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Contents

Do future markets protect the spot markets in developing countries? The case of the Egyptian wheat market

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Abstract

Egypt is considered a net wheat importer, with the Egyptian market being vulnerable to future wheat markets because of the effect future market price discovery can have on the stability of spot prices. This study assesses the relationship between Egyptian wheat spot prices and future wheat prices in Paris (MATIF) and USA (CBOT). Markov switching-vector error correction methods are used to estimate two regimes by splitting the sample into high and low volatility regimes. This study also examines the dynamic conditional correlation between the prices considered using the asymmetric DCC-GARCH. Results suggest a high volatility regime observed, especially during the extreme market events of the food crisis in 2007-08 and 2010 and following the two revolutions in Egypt in 2011 and 2013 and the time of the economic reform in 2016. This leads to an unstable market and negative impacts on consumers' welfare and food affordability, meaning that futures markets failed to hedge spot wheat market against price volatility. In addition, results from impulse response functions indicate that a 1% shock in futures markets will lead to a positive shock in the wheat spot market, while for the low volatility regime no significant effect.

Keywords: *Future-spot markets, Food price volatility, Markov switching, Vector error correction, DCC-GARCH.*

1. Introduction

Egypt has been suffering from food insecurity for a long time because of natural resources scarcity, economic instability, political upheaval and an excessive reliance on food imports. After the food price crisis of 2007-08 and a second wave of the crisis in 2010, basic food commodity prices, particularly in developing countries, have increased and been negatively affected by global price volatility. These food price hikes have caused social unrest and a series of revolutions in the Middle East; the so-called Arab Spring began with Tunisia, Egypt, Syria, Libya and Yemen (Ciezadlo, 2011; Bellemare, 2015).

Despite this social outcry, the prevailing economic situation in Egypt is characterized by high food and energy prices, high unemployment rates, unfair wage structures, and a low exchange rate. The GDP growth rates decreased from 5.1% in 2010 to 3.6% in 2017, while inflation measured through the consumer price index grew by 29.8% in 2017 and the unemployment rate remains consistently high at 12.5% (Central Bank in Egypt, 2017). Naturally, the rising unemployment rate worsened the poverty rate,

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which increased from 21.6% in 2009 to 27.8% in 2017, while food insecurity rates increased from 14% of the Egyptian population in 2009 to 16% (15.9 million people) in 2017 (World Food Program, 2019). In 2013, more than 80% of the Egyptian population did not receive enough income to cover consumption needs, and more than 65% of this insufficient income was spent on food, especially wheat (Egyptian Food Observatory, 2013). Inflation measured through the consumer price index increased from 9.1% in January 2015 to 21.9% in December 2017 (Central Bank in Egypt, 2018). Consumers in Egypt have used different strategies to cope with the increasing food prices, such as consuming cheaper food with lower nutrients, reducing their food intake and buying food with credit (Egyptian Food Observatory, 2013). This economic downturn led to structural problems in the functioning of the Egyptian food market. As in Egypt, after the global food crisis and successive crisis, the food markets of these countries suffered evident price distortion, especially for wheat, which was significantly affected by the price volatility.

The economic situation became worse after 2016 with the U.S. dollar appreciated relative to the Egyptian pound by over 100%. This drop hit especially hard in a country that depends significantly on the international market to meet local food demand, making this market specifically vulnerable to food price volatility in international markets. These rising food prices erode consumer purchasing power, exacerbate food security problems and increase the poverty rate. Through the futures market, farmers, traders, and hedgers can protect themselves against market risk and price volatility by looking to lock in delivery prices before making a decision (Wu *et al.*, 2018). The future market was firstly blamed that not protected the developed and less developed countries against food price volatility since the main function of this market is to hedge spot prices against fluctuation (Shawky *et al.*, 2003; Wu *et al.*, 2018; Ahmed, 2021).

The concept of food price volatility is closely related to that of food security. According to the FAO *et al.* (2015), there are food security pillars: food availability, economic and physical access to food, food utilization, and stability over time (vulnerability and shocks). Food price shocks may hit poor countries especially hard and increase the population living below the poverty line, which exacerbates economic instability and political upheaval. Since Egypt is dependent on wheat imports, the Egyptian market is vulnerable to international wheat shocks, which hinders the country's economic access to food. Unaffordability leads to poor access to food, which can lead to nutritional damage, particularly among children. A study by Robles and Torero (2010) found evidence that, following the 2007-08 food crisis, greater reductions in calorie intake were present due to increased food prices. A study by Iannotti and Robles (2011) assessed the negative impact of energy intake associated with food price shocks in Latin America during the 2006 to 2008 period. They confirmed that increases in the prices of basic foods commodities (rice, wheat and maize) negatively affected energy intake, especially for poorer households. Arndt *et al.* (2016) assess the relationship between increases in food prices and child nutrition in Mozambique over the 2008 to 2009 period. They found evidence that increased food prices led to decreased nutritional intake and the prevalence of being underweight, particularly among children. Ivanic and Martin (2008) studied the impact of food crises on household welfare in developing countries of Africa, Latin America and South Asia. Research results indicate that increased food prices lead to more poverty and reduced household welfare. An article by de Brauw (2011) found evidence that a 15% growth in food price inflation in El Salvador resulted in lowered height- for-age among children of the researched households.

Various studies have suggested many causes that may be underlying the recent volatility of food prices around the world. Jacks and Stuermer (2016) conducted a study on the drivers of commodity price booms and busts. They found evidence that commodity demand shocks transmitted into price variability more strongly than commodity supply shocks. Carter *et al.* (2011) investigated the frequency of dramatic commodity booms and busts after the Korean War, specifically, two peaked happened in 1974 and 2008, with their results indicating that supply and demand shocks that coincide with low inventories led to price booms. Roberts and Schlenker (2010) found that 30% of the rise in prices for staple food commodities was due to excess biofuel demand in 2007-08. In 2013, the same researchers analyzed the supply elasticity based on the assumption that past food commodity yield stocks negatively affect inventory levels and futures prices. They found that 20% of the increased prices for staple foods were a result of using one-third of food commodities to produce ethanol.

Using different econometrics techniques, many empirical analyses have studied the causes of food price volatility for crisis periods specifically. Most of these studies found strong evidence that the energy market leads to volatility in agricultural markets (e.g. Du *et al.*, 2009; Meyers and Meyer, 2008; Balcombe and Rapsomanikis, 2008; Serra *et al.*, 2008; De Gorter and Just, 2008). The work by Busse *et al.* (2011) studied the emerging linkages between price volatilities in energy and agricultural in EU market. They assess the price volatility development in food commodities by focusing on the price behavior of rapeseed futures prices, crude oil and related agricultural commodities during the period of the 2006-08 food crisis. Using the dynamic Autoregressive Conditional Heteroskedasticity (GARCH) model, they found evidence for a positive correlation between rapeseed future prices and crude oil prices during the time of the food crisis, which continued to increase afterwards. Furthermore, the crude oil prices showed higher volatility levels than the agricultural commodity prices. Also, the crude oil prices led to volatility in agricultural markets, implying that farmers and consumers will continue to face uncertainty of agricultural prices in the future.

