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INTERNATIONAL CONFERENCE OF AGRICULTURAL ECONOMISTS
ICAE
29th | Milan Italy 2015
UNIVERSITÀ DEGLI STUDI DI MILANO AUGUST 8 - 14
AGRICULTURE IN AN INTERCONNECTED WORLD

# VERTICAL PRICE TRANSMISSION IN THE EGYPTIAN TOMATO SECTOR AFTER THE ARAB SPRING

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**Abstract**

This study assesses price transmission along the Egyptian tomato food marketing chain in the period that followed the Arab Spring, which accentuated economic precariousness in Egypt. Static and time-varying copula methods are used for this purpose. Results suggest a positive link between producer, wholesaler and retailer tomato prices. Such positive dependence is characterized by asymmetries during extreme market events, that lead price increases to be transferred more completely along the supply chain than price declines.

**Keywords:** food prices, asymmetric price transmission, dependence analysis, static and time-varying copula.

**JEL codes:** C5, Q11, Q12, Q18.

IAAE

## 1. Introduction

The prevailing economic situation in Egypt before the 2011 Arab Spring was challenging and partly characterized by high unemployment rates, specially among youth, unfair wage structures, and high food and energy prices. The revolutions accentuated economic precariousness: GDP growth rates decreased from 5.1% in 2010 to 2.2% in 2012, while inflation measured through the consumer price index grew by 9.5% in 2013 (World Bank, 2013). Price increases are bigger if a longer time span is considered: from the 1st week of January 2011 till the 1st week of December 2013, Egyptian food prices increased by 17.7% (Egyptian Food Observatory, 2013).

This economic downturn led to food price instability, food shortages and higher poverty. In 2013, more than 79% of family income was spent on food and more than 80% of Egyptian population earned insufficient income to cover consumption needs. According to the Egyptian Center for Economic and Social Rights (ECESR, 2013), the poverty rate increased from 21.6% in 2008/2009 to 26.3% in 2012/2013. Rising poverty worsened food insecurity that increased from 14% of the Egyptian population in 2009 to 17.2% (13.7 million people) in 2011 (ECESR, 2013). Undernourishment, on the other hand, represented more than 5% of Egyptian population in the 2011-2013 period (Africa Food Security and Hunger, 2014).

Egyptian consumers have used different strategies to cope with recent food price increases: food purchases have been curbed down by 12.2% and more than 26% of consumers have opted for lower quality food products at cheaper prices (Egyptian Food Observatory, 2013). Prevention of malnutrition implies ensuring access to food at fair consumer prices. Assessing food consumer price formation requires analyzing how food prices are transmitted along the food marketing chain, from agricultural producers to final consumers. The objective of this research article is to shed light on this matter by focusing on the tomato sector in Egypt.

Understanding price behavior along the food marketing chain is very useful to assess the functioning of food production, processing and distribution markets, their competition and integration level. Vertical price transmission analyses can help identifying market failures and are a good indicator of the degree of competitiveness and effectiveness of market performance. Competitive behavior is rare in less developed countries (LDCs) due to different market characteristics such as excessive governement intervention, corruption, defficient infrastructures, etc. Since prices drive resource allocation and production decisions, price transmission information is useful for economic agents when taking their economic decisions, policy makers and competition regulatory authorities. Hence, the link between different prices at different levels of the food marketing chain is a very interesting research topic in LDCs. This article characterizes the relationship between producer and wholesaler price levels, and between wholesaler and consumer price levels of tomato markets in Egypt. The analysis is of a pair-wise nature. Pair-wise analyses are usual in the price transmission literature and represent a natural avenue for studying price relationships (Goodwin and Piggott, 2001). Lack of food price data in LDCs is the reason underlying the scarcity of studies on price behavior in these countries. This makes the contribution of the proposed analysis an even more appealing one.

Sound assessment of price links requires knowledge of the joint distribution of the prices considered. Under the assumption that the joint price distribution is Gaussian or t-Student, methods such as vector autoregressive or error correction type of models have been widely used. Univariate distributions of economic time series are usually found to be characterized by excess kurtosis, skewness and nonnormality. Further, related price series may show asymmetric dependence, which is an indicator of multivariate nonnormality (Patton, 2006). As a result, the Gaussian and the *t*-Student distributions have been shown as inappropriate to assess behavior of the type of data we intend to study. Inadequate assumptions of multivariate distributions will lead to biased parameter estimates. Further, since the range of available multivariate distributions is limited, this limits how multivariate dependence can be modeled (Parra and Koodi, 2006).

Assessment of dependence between producer, wholesaler, and retailer levels should be based on flexible instruments that soundly capture the joint distribution function of the variables considered. Recent research has suggested the use of statistical copulas as an alternative. Copulas are statistical instruments that combine univariate distributions to obtain a joint distribution (multivariate distribution) with a particular dependence structure. A key advantage intrinsic to copulas is that they are based on univariate distributions, instead of multivariate ones. This is specially important given the scarcity of multivariate distributions available from the statistical literature.

This paper is organized as follows. In the next section, a brief description of the tomato market in Egypt is offered. In section 3, a literature review of vertical price transmission analyses using time-series econometric techniques is presented. In section 4, the methodological approach is described. The fifth section is devoted to the empirical implementation to assess dependence between producer and wholesaler, and between wholesaler and retailer prices. The last section in this article offers the concluding remarks.

**2. Tomato market in Egypt**

World production of vegetables in 2012 was 1.1 billion tons on an extension of land of 57.2 million hectares. Africa produced 74.1 million tons, representing an increase on the order of 86.5% relative to 2006 and more than 6.5% of worldwide production (FAOSTAT, 2012). Among African countries, Egypt vegetable production expanded from 18.3 million tons in 2006 (FAOSTAT, 2006) to 19.8 million tons in 2012, representing an increase of around 8.2% (FAOSTAT, 2012) and around 26.7% of all vegetables produced in Africa. According to the International Trade Center (ITC), in 2011 edible vegetables global exports and imports were on the order of 66.5 and 65.4 million tons, respectively (ITC 2011). In the same year, African vegetables exports and imports were 4.6 and 6.1 million tons, respectively (FAOSTAT, 2011).

