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Linkages Between Equity and Global Food Markets: New Evidence from Including Structural Changes*

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Abstract

The study provides new and robust evidence to the relationship between stock and food markets in terms of shock and volatility spillovers and dependence structure by focusing on the importance of taking into account structural breaks. The results reveal that variance shifts are correctly detected, and that considering them affects volatility persistence, removes return spillovers, and gives rise to significant shock and volatility transmission. They also provide interesting evidence that stock and food markets are weakly dependent, particularly during the 2007-2009 financial crisis period, thereby showing that portfolio diversification benefits could be exploited between the two types of markets, especially over times of heavy financial market fluctuations. Additionally, the findings put forward a substitution mechanism across food classes, given the similarity of the weak correlations for all commodities regardless of the model specification. The study illustrates relevant implications in terms of optimal portfolio allocation and risk minimizing hedge ratio, and allows international investors and market participants to understand properly the shock and volatility transmission across markets and inter-market correlations in order to make sound decisions.

1. Introduction

The analysis of inter-market linkages in terms of shock and volatility transmission and integration has been intensified, due to the occurrence of several crises throughout past decades, the increased shakiness for the global economy in 2011, the cumbersome threats on international economies in 2012-2013, and the financial liberalization and opening policies of emerging economies (see Chong and Miffre, 2010; Khiyavi et al., 2012; Creti et al., 2013; Gjika and Horváth, 2013; Hammoudeh et al., 2014; Abdelradi and Serra, 2015; Grieb, 2015; and Jouini, 2015). In this study, a deeper analysis of the relationship between equity and food markets is conducted in a time-varying framework to understand well the shock and volatility spillovers and dependence structure. Before we reveal our new suggested ideas, we provide a short compact review of three research strands in connection with food markets by focusing on common ideas and findings in each of these strands.

The first research strand focuses on the linkages across food and agricultural markets. Apergis and Rezitis (2003), and Khiyavi et al. (2012) find volatility spillovers from agricultural input and retail food price markets to agricultural output

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price markets. In addition, the latter authors suggest that market participants should paid more attention to price fluctuations in the input markets in order to regulate well the agricultural output market. Yang et al. (2003) show evidence of volatility transmission patterns between Canadian, European Union and US wheat markets, and outline that all wheat markets show some features of leadership in terms of price.

The second research strand involves empirical studies on the connection between energy and food markets. Chen et al. (2010), and Nazlioglu et al. (2013) find common results indicating that food prices respond significantly to changes in crude oil prices. The latter authors outline that the food price crisis plays a key role in the volatility transmission mechanism between oil and commodity markets. In similar studies and using different types of commodities, Busse et al. (2011), Du et al. (2011), Serra (2011), and Abdelradi and Serra (2015) rather provide evidence of bidirectional volatility transmission between food and oil prices.

The third research strand is devoted to the relationship between stock and commodity markets. Mensi et al. (2013), and Grieb (2015) show evidence of significant volatility transmission between equity and commodity prices. Many other empirical studies examine the variation of the dependence structure between stock and commodity markets over time. For instance, Chong and Miffre (2010), and Creti et al. (2013) find that periods of high turbulence in equity markets affect correlations between commodities and stock returns, which become more volatile during such periods. Therefore, portfolio diversification benefits of investors may be influenced during times of sharp fluctuations in stock markets. In a similar framework, Hammoudeh et al. (2014) find low and positive correlations between the Chinese equity market and commodity futures markets.

Most of the numerous studies on the relationship between stock and commodity markets provide conclusive findings, but some research gaps still exist. In this respect, our study revisits such relationship by paying particular attention on the linkages between equity and global food markets, with a view to providing new empirical evidence in the field by undertaking novel issues that take the related literature forward. To this end, we proceed differently from the existing literature by innovating in different aspects. First, given the importance of food markets at both economic and financial levels, we greatly enlarge the sample of food series by including other prices that are not previously considered. This allows international investors to find beneficial opportunities on building equity/food portfolios with the commodity that minimizes risk without reducing the expected returns. In addition, this allows us to determine whether a substitution mechanism between food prices exists. In other words, is investment in one food price an alternative to the other food prices when building stock/food portfolios?

Second, we diversify the analysis by studying the shock and volatility transmission across markets and carefully exploring the empirical evidence of inter-market correlation patterns in a time-varying framework using multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. Thereby, the study differs from the related literature from the perspective of the empirical methodology, since prior studies focus either on volatility spillovers across markets or on inter-market correlations.[1] In addition, studies on time-varying inter-market linkages were limited to the discussion of conditional correlations, and have not pushed the analysis further to obtain more reliable conclusions, which is of practical importance for investors in order to reveal their potential benefits from investing in the equity and food markets. For this purpose, we bring a more engaging discussion in connection with conditional correlations by investigating an important issue that is generally ignored in previous studies, namely the implications of the 2007-2009 financial crisis on the dependence structure between equity and food markets. This issue allows investors to highlight accurately the sensitivity of the benefits generated from building equity/food portfolios to higher volatile times, unlike what is stated in the related literature that examines such sensitivity based on a visual inspection of conditional correlations, which may lead to no specific conclusions.

Third, we innovate by focusing on the importance of accounting for volatility shifts given the international economic and financial events that may alter the relationship between stock and food markets. In other words, are shock and volatility transmission and inter-market linkages sensitive to the inclusion of structural breaks into models? The intuition behind this is to alleviate the coefficient overestimation generated when neglecting structural changes, which may affect the volatility and conditional correlation patterns (see Lamoureux and Lastrapes, 1990; Aggarwal et al., 1999; and Ewing and Malik, 2005). In addition, accounting for breaks is very important from an economic viewpoint, since changes in the fundamentals of equity and food markets or in the underlying economy are not neglected. To the best of our knowledge, we are the first to address the inclusion of structural breaks in the analysis when examining the stock-food nexus, with a view to providing new and robust evidence to the related literature, which is very useful for investors, policymakers and market participants.

Our findings are of great importance and enhance the understanding of the shock and volatility transmission mechanism and linkages between stock and food markets. They indicate the presence of variance changes in all price returns, especially during the 2007-2009 crisis period, and that the inclusion of these volatility shifts into models decreases the market volatility persistence. Additionally, allowing for break dummies removes the return spillover effects between stock and food markets, and generates shock and volatility spillovers between them. As regards optimal portfolio allocation, the average optimal weights slightly differ across food markets regardless of the model specification, pointing out the indifference of investors as to the choice of the food price to build their stock/food portfolios. Moreover, the average risk minimizing hedge ratios are low for all food markets, suggesting that hedging effectiveness comprising stock and food markets is very good. Conditional correlations between equity and food index returns are found to be weak and time-varying, and decrease during the 2007-2009 financial crisis period,

[1] Inter-market linkages based on conditional correlations have been extensively investigated in the literature on stock markets (see Connolly et al., 2007; Cai et al., 2009; Kenourgios and Samitas, 2011; Syllignakis and Kouretas, 2011; Gjika and Horváth, 2013; and Jouini, 2015). These authors arrive at the common conclusion that conditional correlations are time-varying and evolve according to the market situation (bullish or bearish).

implying that investors can benefit from portfolio diversification, especially during higher volatile times.

The remainder of the paper is structured as follows. The econometric methodology to use in the study is presented in Section 2. Section 3 describes the data, and provides a preliminary analysis. Section 4 displays the empirical results, and discusses their practical importance and implications. Within this context, results of models without breaks are discussed first to give the background to the analysis of models with structural changes. Concluding comments are provided in Section 5.

2. Econometric methodology

Our methodology involves the following steps. First, a structural change approach is used to detect correctly volatility shifts in the stock and food price returns. These breaks in volatility are incorporated into models in order to examine their effects on the relationship between equity and food markets. Second, a univariate GARCH model is applied to study the volatility patterns of each market. Third, shock and volatility spillovers are examined by employing a bivariate GARCH process. Fourth, optimal portfolio allocation and risk minimizing hedge ratio are established. Lastly, dependence structure between equity and food markets is analysed based on conditional correlations.

2.1 Structural breaks in volatility

Inclan and Tiao (1994) develop an iterated cumulative sums of squares (ICSS) algorithm, which is applied to a cumulative sums of squares IT statistic for testing the null hypothesis of a constant unconditional variance against the alternative of a shift in the unconditional variance.[2] The IT statistic does not present good finite-sample properties (oversized) when applied to a dependent process, including GARCH process, as the method is designed for *i.i.d.* processes (see de Pooter and van Dijk, 2004; and Sanso et al., 2004). To avoid these size distortions and to make the method suitable for a dependent process, Sanso et al. (2004) propose a nonparametric adjustment based on the quadratic spectral or Bartlett kernel to a κ_2 statistic that takes the fourth order moment (kurtosis) properties and conditional heteroscedasticity into explicit consideration. These authors show, via Monte Carlo experiments, that the κ_2 statistic is correctly sized, but slightly less powerful, for several considered scenarios compared to other suggested statistics, and that the statistic should be used in applied research.

In this study, to test for multiple shifts in the unconditional variance of the stock and food index returns, the ICSS procedure is implemented with the κ_2 statistic.[3] In addition, we use the quadratic spectral window with automatic bandwidth selection based on the procedure of Newey and West (1994), and the response surfaces to generate critical values for our sample size. A 5% significance

[2] Hillebrand (2005) argues that a change in the unconditional variance leads up to a shift point in the GARCH model governing conditional volatility.

[3] Technical details on the ICSS(κ_2) procedure are provided in Sanso et al. (2004).

level is used to detect endogenously the number of volatility changes and their locations.