The work by Kakhki *et al.*, 2019 studied the price fluctuation of barley in the Iran Mercantile Exchange, Iran‘s domestic free market, and the World Market. By using the BEKK-GARCH model and they found evidence that the shocks and volatility of the world and Iran free-market are passed to the Iran Mercantile Exchange. Cinar(2018) has also applied the BEKK- GARCH model to study the volatility transmission across the prices of corn, wheat, and barley in the Turkish market. Results indicate that there is a volatility spillover from the corn and barley market to the wheat market. Cinar and Keskin (2018) have analyzed the spillover effect on prices of imported energy and soybean that are widely used to determine broiler prices in the Turkish market. They have used the Vector Error Correction Model (VECM). They have found evidence that increases in energy and soybean prices lead to increases in broiler prices.

The study by Wright (2014) found evidence that, after the fall of 2006, the volatility of futures prices for most of the major crops has been dramatically increased with increases in food prices. The strong evidence of the co-movement between futures and spot prices has been found by Fattouh *et al.* (2013) that interpreted by the common economic fundamentals between the future and cash prices. Research carried out by Prakash and Gilbert (2011) implies that the magnitude of futures markets traders' positions in agricultural commodity markets has considerably increased, which has raised concerns with respect to increased food price volatility due to various factors, such as changes in supply and demand fundamentals, rising expectations and speculation (Baldi *et al.*, 2011). The work by Adjemian *et al.* (2013) studied the non-convergence of the futures and spot prices causes in the grain market (corn, soybeans, and wheat) in the U.S. during the period from 2005-2010. Results imply that the futures prices are settled higher than the cash prices in delivery markets. This reflecting the non-convergence of the futures and spot prices, which is leading to concerns the hedgers, traders, farmers, and policymaker that resulting in less hedging effectiveness and market risks.

The study by Chen *et al.* (2016) to assess the relationship between spot and futures oil prices. They examined the impact of structural breaks on cointegrating relationships, market efficiency under the expectation hypothesis and the no-arbitrage rule, causalities, and forecasting performance of futures oil volatility. Results indicate that the structural break, that detected by authors, endogenously resulting in an influence on these four critical issues.

There are several studies found evidence that future markets lead to stabilizing spot prices in developed countries, and makes the food markets working efficiently (Dower and Anderson, 1977; Danthine, 1978; Streit, 1980; Gupta and Mayer, 1981; Theissen, 2012; Kim and Lim, 2019), while this study explores the efficiency of future markets in food commodities in Egypt as one of the developing countries.

A study by Hull (1997) assessed the linkage between futures and spot prices, finding that futures and spot prices move together in the long-run. There are many other studies that have studied the relationship between futures and spot prices (e.g. Baklaci and Tutek, 2006; Baldi *et al.*, 2011; Giot, 2003; Garcia and Leuthold, 2004; Hernandez and Torero, 2010). Studies on the causal relationship between futures and spot prices have found evidence for relationships between futures and spot prices because of price discovery in the futures market and the flow of information available on the spot prices, indicating that futures prices lead the spot prices (Brooks *et al.*, 2001; Yang *et al.*, 2001). Other studies, on the other hand, have found evidence that spot prices lead the futures prices (Kuiper *et al.*, 2002; Mohan and Love, 2004). The link between futures and spot prices at different levels has been examined by Hernandez and Torero (2010), Baldi *et al.* (2011) and Sendhil and Ramasundaram (2014). Wu *et al.* (2018) studied asymmetric price transmission between futures and spot prices in the grain markets. They found evidence that there is asymmetric price transmission between futures and spot prices in the grain markets. The corn spot price is likely to be adjusted more quickly to prices increases in the futures market than the prices decreases. In contrast, the soybean market adjusts more quickly to futures price decreases than price increases. The study by Adämmer and Bohl (2016) to assess the impact of food futures contracts in Europe on food prices. They have used future and spot and futures prices for canola, wheat, and corn for their analysis. Results indicate that the influence of the futures price on the spot prices is higher in the period of the first food crisis from 2007 to 2009 and in the second wave of the food crisis from 2010 to 2013. While this influence has vanished during higher trade activity in futures markets.

Some empirical analyses have addressed the volatility impact of futures markets on spot prices using the GARCH model (Yilgor and Mebounou, 2016; Baklaci and Tutek, 2006; Bohl and Stephan, 2013; Bozic and Fortenbery, 2015).

Worldwide, Egypt is considered a net importer of grain and top importer of wheat, with most of its wheat imported from former Soviet Union countries, the USA and France. Wheat is the most commonly consumed grain in Egypt and the key to household economies in rural areas, since most Egyptian farming households are net buyers of wheat on top of their own production in order to meet their consumption needs. Hence, the impacts of wheat price spikes on poor households are particularly impactful. Bread is the largest food staple and plays a central dietary role among Egypt's population of more than 100 million people. Egyptians call bread "Aish baladi": Baladi means traditional or authentic in English, while the word "Aish" means life, indicating the importance of bread in Egyptian heritage. Bread is considered a commodity that Egyptians cannot live without in their daily diet.

Egyptian wheat prices reflect price discovery information occurring in wheat future markets. For this purpose, this research article contributes to the literature by assessing the link between futures and spot prices in the Egyptian wheat market. To date, many other studies have focused on US and EU markets. In addition, we investigate whether the futures markets facilitating the transmission of information to the spot market reduces market failures and the effectiveness of market performance. Moreover, we examine whether the futures market reduces, increases or stabilizes spot price volatility by using two different methods: the Markov-Switching Vector Error Correction Model (VECM) and the asymmetric DCC-GARCH model.

This paper is organized as follows: in the following section, we provide a brief description of the wheat market in Egypt. In section three, the methodological approach is described. The fourth section is devoted to the empirical analysis implemented to assess the relationship and the continual volatility correlation between futures and spot prices in the Egyptian wheat market. The last section of this article offers concluding remarks and policyrecommendations.

2. An overview of Egypt's wheat market and policy implications

Bread is considered a necessary staple in the daily meals of Egyptians. Egyptian bread is mainly produced with wheat, making Egypt dependent on wheat imports amounting to around 12.5 million metric tons (MMT) in 2018 represent 20% of all agricultural imports, which is expected to increase by 0.8% in 2019. Egypt is considered the biggest wheat importer in the world, and wheat is the largest grain imported by Egypt. Wheat represents the largest food staple for the Egyptian's population of more than 100 million people. It is also the largest grain crop produced in the country, representing 10% of the total agricultural production value in 2017 (FAOSTAT 2017).

