we have to assure that these markets do not exhibit co-movements in the long-run. Otherwise, we have to account for deviations of the long-run errors in our VAR framework and therefore estimate a vector error correction model (VECM). To check for the existence of a pairwise long-run relationship between futures prices for corn, cotton, and wheat, we have applied three different test procedures, viz. the unrestricted Johansen (1988, 1991) framework, the two-step Engle and Granger (1987) methodology, and the threshold cointegration approach proposed by Enders and Siklos (2001).[6] The resulting test statistics are reported in Table 2 and clearly confirm that the null of no cointegration cannot be rejected in any case. Thus, we feel legitimized in proceeding by estimating VAR models in first differences, i.e. using the return series.

2.2. Empirical framework

In order to analyze the volatility spillover effect between agricultural futures markets, we apply a framework which allows us to estimate the parameters of interest in an internally consistent fashion. According to Elder (2003), this framework is based on a structural vector autoregression (SVAR) that is modified to accommodate GARCH-in-mean errors. We use the conditional standard deviation of the one-step-ahead forecast error for the return of the first nearby futures contract for corn and cotton, respectively, as our measure of volatility which potentially influences the returns for other agricultural futures contracts, i.e. cotton and wheat.

Thus, in each case we consider the following bivariate structural system, which consists of a linear function of the lagged terms plus a term related to the conditional variance:

$$AY_t = c + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots + \Gamma_p Y_{t-p} + \Lambda(L) H_t^{1/2} + \varepsilon_t, \quad t = 1, \ldots, T, \tag{1}$$

[4] See Beckmann and Czudaj (forthcoming) for a related study that is based on a similar dataset.

[5] Promising alternatives provided in the literature are those of rolling contracts on the first day of the final month of trading or linking the nearest futures contract on the business day prior to the 15th calendar day of the contract month to the following contract on the next day (Gutierrez, 2013; Ma et al., 1992).

[6] Unit root test results suggest that the logarithm of each futures price series is integrated of order one, i.e. $I(1)$. The corresponding test statistics are available upon request.

Table 3
Coefficient estimates.

Setting	Equation	Conditional variance	Constant	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$	$H_{1,1}(t)^{1/2}$	$A_{2,1}$
(1)	Corn	$H_{1,1}(t)$	0.00^{***}	0.1393^{***}	0.00	0.00	-0.2693^{***}
			(0.00)	(0.0233)			(0.0169)
	Cotton	$H_{2,2}(t)$	0.00^{***}	0.0636^{***}	0.9161^{***}	-0.2641^{*}	
			(0.00)	(0.0113)	(0.0152)	(0.1523)	
(2)	Corn	$H_{1,1}(t)$	0.00^{***}	0.1407^{***}	0.00	0.00	-0.7397^{***}
			(0.00)	(0.0229)			(0.0143)
	Wheat	$H_{2,2}(t)$	0.00^{***}	0.0443^{***}	0.9446^{***}	0.4353^{***}	
			(0.00)	(0.00)	(0.00)	(0.1203)	
(3)	Cotton	$H_{1,1}(t)$	0.00^{***}	0.1935^{***}	0.00	0.00	-0.2014^{***}
			(0.00)	(0.0333)			(0.0173)
	Wheat	$H_{2,2}(t)$	0.00^{***}	0.0187^{***}	0.9766^{***}	-0.0546	
			(0.00)	(0.00)	(0.00)	(0.0909)	

Note: The table reports the parameter estimates for the matrices F and G in the bivariate GARCH-in-mean VAR model given by Eqs. (1) and (3). Standard errors are stated in parentheses. The coefficient of 0.00 shows that the non-negativity constraint is binding. $H_{1,1}(t)^{1/2}$ represents the parameter estimate for the conditional standard deviation of the corn or cotton futures return given in matrix Λ in Eq. (1). All other parameter estimates for the VAR models (constants and lagged regressors) are available upon request. * Statistical significance at the 10% level, ** at the 5% level, *** at the 1% level.

where Y_t contains the futures returns, A and Γ_i denote 2×2 coefficient matrices, and $\varepsilon_t|\psi_{t-1} \sim \text{iid } N(0, H_t)$. $H_t^{1/2}$ is diagonal, $\Lambda(L)$ denotes a matrix lag polynomial, and ψ_{t-1} represents the whole information set at time $t-1$. We assume that the structural errors ε_t are uncorrelated and impose exclusion restrictions on the matrix A to ensure that the system given in Eq. (1) is identified (Elder, 2003; Elder and Serletis, 2010). This approach allows the matrix of conditional standard deviations $H_t^{1/2}$ to affect the conditional mean. To test whether there is an operating volatility transmission between agricultural futures returns implies the testing of restrictions on the elements of $\Lambda(L)$ that, for instance, relate the conditional standard deviation of corn futures returns to the conditional mean of Y_t. We therefore check if the volatility of corn and cotton futures returns has affected the returns of other agricultural futures, i.e. cotton and wheat, in a statistically significant way.