2.2 Univariate GARCH models

The literature encompasses various GARCH-type models that are developed to analyse the volatility patterns of economic and financial time series. Lamoureux and Lastrapes (1990), and Aggarwal et al. (1999) argue that these models provide overestimated coefficients when ignoring structural changes, if exist. We are first interested in studying the volatility dynamics of each market by incorporating the variance shifts detected by the above ICSS(κ_2) algorithm into the model to illustrate the market volatility pattern under structural change. Formally, for each market, we augment the volatility equation of the univariate AR(1)-GARCH(1, 1) process with a set of dummy variables as follows:[4]

$$\begin{cases} r_t = a_0 + a_1 r_{t-1} + \varepsilon_t, \qquad \varepsilon_t / I_{t-1} \rightarrow N\left(0, h_t\right) \\ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta\, h_{t-1} + d_1 D_1 + d_2 D_2 + \cdots + d_m D_m \end{cases} \tag{1}$$

where r_t is the price return at time t, I_{t-1} is the market information set available at time $t-1$, and h_t is the conditional volatility. The coefficients ω, α and β measure respectively the mean variance level, the effect of past news, and the effect of the one-period lagged volatility on the present market volatility level. The sum of α and β is of great importance since it pertains to volatility persistence for a given shock. Indeed, if this sum is close to unity, the shock is highly persistent. The dummy variables $D_1, D_2, \ldots, D_m$ take one from each point of volatility shift onwards and zero elsewhere (see Lamoureux and Lastrapes, 1990; and Aggarwal et al., 1999), and m is the number of structural breaks in volatility. The model is estimated using the maximum likelihood method based on the BFGS (Broyden-Fletcher-Goldfarb-Shanno) optimization algorithm.

2.3 Bivariate GARCH models

The multivariate GARCH processes are more useful in studying volatility transmission across time series than univariate processes. For this purpose, we examine the shock and volatility transmission across equity and food index returns by applying the following bivariate VAR(1)-GARCH(1, 1) process:[5]

$$\begin{cases} R_t = \mu + \Phi R_{t-1} + u_t, \qquad u_t / I_{t-1} \rightarrow N\left(0, H_t\right) \\ \qquad\qquad u_t = P_t v_t \end{cases} \tag{2}$$

[4] Using the Bayesian information criterion, we opt for an AR(1)-GARCH(1, 1) model for all markets compared to other AR-GARCH models with different lags.

[5] Compared to other VAR-GARCH models with different lags, we opt for the bivariate VAR(1)-GARCH(1, 1) model for all food markets based on the Bayesian information criterion.

where R_t is a (2×1) vector of stock and food price returns, μ is a (2×1) vector of constant terms, Φ is a (2×2) matrix of autoregressive coefficients, u_t is a (2×1) vector of error terms whose conditional variance-covariance matrix is given by H_t, $v_t = (v_{1t}, v_{2t})'$ is a sequence of *i.i.d.* random vectors, and $P_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}\right)$ with $h_{11,t}$ and $h_{22,t}$ the conditional variances of equity and food index returns, respectively.

In this study, to account for volatility shifts, we follow Ewing and Malik (2005) who propose augmenting the BEKK (Baba-Engle-Kraft-Kroner) parameterization of H_t, developed by Engle and Kroner (1995), with a set of dummy variables as follows:

$$H_t = C'C + A'u_{t-1}u'_{t-1}A + B'H_{t-1}B + \sum_{i=1}^{m} D'_i X'_i X_i D_i \tag{3}$$

where C is a (2×2) lower triangular matrix of constant terms, and A and B are two square matrices whose diagonal coefficients measure respectively the effects of past own shocks and past own volatility on the present conditional volatility level of index returns. However, the off-diagonal coefficients of the matrices A and B measure the shock and volatility transmission across markets over time. D_i is a (2×2) square diagonal matrix of coefficients, and X_i is a (1×2) row vector of variance change variables. The first (second) element of X_i is the dummy variable for the stock (food) returns. For instance, if the variance of stock returns encompasses a break at time k, the first element of X_i takes zero before time k and one from time k onwards.

Expanding equations of conditional variances in the bivariate GARCH process gives

$$\begin{aligned} h_{11,t} &= c_{11}^2 + c_{21}^2 + a_{11}^2 u_{1,t-1}^2 + a_{21}^2 u_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + b_{21}^2 h_{22,t-1} + 2a_{11}a_{21}u_{1,t-1}u_{2,t-1} + 2b_{11}b_{21}h_{12,t-1} \\ &+ d_{1,11}^2 X_{11}^2 + d_{2,11}^2 X_{21}^2 + \cdots + d_{m,11}^2 X_{m1}^2 \end{aligned} \tag{4}$$

$$\begin{aligned} h_{22,t} &= c_{22}^2 + a_{12}^2 u_{1,t-1}^2 + a_{22}^2 u_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + b_{22}^2 h_{22,t-1} + 2a_{12}a_{22}u_{1,t-1}u_{2,t-1} + 2b_{12}b_{22}h_{12,t-1} \\ &+ d_{1,22}^2 X_{12}^2 + d_{2,22}^2 X_{22}^2 + \cdots + d_{m,22}^2 X_{m2}^2 \end{aligned} \tag{5}$$

These equations clearly show the shock and volatility spillovers across stock and food index returns over time. The model is estimated using the maximum likelihood method based on the BFGS optimization algorithm.

2.4 Optimal portfolio allocation and hedging strategy

The proper specification of the bivariate VAR-GARCH process leads to accurate estimation of the conditional variance-covariance matrix, which has important economic implications and helps market participants take decisions about pricing, optimal portfolio allocation, and risk management. We first follow Kroner and Ng (1998) to understand the importance of the variance-covariance matrix in order to clarify the usefulness of the conditional volatilities of stock and food index returns ($h_{11,t}$ and $h_{22,t}$) and the conditional covariance between them ($h_{12,t}$) in taking the above financial decisions by computing the optimal holding of the stock portfolio as 0 if $w_{12,t} < 0$, $w_{12,t}$ if $0 \le w_{12,t} \le 1$, and 1 if $w_{12,t} > 1$, where

$$w_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}} \tag{6}$$

Under these conditions, the optimal holding of the food portfolio is $1 - w_{12,t}$.

We second compute the dynamic risk minimizing hedge ratio for the stock/food portfolio based on the following measure proposed by Kroner and Sultan (1993):[6]

$$\beta_{12,t} = \frac{h_{12,t}}{h_{22,t}} \tag{7}$$

To minimize the stock/food portfolio risk, a hedge ratio of $\beta_{12,t}$ suggests that one dollar long in the stock market should be shorted by about $\beta_{12,t}$ dollar of the food market.

As the optimal portfolio weights, the hedge ratios change with time at the arrival of new information. In this study, we employ the average optimal weights and hedge ratios to provide the implications of the results for portfolio and hedging strategies.

2.5 Conditional correlations

The intensity of the linkages between stock and food index returns is assessed through the conditional correlation coefficient that is computed based on the conditional volatilities and covariance between returns obtained consistently from the estimation of the above bivariate VAR-GARCH model as:

[6] Kroner and Sultan (1993) argue that their strategy is more efficient than conventional methods, as it provides greater risk reduction for investors to compensate the transaction costs of rebalancing their considered portfolios.

$$CCor_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t}\, h_{22,t}}} \tag{8}$$

The test of Tse (2000) can be applied to ensure that correlations between the equity market and each food market are time-varying. It tests the null hypothesis of constant conditional correlations against the alternative hypothesis of dynamic conditional correlations, and is Chi-squared distributed with one freedom degree for bivariate GARCH models. Monte Carlo simulations reveal that the Tse's test has good power properties and is robust to non-normality, which is advantageous, since our index returns are non-normally distributed, as evidenced below.

3. Data and descriptive analysis

We consider daily data on the US stock price index, S&P 500, and four different food prices (barley, maize, sorghum, and wheat)[7] over the period from April 6, 2005 to January 31, 2012 (yielding 1780 observations). A salient feature is that relying on many food prices allows us to detect dissimilarities in the linkages between equity and food markets so that investors will be more aware of opportunities to build stock/food portfolios with the food market that allows minimizing risk without lowering the expected returns, or there is evidence of homogeneity with regard to risk-adjusted return performance. As argued by Bollerslev and Wright (2001), opting for high data frequency (daily data) provides more relevant information, as the sample size is large, thus leading to reliable findings on shock and volatility transmission across markets and inter-market linkages. The choice of the time period allows us to avoid the sensitivity of the relationship between equity and food index returns to the recessions and turmoils that have occurred from 2012 onwards due to many economic and financial uncertainties. This aims to consider homogeneous and stable sub-samples before and after the 2007-2009 crisis period, thus leading to more reliable conclusions and accurate interpretations of the implications of this crisis on the inter-market linkages. In contrast, we claim that the time span is enough to estimate GARCH-type models. The data on food prices were collected from the International Grains Council database, and the S&P 500 index was gathered from the S&P Dow Jones Indices LLC database.

Daily movements in the stock and food prices and returns[8] are depicted in Figures 1 and 2, respectively. From Figure 1, we clearly observe that equity and food prices are time-varying, exhibit phases of increasing and decreasing trends, and share common characteristics.[9] The food prices behave in a similar manner throughout the period under study, experience an upward peak due to the 2007-2008 world food price crisis, and record a peak in early 2011. Particular attention should be paid by

[7] To the best of our knowledge, the barley, maize and sorghum prices have not been previously considered in the analysis of shock and volatility spillovers and dependence structure between equity and food markets.

[8] Returns are defined as the first log-difference of the price indexes.

[9] As underlined by Choi and Hammoudeh (2010), commodity traders are interested in both equity and commodity evolution patterns to come into view the trend of each market.

authorities to these excessive fluctuations of food prices, since they serve out inflationary pressures, as outstandingly reported by the G20 in its 2009 Pittsburgh summit. For the stock price index, the increases recorded in the first two years of the sample were followed by a sharp drop during the 2007-2009 global financial crash. A rise has been observed since mid-2009 before the stock price index slightly declines in late 2011. Therefore, equity and food prices are sensitive to major international events, which is reflected in the market returns that show large fluctuations during these periods, as illustrated by Figure 2. All these insights may support the application of the above structural change approach to detect break dates in the stock and food price returns.