According to USDA-FAS (2019) report, 28 import tenders for 6.64 million metric tons (MMT) of wheat in the 2017-18 marketing year were issued by The General Authority for Supply Commodities (GASC) compared to

5.85 MMT in the previous year. The most of the wheat were imported from Russia, Romania, Ukraine and France (5.2 MMT, 1.06 MMT, 355,000 MT, and 60,000 MT, respectively). During the 2018-19 marketing year, GASC purchased 8% more when compared to the year before, and the largest wheat exporters to Egypt were Russia, Romania, Ukraine, France, and the United States in amounts of 3.9 MMT, 960,000 MT, 480,000 MT, and 300,000 MT, respectively.

Wheat is extremely important for African economies, which devoted 10.4 million hectares to produce 27.2 million tons in 2017, roughly a quarter of the cereals produced in Africa (FAOSTAT, 2017). Wheat is the most commonly grown grain in Egypt, which is Africa's largest wheat-producing country. Jointly, Egypt, Morocco, Algeria and Tunisia represent 71.5% of the total African wheat production (FAOSTAT, 2017). In 2018, Egypt's wheat consumption was 20.1 MMT, which increased by 1.6% compared to the previous year as demand for this commodity for both household and industrial consumption, as well as animal feed, rose. With the population growing at 2.4% per annum, wheat consumption is expected to continue increasing by 1.5% in 2019 (USDA-FAS, 2019). The Egyptian government allocates annually 4.8 billion USD to its bread and food subsidies program. However, this subsidized system is working inefficiently and enabling bakeries and grocery stores to resell subsidized bread on the black market, leading to price distortions between the free and subsidized markets.

There are 450 private, public and public-private mills in Egypt. The milling capacity of both the public and public-private mills ranges from 50,000-55,000 metric tons per day, while the milling capacity of private mills is 20,000 metric tons per day. 81 of the public mills and 75 private mills produce 82% high extraction wheat for subsidized baladi bread production. The private sector mills produce 72% extraction wheat that's sold to around 20,000 private bakeries. They could stop producing this kind of wheat and instead make 82% extraction wheat if they had government contracts to produce subsidized baladi bread. Wheat is a very sensitive product for the Egyptian policy, with more than 40% of the population living under the poverty line, guaranteeing availability and access to food with low prices is rather challenging for the Egyptian government that to assure the food security for those people, meaning that wheat policy is one of the highest priorities for the Egyptian government.

Farmers have two outlets to sell their wheat. The first is to sell their wheat to the government, which was an attractive option to farmers because they received support prices that were 50% higher than international prices. However, after the economic reform in 2016[1], the government decided to decrease the subsidy to just 5% more than international prices. The second is to sell to private traders at the farm gate. Farm-

[1] In 2016, Egyptian government has requested a loan from the World Bank at a low interest rate to support the transformational economic reform agenda of the government. To qualify for this loan the World Bank has asked for the reduction of subsidies on fuel and food.

ers do not sell all their production; they keep part of it for the next season's seeding, feed and personal consumption (USDA-FAS, 2014). Before 2018, the Egyptian government was receiving the wheat the farmers with subsidized prices and deliver it to the bakery to sell bread to poor consumers at subsidized prices with 5 piasters while it cost more than 25 piasters. In 2018, the Egyptian government decided to extremely reduce the number of beneficiaries of its food subsidy program, adding complex criteria regarding who can receive the food subsidy (USDA-FAS, 2019). As a result, most poor consumers in Egypt suffer from increased food prices particularly wheat. Moreover, the wheat value chain in Egypt, is also still in need of better mechanisms to increase performance and production efficiency (USDA-FAS, 2019).

Subsidized wheat has been supplied to farmers and end consumers in Egypt countries for many years. Nevertheless, the governments have decided to lift subsidies as mentioned above. Thus both farmers and consumers have become exposed to international wheat price developments. Given the experience with serious harvest shortfalls in the Black Sea region and skyrocketing world market prices, budget constraints and repeated wheat export restrictions by the Black Sea exporters, the Egyptian government should intervene to increase grain self-sufficiency by boosting the development of the domestic grain sector. Besides large wheat import dependency, still, large amounts of wheat are stored in jute bags in open fields, with storage losses adding up to more than 15%. In addition, the frequent fumigation to control insects may reduce farmers' income and increases consumers' expenses, as wheat losses during storage may translate into lost income for farmers and higher food end consumer prices (Abouhussein and Sawan, 2010). Egypt generates large amounts of lignocellulosic waste annually. For example, agricultural waste in Egypt amounts to around 33.5 million tons annually with a wheat straw of 6.9 million tons the most abundant residue, while the farmers can use these by-products as inputs (e.g. fertilizers) to reduce the farmer's cost and improve the wheat productivity.

3. Methodology

This paper studies the price linkages, which requires knowledge of the joint distribution of the prices considered. The Markov Switching Vector Error Correction (MS-VEC) model and asymmetric DCC-GARCH model have been used for this purpose. Many empirical analyses have studied the links between two or more variables using regime shift approaches, having found evidence that ignoring structural breaks when using econometric applications can lead to biased estimation (Perron, 2006; Hansen, 2009). Following Balcilar *et al.* (2015), the nonlinear MS-VEC time-varying model has been used in this study to assess the links between two pairs of prices: futures wheat prices in the US–Egyptian wheat spot prices (*CBOT*, *spot*) and futures wheat prices in France–Egyptian wheat spot prices (*MATIF*, *spot*).

The MS-VEC model is widely used to assess dependence between prices to characterize non-stationary and co-integrated data and inform on both their short and long-run dynamics. The Markov Switching (MS) models were introduced in the literature by Hamilton (1990) as nonlinear time-series models using univariate Markov switching autoregressive models. MS models were developed and extended to multivariate MS-VAR and MS- VEC models by Krolzig (1997, 1999). Several studies have addressed structural breaks using MS-VEC models toassess how prices are transmitted (Brümmer *et al.*, 2009; Rezitis *et al.*, 2013; Busse *et al.*, 2012; Ihle and von Cramon-Taubadel, 2008). This paper contributes to the literature by examining the dependence between prices using a MS-VEC model to capture the co-integration efficiently with time-varying that reflects regime switching. This model has the structure to assess permitted asymmetric inference for impulse response function (IRF). Our research uses the MS-VEC model based on the Bayesian Monte Carlo Markov Chain (MCMC) method and estimates the IRF by relying on the regime-dependent IRFs (RDIRF) approach (Balcilar *et al.*, 2015).

