Understanding Return And Volatility Spillovers Among Major Agricultural Commodities

Amine Lahiani, University of Orléans & ESC Rennes Business School, France
Duc Khuong Nguyen, IPAG Business School, France
Thierry Vo, ESCP Europe Business School & University Paris 1 Panthéon-Sorbonne, France

ABSTRACT

We provide comprehensive evidence of return and volatility spillovers for the four major agricultural commodities including sugar, wheat, corn and cotton over the recent period 2003-2010. Our results from the recent VAR-GARCH model of Ling and McAleer (2003) that allows for simultaneous shock transmissions of conditional volatilities of returns across commodities show the existence of substantial volatility spillover linkages between agricultural commodity returns and volatilities. Our findings are also particularly insightful for optimal portfolio designs and risk management through the computation of optimal weights and hedge ratios.

Keywords: Agricultural Commodities; Volatility Spillovers; Optimal Hedging; VAR-GARCH

1. INTRODUCTION

The market prices of agricultural commodities have recently experienced important swings and extreme movements. Until the year 2007, the evolution of FAO Food Price Index (FFPI) was quite stable, but it has grown up with an average annual growth of 59% over the period from March 2007 to March 2008. Since the evolution of FFPI can be interpreted as the global trends of agricultural commodities, some actors such as producers, consumers and investors have expressed serious concerns about the movements of agricultural commodities as well as their comovements. The reason is that price fluctuations will not only cause irregularities in agricultural markets and inflation threats, but also induce higher costs for importers, exporters, and final consumers.

It is now a common knowledge that the price fluctuations in agricultural commodities markets arise from supply and demand conditions which, in turn, depend on weather, market states, business cycles and geopolitical situations. In addition, the climate change and natural disasters are largely beyond the control of market participants. Agricultural commodity prices can thus vary very substantially and hedging against their unfavorable movements through, for example, futures markets become a primary and imperative task for all market participants. It is worth noting that this task naturally requires an accurate modeling and forecasting of commodity price patterns, conditionally on their comovement. These insights are indeed needed for derivative pricing, portfolio optimization, risk management, and hedging strategies.

Several papers have examined dynamic changes in agricultural commodities prices. For instance, Malliaris and Urrutia (1996) consider futures prices of soybeans, oats, corn and wheat for the period 1981-1991 and show evidence of cointegration between them. They explain this long-run comovement by the fact that agricultural commodities have some essential properties in common such as geographical areas, seasonality and climatic situations as well as worldwide demand. Accordingly, one agricultural commodity can be substituted or complementary to another agricultural commodity. Chatrath et al. (2002) shows that the future prices of agricultural commodities are better estimated when seasonality and contract maturity effects are introduced in univariate ARCH-type models. Dahl and Iglesias (2009) propose a GARCH(1,1)-AR(m) functional specification to examine the influence of the spot price risk (conditional volatility) on the spot prices of six agricultural products, and provide strong evidence to support the classical rational expectations model of commodity markets, according to which the expected spot price risk is a driver of agricultural commodity spot prices. Recently, the food-energy nexus and the food-stock market nexus have become a crucial issue for portfolio management and economic policy actions following the rising food prices (e.g., Serra, 2011; Du et al., 2011; Nazlioglu et al., 2013; Mensi et al., 2013; Creti et al., 2013). For example, Du et al. (2011) investigate the factors that potentially affect volatility of crude oil prices and the possible linkage between this volatility and several agricultural commodity markets, using Bayesian Markov Chain Monte Carlo methods. They provide evidence of volatility spillover among crude oil, corn, and wheat markets after the fall of 2006, which can be explained by the tightened interdependence between crude oil and these commodity markets induced by ethanol production. Nazlioglu et al. (2013) document that increasing oil prices is the main driving factor of the recent upward movements in agricultural markets. Creti et al. (2013) examine the links between price returns for 25 commodities including agricultural products and stocks over the period 2001-2011. Using the DCC-GARCH methodology, the authors show evidence of evolving correlations between commodity and stock markets, particularly since the 2007–2008 financial crisis.