Following Engle and Kroner (1995), a bivariate GARCH approach is applied to model the conditional variance H_t:

$$h_t = c_v + \sum_{j=1}^{J} F_j vec\left(\varepsilon_{t-j}\varepsilon'_{t-j}\right) + \sum_{i=1}^{I} G_i h_{t-i}, \quad z_t \sim \text{iid } N(0, I), \quad \varepsilon_t = H_t^{1/2} z_t, \quad (2)$$

where $h_t = vec(H_t)$, c_v represents a 4-dimensional vector of intercept terms, and F and G denote 4×4 coefficient matrices. Given that the structural disturbances are not contemporaneously correlated, the conditional variance matrix H_t is diagonal and so Eq. (2) can be written as:

$$diag(H_t) = c_v + \sum_{j=1}^{J} F_j diag\left(\varepsilon_{t-j}\varepsilon'_{t-j}\right) + \sum_{i=1}^{I} G_i diag(H_{t-i}). \quad (3)$$

Following Elder and Serletis (2010), this bivariate GARCH-in-mean VAR model, given by Eqs. (1) and (3), is estimated by means of full information maximum likelihood (FIML). This procedure avoids generated regressor problems pointed out by Pagan (1984) which would arise if one estimates the variance function parameters separately from the conditional mean parameters.

Finally, the impulse response is simulated from the maximum likelihood estimates (MLE) of the parameters and the confidence intervals are achieved by simulating 1000 impulse responses based on parameter values drawn from the sampling distribution of the MLE using the Metropolis–Hastings (MH) algorithm with independence kernel (see Elder (2003) and Hamilton (1994) for details).

2.3. Empirical results

The model described above has been estimated for three agricultural futures markets and the results for three bivariate settings are reported: (1) corn and cotton, (2) corn and wheat, and (3) cotton and wheat.[7] According to information criteria, we have estimated the bivariate GARCH-in-mean VAR model given by Eqs. (1) and (3) with four lags in each case.[8] The parameter estimates are given in Table 3. Columns 4–6 state the estimates of the variance function parameters of the bivariate GARCH-in-mean VAR. These are highly significant and indicate that the GARCH-in-mean is necessary to capture important dynamics in the data. In order to ensure robustness in this finding, we have also estimated a structural VAR without the term related to the conditional variance and have calculated the Schwarz information criterion (SIC). In comparison to our models, the SIC for a conventional homoscedastic VAR turned out to be larger, which points in favor of our approach.

More importantly, the seventh column of Table 3 reports the coefficient on the conditional standard deviation of the corn futures return in the cotton and the wheat futures return equation and the conditional standard deviation of the cotton futures return in the wheat futures return equation, respectively. This coefficient gives the impact of the volatility of futures prices for one agricultural commodity on the futures prices of another. In the first two cases, the coefficient turns out to be statistically significant and, generally, this finding provides evidence of volatility spillover effects in agricultural futures markets. More precisely, the cotton market is affected negatively by the volatility of corn futures returns, while the impact of the volatility transmission on the market for soft red wheat appears to be positive.

In addition, to support our finding of significant short-run effects between agricultural futures markets, we have conducted an impulse response analysis in our framework. For instance, the dynamic response of cotton futures returns to a positive shock of the corn futures returns that equals an unconditional standard deviation of the change in corn futures returns is given in Fig. 2. To check for significance, we have also simulated one-standard error bands. Thus, Fig. 2 shows that the shock causes a mainly significant decrease in cotton futures returns over the next four days, while thereafter returns start to increase before convergence is achieved on the sixth working day after the occurrence of the shock. This also indicates that shocks are very short-lived. The same has been found for the other two settings (see Figs. 3 and 4).[9]

[7] The findings for other possible configurations are available upon request. We have decided to focus on three representative settings in order to save space and to keep the analysis traceable. However, all other results draw qualitatively a similar picture.

[8] This assures that our residuals are not affected by serial correlation. In addition, to check for robustness we have estimated our models with several other lag orders and obtained qualitatively the same results.

[9] All other impulse responses support our findings, but, to save space, are not provided. They are available upon request.