Tomato is the most relevant vegetable in terms of world production and consumption (FAOSTAT, 2012). Global tomato production expanded from 131.3 million tons in 2006 (FAOSTAT, 2006) to 161.7 million tons in 2012 (FAOSTAT 2012). More than 30% of tomato production is used by the processing industry. In 2012, international exports and imports of tomato were estimated to be 7.1 and 6.9 million tons, respectively (ITC, 2012). Tomato production is distributed among 170 countries, being Egypt the fifth largest global producer after China, India, United States, and Turkey. These five countries represent around 62% of total world tomato production (FAOSTAT, 2012). Tomato is extremely important for African economies that in 2012 devoted 21.5 million hectares to produce 17.9 million tons, representing 24.19% of the vegetables produced in Africa (FAOSTAT, 2012). African exports (imports) of tomato were estimated to be on the order of 535.3 (60) thousand tons in 2011 (FAOSTAT, 2011).

Tomato is the first vegetable in terms of consumption and production in Egypt. While food consumption patterns involve a frequency of vegetables consumption of 6.5 days a week, tomato is consumed, on average, 5.8 days a week (Egyptian Food Observatory, 2013). In 2012, tomato harvest in Egypt exceeded 8.6 million tons, grown on more than 216 thousand hectares, representing 28% of the area cultivated with vegetable crops (FAOSTAT, 2012). Egypt, with half of tomato production, is the largest producer in Africa (FAOSTAT, 2012). Egyptian exports of tomato were 62.2 thousand tons in 2011, and the main destinations were the Kingdom of Saudi Arabia, Netherlands and United Kingdom. Egyptian tomato imports were 5.3 thousand tons (ITC, 2012). More than 30% of the domestic tomato production is processed by 14 companies into tomato paste and other products

Income derived from tomatoes fluctuates highly, mainly due to price instabilities. Net returns in 2007 were on the order of 170 US$ per feddan. In winter 2011/2012, net returns increased to 3,000 US$ per feddan, and decreased to be 1,200 US$ feddan in the summer 2012 (USDA, 2014). While tomatoes are grown in Egypt throughout the year in different regions, most production occurs in the Upper Egypt, especially in the governorate of Qena (SIS, 2013). Most production is channeled through two main wholesale markets in Egypt: El Abour market in Cairo and El Hadra market in Alexandria, and subsequently distributed to retail markets after tomatoes have been sorted, processed, and repackaged.

Small and poor tomato producers suffer from low yields and high income instability. Further, they often rely on the black market, where prices are usually very high, to acquire their inputs (Boutros, 2014). After the implementation of the public-private partnership between USAID, ACDI-VOCA, Heinz International and 13 domestic tomato processors, in order to improve economic sustainability of small tomato producers, producers sell 30% of their production through forward contracts to processor companies. This increases the range of market outlets reducing wholesaler market power (USDA, 2014).

## 3. Literature review

According to their methodological approach, price transmission analyses can be classified into structural and non-structural studies. While structural models rely on economic theory, non-structural analyses identify empirical regularities in the data. Our approach to studying price transmission along the Egyptian marketing chain is based on non-structural time-series models. Time series data often violate the most common assumptions of conventional statistical inference methods, which may lead to obtaining completely spurious results. Cointegration and error correction models (ECM) have been introduced in the literature (Engle and Granger, 1987) to characterize nonstationary and cointegrated data and inform both on their short and long-run time-variation. Time-varying and clustering volatility, another common characteristic of time-series, is typically modeled through generalized autoregressive conditional heteroskedasticity (GARCH) models.

The work by Chang (1998) relies on Engle and Granger (1987) cointegration techniques, to study long run relationships among Australian beef prices at the farm, wholesale and retail levels. Evidence is found that all three prices are non stationary and maintain a long-run equilibrium relationship, being the retail price the one that drives price patterns. Price time series may also be characterized by asymmetric adjustment to long-run equilibrium. Recent literature in this area has relied on smooth transition or discrete threshold time-series models that usually allow for autoregressive and error correction patterns. The work by Abdulai (2002) analyzes the relationship between producer and retail pork prices in Switzerland, by employing threshold cointegration tests. Results indicate that price transmission between producer and retail market levels is asymmetric, since increases in producer prices are transferred more rapidly to retailers than producer price declines. Using an asymmetric error-correction model, Von Cramon-Taubadel (1998) obtains the same results for the German pork market. Vavra and Goodwin (2005) use threshold vector error correction models (TVECM) to appraise the links between retail, wholesale and farm level prices for the US beef, chicken and egg markets. Research results indicate that there are significant asymmetries, both in terms of speed and magnitude of the adjustment, in response to positive and negative price shocks. Evidence of asymmetric price transmission along the food marketing chain is also found by Seo (2006), Saikkonen (2005), Goodwin and Holt (1999), Serra and Goodwin (2003), Meyer and von Cramon-Taubadel (2004), among others.

TVECM are used by Pozo et al. (2011) to examine price transmission among farm, wholesale and retail US beef markets. Results show that there is no evidence of asymmetric price transmission in any of the models. To the best of our knowledge, the work by Gervais (2011) is the first paper focusing on potential nonlinearities in both the long- and short-run. Gervais (2011) studies the US pork marketing chain, from farm to consumer markets. Results indicate the importance of testing for linearity in the long-run relationship between prices. Results also show that a decrease in farm prices is eventually transferred to consumers.

There are few studies that have addressed vertical price transmission along the food chain in developing countries. Guvheya et al. (1998) assess vertical price transmission in Zimbabwe tomato market using causality and Houck (1977) methods. Price transmission between farm and wholesale market levels is characterized by price asymmetries, but price transmission from wholesale to retail markets is symmetric. Iran horticultural markets (date and pistachio) have been studied by Moghaddasi (2008). Houck (1977) approach is used to characterize the pistachio market and ECM the date market. Results indicate that there is asymmetry in price transmission from farm to retail markets. Granger and Lee (1989) asymmetric ECM is used by Acquah (2010) to examine and confirm existence of asymmetry in price transmission between wholesaler and retailer maize prices in Ghana.