By focusing on modeling bivariate distributions, let F_{xt} and F_{yt} be the bivariate distribution functions of 2 random variables (x, y) with the time series vector X_t and $_t \in \{1,2, \dots . T\}$ that represent the time period, which can be captured as follows: $X_t = [F_{xt}, F_{yt}]¢$. And let

$$\Im_t = \{X_\tau | \tau = t, t-1, 1-p\},$$

where p is a nonnegative integer. According to Balcilar *et al.* (2015), there exists a probability density function that can be expressed as

$f(X_t | \Im_t, \theta) F_{xt}$ where θ is the parameters, and $\theta_0 \in \Theta$, which refers the true value of θ where Θ is the parameter space. The MS-VEC model can be defined as:

$$\Delta X_t = \mu_{S_t} + \sum_{k=1}^{p-1} G_s^{(k)}{}_t \Delta X_{t-1} + \Pi_{S_t} X_{t-1} + \varepsilon_t, \quad t = 1,2, \dots, T \tag{1}$$

Where $S_t \in \{1,2, \dots, q\}$ and S_t is the stochastic variable or regime variable with q, as the Markov process states. P is the order of the MS-VAR model, $\{X\tau | \tau = t, t-1, 1-p\}$; ε_t is the error term. According to the Markov process, the regime variable follows a q, with a transition probability matrix that can be formalized as follows:

$$P = \begin{bmatrix} P_{11} & P_{12} \cdots & P_{1q} \\ \vdots & \vdots & \vdots \\ P_{q1} & P_{q2} \cdots & P_{qq} \end{bmatrix}, \tag{2}$$
$$\sum_{j=1}^{q} P_{ij} = 1 \; for \; i, j = \{1,2, \dots, q\}$$

Where P_{ij} is the probability of the regime j and i at time t and $t-1$, respectively. The unique feature of this model is that all parameters considered in the analyses depend on the regime variable S_t.

The long-run relationship between the variables can be described as follows:

$$\prod s_t = \alpha_{St} \; \beta', \tag{3}$$

Where $\prod s_t$ is the matrix capturing long-run relationships between the variables expressed in equation (1), which can indicate switching in three different ways: switching the in the regime dependent adjustment weighting matrix ($\boldsymbol{\alpha}$), the long-run independent co-integrating vector (β') or both. In this regard, the biggest advantage of the MS- VEC model described in equations (1) to (3) is the speed at which variables considered are adjusted to the long-run equilibrium varied cross breaks. The macroeconomic time series characterized by the extreme events (crisis time) and crisis-recovery (Balcilar *et al.*, 2015; Durland and McCurdy, 1994; Diebold *et al.*, 1994; Kim and Yoo, 1995; Filardo and Gordon, 1998). For this purpose, our analysis relies on two regime models that divided the series into high and low regimes depending on the spot's and future's prices variance-covariance matrix that analyze the short-term time-varying interactions of the prices considered and assesses the response to disequilibrium from this parity.

Our paper contributes to the literature by examining the regime-switching behavior of the price series using a dynamic MS-VEC model. A key advantage intrinsic to this model is that it can study the dynamic interactions between two or more variables over the full sample at unknown periods based on the parameter switches in the time series. Also, this model can estimate probabilistic inferences about the time breaks that can happen during extreme market events (regime occurs) and determine the dates of the regime changes. This model can be applied to assess the regime dependence impulse response functions (IRF).

The MS-VEC model can be estimated through a two stage estimation process. The first stage consists of estimating Johansen's procedure (1988, 1991) to determine the number of co-integration analyses that could drive the equilibrium errors $z_t = X_{t-1}\beta'$. The MS-VEC is estimated in a second stage, either through a maximum likelihood (ML), expectation maximization (EM) or Bayesian MCMC parameter estimation based on the Gibbs sampling methods. We use the latter, which consists of drawing the regimes given the model parameters and transition probabilities[2]. The IRFs of the MS-VEC model have been used to study how a given shock in one variable could be transmitted to another variable in the model over the time period.

Our analysis relies on regime-dependent IRFs (RDIRF) that can determine the response of the variable to a certain shock over the time variation. The RDIRF function can be expressed as:

$$\theta_{ki,h} = \left(\frac{\P E_t X_{t+h}}{\P u_{k,t}} \middle| s_t = \cdots s_{t+h} = i \right) \quad \text{for } h \geq 0 \tag{4}$$

[2] For more details, please see Balcilar et al. (2015) and Fruehwirth-Schnatter (2006).

Where $\theta_{ki,h}$ is the k-dimensional response vector which predicts the response of endogenous variables at time $t+h$ after one standard deviation shock and $h = 1,2, \ldots, H$ is the propagation of the shocks with $k-th$ initial disturbance at time t, conditioned on regime i. $u_{k,t}$ represents the structural shock to the $k-th$ (Balcilar *et al.*, 2015; Ehrmann *et al.*, 2003).

Following Balcilar *et al.* (2015), we combine the MCMC integration with the RDIRF analysis to study the dynamic response of the shocks occurring during extreme market events or crises-recovery periods. We also make this combination to investigate the prediction of future prices considered in our analyses by using the simulations of the artificial histories for the variables[3] after determining the structural shocks by using a Gibbs sampler, through which we can obtain the RDIRFS posteriors. The standard deviation confidence bands have been estimated using MCMC integration with Gibbs sampling of 50,000 posteriors with a burn-in of 20,000.

Time-varying and clustering volatility, another common characteristic of time-series, is typically modeled through generalized autoregressive conditional heteroskedasticity (GARCH) models. In this study, we apply Asymmetric-DCC GARCH models.

This analysis uses Asymmetric-Dynamic Conditional Correlation with Multivariate Generalized Autoregressive Conditional Heteroscedasticity (ADCC-GARCH) techniques to characterize the time-varying conditional correlation, which allows the parameters to change with changing environments across time. An ADCC-GARCH model can be estimated through a two stage estimation processes. The first stage consists of estimating marginal models that filter information contained in univariate distributions, enabling standardized, independent and identically distributed ($i.\ i.\ d$) residuals to be derived; we have used an ARMA model for this purpose. The ADCC-GARCH were estimated in the second stage. The maximum likelihood method has been applied on the uniform residuals to estimate the ADCC-GARCH. Since the theory of ADCC-GARCH applies to stationary time-series, tests for unit roots are run on considered data. Results support the presence of a unit root in all series used in the analysis. Univariate ARMA (p_a, q_a) marginal models capture univariate first difference of logged price patterns with p_a representing the number of autoregressive parameters of the ARMA model; q_a is the number of moving average components.