Very little is however known about the conditional correlations and volatility spillover effects across agricultural commodities. This article also addresses these issues by using the generalized VAR-GARCH model, introduced by Ling and McAleer (2003). This model offers the possibility to explore the conditional volatility dynamics of the commodity prices as well as the conditional correlation cross effects and volatility transmission between them. The obtained estimates can be used to calculate optimal portfolio designs and compute optimal hedge ratios. Hammoudeh et al. (2009) find that the VAR(1)-GARCH(1,1) model is useful and suitable for modeling the dynamic volatility and volatility transmission for three major sectors (Service, Banking and Industrial/or Insurance) in four Gulf Cooperation Council (GCC) countries. Arouri et al. (2011) explicitly show the superiority of this model to alternative competing models such as CCC-GARCH, DCC-GARCH and BEKK-GARCH using oil and stock market data.

Overall, while existing studies mainly focus on the volatility spillover between energy and agricultural commodities markets or between stock and agricultural commodities markets, we contribute to this related literature by analyzing the return and volatility spillovers among the four major agricultural commodities. Moreover, our multivariate VAR-GARCH model allows not only the direct transmission of return shocks and volatility, but also the multivariate interactions among the considered commodities. Finally, our empirical results enable us to straightforwardly build the optimal portfolio designs and hedging strategies.

Our results show evidence of significant return and spillovers across the four major agricultural commodities. They also indicate the existence of three distinct sets of shock-sensitivity levels: the really low news-sensitivity commodities (cotton and corn), the high news-sensitivity commodity (sugar), and the middle-news sensitivity commodity (wheat). Finally, optimal weights and hedge ratios are found to be time-varying.

The rest of this paper is organized as follows. Section 2 introduces the empirical framework and estimation procedure. Section 3 describes the data used and their statistical properties. Section 4 reports a discussion of the obtained results, while some concluding remarks are provided in section 5.

2. ECONOMETRIC METHOD

We adopt the multivariate VAR(1)-GARCH(1) model of Ling and McAleer (2003) to investigate the cross correlation effects and volatility spillovers across four agricultural commodity markets. We specify the conditional mean equation for the agricultural commodity *i* as follows:

$$\begin{aligned} R_{i,t} &= \mu_i + \phi_i R_{i,t-1} + \varepsilon_{i,t} \\ \varepsilon_{i,t} &= h_{i,t}^{1/2} \eta_{i,t} \end{aligned} \tag{1}$$

where $R_{i,t}$ is the return series, defined as the difference in the logarithm of two successive prices. $\varepsilon_{i,t}$ is the error term. $\eta_{i,t}$ refers to a sequence of independent and identically distributed (*i.i.d.*) random shocks. $h_{i,t}$ is the conditional variance of the agricultural commodity *i* and is specified as:

$$\begin{aligned} h_{i,t} &= c_i + \sum_{j=1}^{4} \alpha_{ij} \varepsilon_{j,t-1}^2 + \sum_{j=1}^{4} \beta_{ij} h_{j,t-1} \\ &= c_i + \alpha_{i1}\varepsilon_{1,t-1}^2 + \beta_{i1}h_{1,t-1} + \alpha_{i2}\varepsilon_{2,t-1}^2 + \beta_{i2}h_{2,t-1} + \alpha_{i3}\varepsilon_{3,t-1}^2 + \beta_{i3}h_{3,t-1} + \alpha_{i4}\varepsilon_{4,t-1}^2 + \beta_{i4}h_{4,t-1} \end{aligned} \tag{2}$$

In Eq. (2) $h_{j,t-1}$ refers to the own past volatility shock for $i = j$ and to past conditional variances of the other agricultural commodities for $i \neq j$. The sum $\sum_{j=1}^{4} \alpha_{ij} \varepsilon_{j,t-1}^2$ captures the effects of own past shocks (when $i = j$) and past shocks of commodity *j* (when $i \neq j$) on the conditional volatility of commodity *i*. The sum $\sum_{j=1}^{4} \beta_{ij} h_{j,t-1}$ represents the impacts of the past conditional volatilities. As we can see, the theoretical model of Ling and McAleer (2003) allows the conditional variance of a specific agricultural commodity to fluctuate depending on not only on the own past shock and volatility, but also on the cross effects of past return innovations and volatilities across return series. Finally, let ρ denote the constant conditional correlation, the conditional covariance between the i^{th} and the j^{th} agricultural commodity returns can be defined as:

$$h_{ij,t} = \rho * \sqrt{h_{i,t} * h_{j,t}} \tag{3}$$

At the empirical stage, we use the quasi-maximum likelihood estimation (QMLE) to estimate the vector of unknown parameters in order to account for any departure of agricultural commodity return series from normality condition.