Negassa (1998) focuses on vertical price transmission in grain markets in Ethiopia by using correlation coefficients and casualty methods and finds evidence of symmetries. Minten and Kyle (2000) examines price asymmetry in urban food markets in Zair. Evidence is found that prices are symmetrically passed between producer and wholesaler market levels, but transmitted asymmetrically between wholesaler-retailer markets. Alam et al. (2010) apply an ECM on rice market prices in Bangladesh. Prices along the chain are positively linked and wholesalers set market prices. Evidence of asymmetric price transmission is also found.

More recently, other methodological approaches based on the use of statistical copulas have started to gain interest among economists interested in price transmission analyses. These methods rely on direct examination of the joint probability distribution function of the variables that are being studied and pay special attention to the nature of jointness between these variables. The work by Serra and Gil (2012) studies dependence between two pairs of prices: crude oil and biodiesel blend prices, and crude oil and diesel prices in Spain, with a special focus on this dependence during extreme market events. Statistical copulas are used for such purpose. Results prove asymmetric dependence between crude oil and biodiesel prices, which protects consumers against extreme crude oil price increases. Diesel prices, in contrast, equally reflect crude oil price increases and decreases. The work by Goodwin et al. (2011) studies the joint distribution of North American lumber prices in different markets (Eastern Canada, North Central US, Southeast US, Southwest US). Copula models are used to obtain the correlation between prices at the geographical locations considered. Results indicate that market adjustments are generally larger in response to large price differences which reflect more substantial disequilibrium conditions.

The unpublished article by Qiu and Goodwin (2013) relies on the application of static and time-varying copula models to the empirical study of the links between farm-retail and retail-wholesale prices for US hog/pork markets. Results indicate that farm and wholesale markets are closely related to each other, while retail price adjustment is less dependent on the other two markets. Farm-retail and retail-wholesale price adjustments have relatively constant dependence structures. Also, results confirm the existence of time-varying and asymmetric behavior in price co-movements between farm and retail markets. Positive upper and zero lower tail dependencies provide evidence that big increases in farm prices are matched at the retail level, while negative shocks at the farm level are less likely to be passed to consumers.

Our paper contributes to the literature by assessing dependence between producer-wholesaler and wholesaler-retailer price levels in tomato markets in Egypt. During the political transition period, Egypt suffered from food insecurity and food price instability. It is thus important to pay special attention to extreme upturns and downturns of the tomato market, as these are likely to have a stronger impact on food security and economic issues. Since we assess a period of important changes, not only static, but also time-varying copulas are used in order to allow for changes in price patterns. To our knowledge, this is the first attempt to study vertical price transmission in LCD countries using this methodology.

## 4. Methodology

Multidimensional copula functions are used to assess dependence between prices at different levels along the tomato supply chain in Egypt. While copulas have been widely used in the financial economics literature (Patton 2006, 2012; or Parra and Koodi 2006), empirical studies that use copulas to assess dependency along the food marketing chain are more scarce, even more so in developing economies. Statistical copulas have the advantage of allowing high flexibility when studying correlation between two or more variables. A copula function is a multivariate distribution function defined on the unit cube $\left[0,\ 1\right]^n$, with uniformly distributed marginals. Copulas are based on the Sklar's (1959) theorem that shows how multivariate distribution functions characterizing dependence between $n$ variables, can be decomposed into $n$ univariate distributions and a copula function, the latter fully capturing the dependence structure between variables.

Recall our analysis is of a pairwise nature. Let $F_x$ and $F_y$ be the univariate distribution functions of two random variables $(x, y)$. $H(x, y)$ is assumed to represent the joint distribution function. According to the Sklar's theorem, there exists a copula $C(.)$ that can be expressed as (Embrechts et al., 2001):

$$H(x, y) = C(F_x(x), F_y(y)) = C(u, v), \tag{1}$$

where $C(.)$ is a 2-dimensional distribution function with uniformly distributed margins $u \sim Unif(0,1)$ and $v \sim Unif(0,1)$. The joint density function can be defined as:

$$h(x, y) = f_x(x) f_y(y) c(u, v), \tag{2}$$

where $c$ is the copula density and $f_x(x)$ and $f_y(y)$ are the univariate density functions of the random variables.

Different copula families and specifications represent different dependence structures. Our analysis will consider both elliptical (Gaussian and Student's *t* copulas) and Archimedean (Gumbel, Symmetrized Joe-Clayton-SJC copulas) copulas. Elliptical copulas are based on the elliptical distribution, while Archimedean are a group of associative copulas that have the advantage of reducing dimensionality issues during the estimation process. Copulas may also be categorized as static and time-varying. A static copula implies parameter constancy over time, while a time-varying copula allows the parameters to change with changing environment. In order to ensure that the copulas correctly fit our data, a series of time-varying dependence and goodness of fit (GoF) tests are conducted. As a result, price dependency along Egyptian tomato marketing chain is modeled using four copulas. The Gaussian copula is selected for being the benchmark copula in economics. The Gumbel, the Student's *t*, and the SJC copula are selected based on statistical selection criteria (the log-likelihood value and goodness of fit statistics described below).