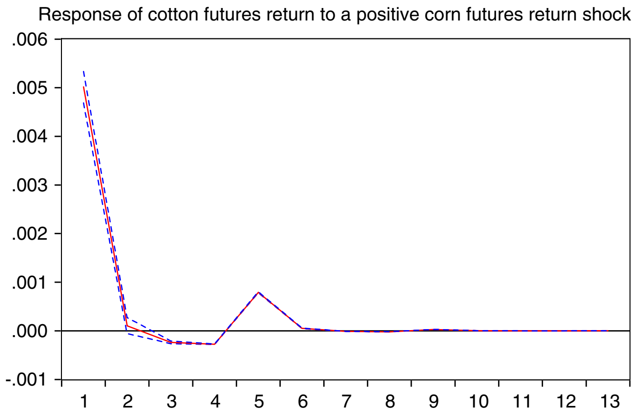

Fig. 2. Impulse response for the bivariate GARCH-M VAR. Note: The impulse response is simulated from the maximum likelihood estimates (MLE) of the parameters and the confidence intervals are achieved by simulating 1000 impulse responses based on parameter values drawn from the sampling distribution of the MLE using the MH algorithm with independence kernel (see Elder (2003) and Hamilton (1994) for details).

Our findings are in line with the result that cointegration is not detected for any of the configurations. Volatility transmission is a short-run phenomenon and the impacts we identify die out in the long-run. The underlying economic reasons for short-run spillovers range from reallocation of portfolios till simple expectation or contagion effects. What we might conclude, however, is that such effects can have significant implications: a simple example is a negative spillover which suggest a hedging possibility between two markets. Positive spillovers resulting from contagion effects are also a possible concern for policymakers. Finally, a positive viewpoint is that cross-market volatility simply reflects market efficiency in terms of eliminating arbitrage opportunities across futures markets.

3. Conclusion

Applying a GARCH-in-mean VAR model, we have shown that a volatility spillover can be observed in agricultural futures markets in the short-run. More precisely, we have demonstrated that the impact of the volatility of corn futures returns on the returns of cotton and wheat futures is statistically significant, but differs for both markets. This indicates that potential speculation effects on one market could be contagious for other markets and cause an increase in volatility in agricultural futures markets. Therefore, the recent rise in the interdependence of futures markets could be held responsible for the huge increase in volatility in agricultural prices in the last years.

For this reason, it is not surprising that the increase in volatility of agricultural futures markets is expected to continue in the future.

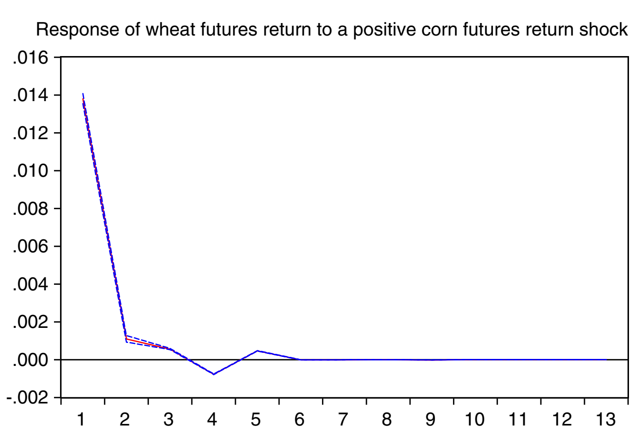

Fig. 3. Impulse response for the bivariate GARCH-M VAR. Note: See Fig. 2 for details.

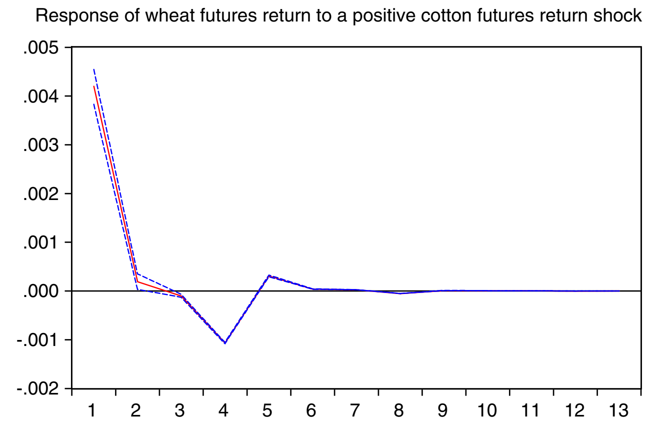

Fig. 4. Impulse response for the bivariate GARCH-M VAR. Note: See Fig. 2 for details.

Through contagion effects, an increase of volatility in a specific market, which might be due to fundamental or non-speculative factors, is likely to transmit to other markets. In terms of policy implications, a reasonable conclusion might be that the frequently adopted macro-prudential approach of supervising is superior to focusing on particular markets. However, the finding that volatility transmission is a short-run phenomenon leaves little room for direct ex-post policy actions. Considering that cross-market volatility may reflect market efficiency, it becomes even clearer that the task for policymakers is to analyze the origins of market volatility. Only some of the numerous possible reasons may then require political means. In this context, a distinction between positive and negative spillover effects is also important, since only positive volatility spillovers bear the risk of increasing volatility across markets.

Finally, our paper offers an interesting starting point for further research. In particular, investigating different sources of volatility in agricultural futures markets might be an interesting research topic for the future. In particular, the frequently discussed link between the engagement of speculators and volatility remains on the research agenda.

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