Once the empirical results become available, they can be used to make decisions about portfolio's allocation and risk management. Typically, one can compute the optimal weights and hedging ratios for a diversified portfolio of paired agricultural commodities. For this purpose, Kroner and Ng (1998) show how optimal weights are determined so that investors minimize the risk of their portfolio without lowering its expected return. Concretely, the optimal weights of a two-asset portfolio (commodities 1 and 2) at time *t* respect the following relation:

$$w_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}} \text{ with } w_{12,t} = \begin{cases} 0, & if\ w_{12,t} < 0 \\ w_{12,t}, & if\ 0 \le w_{12,t} \le 1 \\ 1, & if\ w_{12,t} > 1 \end{cases} \tag{4}$$

where $w_{12,t}$ is the weight of the 1st asset in a one-dollar portfolio of two agricultural commodities. $h_{12,t}$ is the conditional covariance between the two agricultural commodities. $h_{11,t}$ and $h_{22,t}$ are the conditional variances of the 1st and 2nd agricultural commodities respectively. Thus, $1 - w_{12,t}$ is the weight of the 2nd asset in the said portfolio.

One can also compute the optimal hedge ratios, based on the work of Kroner and Sultan (1993). For a portfolio of two agricultural commodities, the optimal hedge ratio is the one that minimizes the risk of this portfolio and is given by:

$$\theta_t = \frac{h_{12,t}}{h_{22,t}} \tag{5}$$

The hedging strategy thus consists of having a long position (buy) of $1 in the 1st agricultural commodity and a short position (sell) of $ θ_t in the 2nd agricultural commodity at time *t*. The strategy is the most effective when the hedge ratio is the most inexpensive.

3. DATA

We use daily spot price data of the world's four major agricultural commodities (Wheat, Sugar, Cotton and Corn) over the recent period from October 3, 2003 to August 31, 2010. All data are expressed in US dollar to avoid the effects of exchange rates and extracted from the Food Administration Organization (FAO) database. Daily returns are computed from daily spot price data by taking the natural logarithm of the ratio between two successive prices. Unlike the previous research which essentially uses low frequency data, we employ daily spot price data to catch the quickness and intensity of the dynamic linkages between agricultural commodities returns.

Table 1: Unit Root Tests

	Price Series		**Return Series**	
	ADF	**PP**	**ADF**	**PP**
Wheat	-0.07a	-0.20a	-21.51***a	-32.49***a
Cotton	-1.75c	-1.85c	-40.30***a	-40.27***a
Sugar	-1.68c	-1.76c	-40.71***a	-40.71***a
Corn	-0.01a	-0.12a	-39.46***a	-39.46***a

Notes: This table reports the results of unit root tests (Augmented Dickey-Fuller and Phillips-Perron). [a] stands for no constant and no deterministic trend, [b] for constant and no deterministic trend, and [c] for constant and deterministic trend.

Table 2: Descriptive Statistics for Commodity Returns

	Wheat	**Cotton**	**Sugar**	**Corn**
Mean (%)	0.030	0.018	0.072	0.036
Max (%)	8.284	7.599	8.494	8.473
Min (%)	-10.357	-7.501	-7.757	-12.365
Standard deviation	0.012	0.0019	0.019	0.021
Skewness	-1.146	-0.080	-0.116	-0.202
Kurtosis	15.405	4.512	4.532	5.117
J.B	11855.18***	172.285***	140.182***	345.912***
ARCH(20)	144.336***	35.703***	32.726**	40.422***

Notes: J.B and ARCH(20) are the empirical statistics of the Jarque-Bera test for normality and the LM ARCH test for conditional heteroscedasticity respectively. ** and *** indicate rejection of the null hypotheses of normality and conditional homoscedasticity at the 5% and 1% levels, respectively.

Tables 1-2 present some diagnosis tests for the price and return series. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests indicate that the price series are integrated of order one and the returns series of the four commodities are stationary at the 5% level. The average daily commodity returns are all positive and range from 0.018% (cotton) to 0.072% (sugar). Their daily unconditional volatility in terms of standard deviations is relatively high and ranges from 1.2% (wheat) to 2.1% (corn). All the return series are negatively skewed and have leptokurtic behavior (kurtosis coefficients above three). This deviation from normality is confirmed by Jarque-Bera test statistics. In addition, the results of the Engle (1982) ARCH test show evidence of conditional heteroscedasticity since the null of no ARCH effects is rejected for all the series. These findings support our decision to employ GARCH-type model to simultaneously capture persistence, heteroscedasticity and cross effects of volatilities and shocks.