Figure 1 Time-varying dynamics of stock and food prices

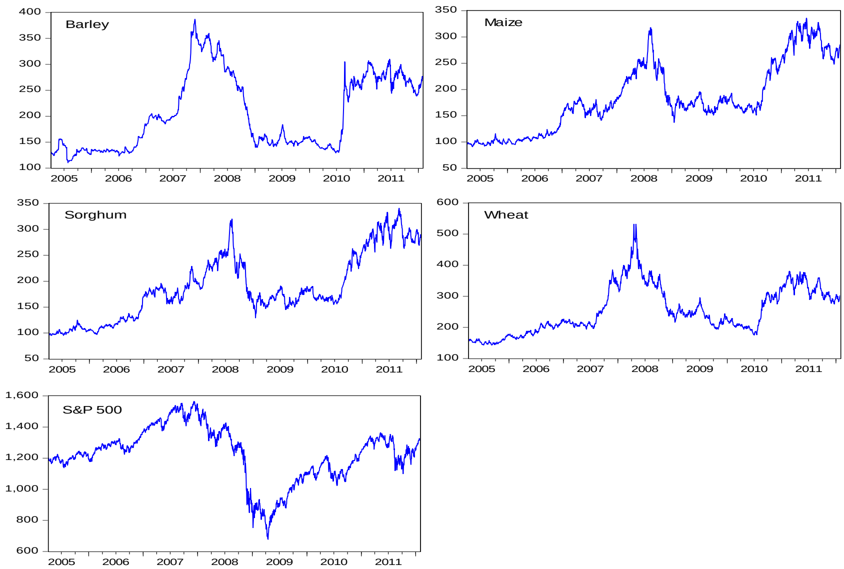
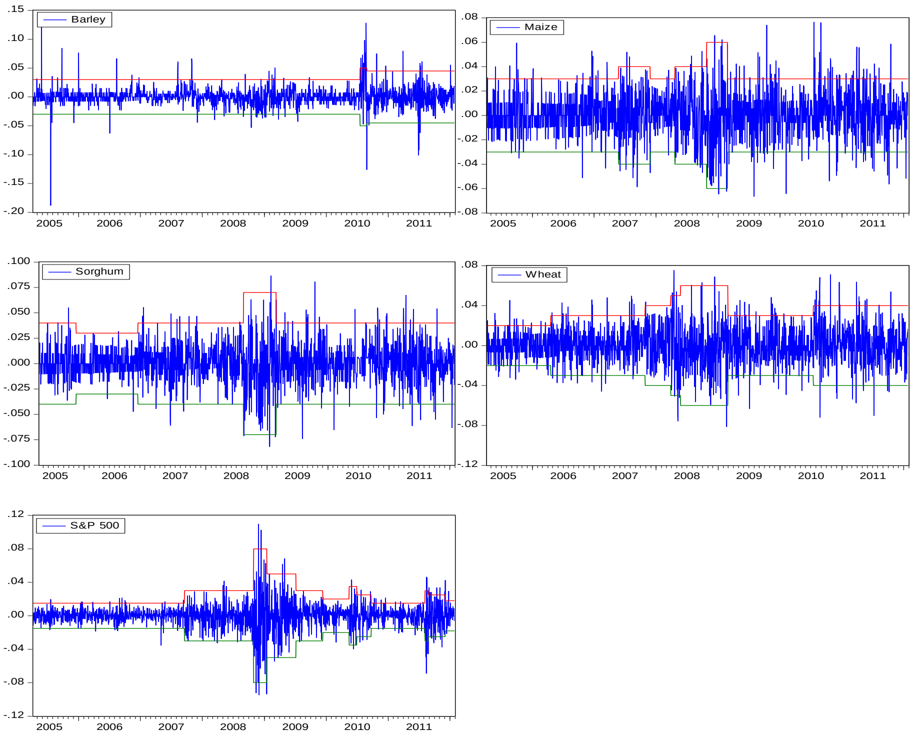


Figure 2 Time-varying dynamics of stock and food market returns



Descriptive statistics regarding the daily market returns are presented in Table 1. All markets experience positive and relatively small average index returns. The maize and sorghum record the highest average returns, while the S&P 500 index has the lowest average returns over the sample period. The returns behave similarly in terms of volatility: the standard deviation of maize, sorghum, wheat and to a lesser extent barley returns is slightly higher than that of the stock returns. Based on the benefit-risk trade off, we cannot arbitrate between the stock market and food markets because the former exhibits the lowest average yield and risk, and the latter are more profitable and slightly more volatile. All index returns, except maize, are skewed to the left, as indicated by the negative skewness value. This implies that for investors, it is more likely to find large negative market returns for the barley, sorghum, wheat and stock prices rather than large positive market returns. The kurtosis value is greater than three, the value of the normal distribution, for all market index returns, indicating that they are leptokurtic (fat tails). This deviation from the normal distribution is enhanced by the Jarque-Bera test that rejects the null hypothesis of normality for all index returns, thus justifying recourse to the Student's-t distribution when estimating the above GARCH-type models by the maximum likelihood method.

The ADF test rejects the null hypothesis of unit root, suggesting that equity and food returns are stationary.[10] The Ljung-Box test reveals persistence phenomenon for the barley and equity returns, since there is evidence of significant autocorrelation.[11] We also applied the Ljung-Box test to squared returns and found evidence of ARCH effects in all index returns, supporting the application of the κ_2 statistic to detect variance shifts in the index returns, and the GARCH processes to study the time-varying volatility dynamics of stock and food markets. We also found that stock price returns are positively and weakly linked to food returns, as indicated by the low unconditional correlations that range from 0.004 (S&P 500/maize) to 0.053 (S&P 500/barley),[12] thus illustrating attractive opportunities for international investors to invest in the stock and food markets. The weak connection between markets will be examined later based on powerful modeling procedures, since this preliminary analysis just gives initial insights on the linkages between the stock index and each commodity.

Table 1 Descriptive statistics of index returns

	Barley	Maize	Sorghum	Wheat	S&P 500
Mean (%)	0.042	0.060	0.061	0.037	0.005
Std. Dev.	0.016	0.019	0.019	0.019	0.015
Skew.	-0.114	0.009	-0.113	-0.021	-0.291
Kurt.	23.403	3.994	4.614	4.243	12.063
ADF	-38.040	-40.149	-39.813	-41.665	-34.266
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
JB	30861.630	73.284	196.800	114.589	6113.201
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LB(12)	65.073	14.045	12.766	15.248	55.344
	[0.000]	[0.298]	[0.386]	[0.228]	[0.000]
$LB^2(12)$	147.050	141.520	276.460	209.850	2005.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Corr.	0.053	0.004	0.011	0.008	-
	[0.027]	[0.867]	[0.640]	[0.726]	

Notes: ADF is the Augmented Dickey-Fuller test for unit root; JB is the Jarque-Bera test for normality; LB is the Ljung-Box test for no autocorrelation applied to the returns; LB^2 is the Ljung-Box test for no autocorrelation applied to the squared returns; and Corr. is the unconditional correlation between S&P 500 and food returns. The values in brackets are the significance levels of the tests.

4. Results and implications

GARCH-type models without variance breaks are investigated first to give the background to the analysis of models with structural changes concerning volatility dynamics, return, shock and volatility spillovers, portfolio management and hedge ratio, structure dependence, and implications of crisis events on the interrelations between equity and food markets.

[10] The KPSS (see Kwiatkowski et al., 1992) stationarity test is also applied to confirm that index returns are stationary.

[11] First autocorrelation coefficients are significant for all markets, thereby justifying the inclusion of autoregressive terms in the mean equation of the above GARCH-type models.

[12] The correlation coefficients are not statistically significant, except that between equity and barley markets at the 5% level (see Table 1).

4.1 Detection of volatility shifts

The volatility shifts detected by the above ICSS algorithm are shown in Table 2.[13] The results show evidence of two breaks for barley, five breaks for maize, four breaks for sorghum, six breaks for wheat, and eleven breaks for S&P 500. A substantial feature is that some variance shifts are detected in close dates for stock and food markets, as volatility fluctuations occur simultaneously in several markets due to important international events. For instance, in early 2009, a volatility shift is detected in the stock market and three food markets (maize, sorghum and wheat). In addition, in mid-2010, the stock market and two food markets (barley and wheat) experience a variance change. The results suggest that several volatility shifts for stock and food price returns occur most often during the 2007-2009 world food and financial crises, which is unsurprising given the implications of these crises on stock and food prices at the international level, thus rising the investment risk in the equity and food markets. Other important world events may coincide with many variance breaks for equity index returns, such as the world economic uncertainty observed in 2011.[14] These results support the above insights detected from the plots of the stock and food returns. The variance shifts are taken into account when estimating the GARCH-type models, with a view to inferring an accurate knowledge about the relationship between stock and food markets in terms of shock and volatility transmission and dependence structure.

Table 2 Detection of volatility shifts in index returns

Breaks	Barley	Maize	Sorghum	Wheat	S&P 500
1	20/7/2010	24/5/2007	15/11/2005	19/4/2006	18/9/2007
2	30/8/2010	27/11/2007	20/11/2006	29/10/2007	29/10/2008
3		21/4/2008	13/8/2008	27/3/2008	15/1/2009
4		24/10/2008	25/2/2009	23/5/2008	7/7/2009
5		25/2/2009		27/2/2009	11/12/2009
6				16/7/2010	17/5/2010
7					30/6/2010
8					23/9/2010
9					8/8/2011
10					25/8/2011
11					5/12/2011

Notes: The volatility shifts in index returns are detected by the ICSS(κ_2) algorithm over the period from April 6, 2005 to January 31, 2012. The quadratic spectral window with automatic bandwidth selection based on the procedure of Newey and West (1994), and the response surfaces to generate critical values for the sample size are used.

4.2 Market volatility dynamics

The estimate results of the benchmark univariate AR-GARCH models[15] are provided in Table 3. For the mean equation, the autoregressive term is statistically

[13] Graphical presentation of the periods with different level of volatility for all index returns is illustrated in Figure 2.

[14] Determination of the actual causes of the detected break dates is beyond the scope of the current study that mainly focuses on the impact of these breaks on the relationship between stock and food markets. Within this context, Ewing and Malik (2013) argue that intra-daily data can be used to isolate the real events that may coincide with the detected volatility shifts.

[15] The benchmark univariate AR-GARCH model is simply the model given by Eq. (1) by setting $d_1 = d_2 = \cdots = d_m = 0$.

significant at the conventional levels for the stock market and two out of four food markets. This implies that the present movements of the corresponding market index returns are sensitive to the own returns of the previous time period. The ARCH coefficient is statistically different from zero at the 1% level for all returns, thus suggesting that past news affect conditional volatility of the stock and food markets. We also find that the GARCH coefficient, which measures the effect of the one-period lagged volatility on the present volatility level, is statistically significant at the 1% level for all equity and food returns.[16] The sum of ARCH and GARCH coefficients is very close to unity for all returns, indicating that volatility is highly persistent.[17] The half-life of shocks[18] is about 69 days for S&P 500, 18 days for barley, 53 days for sorghum, and 57 days for maize and wheat. These estimated values reveal that a shock loses half of its original effect in 69 days for the equity market, 18 days for barley, 53 days for sorghum, and 57 days for maize and wheat.