Following Gardebroek and Hernandez (2013), we applied this model:

$$r_{it} = \gamma_0 + \sum_{j=1}^{p} \gamma_j \, r_{it} + \varepsilon_{it}, \qquad (5)$$

$$\varepsilon_{it} = \sqrt{H_{it}} \cdot \varphi_i, \text{ with } \varepsilon_{it} \sim N(0, H_t) \text{ and } \varphi_i \sim N(0, I) \qquad (6)$$

Where r_{it} is the 4 × 1 stochastic vector of price returns for WH, WOP, WWP, and EXCH; γ_0 is a 4 × 1 vector of long –term drifts; γ_j is the 4 × 4 parameters matrices with j= 1,.., p; and ε_{it} is a 4 × 1 vector of ordinary residuals. H_{it} is a $N \times N$ corresponding variance covariance matrix and φ_i the standardized residuals. The conditional variance-covariance matrix H_t for the DCC model could be defined as follows:

$$H_t = D_t R_t D_t \qquad (7)$$

Where R_t is a time-dependent conditional correlation matrix, $D_t = diag\,(h_{11,t}^{\frac{1}{2}} \ldots \ldots h_{NN,t}^{\frac{1}{2}})$ and $h_{NN,t}$ is a conditional variance GARCH (1,1) that could be specified as:

$$h_{NN,t} = \omega_i + \alpha_i \, \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}, \; i = 1, \ldots \ldots, 4.$$

The dynamic conditional variance can be defined as:

$$Q_t = (1 - \alpha - \beta)\,\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \qquad (8)$$

Where Q_t is the 4 × 4 symmetric unconditional variance matrix between the series, α and β are the non-negative adjustment parameters satisfying $\alpha + \beta < 1$; these parameters are estimated using an autoregressive moving average model (ARMA). $\bar{Q}$ is the 4 x 4 unconditional covariance between the u_t, and $u_{it} = \epsilon_{it}/\sqrt{h_{iiiiit}}$.

[3] The artificial histories could be estimated by using the estimated value instead of parameters used in the model, and then we can calculate the variance covariance matrix to obtain the residuals, lastly we can estimate the endogenous variables.

The dynamic conditional correlation can be expressed as:

$$R_t = diag(Q_{ii,t}^{-1/2})\, Q_t diag(Q_{ii,t}^{-1/2}) \quad (9)$$

According to Engle (2002), the DCC model is estimated through maximizing the log-likelihood for the dynamic conditional variance, as follows:

$$L(\alpha,\beta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(2ln|D_t| + \varepsilon_t' (D_t D_t)\varepsilon_t) - \frac{1}{2}\sum_{t=1}^{T}(ln|R_t| + \varepsilon_t' (R_t^{-1})\varepsilon_t) \quad (10)$$

To capture the maximization of the dependency changes over time, we maximize the value in the previous equation, as shown in the equation below:

$$L(\alpha,\beta) = -\frac{1}{2}\sum_{t=1}^{T}(2.\,ln|R_t| + \varepsilon_t' (R_t^{-1})\varepsilon_t) \quad (11)$$

The limitation of the symmetric dynamic conditional correlation is that this approach does not respond to positive and negative price shocks (Cappiello *et al.*, 2006). Most of the food price research to-date has found evidence that price time series may be asymmetric to reflect market shocks. Thus, estimating the DCC-GARCH model ignoring the asymmetric effect could lead to inaccurate results.

Evidence of asymmetries within the food and energy marketing chain is abundant. These asymmetries tend to be more pronounced as we move to extreme tails of the distribution (i.e., when price increases or declines are larger), which we capture through ADCC as proposed by Cappiello *et al.* (2006). This allows for asymmetric dynamic conditional correlation in any direction and nests symmetry as a special case. The ADCC is an extension of the dynamic conditional variance, which can be specified as:

$$Q_t = (1-\alpha-\beta)\bar{Q} - g.\bar{\Psi}_t + \alpha u_{t-1}\acute{u}_{t-1} + \beta Q_{t-1} + g.(\xi_{t-1}\,\xi_{t-1}') \quad (12)$$

Where $\bar{\Psi}_t = E\,[\overline{\xi_{t-1}\,\xi_{t-1}'}]$ and $\overline{\xi_{t-1}} = (I\,[\overline{u_t} < 0]o\;\overline{u_t})$ implies the element by element Hadamard product (o), and g - denotes the asymmetric term. Thus, if $g = 0$, $[\alpha_{ij}] = [\sqrt{\alpha}]$, $[\beta_{ij}] = [\sqrt{\beta}]$, the model tends to be symmetric DCC, while if $[g_{ij}] = [\sqrt{g}]$, $[\alpha_{ij}] = [\sqrt{\alpha}]$, $[\beta_{ij}] = [\sqrt{\beta}]$, the model tends to be ADCC. G expresses periods where both series experience negative shocks (bad news) and $[\xi_{t-1}\,\xi_{t-1}'] = I_t$.

4. Empirical analysis

The empirical application aims to examine the relationship between nominal domestic prices of wheatin the Egyptian market and futures prices associated with Chicago, USA (CBOT) and Paris, France (MATIF). The Egyptian market mainly imports either soft wheat or milling wheat; for this purpose we have selected a CBOT-traded soft red winter wheat and an MATIF-traded milling wheat. The analysis is based on monthly price series and expressed in US dollar per ton observed from January 1998 to December 2017, yielding a total of 240 observations. The futures prices were obtained from the Agriculture and Horticulture Development Board (AHDB) (https://cereals-data.ahdb.org.uk/archive/), while the Egyptian wheat spot prices (farm gate prices) were obtained from the Central Agency for Public Mobilization and Statistics (CAPMAS) (https://www.capmas.gov.eg/HomePage.aspx).

Prices are expressed in U.S. dollars per ton and studied in pairs. The period of analysis is of interest because it includes the first and second wave of the food crises in 2007-08 and 2010, the Egyptian revolutions in 2011 and 2013 and the time of the economic reform in 2016. Thus, this period is likely to reflect the impacts of political and economic instability. The summary statistics for the first differenced logged price series illustrate evidence of a non-normal price series characterized by skewness, kurtosis and ARCH effects. Standard unit root tests were carried out, indicating that the series are non-stationary and contain unit roots; for this reason, we havetaken the first difference of the price series before estimating ARMA and ADCC-GARCH models.[4]

The Johansen (1988, 1991) and Stock-Waston (1988) cointegration tests were conducted to assess the existence of an equilibrium relationship between the pairs of prices studied. Test results suggest that there is a long-run relationship be-

[4] Details from summary statistics and unit root testing are available from the authors upon request.

Table 1 - Johansen λ_{trace} test and Stock-Watson for co-integration and co-integration relationship.