The bivariate Gaussian copula can be expressed as:

$$C_R^{Ga}(u,v;R_{12}) = \int_{-\infty}^{\Phi^{-1}_{(u)}} \int_{-\infty}^{\Phi^{-1}_{(v)}} \frac{1}{2\pi\sqrt{\left(1-R_{12}^2\right)}} \exp\left\{ \frac{-(r^2 - 2R_{12}rs + s^2)}{2\left(1-R_{12}^2\right)} \right\} drds, \tag{3}$$

where $R_{12}$ is the correlation coefficient of the corresponding bivariate normal distribution, $-1 < R_{12} < 1$, and $\Phi$ denotes the univariate normal distribution function. A drawback of the Gaussian copula is that it assumes that variables $u$ and $v$ are independent in the extreme tails of the distribution. Hence, the Gaussian copula does not allow for lower and upper tail dependence. It thus represents dependence in the central region of the distribution. The implication for our analysis is that the Gaussian copula assumes that price transmission along the food market chain does not occur for very high/low market prices.A bivariate student's *t* copula can be expressed as:

$$C_{\gamma,R}^{t}(u,v) = \int_{-\infty}^{t_\gamma^{-1}(u)} \int_{-\infty}^{t_\gamma^{-1}(v)} \frac{1}{2\pi\sqrt{\left(1-R_{12}^2\right)}} \exp\left\{ 1 + \frac{r^2 - 2R_{12}rs + s^2}{\gamma\left(1-R_{12}^2\right)} \right\}^{-(\gamma+2)/2} drds, \tag{4}$$

where $R_{12}$ is the correlation coefficient of the corresponding bivariate *t*-distribution with $\gamma$ degrees of freedom (as explained by Embrechts et al. 2001, $\gamma > 2$ for the correlation to be defined), and $t_\gamma$ denotes the bivariate distribution function. When $\gamma > 30$, the Student's *t* copula tends to the Gaussian copula (Goodwin 2012). The student's t copula assumes positive and symmetric lower and upper tail dependence.

The Gumbel copula can be expressed as (Manner 2007):

$$C_{\phi}^{Gu}(u,v) = \exp\left( -\left[ \left(-\ln(u)\right)^{\theta} + \left(-\ln(v)\right)^{\theta} \right]^{1/\theta} \right). \tag{5}$$

This copula measures right tail dependence, which can be expressed as $\lambda_r = 2 - 2^{1/\alpha}$, but assumes left tail dependence to be $\lambda_l = 0$. In terms of our case analysis, this copula relies on the assumption that price transmission between different market levels only takes place for high market prices. The Joe-Clayton copula can be expressed as:

$$C^{jc}_{\tau^U,\tau^L}(u,v)=1-\left(1-\left\{\left[1-(1-u)^k\right]^{-\gamma}+\left[1-(1-v)^k\right]^{-\gamma}-1\right\}^{-1/\gamma}\right)^{1/k} \tag{6}$$

where $k=1/\log_2(2-\tau^U)$, $\gamma=-1/\log_2(\tau^L)$, $\tau^U\in(0,1)$, and $\tau^L\in(0,1)$. Joe-Clayton copula has two parameters, $\tau^U$ and $\tau^L$, that measure the upper and lower tail dependence, respectively. This copula characterizes tail dependency, i.e., it models price behavior during extreme events. As noted in the literature review above, evidence of asymmetries in vertical price transmission within the food 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 the static symmetrized Joe-Clayton (SJC) specification. More specifically, this copula models the probability that relevant increases (declines) in the prices studied occur together. The Joe-Clayton copula implies asymmetric dependence, even when $\tau^U=\tau^L$. The Symmetrized Joe-Clayton (SJC) copula allows overcoming this problem (Patton, 2006) and can be specified as:

$$C^{sjc}_{\tau^U,\tau^L}(u,v)=0.5\left(C^{jc}_{\tau^U,\tau^L}(u,v)+C^{jc}_{\tau^U,\tau^L}(1-u,1-v)+u+v-1\right). \tag{7}$$

Use of time-varying copulas was seen to be necessary after some testing procedures that will be discussed below. Hence, dependency during the period studied was not found to remain constant. The dynamic Student's *t* copula and SJC copula were chosen, on the basis of the highest log-likelihood values, to capture dependency changes. Time-varying versions of Student's *t* copula define the correlation parameter to evolve through time as shown in equation (8) below (Patton, 2006):

$$\rho_t=\Lambda\left(\omega_\rho+\beta_\rho\rho_{t-1}+\alpha_\rho\frac{1}{10}\sum_{i=1}^{10}t_\gamma^{-1}\left(u_{t-i}\right)t_\gamma^{-1}\left(v_{t-i}\right)\right) \tag{8}$$

where $t_\gamma^{-1}$ is the inverse of the *t* distribution of $\varepsilon_t$ with $\gamma$ degrees of freedom, and $\Lambda=(1+e^{-x})^{-1}$ is the modified logistic function. The time-varying version of the SJC copula is defined following Patton (2006):

$$\tau_t^U = \Lambda\left(\omega_U + \beta_U \tau_{t-1}^U + \alpha_U \frac{1}{10}\sum_{i=1}^{10}\left|u_{t-i} - v_{t-i}\right|\right), \tag{9}$$

$$\tau_t^L = \Lambda\left(\omega_L + \beta_L \tau_{t-1}^L + \alpha_L \frac{1}{10}\sum_{i=1}^{10}\left|u_{t-i} - v_{t-i}\right|\right) \tag{10}$$

where $\Lambda = (1+e^{-x})^{-1}$ denotes the logistic transformation that keeps the upper and lower tails ( $\tau_t^U, \tau_t^L$ ) in the (0, 1) range.

Copulas can be estimated through two stage estimation processes. The first stage consists of estimating marginal models that filter information contained in univariate distributions and allow deriving standardized, independent and identically distributed (*i.i.d.*) residuals from the filtration. The copula is estimated in a second stage either through parametric or non-parametric methods. We use the latter, that consist of transforming the *i.i.d.* residuals into $Unif(0,1)$ using the non-parametric empirical cumulative distribution function (EDF). The empirical EDF method is especially convenient when the true distribution of the data is not known. The maximum likelihood method is applied on the uniform residuals to estimate copula parameters. The two-stage estimation technique can be formalized as follows (Patton, 2012):

$$\phi_u = \arg\max_{\phi_u} \frac{1}{T}\sum_{j=1}^{T} \log f_i(u_j;\phi_u), \tag{11}$$

$$\phi_v = \arg\max_{\phi_v} \frac{1}{T}\sum_{j=1}^{T} \log f_i(v_j;\phi_v),$$

$$\theta = \arg\max_{\theta} \frac{1}{T}\sum_{j=1}^{T} \log c(F(u_j;\phi_u), F(v_j;\phi_v);\theta). \tag{12}$$

where $\phi_u$ and $\phi_v$ represent parameter estimates of marginal distributions and $\theta$ is the copula estimated parameter vector. Since the theory of copulas applies on stationary time-series, tests for unit roots are run on our data. Results support the absence of a unit root in producer, wholesaler and retailer prices.