The Ljung-Box test for no autocorrelation applied to the standardized residuals and squared standardized residuals of the univariate AR-GARCH model is computed. The results reported at the bottom of Table 3 suggest that the models fit well the time series, as there is evidence of no serial correlation and absence of ARCH effects. Therefore, volatility dynamics of stock and food markets are examined accurately.

We now turn into the discussion of the estimation results of the univariate AR-GARCH process with volatility shifts (see Table 4). We first implement the likelihood ratio test to support the inclusion of volatility shifts into models. The test statistic is calculated as twice the difference between the two maximum log-likelihood values of the univariate AR(1)-GARCH(1, 1) models with and without breaks, and asymptotically Chi-squared distributed with m freedom degrees, where m is the number of dummy variables. The findings shown at the bottom of Table 4 outline that the test rejects the null hypothesis of no breaks in the process at the 1% level for all cases, thus supporting the inclusion of structural changes into models.[19]

[16] Past own volatility has a more predictive power on current volatility than past shocks, since the GARCH coefficient is greater that the ARCH coefficient for all index returns, implying that conditional volatility of equity and food markets is more sensitive to past own volatility than to past news.

[17] This finding is aligned with most of the previous empirical works that show evidence of high volatility persistence for high data frequency (see Ewing and Malik, 2013; and Jouini, 2015).

[18] Half-life of shocks is simply the estimate of half-life j in days such that $(\alpha+\beta)^j = 0.5$, where α and β are the ARCH and GARCH coefficients, respectively. It gives the number of days during which a shock loses half of its original effect.

[19] The overwhelming majority of dummy variable coefficients are statistically significant at the conventional levels (results not reported).

Table 3 Estimation results of the univariate AR(1)-GARCH(1, 1) models without breaks

	Barley	Maize	Sorghum	Wheat	S&P 500
a_0	1.5E-4	7.2E-4*	8.4E-4**	3.4E-4	8.4E-4***
	(2.3E-4)	(4.0E-4)	(4.0E-4)	(3.8E-4)	(1.9E-4)
a_1	0.055**	0.039	0.045**	-0.008	-0.070***
	(0.024)	(0.024)	(0.022)	(0.024)	(0.024)
ω	2.2E-5***	4.5E-6**	5.4E-6**	4.2E-6	1.1E-6**
	(6.9E-6)	(2.2E-6)	(2.5E-6)	(2.8E-6)	(4.4E-7)
α	0.216***	0.047***	0.058***	0.043***	0.101***
	(0.055)	(0.011)	(0.013)	(0.014)	(0.016)
β	0.746***	0.941***	0.929***	0.945***	0.889***
	(0.050)	(0.014)	(0.017)	(0.020)	(0.014)
Half-life	17.892	57.415	52.971	57.415	68.968
LB(12)	15.683	13.010	8.459	13.125	12.939
	[0.206]	[0.368]	[0.748]	[0.360]	[0.373]
$LB^2(12)$	1.394	6.276	7.940	8.504	12.039
	[1.000]	[0.902]	[0.790]	[0.745]	[0.443]

Notes: The dummy variable coefficients $d_1, d_2, \ldots, d_m$ in Eq. (1) are not reported. Half-life of shocks is the estimate of half-life *j* in days such that $(\alpha+\beta)^j = 0.5$; LB is the Ljung-Box test for no autocorrelation applied to the standardized residuals; and LB^2 is the Ljung-Box test for no autocorrelation applied to the squared standardized residuals. The values in parentheses are the standard errors and in brackets are the significance levels of the tests. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

After allowing for structural changes, the present movements of the barley, sorghum and stock index returns are still sensitive to their past own returns, as evidenced by the statistical significance of the autoregressive coefficient in the mean equation. Past news and volatility still have a significant impact on the present conditional volatility level for equity and food index returns. Additionally, the effect of past own news on volatility has decreased (increased) for stock, barley and wheat (maize and sorghum) returns. However, the impact of past own volatility on current volatility has dropped for all market index returns.[20] As a result, volatility persistence decreases for all markets, suggesting that the omission of break dates results in overestimated coefficients (see Lamoureux and Lastrapes, 1990). Volatility is relatively highly persistent for all food markets, as the sum of ARCH and GARCH coefficients remains fairly high. This finding is aligned with Vivian and Wohar (2012) who find that volatility is highly persistent for many commodities even after taking into account structural changes. However, for the stock index returns,

[20] The predictive power of past own volatility on current volatility is still more important than that of past shocks.

volatility persistence is relatively low, which is consistent with Schwert (1989) who argues that volatility increase recorded around the 1987 financial turmoil quickly drops too much. The half-life of shocks drops dramatically, as it becomes about one day for S&P 500, 4 days for barley and sorghum, and 2 days for maize and wheat. To sum up, the inclusion of variance shifts into models influences the shock and volatility dynamics of the stock and food markets. As for models without breaks, models with volatility shifts fit well the stock and food index returns, as the Ljung-Box test concludes in favour of no autocorrelation and no ARCH effects in the residuals.

Table 4 Estimation results of the univariate AR(1)-GARCH(1, 1) models with breaks

	Barley	**Maize**	**Sorghum**	**Wheat**	**S&P 500**
a_0	1.1E-4	7.6E-4*	8.7E-4**	3.8E-4	6.6E-4***
	(2.2E-4)	(4.2E-4)	(4.1E-4)	(4.0E-4)	(2.0E-4)
a_1	0.054**	0.035	0.041*	-0.001	-0.082***
	(0.024)	(0.025)	(0.025)	(0.025)	(0.020)
ω	3.0E-5***	5.6E-5**	3.8E-5*	5.4E-5*	2.9E-5***
	(7.8E-6)	(2.9E-5)	(2.0E-5)	(3.0E-5)	(5.4E-6)
α	0.150***	0.067***	0.073***	0.036*	0.031***
	(0.042)	(0.022)	(0.024)	(0.019)	(0.005)
β	0.695***	0.675***	0.778***	0.611***	0.348***
	(0.061)	(0.136)	(0.087)	(0.187)	(0.120)
Half-life	4.116	2.323	4.296	1.592	0.714
LR	41.340	30.600	23.758	52.542	74.788
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LB(12)	17.027	15.092	7.637	14.773	10.613
	[0.149]	[0.236]	[0.813]	[0.254]	[0.562]
$LB^2(12)$	0.944	9.735	7.184	11.003	17.148
	[1.000]	[0.639]	[0.845]	[0.529]	[0.144]

Notes: The dummy variable coefficients $d_1, d_2, \ldots, d_m$ in Eq. (1) are not reported. Half-life of shocks is the estimate of half-life *j* in days such that $(\alpha+\beta)^j = 0.5$; LR is the likelihood ratio test for the null hypothesis of an AR(1)-GARCH(1, 1) model without breaks against the alternative hypothesis of an AR(1)-GARCH(1, 1) model with breaks, and asymptotically Chi-squared distributed with freedom degrees equal to the number of volatility breaks for each market; LB is the Ljung-Box test for no autocorrelation applied to the standardized residuals; and LB^2 is the Ljung-Box test for no autocorrelation applied to the squared standardized residuals. The values in parentheses are the standard errors and in brackets are the significance levels of the tests. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

4.3 Spillover effects

It is judicious to estimate first the bivariate VAR-GARCH process by ignoring structural changes[21] to give the background to the analysis of shock and volatility spillovers between stock and food markets when allowing for shifts in variance. The estimation results of the four bivariate VAR(1)-GARCH(1, 1) models[22] without volatility breaks are reported in Table 5. The findings suggest that past performance affects the current performance of the equity, barley, maize and sorghum returns, thus implying short-term predictability in stock and food price changes, as evidenced by the statistical significance of the coefficient ϕ_1 in the stock equation and the coefficient ϕ_2 in the corresponding food equation. However, for wheat, the coefficient for first-lagged returns ϕ_2 is not statistically significant. The highest food market response to past own returns is observed for barley followed by sorghum and maize, with estimates of 0.137, 0.054 and 0.044, respectively. Moreover, the most important effect of past returns on the current equity returns is observed when estimating a process with wheat, with an estimate of -0.094. As regards the interactions between stock and food markets, the results reveal significant return spillovers between S&P 500 and barley, as indicated by the statistical significance of the coefficient ϕ_1 in the barley equation and the coefficient ϕ_2 in the equity equation. Additionally, there is evidence of return transmission from the other food markets to the equity market, as evidenced by the statistical significance of the coefficient ϕ_2 in the stock equation.

Regarding conditional volatility, the results reveal that stock (food) volatility is significantly influenced by past own unexpected shocks and volatility, as indicated by the statistical significance of the coefficients of $u_{1,t-1}^2$ and $h_{11,t-1}$ ($u_{2,t-1}^2$ and $h_{22,t-1}$) in the stock (food) equation. The effect of previous volatility on current volatility is more important than that of previous shocks for stock and food markets. These findings are aligned with the results of the univariate AR-GARCH process, and suggest that information flows from past news and volatility to the present volatility level of the equity and food index returns.

[21] The bivariate VAR-GARCH model without breaks is simply the model given by Eq. (3) by setting $D_i = 0$ for $i = 1, 2, \ldots, m$.

[22] Each bivariate VAR(1)-GARCH(1, 1) model is estimated for a vector of two variables consisting of the stock index returns coupled with each food price returns.