Johansen co-integration tests for (EGYPT - CBOT)					
Cointegration Vector					
H_0	H_a	Eigenvalues	λ_{max}	$P - Value$	Trace 95%
$r = 0$	$r > 0$	0.056	13.794	0.024	15.410
$r \leq 1$	$r > 1$	0.013	3.264***	0.312**	3.840
Cointegration equation					
Egypt − 0. 439** CBOT − 4. 043** = ECT (-3.167) (-7.441)					

Stock-Watson co-integration tests for (EGYPT - CBOT)				
H_0: $q(k, k - r)$	Statistic	Critical values		
		1%	2%	3%
$q(2, 0)$	-10.752***	-3.960	-3.410	-3.120
$q(2, 1)$	-10.774***	-3.960	-3.410	-3.120

Johansen co-integration tests for (EGYPT - MATIF)					
Cointegration Vector					
H_0	H_a	Eigenvalues	λ_{max}	$P - Value$	Trace 95%
$r = 0$	$r > 0$	0.082	20.321	0.005	15.410
$r \leq 1$	$r > 1$	0.014	3.328**	0.145**	3.840
Cointegration equation					
Egypt − 0. 634** CBOT − 2.628** = ECT (-4.364) (-3.661)					

Stock-Watson co-integration tests for (EGYPT - MATIF)					
H_0: $q(k, k - r)$		Statistic	Critical values		
			1%	2%	3%
$q(2, 0)$		-10.705***	-3.960	-3.410	-3.120
$q(2, 1)$		-10.728***	-3.960	-3.410	-3.120

*Note: r is the cointegration rank. ** denotes statistical significance at the 5% level.*

tween spot prices and futures markets (Table 1). Linear VEC and MS-VEC models with two lags are fit to spot and futures prices. Using the Bayesian Monte Carlo Markov Chain (MCMC) method, the MS-VEC model has been applied with Gibbs sampling by employing 50,000 posterior draws and 20,000 burn-in (following Balcilar *et al.*, 2015). The number of lags (one lag) is chosen through the Akaike information criterion (AIC) and the Bayesian information criterion of Schwarz's (BIC).

The first stage of estimating DCC-GARCH consists of estimating marginal models (ARMA) that filter information contained in univariate distributions and enable deriving standardized, independent and identically distributed (*i.i.d.*) residuals from the filtration. From estimating the mean model across the future (CBOT and MATIF) and spot prices, we can observe that Egyptian wheat spot prices are positively affected by CBOT price levels only, while the CBOT prices are influenced by MATIF price levels. The current price levels of the MATIF future market were positively influenced by price levels during the last month.

Turning to the conditional variance-covariance equation, from estimating the Wald test, we found that the adjusted parameter $\alpha + g$ is

Table 2 - Result for the MS-VCM model for price pair ($EGYPT$ - $CBOT$).

Variable	*EGYPT*	*CBOT*
C	0.002 (0.004)	0.001 (0.004)
$\Delta EGYPT_{t-1}$	0.016 (0.064)	-0.037 (0.065)
$\Delta CBOT_{t-1}$	0.071** (0.025)	0.163** (0.067)
EC_{t-1}	-0.054**(0.016)	0.009 (0.017)
Transition probability matrix:		$\begin{bmatrix} 0.874 & 0.125 \\ 0.164 & 0.835 \end{bmatrix}$
Regime properties	*Probability*	*Observations*
Regime 1	0.791	189.6
Regime 2	0.351	84.2
Ljung-Box Q(5)	18.250	13.262

*Note: ** denotes statistical significance at the 5% level.*

Table 3 - Result for the MS-VCM model for price pair (*EGYPT- MATIF*).

Variable	*EGYPT*	*MATIF*
C	-0.251**(0.048)	0.8297 (0.782)
$\Delta EGYPT_{t-1}$	0.030 (0.064)	-0.020 (0.0512)
$\Delta CBOT_{t-1}$	-0.006 (0.080)	0.367** (0.064)
EC_{t-1}	-0.060**(0.016)	0.028** (0.013)
Transition probability matrix:		$\begin{bmatrix} 0.786 & 0.145 \\ 0.179 & 0.899 \end{bmatrix}$
Regime properties	*Probability*	*Observations*
Regime 1	0.812	194.88
Regime 2	0.258	61.92
Ljung-Box Q(5)	20.220	10.142

*Note: ** denotes statistical significance at the 5% level.*

equal to zero at the 1% level significance, implying that a dynamic conditional correlation between the future-spot prices in the DCC model is a plausible assumption. The Ljung-Box test resultspresented in Table 4 allow for the null of no autocorrelated residuals to be accepted. The Lagrange-Multiplier (LM) tests (Table 4) implemented to test for ARCH residuals provide evidence that the DCC model is well specified. The results of the Hosking multivariate portmanteau tests for cross-correlation (multivariate residual autocorrelations) also indicate that there is no cross-correlation in squared residuals. The asymmetric dependence has not been found meaning that extreme increases or decreases in futures prices are likely to be passed to wheat spot prices in Egypt.

The long-run average probabilities of low and high-volatility regimes results are also presented in Tables2 and 3, indicating that the high volatility regimes occurred on 84.2 occasions, while the low volatility regimes occurred on 198.6 occasions for CBOT-spot price pairs. For the MATIF-Spot price pairs, high volatility regimes

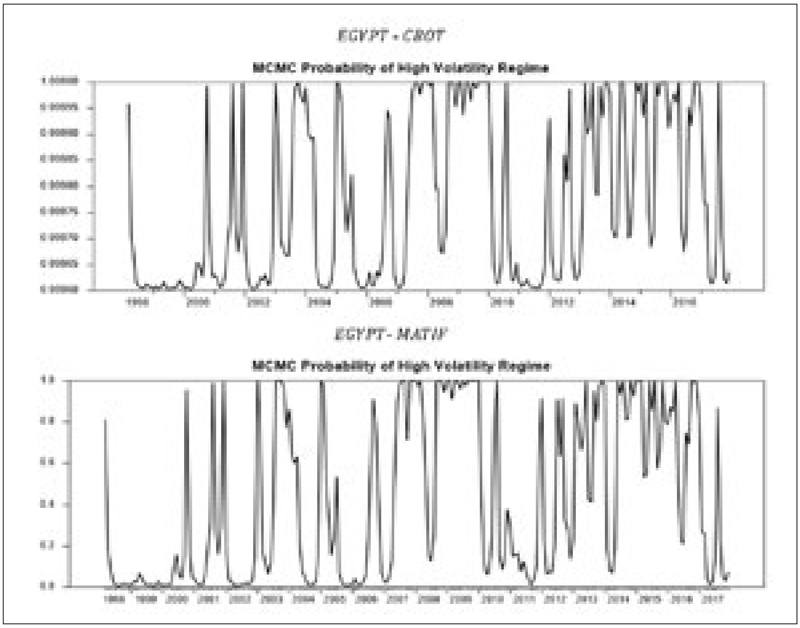

Figure 1 - Monte Carlo Markov Chain smoothed probability estimates of high volatility.

Figure 2 - Impulse responses of CBOT and MATIF future prices to wheat spot prices in Egypt in MS-VEC models.