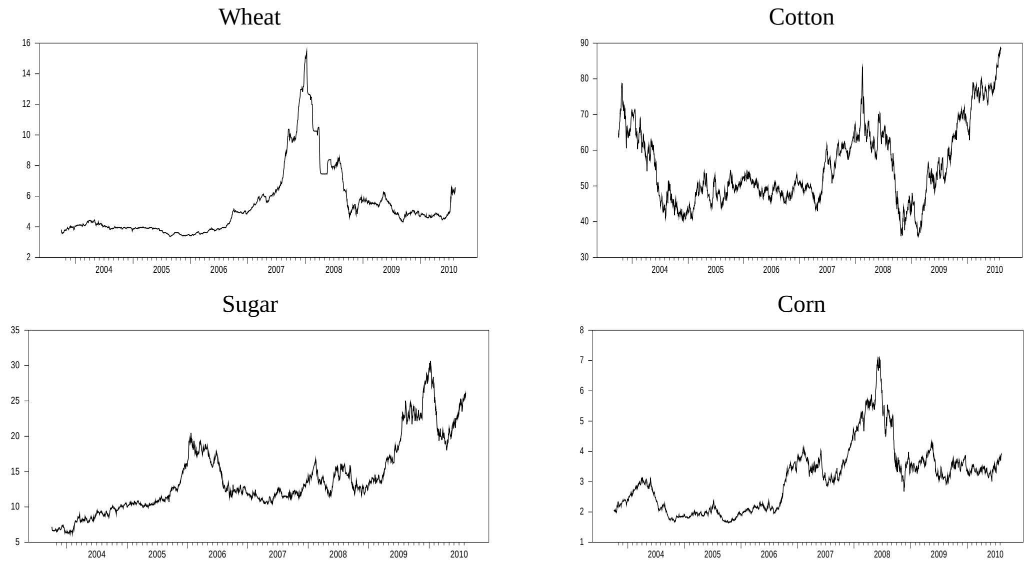

Figure 1: Time-Paths of Daily Prices of the Four Major Agricultural Commodities

The price dynamics of the agricultural commodities prices, as depicted in Figure 1, differ largely along the time period we considered. However, some common features could be observed. First, the four prices series show an upward trend which is indicative of rising price tendency in the commodities markets which may be due to inflation and supply/demand volumes. Second, the four commodities share the fact that their prices have known a peak around year 2008 which corresponds to the global financial crisis.

4. RESULTS AND DISCUSSIONS

The issue of return and volatility shocks transmission between commodities markets is of great complexity because there are many transmission channels that one could investigate. As reported by Arouri et al. (2011) these channels include cross-market hedging, changes in common information, and expectations of market participants. Here our objective is to investigate how return and volatility shocks are transmitted between the four major agricultural commodities.

4.1 Return and Volatility Dependencies

Table 3 presents the unconditional correlation coefficients between the world's four major agricultural commodities, they are all positive, but the level is still weak, suggesting the high potential of diversification and portfolio's efficient risk management among these commodities. Therefore, holding a portfolio of at least two assets among the four agricultural commodities would lower the portfolio's risk and improve its expected returns.

Table 3: Constant Conditional Correlation (CCC) between Agriculture Returns Series

	Wheat	Cotton	Sugar	Corn
Wheat	1.000			
Cotton	0.144	1.000		
Sugar	0.100	0.160	1.000	
Corn	0.336	0.282	0.152	1.000

Table 4 reports the estimated parameters in the conditional mean and variance equations of the VAR(1)-GARCH(1,1) for the world's four major agricultural commodities. Own past shocks are the most important for Sugar, owing potentially to the fact that this commodity is likely the most traded by agricultural commodity market participants and thus price fluctuations are frequent. There is also evidence of return dependencies between commodities. The one-period lagged returns of wheat and corn affect positively and significantly the current value of wheat. Similarly the one-period lagged return of cotton and corn have a positive and significant impact on the current returns of sugar. No interdependencies are, however, found between the current returns of cotton/corn and the one-period lagged returns of the remaining commodities. These results show three distinct sets of shock-sensitivity levels: the really low news-sensitivity commodities (cotton and corn), the high news-sensitivity commodity (sugar), and the middle-news sensitivity commodity (wheat). In this scheme of things, risk-loving traders should keep their eyes on the high news-sensitive agricultural commodities like sugar, while risk-averse traders should focus on the least news-sensitive commodity group such as corn and cotton.