Table 5 Estimation results of the bivariate VAR(1)-GARCH(1, 1) models without breaks

	S&P 500	Barley	S&P 500	Maize	S&P 500	Sorghum	S&P 500	Wheat
μ	5.0E-4**	2.2E-5	5.3E-4**	5.1E-4	5.7E-4***	6.3E-4	5.7E-4**	3.9E-4
	(2.0E-4)	(5.3E-4)	(2.2E-4)	(4.5E-4)	(2.1E-4)	(4.4E-4)	(2.4E-4)	(4.9E-4)
ϕ_1	-0.088***	-0.046**	-0.086***	-1.3E-4	-0.085***	0.007	-0.094***	0.016
	(0.022)	(0.023)	(0.017)	(0.026)	(0.019)	(0.029)	(0.020)	(0.029)
ϕ_2	0.064***	0.137***	0.026***	0.044**	0.017*	0.054***	0.022**	-0.008
	(0.012)	(0.040)	(0.009)	(0.021)	(0.009)	(0.020)	(0.011)	(0.020)
c	1.4E-6**	4.4E-5***	1.1E-6*	3.8E-6	1.2E-6**	3.1E-6	1.6E-6***	2.1E-6***
	(5.7E-7)	(1.4E-5)	(5.7E-7)	(7.1E-6)	(5.7E-7)	(3.2E-6)	(5.9E-7)	(5.9E-7)
$u_{1,t-1}^2$	0.064***	0.036	0.088***	0.001	0.089***	4.0E-4	0.099***	0.003
	(0.014)	(0.037)	(0.012)	(0.002)	(0.013)	(0.001)	(0.012)	(0.004)
$u_{2,t-1}^2$	0.003	0.333*	0.003	0.022***	0.002**	0.027***	3.6E-4	0.021***
	(0.003)	(0.189)	(0.002)	(0.006)	(0.001)	(0.006)	(6.4E-4)	(0.006)
$h_{11,t-1}$	0.924***	0.002**	0.899***	1.8E-4	0.899***	7.9E-5	0.885***	0.004
	(0.013)	(0.001)	(0.013)	(3.3E-4)	(0.012)	(2.4E-4)	(0.016)	(0.010)
$h_{22,t-1}$	9.6E-4	0.560***	2.3E-4	0.967***	1.9E-4	0.965***	0.007	0.967***
	(0.001)	(0.149)	(2.4E-4)	(0.007)	(1.6E-4)	(0.008)	(0.005)	(0.011)
$u_{1,t-1}u_{2,t-1}$	0.027*	-0.220	-0.031***	0.010	-0.027**	0.007	-0.012	0.015
	(0.015)	(0.168)	(0.012)	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)
$h_{12,t-1}$	-0.059	0.069***	0.029*	-0.026	0.026**	-0.017	-0.160***	0.130
	(0.038)	(0.024)	(0.015)	(0.024)	(0.011)	(0.027)	(0.059)	(0.152)
LB(12)	13.010	9.283	13.337	13.112	13.591	8.560	12.749	13.946
	[0.368]	[0.679]	[0.345]	[0.361]	[0.328]	[0.740]	[0.388]	[0.304]
$LB^2(12)$	17.314	1.8653	9.922	10.985	10.123	15.193	17.012	11.933
	[0.138]	[1.000]	[0.623]	[0.530]	[0.605]	[0.231]	[0.149]	[0.451]

Notes: The dummy variable coefficients $d_{i,11}^2$ and $d_{i,22}^2$ ($i=1,2,\ldots,m$) in Eqs. (4) and (5) are not reported. LB is the Ljung-Box test for no autocorrelation applied to the standardized residuals; and LB^2 is the Ljung-Box test for no autocorrelation applied to the squared standardized residuals. The values in parentheses are the standard errors and in brackets are the significance levels of the tests. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

As regards shock and volatility transmission across markets, it is interesting to point out that stock volatility is directly influenced by past news from only the sorghum market, as indicated by the statistical significance of the coefficient of

$u_{2,t-1}^2$ in the stock equation. However, stock volatility is not directly affected by past volatility of any food market, as evidenced by the insignificance of the coefficient of $h_{22,t-1}$ in the equity equation. For food markets, volatility in the barley market is directly affected by past volatility from the equity market, as evidenced by the statistical significance of the coefficient of $h_{11,t-1}$ in the barley equation. For the other food markets, volatility is not directly influenced by neither past shocks nor past volatility from the stock market, as indicated by the insignificance of the coefficients of $u_{1,t-1}^2$ and $h_{11,t-1}$ in the food equations. Overall, the findings support the existence of shock transmission from the sorghum price to the equity market, and volatility transmission from stock to barley.

Regarding indirect impacts, volatility in the stock market is indirectly affected by news in barley, maize and sorghum markets and by volatility in maize, sorghum and wheat markets, as shown by the statistically significant coefficients of $u_{1,t-1}u_{2,t-1}$ and $h_{12,t-1}$ in the equity equation. For food markets, volatility in all food markets is not indirectly affected by past news from the equity market, as indicated by the insignificant coefficients of $u_{1,t-1}u_{2,t-1}$ in the food equations. However, volatility in only the barley market is indirectly affected by past volatility from the stock market, as indicated by the statistically significant coefficient of $h_{12,t-1}$ in the barley equation.

As for the case of univariate AR-GARCH processes, the Ljung-Box test is conducted on the standardized residuals and squared standardized residuals of the bivariate VAR-GARCH models. The results reported in Table 5 show that the test concludes in favour of no serial correlation and no conditional heteroscedasticity in the residuals. Therefore, the bivariate VAR-GARCH models without breaks are specified properly, which allows capturing accurately the linkages between stock and food markets.

Before discussing the estimation results of models with structural changes, as for the univariate AR(1)-GARCH(1, 1) model, we first compute the likelihood ratio test to support the model with volatility breaks. For the bivariate VAR(1)-GARCH(1, 1) models, the test statistic is asymptotically Chi-squared distributed with a number of freedom degrees equal to the number of restrictions from the model with volatility shifts to the model without structural changes. The results provided at the bottom of Table 6 conclude in favour of models with structural breaks, as the test rejects the null hypothesis at the 1% level for all cases.[23]

The mean equation indicates that past performance still affects the current performance of stock, barley, maize and sorghum returns, as indicated by the statistical significance of the coefficient ϕ_1 in the equity equation and the coefficient ϕ_2 in the corresponding food equation. However, as regards return spillovers, the

[23] It is worth noting that the overwhelming majority of dummies are statistically significant at the conventional levels (results not shown).

Table 6 Estimation results of the bivariate VAR(1)-GARCH(1, 1) models with breaks

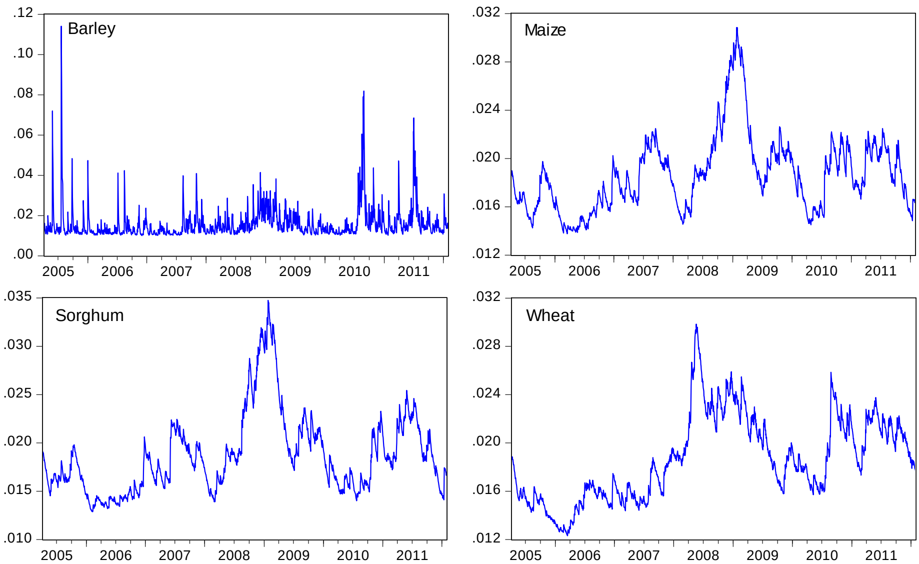
	S&P 500	Barley	S&P 500	Maize	S&P 500	Sorghum	S&P 500	Wheat
μ	5.3E-4**	-2.0E-5	5.0E-4**	6.8E-4	5.9E-4**	8.4E-4*	5.9E-4**	3.6E-4
	(2.7E-4)	(5.7E-4)	(2.6E-4)	(4.8E-4)	(2.4E-4)	(4.7E-4)	(2.6E-4)	(5.3E-4)
ϕ_1	-0.087***	-0.034	-0.092***	-0.024	-0.092***	-0.020	-0.094***	-9.0E-4
	(0.020)	(0.029)	(0.015)	(0.022)	(0.016)	(0.031)	(0.014)	(0.032)
ϕ_2	0.066***	0.137***	0.027**	0.046**	0.017	0.054***	0.018	-0.007
	(0.017)	(0.035)	(0.013)	(0.020)	(0.012)	(0.018)	(0.015)	(0.026)
c	1.1E-6**	1.0E-5***	1.1E-6*	7.0E-5***	1.2E-6***	1.5E-5***	9.4E-7*	2.5E-5***
	(4.7E-7)	(4.7E-7)	(5.9E-7)	(5.9E-7)	(4.2E-7)	(4.2E-7)	(5.4E-7)	(5.4E-7)
$u_{1,t-1}^2$	0.043***	0.078**	0.070***	0.088*	0.069***	0.018	0.082***	0.029*
	(0.011)	(0.039)	(0.012)	(0.050)	(0.012)	(0.030)	(0.013)	(0.016)
$u_{2,t-1}^2$	0.006**	0.298*	1.2E-5	0.050	3.6E-4	0.091***	0.002**	0.040*
	(0.003)	(0.180)	(1.4E-4)	(0.036)	(7.7E-4)	(0.023)	(0.001)	(0.024)
$h_{11,t-1}$	0.918***	0.002**	0.878***	0.002	0.911***	0.002	0.877***	2.7E-4
	(0.010)	(0.001)	(0.020)	(0.006)	(0.012)	(0.003)	(0.015)	(0.001)
$h_{22,t-1}$	0.004**	0.483***	0.009*	0.037	0.001	0.670***	0.003***	0.502***
	(0.002)	(0.128)	(0.005)	(0.119)	(0.001)	(0.171)	(0.001)	(0.126)
$u_{1,t-1}$	0.032**	-0.305	0.002	-0.133***	0.010	-0.081	-0.027**	0.068**
$u_{2,t-1}$	(0.008)	(0.192)	(0.010)	(0.046)	(0.010)	(0.068)	(0.011)	(0.030)
$h_{12,t-1}$	-0.119***	0.064***	-0.176***	-0.015	-0.062*	0.068	-0.104***	0.023
	(0.028)	(0.023)	(0.048)	(0.017)	(0.035)	(0.054)	(0.030)	(0.047)
LR	66.030		46.328		52.152		71.540	
	[0.000]		[0.000]		[0.000]		[0.000]	
LB(12)	13.394	12.270	12.403	11.321	11.743	7.9409	11.804	14.240
	[0.341]	[0.424]	[0.414]	[0.502]	[0.467]	[0.790]	[0.462]	[0.286]
$LB^2(12)$	17.614	1.6827	16.093	16.476	15.249	14.313	8.764	12.059
	[0.128]	[1.000]	[0.187]	[0.170]	[0.228]	[0.281]	[0.723]	[0.441]