Univariate ARMA($p_a$,$q_a$)-GARCH($p_g$,$q_g$) marginal models capture univariate price patterns with $p_a$ representing the number of autoregressive parameters of the ARMA model; $q_a$ the number of moving average components, $p_g$ the number of autoregressive terms in the GARCH specification and $q_g$ the number of lags of squared innovations. ARMA models price-level behavior as a function of autoregressive and moving average terms. Residuals are modeled through GARCH specification in order to allow for time-varying and clustering volatility:

$$P_t = c + \sum_{i=1}^{pa} \eta_{1i} P_{t-i} + \sum_{i=1}^{qa} \eta_{2i} \varepsilon_{t-i} + \varepsilon_t \tag{13}$$

$$\sigma_t^2 = \omega_i + \sum_{i=1}^{pg} \omega_{i2} \sigma_{t-i}^2 + \sum_{i=1}^{qg} \omega_{i1} \varepsilon_{t-i}^2 \tag{14}$$

where $P_t$ are the prices considered, $c$ is the constant of the conditional mean model, $\eta_{1i}$ is the coefficient representing the autoregressive component, $\eta_{2i}$ is the coefficient representing the moving average component, being $\varepsilon_t$ a normally distributed error term, $\omega_i$ is the constant in the conditional volatility model, being $\omega_{i1}$ and $\omega_{i2}$ the coefficients representing the lagged square residuals and variance, respectively.[1] Log-likelihood methods assuming normally distributed errors are used in model estimation.

Two types of time-varying dependence tests are used to determine whether time-varying copulas need to be considered (Patton, 2013). The first focuses on rank correlation breaks between *u* and *v* at some unknown date and is based on the "sup" test statistic (Patton, 2013):

$$\tilde{B}_{\sup} = \max_{t^* \in \left[t_L^*, t_U^*\right]} \left| \vartheta_{1,t} - \vartheta_{2,t} \right|, \tag{15}$$

where $\vartheta_{1,t^*} \equiv \dfrac{12}{t^*} \sum_{t=1}^{t^*} {}_{1t} u_t - v_t - 3$ and $\vartheta_{2,t^*} \equiv \dfrac{12}{T - t^*} \sum_{t=1}^{t^*} {}_{1t} u_t - v_t - 3$ . In order to have enough observations to estimate the pre- and post-break parameters, the interval $[t_L^*, t_U^*]$ is usually defined as $[0.15T, 0.85T]$, where $T$ is the number of observations. The critical value of $\tilde{B}_{\sup}$ can be determined through a bootstrap process defined in Patton (2013). The second test is the ARCH LM test for time-varying volatility (Engle, 1982). This test focuses on autocorrelation in dependence, captured by an autoregressive model such as the following:

[1] The univariate model was specified according to parsimony and statistical significance.

$$u_t v_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i} v_{t-i} + e_t \, , \tag{16}$$

where $e_t$ is the error term. The null of a constant copula implies $\alpha_i = 0, \forall i \geq 1$ , which can be tested through the following statistic:

$$\hat{A}_p = \hat{\alpha} R' \left( R \hat{V}_\alpha R' \right)^{-1} R \hat{\alpha} \, , \tag{17}$$

where $\hat{\alpha} \equiv \left[ \alpha_0, ......, \alpha_p \right]'$, $R = \left[ 0_{p \times 1} \vdots I_p \right]$ and $\hat{V}_\alpha$ is the OLS estimate for the covariance matrix. A bootstrap process described in Patton (2013) is used to determine the test critical values.

Goodnes of fit (GoF) tests are used to assess to what extent an estimated copula model is different from the unknown true copula. Comparison of estimated with unknown copula is made through the Kolmogorov-Smirnov (*KSc*) and the Cramer-von-Mises (*CvMc*) tests (Genest and Rémillard 2008, 2009; and Rémillard 2010). These tests can be expressed as follows:

$$KSc = \max_t \left| C(u, v; \hat{\theta}_T) - \hat{C}_T (u, v) \right| \tag{18}$$

$$CvMc = \sum_{t=1}^{T} \left\{ C(u, v; \hat{\theta}_T) - \hat{C}_T (u, v) \right\}^2 . \tag{19}$$

The empirical copula has been often used to provide a nonparametric estimate of the true unknown copula. However, the empirical copula is not a valid approach when the true underlying copula is time-varying. The problem can be addressed by using the fitted copula to derive a Rosenblatt (1952) transform of the data that yields a vector of *i.i.d.* mutually independent *Unif* (0,1) variables. The GoF tests are then computed as:

$$KSr = \max_t \left| C(\underline{u}, \underline{v}; \hat{\theta}_T) - \hat{C}_T (\underline{u}, \underline{v}) \right| \tag{20}$$

$$CvMr = \sum_{t=1}^{T} \left\{ C(\underline{u}, \underline{v}; \hat{\theta}_T) - \hat{C}_T (\underline{u}, \underline{v}) \right\}^2 \tag{21}$$

where $\underline{u}$ and $\underline{v}$ are the Rosenblatt transformations. Rémillard (2010) proposes a bootstrap process in order to determine the critical values for tests $KSc$ and $CvMc$. Patton's (2013) recommendation is followed to obtain the critical values of $KSr$ and $CvMr$.

Conducting goodness of fit tests on the marginal models is essential for copula model estimation. In order to make sure that the residuals obtained from univariate models have no autocorrelation, the Ljung-Box tests are used. The LM tests of serial independence of the first four moments of $u_t$ and $v_t$ are estimated by regressing $\left(u_t - \bar{u}\right)^k$ and $\left(v_t - \bar{v}\right)^k$ on 10 lags for each price series, for k= 1,2,3,4. We also use the Kolmogorov-Smirnov (KS) test to make sure that the transformed series are $Unif(0,1)$ (see Patton 2006 for further details).