Turning out to the conditional volatility equations, the empirical results show that the estimates of the ARCH and GARCH coefficients related to own past shocks and volatilities are significant at the conventional levels in most cases. There is a strong evidence of sensitivity to own conditional volatility for each commodity. This is thus indicative that own past volatility of a particular commodity is useful to forecast its future volatility. Additionally, the current volatility of a given commodity depends on past shocks affecting its return dynamics as shown by the significant ARCH terms.

The magnitude of the cross-market shock effects in the volatility equations is obviously smaller (between -0.0557 and 0.0375) than the own shock effects (between 0.0290 and 0.1134). It means that the transmission of external shocks across the four agricultural commodities is not much considerable, which suggests that all agricultural commodities do not belong to a unique group, but each agricultural commodity should be taken separately in the short run. More precisely, the conditional volatility of wheat is affected positively by past shocks to sugar returns, but negatively by shocks to cotton and corn returns. Cotton is cross-shock affected positively by past shocks to corn returns, but negatively by past shocks to wheat and sugar returns. Cotton thus shares some common shocks with the wheat and sugar and the negative cross-effects lead to a reduction in the cotton's conditional volatility. Besides its own shocks, the volatility of sugar is only sensitive to shocks to corn returns. Finally, the volatility of corn returns receives positive impacts from both wheat and sugar markets.

Regarding the volatility spillover effects across the four commodities, we observe various directions of volatility transmission. Indeed, there is no direct transmission of volatility neither from the wheat market to the remaining markets nor from the cotton and the sugar markets to the sugar and corn markets respectively. By contrast, there is a significant volatility spillover from the cotton market to the wheat and corn markets, from the sugar market to the cotton market and finally from the corn market to the remaining three commodity markets.

Table 4: VAR(1)-GARCH(1,1) Estimation Results

Commodity	Wheat	Cotton	Sugar	Corn
Mean Equation				
constant($\times 10^2$)	0.0217	0.0468	0.0810^{*}	0.0773^{*}
wheat(t-1)	0.1885^{***}	-0.0221	-0.0230	-0.0596
cotton(t-1)	0.0097	0.0141	0.0634^{***}	0.0046
sugar(t-1)	-0.0127	0.0123	-0.0135	0.0117
corn(t-1)	0.0277^{**}	0.0139	0.0582^{**}	0.0366
Variance Equation				
Constant($\times 10^3$)	0.0650^{**}	0.1880	2.7080^{**}	1.4830^{***}
$\varepsilon_{wheat,t-1}$	0.0674^{***}	-0.0557^{***}	-0.0008	0.0375^{**}
$\varepsilon_{cotton,t-1}$	-0.0083^{**}	0.0294^{***}	-0.0167	0.0054
$\varepsilon_{sugar,t-1}$	0.0126^{***}	-0.0098^{*}	0.1134^{***}	0.0244^{**}
$\varepsilon_{corn,t-1}$	-0.0200^{***}	0.0162^{***}	-0.0465^{**}	0.0290^{***}
$h_{wheat,t-1}$	0.9323^{***}	0.0003	0.5792	0.0086
$h_{cotton,t-1}$	-0.0563^{**}	0.9658^{***}	-0.0422	-0.1155^{***}
$h_{sugar,t-1}$	-0.0062	-0.1662^{**}	0.7205^{***}	-0.1385
$h_{corn,t-1}$	0.0417^{***}	0.0924^{***}	0.5138^{**}	0.9706^{***}
AIC		-22.014		
BIC		-21.823		

Notes: The optimal lag order for the VAR model is selected using the AIC and BIC information criterion. Standard errors are not reported to conserve space, but available from request addressed to the corresponding author. *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% levels, respectively.

In particular, corn is consistently the commodity that transmits its volatility shocks to all the other markets. This result should not be surprising since the high-fructose corn syrup (HFCS), derived from corn, is used as an alternative to sugar. The HFCS has, indeed, the double advantage of having a similar flavor to sugar and being cheaper to produce than sugar. At wholesale, it is often priced at $0.05-0.08 per pound lower than refined cane and beet sugar. It is also commonly found in soft drinks (Coca-Cola, Sprite, Fanta, Dr. Pepper, etc.), cereals (Kellogg's, Cheerios), sauce (Heinz Tomato Ketchup, and BBQ Barbecue), desserts (pies, cookies, ice cream, and yogurt), fast foods (Burger King, KFC, McDonald's, Subway, and Taco Bell), beers, canned fruits, preserved meats and peanut butters. In 2010, farmers harvested 830 million metric tons of corn across the world and the HFCS accounts for 37% (7.8 million metric tons) of the caloric sweetener market, while sugar accounts for 50% (10.1 million metric tons).