Notes: The dummy variable coefficients $d_{i,11}^2$ and $d_{i,22}^2$ ($i=1,2,\ldots,m$) in Eqs. (4) and (5) are not reported. LR is the likelihood ratio test for the null hypothesis of a VAR(1)-GARCH(1, 1) model without breaks against the alternative hypothesis of a VAR(1)-GARCH(1, 1) model with breaks, and asymptotically Chi-squared distributed with a number of freedom degrees equal to the number of restrictions from the model with volatility shifts to the model without structural changes; LB is the Ljung-Box test for no autocorrelation applied to the standardized residuals; and LB^2 is the Ljung-Box test for no autocorrelation applied to the squared standardized residuals. The values in parentheses are the standard errors and in brackets are the significance levels of the tests. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

results have changed since only the coefficient ϕ_2 for first-lagged barley and maize returns is statistically significant in the stock equation. These findings outline that allowing for structural changes reduces the return transmission from food markets to the S&P 500, and removes the spillover effect between barley and equity markets.

For volatility,[24] equity and food (except maize) volatility still responds significantly to past own news and volatility, implying that past unexpected shocks and volatility can forecast conditional volatility of the stock and food index returns. The effect of past own volatility on current volatility is more important than that of past own shocks for stock and corresponding food markets. An interesting feature is that accounting for breaks reduces the predictive power of past own shocks and volatility on current volatility of the S&P 500 index, as evidenced by the coefficients of $u^2_{1,t-1}$ and $h_{11,t-1}$ in the stock equation. Additionally, the impact of previous shocks has decreased for barley and increased for the other food returns, as indicated by the coefficient of $u^2_{2,t-1}$ in the food equation. However, the effect of past own volatility on current volatility has considerably dropped for all food index returns, as mentioned by the coefficient $h_{22,t-1}$ in the food equation. All these findings are somehow aligned with the results of univariate AR-GARCH models.

Figure 3 Conditional standard deviation of food index returns for models without breaks



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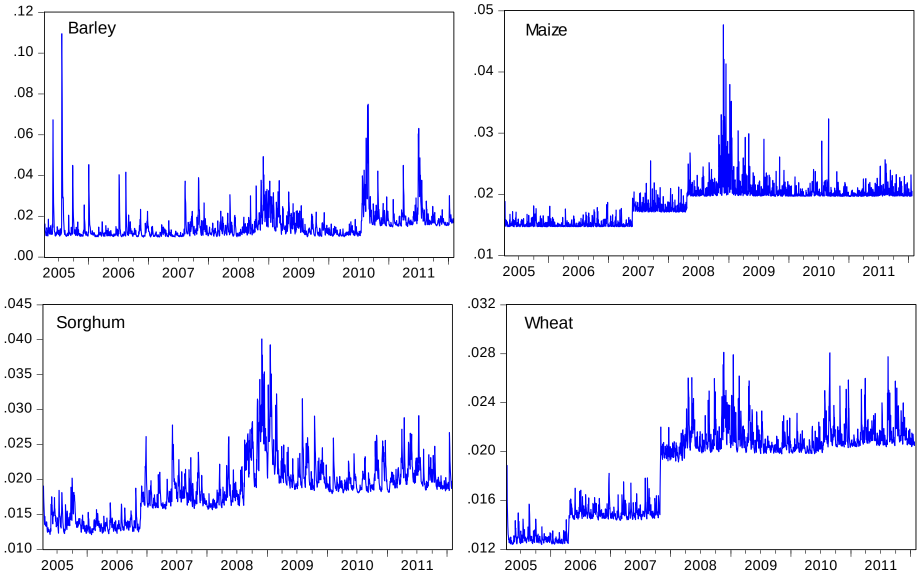
[24] The evolution patterns of the conditional standard deviation of food index returns for models without and with structural breaks plotted in Figures 3 and 4 show evidence of high volatility during the 2007-2009 financial crisis period and to a lesser extent in 2010 and 2011, thereby supporting the results of the above structural change approach.

Figure 4 Conditional standard deviation of food index returns for models with breaks



As regards cross effects, what is interesting is that the direct effect of past shocks and volatility in the food markets on the stock market and in the equity market on the food markets becomes more pronounced than for the case without structural breaks. In this regard, stock volatility is now directly influenced by news from the barley and wheat markets and by volatility from the barley, maize and wheat markets. Additionally, barley, maize and wheat volatility is directly affected by news from the stock market, and that volatility in only barley market is directly affected by volatility from the equity market. From these results, we point out that the direct effect of past shocks in the stock market on the food markets is more pronounced than the direct impact of past news in the food markets on the equity market. However, the direct effect of past volatility in the stock market on the food markets is less pronounced than the direct impact of past volatility in the food markets on the equity market. Therefore, as reported in Figures 5 and 6, the findings support the existence of significant shock spillovers between stock and barley markets, and stock and wheat markets. There are also volatility spillovers between equity and barley markets. In addition, there is evidence of shock transmission from the stock price to the maize market, and volatility transmission from maize and wheat to S&P 500.

Figure 5 Shock spillovers between stock and food returns for models with breaks

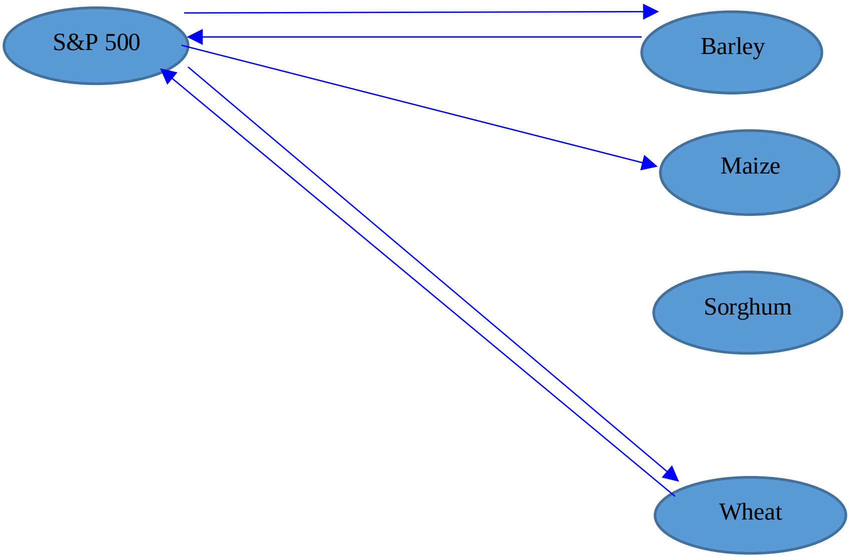
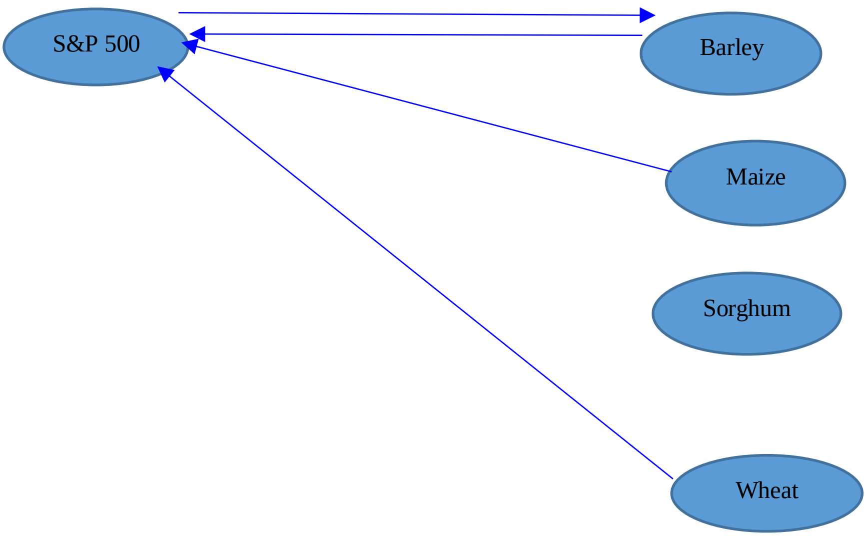


Figure 6 Volatility spillovers between stock and food returns for models with breaks



To summarize, accounting for structural breaks into models provides evidence of significant shock and volatility transmission between equity and food index returns. Within this framework, Fleming et al. (1998) argue that expectations across markets could be affected by changes in common information and cross-market hedging to which are usually attributed the volatility spillovers between markets (see also Ewing and Malik, 2013). Within this context, our findings could be deemed as a consequence of cross-market hedging performed by stock and food market participants. These relevant insights are of great interest for international investors to be aware of beneficial opportunities on building equity/food portfolios since food prices become part of portfolio allocation (see Dwyer et al., 2011; and Vivian and Wohar, 2012), and for food market participants to establish accurate strategies and manage contagion that may be due to stock market shocks.

The findings also indicate that volatility in the equity market is indirectly affected by news in two out of four food markets and by volatility in all food markets. Moreover, volatility in maize and wheat markets is indirectly affected by news in the equity market. However, volatility in only the barley market is indirectly influenced by past volatility from the stock market. These results indicate that the indirect effects are sensitive to the inclusion of variance shifts into the model. As for models without volatility shifts, models with breaks fit well the equity and food time series, as the Ljung-Box test concludes in favour of no serial correlation and no ARCH effects in the residuals of the model.

4.4 Economic implications

The above diagnostic tests lead to properly specified bivariate VAR-GARCH models without and with variance changes, suggesting that conditional volatilities of equity and food market returns and the covariance between them can be used to infer the economic implications of the results in terms of portfolio management and hedge ratio. The obtained results are reported in Table 7.