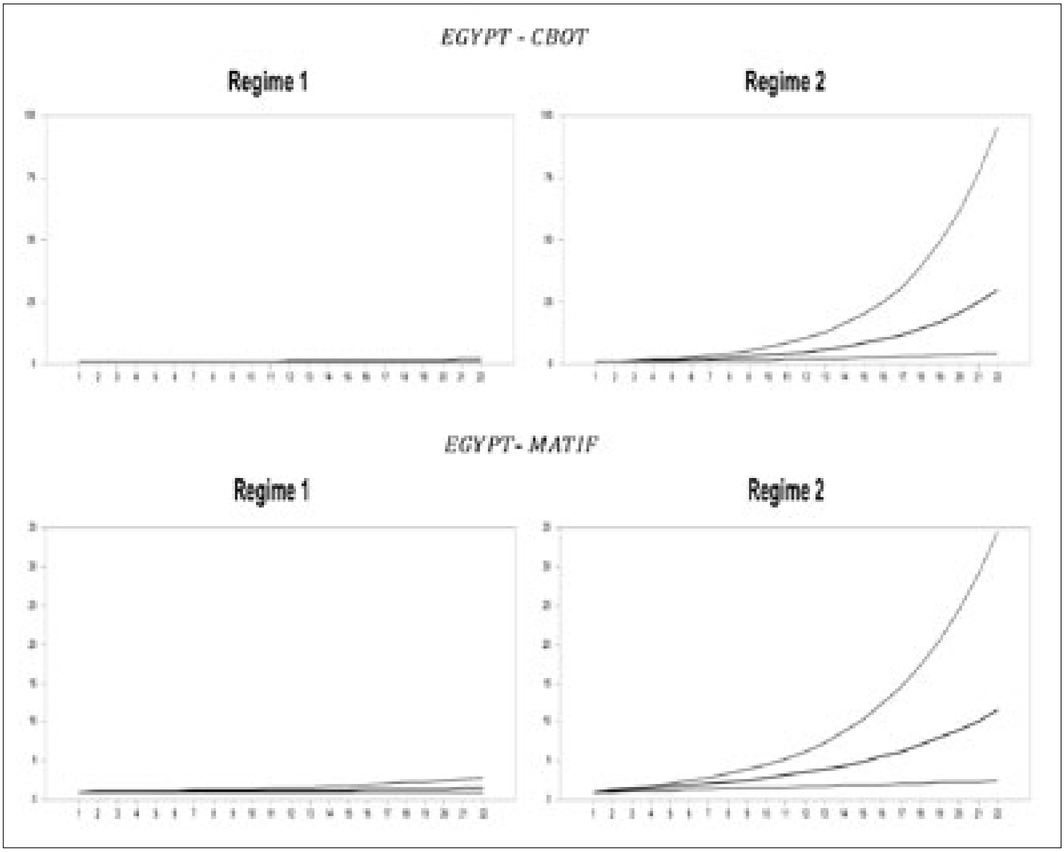

Table 4 - Asymmetric DCC-GARCH model for CBOT future price, MATIF future price, Egyptian wheat spot prices.

Coefficient	*EGYPT* (i = 1)	*CBOT* (i = 2)	*MATIF* (i = 3)	
Conditional mean equation				
Y_0	0.002 (0.004)	-0.001 (0.003)	0.001 (0.002)	
Y_{11i}	-0.019 (0.099)	-0.053 (0.059)	-0.001 (0.044)	
Y_{12i}	0.177** (0.079)	-0.0153 (0.082)	-0.038 (0.059)	
Y_{13i}	-0.110 (0.096)	-0.016** (0.040)	0.362** (0.075)	
Conditional variance equation				
C_i	0.040** (0.001)	0.004 (0.003)	0.009** (0.005)	
α	0.144 (0.116)	-0.040** (0.019)	0.089** (0.028)	
β_i	-0.035** (0.006)	0.186** (0.039)	0.925** (0.028)	
D_i	0.156 (0.204)	0.011 (0.056)	0.110 (0.340)	
$DCC\,(A)$			0.023** (0.010)	
$DCC\,(B)$			0.954** (0.219)	
Wald joint test for all cross-volatility coefficients				
Chi-sq			98.851	
p-Value			0,005	
Ljung-Box test for autocorrelation (H0: no autocorrelation in squared residuals)				
LB (10)	4.857	11.869	10,949	10.637
p-value	0.900	0.293	0,361	0.386
Lagrange multiplier (LM) test for ARCH residuals (H0: no ARCH effects)				
LM (5)	1,750	1,480	1.060	2.410
p-value	0,882	0,914	0,963	0,790

*Note: *(**) denotes statistical significance at the 10% (5%) level.*

occurred on 61.92 occasions, while low volatility regimes occurred on 194.88 occasions.

The smoothed probabilities of the MS-VEC model displayed in Figure 1 shows a high volatility regime between both the spot-CBOT and spot-MATIF price pairs, indicating that high volatility fluctuations were observed in and after the 2007-08 food crisis and supply chock in 2010. These fluctuations increase much more after the 2011 and 2013 revolutions, especially between the spot-CBOT prices, which show higher volatility during this period. This implies that the Egyptian Spot prices are strongly affected by high volatility, especially that which occurs during extreme market events, such as food crises and revolutions.

The impulse response functions were conducted for the futures prices (1 standard deviation) on the spot prices by using the Cholesky factor orthogonalization. The regime dependent impulse response method was used to compute the MS-VEC impulse response that comes from 50,000 posterior draws (Ehrmann *et al.*, 2003;

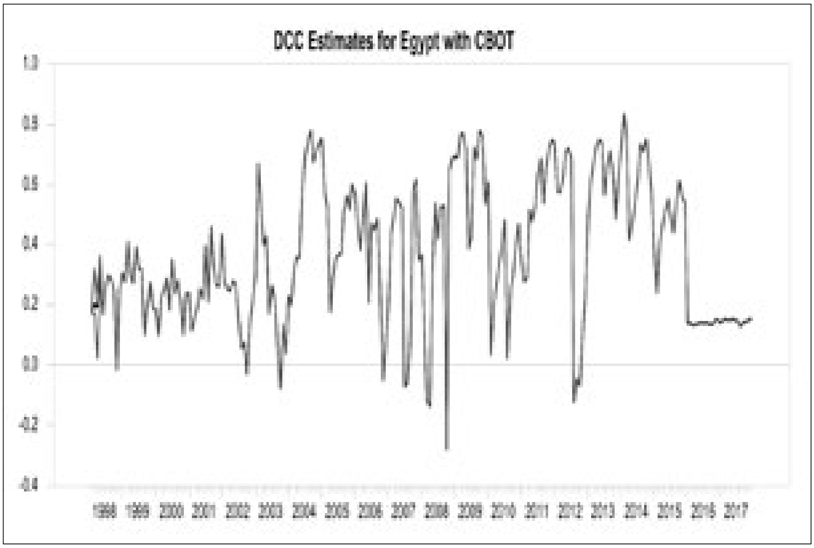

Figure 3 - The dynamic conditional correlation between EGYPT, CBOT.