The volatility of wheat is not significantly influenced by sugar's return volatility, but by that of corn and cotton. The high-intensity positivity of shock spillover from corn to wheat is well justified by their bilateral CCC of 0.336, the highest level among the CCC coefficients. However, the reasons for the cross-volatility effects of cotton on wheat are not obvious as the intercropping is not always practiced all around the world.

4.2 Implications for Portfolio Management

Significant evidence of volatility spillovers among the four agricultural commodities suggests that they should be accounted for when making decisions about portfolio's design and risk management. Our findings thus help in solving this problem through the calculations of the optimal weights and hedging ratios. Table 5 shows the average value of the optimal weights for tow-asset portfolios of agricultural commodities. The average optimal weights of the first asset range from 52% (Sugar/Corn) to 88% (Wheat/Corn). For instance, the weight of wheat in the wheat-cotton portfolio is 78%. Overall, our results suggest that investors should have more wheat than cotton (78%), more wheat than corn (88%), more wheat than sugar (79%), more cotton than sugar (52%), more cotton than corn (55%), and more sugar than corn (52%) within diversified portfolios to minimize risks without lowering the expected returns.

Table 5: Optimal Portfolio Weights

Portfolio	Average Values
Wheat/Cotton	0.78
Wheat/Corn	0.88
Wheat/Sugar	0.79
Cotton/Sugar	0.52
Cotton/Corn	0.55
Sugar/Corn	0.52

Table 6: Hedge Ratios

Portfolio	Average Values
Wheat/Cotton	0.09
Wheat/Corn	0.17
Wheat/Sugar	0.06
Cotton/Sugar	0.16
Cotton/Corn	0.27
Sugar/Corn	0.15

Table 6 reports the average risk-minimizing hedge ratios for two-asset one-dollar portfolios of the four major agricultural commodities. We see that they are smaller than those for equity markets, as found in Hassan and Malik (2007). For example, to minimize the risk in a wheat-cotton portfolio, one dollar long (buy) in wheat should be shorted (selling) by 9 cents of cotton. The hedging effectiveness is highest for the wheat-sugar portfolio. This finding can be explained by the fact that wheat and sugar have the lowest conditional correlation among all the agricultural commodity pairs. The most effective strategy to hedge cotton is to short sugar (16 cents). The least effective strategy to hedge cotton is to short corn (0.27). Finally, the least effective hedging strategy among all agricultural commodities is to hedge long (buy) cotton positions by selling corn (27 cents).

We depict in Figures 2-3 the time-variations in the optimal weights and hedge ratios. The observed evolving patterns as well as the existence of significant peaks show that both portfolio's weights and hedging ratios are not stable over time, and thus require time-varying forecasts in order to guarantee the effectiveness.