When ignoring structural changes, the average optimal weights range from 0.260 for the wheat/stock portfolio to 0.354 for the barley/stock portfolio.[25] A portfolio weight of 0.260 (0.354) indicates that an investor who wants to invest $1000 will obtain a minimum risk from a wheat/stock (barley/stock) portfolio without reducing its expected returns if he holds $260 ($354) in stock (stock) and $740 ($646) in wheat (barley), which allows hedging exposure to the changes in the stock index. After incorporating volatility shifts into models, the average optimal weights are very close to those of models without structural changes, suggesting that the selection of the model does not matter in the context of optimal portfolio allocation. Another feature is that there is evidence of slight differences in the average optimal weights across food markets regardless of the model specification, which implies that investors are somehow indifferent as to the choice of the food price to build their stock/food portfolios. Moreover, our results reveal that investors holding assets should have more food than equity in their portfolios for all markets to get a minimum risk without reducing the expected returns regardless of whether

[25] The results also reveal equal average optimal weights for the maize/stock and sorghum/stock portfolios, with a value of 0.261.

structural breaks are incorporated into the model. The obtained findings outline the usefulness of the bivariate VAR-GARCH process in making optimal portfolio allocation decisions by market participants.

Table 7 Average optimal portfolio weights and hedge ratios

Portfolio		$w_{12,t}$	$\beta_{12,t}$
Barley/S&P 500	Without breaks	0.354	0.157
	With breaks	0.352	0.161
Maize/S&P 500	Without breaks	0.261	0.110
	With breaks	0.249	0.124
Sorghum/S&P 500	Without breaks	0.261	0.142
	With breaks	0.258	0.128
Wheat/S&P 500	Without breaks	0.260	0.110
	With breaks	0.256	0.099

For the model that ignores structural changes, the average hedge ratios range from 0.110 for the maize/stock and wheat/stock portfolios to 0.157 for the barley/stock portfolio, implying that shorting maize and wheat is the most effective hedging strategy.[26] This indicates that $1000 long in stock is shorted by $110 of maize and wheat. However, $1000 long in stock is hedged with a short position of $157 in barley. For sorghum, the average hedge ratio is relatively similar to that of barley, with a value of 0.142. Another interesting result is that the average optimal weights are more than double the average hedge ratios for three out of four food markets. As for the optimal weights, the inclusion of structural breaks into models has no visible impact on the average hedge ratios, as they are very close to those of models without volatility shifts. Additionally, the average hedge ratios are still lower than the average optimal weights.

To summarize, the average risk minimizing hedge ratios are weak for all commodities, implying that hedging effectiveness comprising stock and food markets works very well. This is aligned with the fact that incorporating foods into a diversified portfolio of equities improves the risk-adjusted performance of the consequent portfolio, thus confirming previous empirical results (see Arouri et al., 2011; Jouini, 2013; and Mensi et al., 2013).

Alternative GARCH-type models, namely the DCC-GARCH of Engle (2002) and the VAR-GARCH of Ling and McAleer (2003), are estimated to check the robustness of the findings of portfolio management and hedge ratio. The results (not shown) are similar to those of the VAR-GARCH models without and with volatility breaks considered in this study, thereby confirming the usefulness of such models.

4.5 Dependence structure

As documented above, the test of Tse (2000) is applied to ensure the change of correlations between the equity market and each food market over time. The

[26] This result is consistent with Mensi et al. (2013) who find that among many commodities, the cheapest hedge is reached for wheat (0.103).

results provide evidence of dynamic correlations, as the Tse's test rejects the null hypothesis of constant conditional correlations (p-value equals 0 for all cases). Therefore, linkages between stock and food markets can be assessed in a time-varying framework based on the conditional correlations given by Eq. (8).

The pairwise conditional correlations between the stock index and each commodity are plotted in Figure 7 for models without breaks. The evolution patterns of conditional correlations change over time throughout the period under consideration. Correlations between the equity and barley markets are more turbulent than correlations between the stock index and the other commodities. This indicates that linkages between the stock and barley prices fluctuate more substantially compared to linkages between the equity market and the other food markets. Conditional correlations between the stock and barley index returns record fairly visible drops at the time of the 2007-2009 global financial crisis compared to the other commodities, and rise after mid-2009 (the time of recovery of stock markets) until the end of the study period, thus highlighting increased linkages between equity and barley markets. For maize and sorghum, linkages display similar evolution patterns, and show a downward peak in the middle of 2010, thus reflecting dramatic drops in the pairwise correlations. Conditional correlations increase until mid-2011 before they decrease at the end of the period under study. These changes in conditional correlations may be due to the increased uncertainty for the world economy in 2011 because of several international events, such as the turmoil in the MENA region, the ceiling of US debt and budget crisis, etc.[27] Correlations between the stock and wheat markets are less volatile than correlations for the other food markets throughout the study period. Other downward and upward peaks are located in all conditional links around several common periods, thus reflecting the simultaneous response of stock and food markets to shocks.

After including variance shifts into models, the plots displayed in Figure 8 indicate that conditional correlations are still time-varying for all markets and more volatile for barley, and record downward and upward peaks during different periods. The evolution of the volatility of the conditional correlations over time becomes more pronounced for all food index returns during the 2007-2009 financial crisis period, pointing out the noticeable effect of the global stock market crash. This is consistent with Creti et al. (2013), and Choi and Hammoudeh (2010) who show evidence of high volatility periods for the correlations between the S&P 500 price index and some commodities. In the same context, Creti et al. (2013) indicate that this result highlights the financialization process of commodities stipulating that the price of a commodity depends on many financial determinants and investors' behavior in derivative markets in addition to its primary supply and demand. An interesting finding is that after the inclusion of volatility shifts into models, the impact of the 2007-2009 financial crisis[28] becomes more visible, as conditional

[27] Chong and Miffre (2010) show that linkages between stock and commodity returns drop over highly volatile periods.

[28] The 2007-2009 period is marked by the global stock market crisis that has started in mid-2007 with the crash of two hedge funds of the Bear Stearns companies, and gained momentum in late 2008 with the Lehman Brothers bankruptcy and early 2009 with the propagation around the world. Moreover, a substantial increase in the world food prices has emerged in 2007 and mid-2008, thus creating a global

correlations decrease more during this period for all food index returns compared to the case without structural breaks.[29] Furthermore, correlations rise from mid-2009 until mid-2011 where they record drops before increasing at the end of the sample period.

An interesting feature is that correlations between equity and food price returns are mixed (positive and negative)[30] and small, except for some periods where correlations reach quite high levels. The average conditional correlations are found to be 0.081 (0.070) for S&P 500/barley, 0.051 (0.047) for S&P 500/maize, 0.065 (0.060) for S&P 500/sorghum, and 0.049 (0.036) for S&P 500/wheat when ignoring (accounting for) structural breaks, indicating that barley is most related to the S&P 500 index for both cases. These average correlations are small like the unconditional correlations between equity and food price returns (see Table 1), and are statistically significant at the 1% level (*p*-value equals 0 for all cases). In addition, volatilities of the inter-market correlations are quite similar, as standard deviation is 0.179 (0.216) for S&P 500/barley, 0.142 (0.141) for S&P 500/maize, 0.154 (0.165) for S&P 500/sorghum, and 0.126 (0.165) for S&P 500/wheat when ignoring (incorporating) variance shifts. As seen, there is evidence of weak linkages between the stock index and each commodity, thus suggesting no mutually powerful role between them. This confirms prior studies focusing on commodity markets, such as Creti et al. (2013), and Mensi et al. (2013) who find similar conclusions for the wheat price.

The inclusion of volatility shifts into models does not, in general, influence the intensity of the linkages between stock and food markets, since the magnitude of the average correlations is similar for both cases. This finding has an important and meaningful implication since it shows that the low conditional correlations between stock and food markets are robust to taking into account structural breaks. These insights show evidence of potential earnings for international investors who want to invest in the stock and food markets. Another important implication of the findings is that the similarity of the weak correlations for all stock/food pairs regardless of the model specification puts forward a substitution mechanism between food classes, as the investment in one commodity constitutes an alternative to the other commodities when building equity/food portfolios. This indicates that the considered commodities can be deemed as a homogeneous food class as regards their connection with the equity market, and the economic implications of their results in terms of portfolio management, as reported above.

food crisis and causing social unrest in poor countries. These crisis events prompt us to examine their impact on the linkages between equity and food markets, which is the object of the next subsection.

[29] This is aligned with Creti et al. (2013) who show that times of high financial markets' unrest are marked by the largest decline in the correlations between equity and commodity index returns. They argue that these drops may be explained by the flight-to-quality phenomenon. Indeed, increases in market risk foster the advantages of diversification, thus orienting investors toward commodities as refuge instruments (see Chong and Miffre, 2010; and Silvennoinen and Thorp, 2013).

[30] Negativity of the correlation coefficients may support the view that the behavior of food markets is at most generated by their own market fundamentals.