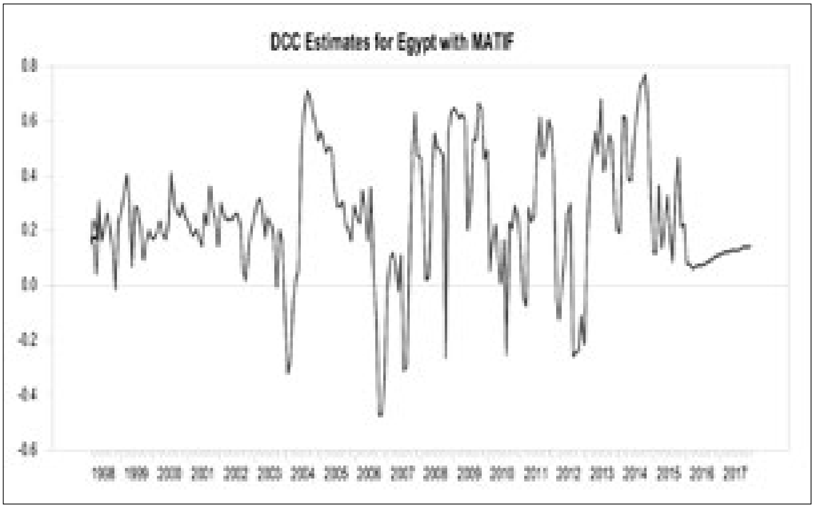

Figure 4 - The dynamic conditional correlation between EGYPT, MATIF.

Balcilar *et al.*, 2015). Figure 2 shows that shock by 1% in the futures markets (CBOT and MATIF) will lead to a significant positive shock in the Egyptian wheat spot prices.

The asymmetric DCC-GARCH model has been estimated to show how the levels of volatility interdependence changes among the pairs of prices considered over time. Given that ignoring the asymmetric price volatility transmission could lead to a biased estimator, we thus applied the asymmetric model to study the positive and negative price shocks together (Table 4).

Estimation results from DCC-GARCH are presented in Table 4 and graphed in Figures 3 and 4 for the CBOT- spot and MATIF-spot price pairs, respectively. The outcomes indicate that dynamic conditional correlation from January 1998 to December 2004 was relatively low and fluctuated in the range from 0 to 0.4. In the period after 2005, the DCC estimates indicate an important increase in the level of the volatility. The dependence increased dramatically from a small or negative that reached values around 0.8 beginning in 2005. Figures 3 and 4 also show a high dependency with very high fluctuations between futures and spot markets, especially one year after the period of the extreme market events, mainly in the range of -2 to 0.8. Such increase in volatility is likely related to the food crisis, supply shock, and economic downturn resulting the Arab Spring revolutions. Results from nonlinear MS-VEC and DCC-GARCH implying that the futures markets are failed to protect the wheat spot prices in Egypt against price volatility, especially in the time of extreme market events, and ultimately lead to less hedging effectiveness since futures prices drive resource allocation and production decisions.

Our results may be cautiously extended to North African and the Middle East countries, with the most important message being that food marketing chains in developing countries can be far from efficient because of the volatility of futures markets and less hedging effectiveness of spot prices that may lead to concerns hedger, investors, farmers, and policymakers, and resulting in market risks. This result has implications for the effectiveness of food security policies and interventions from governments and policymakers.

5. Concluding remarks and policy recommendations

Egypt suffers from food insecurity, poverty and nutritional deficiencies. While food price volatility in developing economies has been widely assessed by previous research, less attention has been paid to less developed countries, mainly due to a lack of price data. Since the food price crisis of 2007-08, economic research has paid substantial attention to food price behavior, given the significant political, economic and social impacts it has. Our work focuses on examining the relationship between wheat spot prices in the Egyptian market and wheat futures prices associated with CBOT in the USA and MATIF in France. We assess how the price discoveryinformation occurring in the futures markets affects the volatility of spot prices. The study is based on monthly data of CBOT, MATIF and spot prices in the Egyptian wheat market from January 1998 and December 2017. The analysis covers an interesting period that includes the first and second food crisis, two revolutions in Egypt and an economic reform. Thus, this analysis shows how an economic and political crisis can affect the consumer prices and the economic welfare in developing countries.

This paper contributes to the literature by studying price volatility behavior of food staples in less developed countries, thus enlarging an area that is rather scarce due to data limitations because of lack of information flows from futures markets to spot prices. In addition, it does so by using MS-VEC and asymmetric DCC-GARCH models. An attractive feature of the MS-VEC model is that it can estimate the low and high volatility regimes by dividing the sample based on the variance and covariance matrix. A main feature of the DCC-GARCH model, onthe other hand, is that it can assess the dynamics of the volatility across the prices considered.

Results from estimating both models indicate that a high volatility regime was observed more frequently during extreme market events, especially during the 2007-08 and 2010 food crises, the two revolutions in 2011 and 2013, and when the government decided to carry out economic reform with devalue the Egyptian pound and extremely reduce the subsidy to the farmers and consumer. A low volatility regime existed before the time of the economic and political crisis. Results also show that symmetries affect short-run price dependencies, with the characteristics of these symmetries depending on the markets studied. This implies that both increasing and decreasing shocks in futures markets affect spot prices in Egypt.

The impulse response functions have been conducted in a nonlinear MS-VEC model, indicating that a shock to the futures markets by 1% will be transmitted to a positive shock in the Egyptian wheat spot market for a high volatility regime, while for the low volatility regime no significant effect of the futures market on the spot prices was implied. Our finding is consistent with the results obtained by Peri *et al.* (2013); Fattouh *et al*. (2013); Adjemian *et al.* (2013); Chen *et al.* (2014), that there are less hedging effectiveness and market risks, and thus futures markets fail to protect the spot prices against fluctuation.

Policies to increase food security are required, such as reducing the dependence on importing food and increase productivity. To increase the wheat productivity could be by the provision of inputs at subsidized prices or the promotion of adopting simple technologies and tools to produce wheat. This could result in lower production costs and thereby consumption prices. Using new heat and disease tolerant varieties may increase productivity; these varieties have already been developed by research institutes in Egypt, but they need to be introduced to farmers. Adopting good agricultural practices may also increase farmers' productivity. Increasing the production efficiency of wheat by training farmers on modern agricultural cultivation practices may increase their wheat yields and reduce their dependence on the international market. The government and policymakers should intervene to improve wheat production in Egypt by addressing the existing market and production inefficiencies across the following: wheat storage improvement to reduce the after-harvest losses, and wheat by-product exploitation to use it as inputs (e.g. fertilizer or animal feed to reduce the farmer income, while improving the soil quality and thus increase the wheat productivity). Developing a market information system using an online market to increase the competitiveness among all actors along the supply chain that can also increase farmers' incomes that make them can maintain grow wheat in the coming seasons. In short, food policies should adopt a comprehensive approach along the supply chain to ensure a commensurate impact on the poor consumer in developing countries.

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