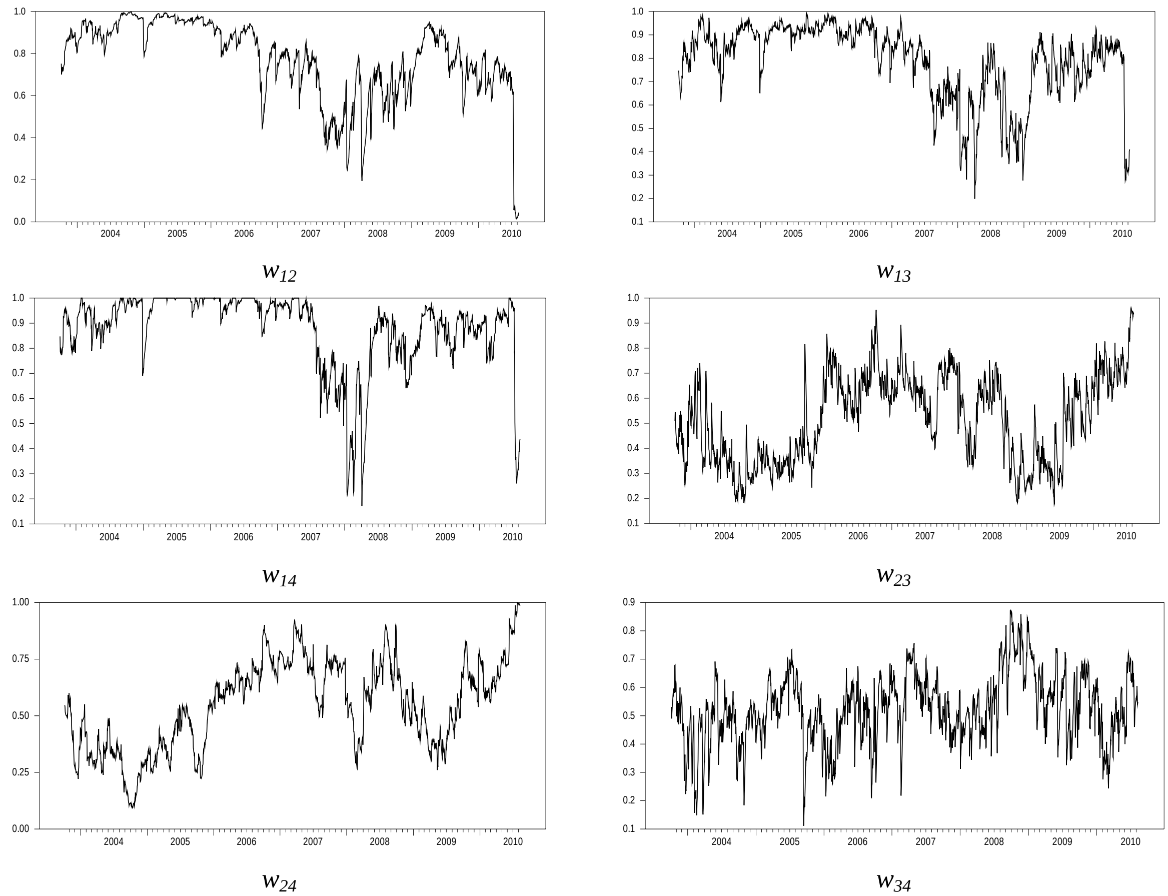

Figure 2: Time-Varying Optimal Weights (1 = Wheat, 2 = Cotton, 3 = Sugar, 4 = Corn)