Figure 7 Time-varying conditional correlations for models without breaks

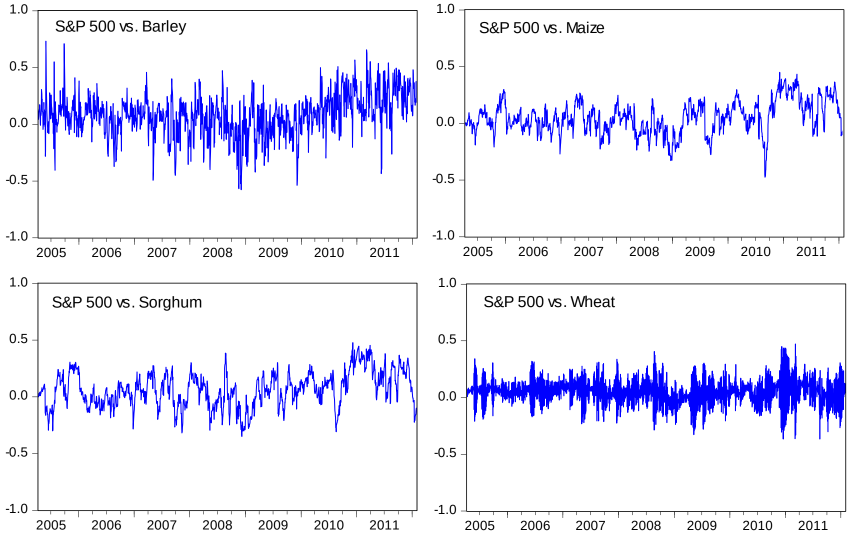
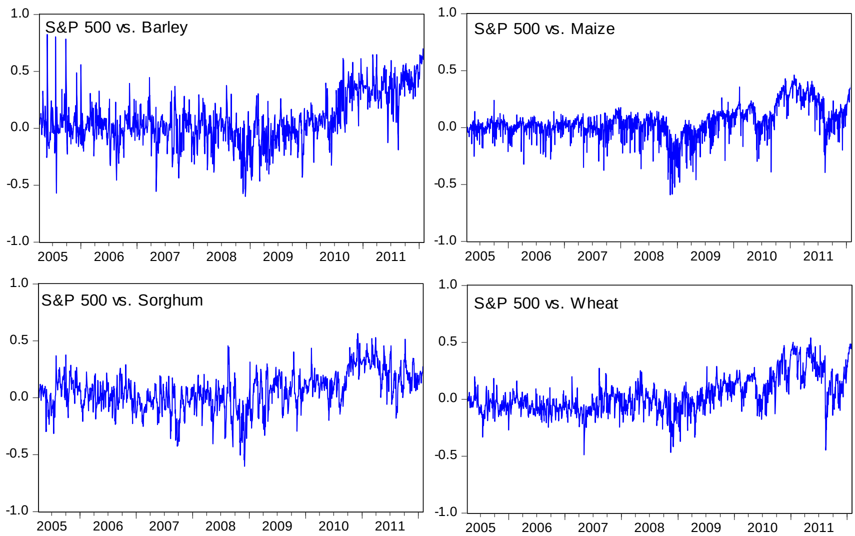


Figure 8 Time-varying conditional correlations for models with breaks



4.6 Implications of crisis events

To highlight the implications of the 2007-2009 stock market crisis on the interactions between equity and food markets,[31] we run a regression for each pairwise

[31] Although the analysis of the effect of crises on the connection between equity markets has been amply increased in the literature (see Kenourgios and Samitas, 2011; Syllignakis and Kouretas, 2011; Gjika and Horváth, 2013; and Jouini, 2015), the impact of such crises on the conditional linkages between stock and

correlation, into which we incorporate a dummy variable, that takes one from July 2, 2007 to June 30, 2009, and zero otherwise. The Ljung-Box test for no serial correlation concludes in favour of highly persistent conditional correlations (3872.9 [0.000] and 8509 [0.000] for barley, 12165 [0.000] and 9719.9 [0.000] for maize, 12166 [0.000] and 7740.4 [0.000] for sorghum, and 8202.6 [0.000] and 11615 [0.000] for wheat, where the first value is for the case without breaks, the second value is for the case with breaks, and the value between [.] is the significance level). This usually leads to high levels of autocorrelation in the residuals, thereby implying that *t*-statistics cannot be well sized. To overcome this drawback, a one-period lagged conditional correlation is incorporated into the regression to mitigate the effects of high autocorrelation.[32]

Table 8 Effect of the financial crisis on conditional correlations for models without breaks

CCor	Constant	Dum.	CCor(-1)	R^2	*F*-stat	RSS	LB(12)
Barley/S&P 500	0.030***	-0.032***	0.749***	0.607	1367.558	22.394	13.321
	(0.004)	(0.007)	(0.019)		[0.000]		[0.346]
Maize/S&P 500	0.004***	-0.005**	0.945***	0.902	8146.932	3.504	6.412
	(0.001)	(0.002)	(0.008)		[0.000]		[0.894]
Sorghum/S&P 500	0.004***	-0.004**	0.950***	0.908	8740.932	3.862	13.546
	(0.001)	(0.002)	(0.007)		[0.000]		[0.331]
Wheat/S&P 500	0.104***	-0.051***	0.793***	0.633	1529.926	10.302	10.119
	(0.005)	(0.010)	(0.022)		[0.000]		[0.606]

Notes: Dum. is a dummy variable that takes one from July 2, 2007 to June 30, 2009, and zero otherwise; CCor(-1) is the one-period lagged conditional correlation; R^2 is the coefficient of determination; *F*-stat is the test of joint significance; RSS is the residual sum of squares; and LB is the Ljung-Box test for no autocorrelation applied to the residuals. The values in parentheses are the HAC (Newey-West) standard errors and in brackets are the significance levels of the test. *** and ** denote statistical significance at the 1% and 5% levels.

When ignoring variance shifts, the results are provided in Table 8. There is evidence of statistically significant intercept and dummy variable coefficient at the conventional levels for all conditional correlations, implying that the financial crisis has predictive power on the linkages between stock and food markets. Another interesting result is that the effect of crisis events is negative, since correlations between equity and food price returns decline during the 2007-2009 financial crisis,[33] as provided by the negative estimate of the dummy variable coefficient. The reduction in the correlation patterns ranges from 0.004 for S&P 500/sorghum to 0.051 for S&P 500/wheat. The one-period lagged correlation coefficient is statistically significant and positive for all food markets. The coefficient of determination suggests that regression models are well fitted, and the *F*-statistic points out to the overall significance of all regressions. The Ljung-Box test supports

food markets has never been previously examined, thus putting forward the related literature. Moreover, the utility of this issue lies in the fact that recourse to portfolio diversification is of great importance in highly volatile times.

[32] We are grateful to one anonymous referee for having recommended this point.

[33] This finding indicates that conditional correlations drop in times of rising food prices and diminishing stock indexes (see Figure 1).

the correctness of the model, as there is evidence of no autocorrelation in the residuals.

After incorporating volatility break dummies into models, the results reported in Table 9 indicate that all coefficients are statistically significant at the 1% level for all conditional correlations. Moreover, as for models without volatility shifts, the estimated coefficient of the dummy variable is negative for all cases, suggesting decreasing linkages between equity and food price returns during the 2007-2009 turmoil period. The coefficient of determination and *F*-statistic conclude in favor of well fitted regression models, and the Ljung-Box test shows evidence of no serial correlation in the residuals of the model.

Table 9 Effect of the financial crisis on conditional correlations for models with breaks

CCor	Constant	Dum.	CCor(-1)	R^2	*F*-stat	RSS	LB(12)
Barley/S&P 500	0.023***	-0.034***	0.816***	0.713	2201.377	23.893	12.219
	(0.003)	(0.007)	(0.018)		[0.000]		[0.428]
Maize/S&P 500	0.023***	-0.033***	0.710***	0.569	1168.877	15.285	5.969
	(0.002)	(0.005)	(0.026)		[0.000]		[0.918]
Sorghum/S&P 500	0.013***	-0.017***	0.871***	0.791	3350.400	10.135	11.865
	(0.002)	(0.004)	(0.011)		[0.000]		[0.457]
Wheat/S&P 500	0.008***	-0.012***	0.890***	0.808	3721.215	9.266	9.982
	(0.002)	(0.003)	(0.013)		[0.000]		[0.618]

Notes: Dum. is a dummy variable that takes one from July 2, 2007 to June 30, 2009, and zero otherwise; CCor(-1) is the one-period lagged conditional correlation; R^2 is the coefficient of determination; *F*-stat is the test of joint significance; RSS is the residual sum of squares; and LB is the Ljung-Box test for no autocorrelation applied to the residuals. The values in parentheses are the HAC (Newey-West) standard errors and in brackets are the significance levels of the test. *** denotes statistical significance at the 1% level.

The same implications that the 2007-2009 financial crisis has on correlations between equity and food markets suggests that food prices behave similarly, and can then be treated as substitutable goods. Overall, crisis events significantly influence the behavior of the conditional linkages between equity and food price returns, as diminishing correlations are observed during the 2007-2009 financial crisis, which constitutes a fresh addition to the related literature. The implication of this finding is that international investors can benefit more from building stock/food portfolios during higher turmoil periods.

Reductions in the conditional correlations during more turbulent times would affect the forecasting of stock and food price returns and volatility and the building of pricing models, and support market participants for broadly understanding the overall economy and equity and food markets. This allows implementing policies and strategies and handling market contagion risks that would be caused by crisis events.

Although most prior empirical studies on equity markets show evidence of increasing conditional correlations during crisis periods, thus supporting the herding behavior, our study on the relationship between equity and food markets reveals negative effect of the global financial crisis on inter-market linkages. This indicates that the evolution of correlations between these markets over time depends on the stock market situation. Thus, we put forward the literature and do not support the herding behavior during the 2007-2009 crisis period for the connection between stock and food markets.

5. Conclusion

A deep analysis of the relationship between stock and food prices with regard to shock and volatility transmission and the evolution of inter-market linkages over time is conducted based on various econometric procedures, with a view to getting new and robust evidence in the field and taking the literature forward. A particular attention is paid to the implications of crisis events on inter-market correlations to examine the sensitivity of portfolio diversification earnings to the times of sharp fluctuations of financial markets. The study allows for the possibility of volatility shifts given the economic and financial unrests that reigned during the period under consideration, which may alter the shock and volatility transmission and linkages between equity and food index returns. Allowing for structural breaks implies that changes in the fundamentals of stock and food markets and in the underlying economy are taken into account. The analysis also expands the sample of food markets to highlight whether there is either a particular commodity that minimizes risk without reducing the expected returns or a substitution mechanism between commodities. Understanding properly the mechanism of shock and volatility transmission across markets and inter-market correlations is very informative for international investors to build beneficial stock/food portfolios, and for market participants to establish appropriate policies in order to protect against contagion effects.

Our results consolidate the understanding of the shock and volatility spillovers and dependence structure between equity and food markets. They show strong evidence of volatility shifts in the equity and food price returns especially during the 2007-2009 turmoil period. Taking into account break dummies affects volatility persistence for all market index returns. Furthermore, return, shock and volatility spillovers across markets are sensitive to the inclusion of variance shifts into models. The findings also have important implications with regard to optimal portfolio allocation and risk minimizing hedge ratio. Indeed, investors are indifferent as to the choice of the food price to build their optimal equity/food portfolios, and incorporating food prices into a diversified portfolio of stocks improves the risk-adjusted return performance of the consequent portfolio regardless of the model specification. The linkages between equity and food markets are found to be weak and time-varying, and decline at the time of the 2007-2009 financial turmoil, implying that investors can benefit from building equity/food portfolios, especially during higher volatile times. A future research study could be undertaken based on wavelet techniques to assess the interactions between equity and food markets.

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