## 5. Empirical analysis

The analysis is based on weekly tomato price data expressed in euro/kg, and observed from the first week of April 2011 to the last week of March 2014, leading a total of 155 observations. Prices at different levels of the marketing chain have been collected: the price received by producers and wholesalers and the price paid by consumers. The three series are obtained from the Egyptian cabinet information and decision support center (IDSC, 2013). Prices are expressed in Egyptian pound per kilo and studied in pairs. Standard unit root tests show that the series are stationary (Table 1). Table 2 presents summary statistics for price series. These statistics provide evidence of non-normal price series, characterized by skewness, kurtosis and ARCH effects.

Results from univariate ARMA-GARCH model, whose specification is chosen through the Akaike's information criterion (AIC) and Bayesian information criterion of Schwarz's (BIC), are presented in Table 3. An ARMA (1,4)-GARCH(1,1) model is fit to producer and wholesaler prices, while an ARMA(2,2)-GARCH(1,1) better represents retailer prices. Conditional mean model results suggest that current price levels are positively influenced by price levels during the last week. Univariate GARCH (1, 1) model parameter estimates are all positive for the three prices considered, which indicates that past market shocks as well as past volatility bring higher current volatility levels. Since $\omega_{i1} + \omega_{i2} < 1$, we can conclude that the three GARCH processes are stationary, being the unconditional long-run variance $\sigma_i^2 = \omega_i / (1 - \omega_{i1} - \omega_{i2})$ around 0.022, 0.143, and 0.176 for producer, wholesaler, and retailer prices, respectively. Hence, in the Egyptian tomato market, consumer prices have long-run volatilities that are above the volatilities at the producer and wholesale price level.

The Ljung-Box test results presented in Table 3, allow accepting the null of no autocorrelated residuals. The LM tests (Table 4) implemented to check for the independence of the first four moments of the transformed variables, provide evidence that the models are well specified. The Kolmogorov–Smirnov (KS) test confirms that the transformed series are *Unif* (0,1) (Patton 2006). Time-varying dependence tests in Table 5 support the use of time varying copulas for both pairs of prices. In Table 6, we present the log likelihood values for a wide range of copulas. Those copulas yielding the highest log likelihood values are selected for a more in depth analysis. Gumbel, Student-*t*, and SJC copula are chosen to represent dependency between both pairs of prices (producer - wholesaler and wholesaler - retailer) . The Gaussian copula is also chosen for both pairs of prices, as the benchmark model in economics.

Results of $KS_C$ and $CvM_C$ GoF tests (presented in Table 7) for producer – wholesaler pair of prices suggest the Student´s *t* constant copula as the one providing the best fit, being the second best fit provided by the Gaussian and the SJC constant copulas. In the wholesaler – retailer case, the SJC constant copula offers the first best fit and Student´s *t* constant copula the second best. For time varying copulas the GoF tests suggest that the Student´s *t* better fits the data relative to SJC copula for both pairs of prices. Given these results, static Gaussian, static and dynamic Student´s t, and static SJC copulas are considered in our analysis. Static copula results are presented in Table 8 and dynamic copula findings in Table 9, respectively.

Results of Gaussian and Student´s t copula presented in Table 8 imply a positive short-run correlation between prices at different market levels. The association is stronger between producer and wholesale prices, than between wholesale and retail prices. Furthermore, the inverse of the degrees of freedom of Student's *t* copulas are 0.170 and 0.216 for producer – wholesaler and wholesaler - retailer pairs of prices, respectively. This implies strong dependence in the tail, which is not captured by the Gaussian copula. It is thus relevant to estimate a copula that allows for dependency for very high/low market prices.

Results of SJC copulas provide support for asymmetric dependency during extreme market events. The SJC copula for the producer – wholesaler price pair shows stronger (52% higher) upper than lower tail dependency, which suggests that price increases tend to be passed from producers to wholesalers more completely than price declines. For the wholesaler - retailer price pair, the lower tail is not statically different from zero. Conversely, the upper tail is statistically significant and on the order of 0.13, which implies that while price increases will be transferred from wholesalers to retailers, price declines will be not. Hence, retailers are more likely to increase prices than to reduce them, which reflects the degree of market power that retail chains have in Egypt.

Time varying student's t copula shows how dependency among the pairs of prices considered changes over time. Estimation results are presented in Table 9 and graphed in Figure 1 for the producer-wholesaler price pair, indicating that dependence from April 2011 to March 2013 was relatively low and fluctuated around 0.4. In the period from March 2013 to December 2013, dependence increased reaching values around 0.8. Such increase is likely to be related to the project involving USAID, ACDI-VOCA, Heinz International and 13 domestic tomato processors, to promote high quality and consistent tomato production. Another aim of this partnership is to increase trust between producers and tomato processors and stabilize their relationships through forward contracts. Under these contracts, more than 30% of tomato production is currently sold to processor companies, increasing tomato market outlets and reducing wholesaler market power in Egypt (USDA 2014). This has led wholesalers to offer higher prices to entice producers to sell tomatoes to them. The reduction of wholesaler market power has led to increased dependency between producer and wholesaler market levels, which is an indicator of more competitive market behavior. Time varying Student's *t* tail dependence displayed in Figure 2 shows a low dependency between wholesaler and retailer market levels, which is on the order of 0.2, that fluctuates over the period studied, mainly in the range from 0 to 0.4. Low dependency between wholesaler and retailer prices may be explained by lack of a competitive structure linking wholesalers and retailers. Fluctuations are not surprising given the economically tumultuous period studied.

## 6. Concluding remarks

Food price analyses along the food chain have started to gain relevance in developing economies as data are becoming available. These analyses are of high political, social and economic interest, especially in light of low income levels and chronic poverty affecting these countries. Egypt suffers from high food prices since the food price crisis in 2007/2008. The revolution of January 25, 2011 came to accentuate price increases.