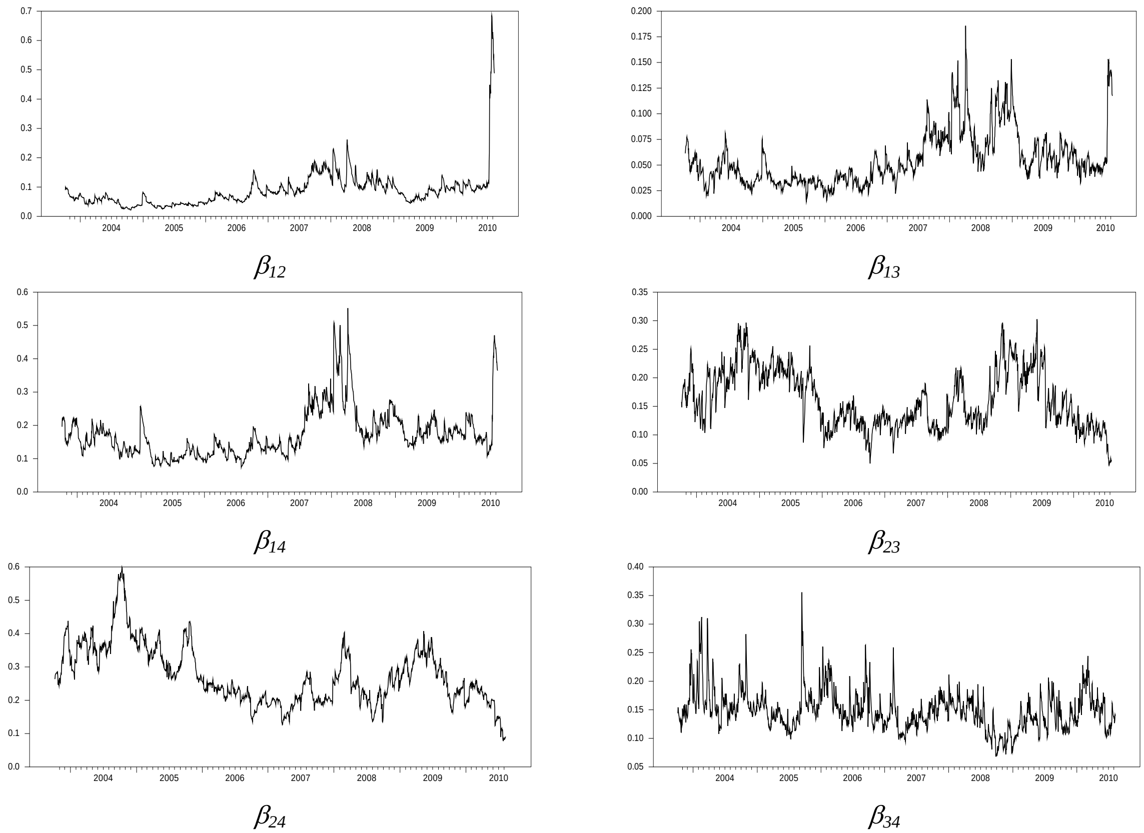

Figure 3: Time-Varying Hedge Ratios (1 = Wheat, 2 = Cotton, 3 = Sugar, 4 = Corn)

5. CONCLUSION

In this article, we employ a four-variable VAR(1)-GARCH(1,1) model to investigate the return and volatility spillovers among the four major agricultural commodities. Our results reveal three important facts: *i*) agricultural commodities have different degrees of sensitivity to past own shock and volatility; *ii*) there is evidence of significant return and volatility transmission across considered commodities; and *iii*) the conditional volatility of corn has an important explanatory power on the volatility of the other commodities. Our findings finally show that optimal portfolios and effective hedging strategies can be carried out to minimize the risk of agricultural commodity portfolios.

AUTHOR INFORMATION

Amine Lahiani, University of Orléans & ESC Rennes Business School, France. E-mail: amine.lahiani@univ-orleans.fr

Duc Khuong Nguyen, IPAG Business School, France. E-mail: duc.nguyen@ipag.fr (Corresponding author)

Thierry Vo, ESCP Europe Business School & University Paris 1 Panthéon-Sorbonne, France. E-mail: thierrylam.vo@gmail.com

REFERENCES

1. Arouri, M., Jouini, J., Nguyen, D.K., 2011. Volatility Spillovers between Oil Prices and Stock Sector Returns: Implications for Portfolio Management. *Journal of International Money and Finance, 30*, 1387-1405.

2. Chatrath, A., Adrangi, B., Dhanda, K.K. (2002). Are Commodity Prices Chaotic? *Agricultural Economics*, *27*, 123–137.
3. Creti, A., Joëts, M., Mignon, V., 2013. On the Links between Stock and Commodity Markets' Volatility. *Energy Economics*, *37*, 16-28.
4. Dahl, C.M., Iglesias, E.M., 2009. Volatility Spill-overs in Commodity Spot Prices: New Empirical Results, *Economic Modelling*, *26*, 601-607.
5. Du, X., Yu, C.L., Hayes, D.J., 2011. Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis. *Energy Economics*, *33*, 497-503.
6. Engle, R.F., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*, 987–1007.
7. Hassan, H., Malik, F., 2007. Multivariate GARCH Model of Sector Volatility Transmission. *Quarterly Review of Economics and Finance*, *47*, 470–480.
8. Hammoudeh, S., Yuan, Y., McAleer, M., 2009. Shock and volatility spillovers among equity sectors of the Gulf Arab stock markets. *Quarterly Review of Economics and Finance*, *49*, 829-842.
9. Kroner, K.F., Ng, V.K., 1998. Modeling Asymmetric Movements of Asset Prices. *Review of Financial Studies*, *11*, 844–871.
10. Kroner, K.F., Sultan, J., 1993. Time-varying Distributions and Dynamic Hedging with Foreign Currency Futures. *Journal of Financial and Quantitative Analysis*, *28*, 535–551.
11. Ling, S., McAleer, M., 2003. Asymptotic Theory for a Vector ARMA-GARCH Model. *Econometric Theory*, *19*, 278–308.
12. Malliaris, A.G., Urrutia, J.L. (1996). Linkages between Agricultural Commodity Futures Contracts. *Journal of Futures Markets*, *16*(5), 595-609.
13. Mensi, W., Beljid, M., Boubaker, A., Managi, S., 2013. Correlations and Volatility Spillovers across Commodity and Stock Markets: Linking Energies, Food, and Gold. *Economic Modelling*, *32*, 15-22.
14. Nazlioglu, S., Erdem, C., Soytas, U., 2013. Volatility Spillover between Oil and Agricultural Commodity Markets. *Energy Economics*, *36*, 658-665.
15. Serra, T., 2011. Volatility Spillovers between Food and Energy Markets: a Semiparametric Approach. *Energy Economics*, *33*, 1155–1164.