Our analysis focuses on tomato prices dependency along the Egyptian supply chain. To do so, we use flexible methods that do not require assumption of restrictive multivariate distribution functional forms. Copula techniques represent a flexible way to study price dependency. In this context, we apply static and time-varying statistical copulas to assess co-movements between two pairs of prices: producer – wholesaler and wholesaler – retailer prices, both in the central and in the extreme regions of the distribution. Results for the producer – wholesaler price pair, involve positive dependence in the central region of the distribution. Further, extreme increases in tomato producer price will be passed on to wholesaler price more completely than producer price declines. Results from wholesaler – retailer price model also show a positive dependence in the central region of the bivariate distribution, though less strong than the one holding for the producer-wholesale price pair. Regarding dependency during extreme market events, asymmetric dependence has been found by which extreme increases in wholesale prices are passed on to retailer prices, while declines are not. As a result, food consumers will not benefit from extreme declines in prices at upper levels of the food chain, but they will have to endure extreme price increases.

Policies, such as provision of inputs at subsidized prices, or the promotion of adoption of technological advances in the production of tomatoes, may imply reduced production costs. Due to the presence of asymmetries, it is not however warranted that this decline in costs will be transferred down the marketing chain until reaching consumers. In order to combat food security in a country where famine is worrisome, further actions down the marketing chain are required in order to increase the competitive behavior of this chain and facilitate smooth price transmission. The lack of competitive behavior in the nexus wholesaler - retailer levels is evidenced by a lower degree of dependency between these two market levels. In this regard, initiatives that reduce wholesaler and retailer market power will be useful, which involves increasing the number of outlets both for unprocessed raw and processed tomatoes.

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**Table 1.**Unit root tests for producer, wholesaler, and retailer tomato price series

| | t-test | Critical values: 1% | Critical values: 5% | Critical values: 10% |
|---|---|---|---|---|
| Dickey-Fuller test for unit root | | | | |
| With intercept | | | | |
| Producer prices | -3.834 | -3.474 | -2.880 | -2.577 |
| Wholesaler prices | -4.898 | -3.474 | -2.880 | -2.577 |
| Retailer prices | -4.573 | -3.474 | -2.880 | -2.577 |
| Augmented Dickey-Fuller test for unit root | | | | |
| With intercept | | | | |
| Producer prices | -5.177 | -3.460 | -2.880 | -2.570 |
| Wholesaler prices | -7.051 | -3.460 | -2.880 | -2.570 |
| Retailer prices | -4.574 | -3.460 | -2.880 | -2.570 |

**Table 2.**Summary statistics for producer, wholesaler, and retailer tomato prices

| | Producer prices | Wholesaler prices | Retailer prices |
|---|---|---|---|
| Mean | 1.609 | 1.887 | 2.820 |
| Standard Deviation | 0.018 | 0.038 | 0.083 |
| T-statistic | 88.295 | 49.643 | 33.909 |
| Skewness | 4.050* | 3.023* | 1.413* |
| Kutosis (excess) | 18.764* | 12.386* | 1.909* |
| Anderson-Darling Test | 28.386* | 13.091* | 6.383* |
| ARCH LM test | 38.300* | 14.615* | 62.980* |
| Number of observations | | | 155 |

Note: *indicates rejection of the null hypothesis at the 5% significance level. The skewness and kurtosis and their significance tests are from Kendall and Stuart (1958). The Anderson-Darling is the well known test for normality. The ARCH LM test of Engel (1982) is conducted using 10 lags

**Table 3.**Univariate ARIMA-GARCH model for producer, wholesaler, and retailer tomato prices

| Variable | Producer prices | Wholesaler prices | Retailer prices |
|---|---|---|---|
| | Conditional mean | | |
| $C$ | 0.609** | 0.681 ** | 0.126** |
| | (0.161) | (0.138) | (0.048) |
| $\phi_1$ | 0.621** | 0.629 ** | 1.781** |
| | (0.099) | (0.071) | (0.059) |
| $\phi_2$ | — | — | -0.826** |
| | | | (0.051) |
| $\theta_1$ | 0.291** | 0.046** | -0.574** |
| | (0.106) | (0.098) | (0.095) |
| $\theta_2$ | 0.054 | 0.232** | -0.296** |
| | (0.085) | (0.087) | (0.089) |
| $\theta_3$ | 0.440** | 0.067** | — |
| | (0.078) | (0.084) | |
| $\theta_4$ | 0.380** | 0.282** | — |
| | (0.088) | (0.081) | |
| | Conditional variance | | |
| $\omega_i$ | 0.002** | 0.005** | 0.041** |
| | (2.509e-07) | (1.439e-06) | (0.001) |
| $\omega_{i1}$ | 0.325** | 0.413** | 0.437 |
| | (0.026) | (0.017) | (0.031) |
| $\omega_{i2}$ | 0.582** | 0.554** | 0.329** |
| | (0.009) | (0.004) | (0.016) |
| Ljung-Box Q(10) | 8.929 | 11.199 | 7.759 |

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

**Table 4.**LM tests on the transformed prices ($u_t$ and $v_t$)

| | **Producer prices** | **Wholesaler prices** | **Retailer prices** |
|---|---|---|---|
| First moment LM test | 0.869 | 0.627 | 0.784 |
| Second moment LM test | 0.984 | 0.627 | 0.912 |
| Third moment LM test | 0.997 | 0.767 | 0.966 |
| Fourth moment LM test | 0.880 | 0.862 | 0.982 |
| KS test | 0.317 | 0.318 | 0.531 |

Note: this table presents p-values from LM test of serial independence (Patton, 2006) of the first four moments of $u_t$ and $v_t$ and Kolmogorov–Smirnov (K-S) tests.

**Table 5.**Time-varying rank correlation between prices

| Price pair | Break | | | | AR(*p*) | | |
|---|---|---|---|---|---|---|---|
| | 0.20 | 0.50 | 0.85 | Anywhere | 1 | 5 | 10 |
| Producer - wholesale | 0.075 | 0 | 0.285 | 0.002 | 0.002 | 0 | 0.008 |
| Wholesale-retail | 0.066 | 0 | 0.298 | 0.002 | 0.002 | 0 | 0.008 |

Note: this table presents *p*-values from tests for time varying dependency by using one-time break correlations and autocorrelation (AR) tests, based on 1000 bootstrap replications.

**Table 6.**Log likelihood values for static copulas

| | Producer -Wholesaler | Wholesaler - Retailer |
|---|---|---|
| | *Log Likelihood* | *Log Likelihood* |
| Gaussian | 12.151 | 3.363 |
| Clayton | 8.217 | 1.774 |
| Rotated Clayton | 12.966 | 4.726 |
| Plackett | 11.034 | 2.726 |
| Frank | 10.792 | 2.426 |
| Gumbel | 13.659 | 4.822 |
| Rotated Gumbel | 11.265 | 2.938 |
| Student's t | 13.431 | 4.919 |
| Symmetrised Joe Clayton | 14.662 | 4.919 |

**Table 7.**Goodness of fit tests for copula models

| | $KS_C$ | $CvM_C$ | $KS_R$ | $CvM_R$ |
|---|---|---|---|---|
| | Producer - Wholesaler | | | |
| Gaussian | 0.120 | 0.030 | | |
| Gumbel | 0.020 | 0.050 | | |
| SJC | 0.030 | 0.110 | | |
| Student's t | 0.120 | 0.130 | | |
| Time-Varying SJC | | | 0.820 | 0.360 |
| Time-Varying Student's t | | | 0.880 | 0.430 |
| | Wholesaler - Retailer | | | |
| Gaussian | 0.190 | 0.410 | | |
| Gumbel | 0.050 | 0.220 | | |
| SJC | 0.300 | 0.590 | | |
| Student's t | 0.200 | 0.470 | | |
| Time-Varying SJC | | | 0.180 | 0.150 |
| Time-Varying Student's t | | | 0.320 | 0.460 |

Note: this table presents *p*-values from goodness of fit tests for four different copula models using 100 bootstrap replications. $KS_C$ and $CvM_C$ tests refer to the Kolmogorov-Smirnov and Cramer-von Misses tests respectively, applied to the empirical copula of the standardized residuals. $KS_R$ and $CvM_R$ tests refer to the Kolmogorov-Smirnov and Cramer-von Misses tests respectively, applied to the empirical copula of the Rosenblatt transform of these residuals.

**Table 8.**Results from static copulas

| | | |
|---|---|---|
| Producer - Wholesaler | | |
| Gaussian | | 0.381** |
| | | (0.074) |
| Log likelihood | | 12.151 |
| SJC($\tau^L, \tau^U$) | 0.141** | 0.297** |
| | (0.081) | (0.095) |
| Log likelihood | | 14.662 |
| Student's t ($\rho, \nu^{-1}$) | 0.388** | 0.170** |
| | (0.071) | (0.101) |
| Log likelihood | | 13.431 |
| Wholesaler - Retailer | | |
| Gaussian | | 0.206** |
| | | (0.087) |
| Log likelihood | | 3.363 |
| SJC($\tau^L, \tau^U$) | 0.002 | 0.174** |
| | (0.002) | (0.089) |
| Log likelihood | | 4.919 |
| Student's t ($\rho, \nu^{-1}$) | 0.191** | 0.216** |
| | (0.091) | (0.108) |
| Log likelihood | | 4.919 |

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

**Table 9**.Time varying Student's *t* copula

| | | Producer - Wholesaler | Wholesaler -Retailer |
|---|---|---|---|
| Student's t | $\widehat{\omega}$ | 0.056 | 0.459** |
| | | (0.042) | (0.105) |
| | $\widehat{\alpha}$ | 0.190 ** | 0.446** |
| | | (0.043) | (0.155) |
| | $\widehat{\beta}$ | 0.950** | 0.102** |
| | | (0.026) | (0.179) |
| | $\gamma^{-1}$ | 0.213** | 0.168** |
| | | (0.063) | (0.129) |
| | Log likelihood | 18.651 | 6.598 |

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

**Figure 1.**Time varying Student *t* copula for Producer - Wholesaler price pair

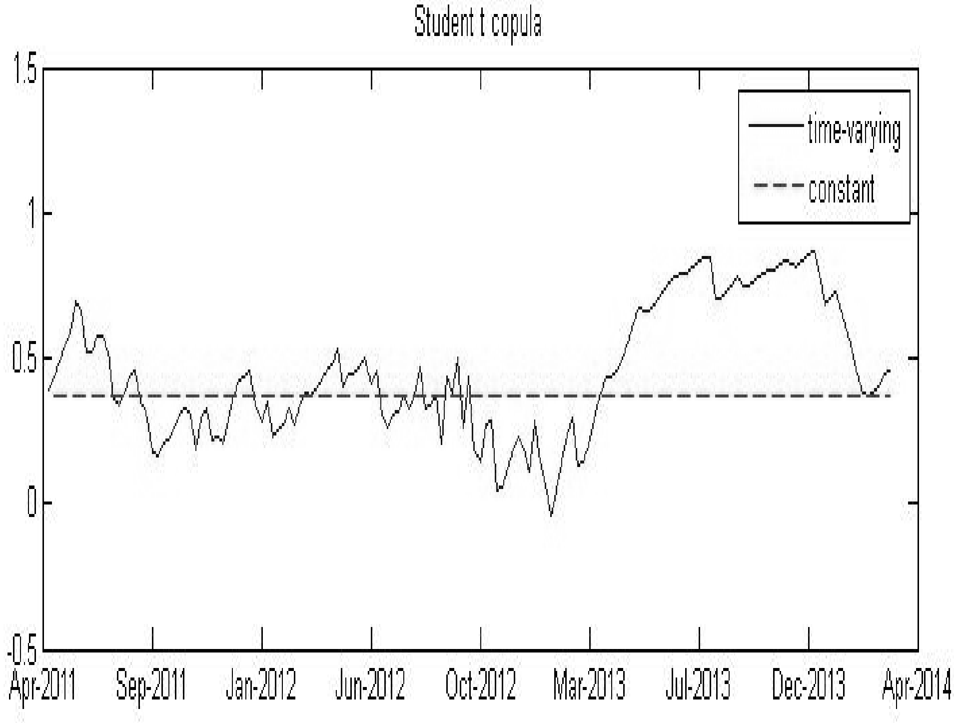


**Figure 2.**Time varying Student *t* copula for Wholesaler - Retailer price pair