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Doctoral Thesis:

"Using statistical copulas to measure dependence in the agrofood sector"

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Abstract

This thesis has been pursued in three papers whose nexus is the use of statistical copulas for the purpose of assessing dependence in the field of agrofood economics. The first paper aims at determining how the introduction of agricultural revenue insurance contracts in Spain will affect the cost of purchasing insurance, relative to yield insurance schemes. The empirical analysis focuses on the apple and orange sectors in Spain. Statistical copulas are used to jointly model price and yield perils. Monte Carlo simulation methods are employed to simulate premium rates both under revenue and yield insurance. Results indicate that revenue insurance is likely to reduce the price of agricultural insurance in Spain, which may result in higher acceptance and demand for agricultural insurance programs.

The second paper aims to study dependence between producer and consumer prices for millet markets in Niger. Links between prices considered are assessed by cointegration analysis and statistical copula methods. Results indicate a positive link between producer and consumer prices, which is stronger the closer the markets are. Evidence of asymmetric price behavior is also found.

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

Resumen

Esta tesis se compone de tres artículos científicos cuyo nexo de unión es el uso de copulas estadísticas para analizar dependencia en el ámbito de la economía agroalimentaria. En el primer artículo, se estudia cómo la introducción de los contratos de seguro de ingresos agrícolas en España puede afectar el coste de la contratación de un seguro, en comparación con el tradicional seguro de rendimientos agrícolas. El análisis empírico se centra en los sectores de la manzana y la naranja en España. Las cópulas estadísticas se utilizan para modelar la dependencia entre los precios y los rendimientos agrarios. Los métodos Monte Carlo se utilizan para simular del importe de las primas del seguro de ingresos y del seguro de rendimientos. Los resultados indican que es probable que el seguro de ingresos reduzca el costo de los seguros agrarios en España, lo que puede conllevar una mayor aceptación y demanda de programas de seguros agrícolas.

El segundo artículo tiene como objetivo estudiar la dependencia entre los precios al productor y al consumidor en el mercado del mijo en Níger. Los vínculos entre los precios considerados son evaluados mediante un análisis de cointegración y el método estadístico de cópula. Los resultados sugieren la existencia de una relación positiva entre el precio del productor y del consumidor, la cuál aumenta cuanto más próximos se encuentren los mercados. También se han hallado evidencias de asimetría en el comportamiento de los precios.

El último artículo evalúa la transmisión de precios a lo largo de la cadena de comercialización alimentaria egipcia del tomate. El estudio se centra en el período posterior a la Primavera Árabe. Métodos de copula estática y dinámica se utilizan con este propósito. Los resultados sugieren la existencia de una relación positiva entre los precios al productor, mayorista y vendedor al detalle. Esta dependencia positiva presenta asimetrías durante los eventos extremos del mercado, que conllevan que el aumento de los precios se transfiriera de manera más completa a lo largo de la cadena de suministro que las disminuciones de precio.

Dedication

I dedicate my Doctoral thesis to my family. A special feeling of gratitude to my lovely wife, Nourhan who has never left my side. I thank her for her personal support and great patience at all times. I also dedicate this dissertation to my loving parents, Mervat and Ahmed whose words of encouragement and push for tenacity ring in my ears. Finally, I also dedicate my thesis to my lovely daughter, Haidy whose look in her two shiny eyes helps me push forward.

OSAMA

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CHAPTER 1

Introduction

Assessment of dependence between variables is key to research analysis in any scientific discipline. In agricultural economics, scholars have devoted a great deal of attention to study dependence between a myriad of data, including agricultural yields, market prices, agricultural input use, etc. Conventional analyses of dependency between multiple random variables are constrained by the availability of statistical tools and mainly rely on multivariate normal or student's *t* distributions. These distributions have been shown to usually misrepresent the data studied. Kurtosis, skewness and non-normality have been generally found to characterize food prices and agricultural yields. Further, dependency between variables may be stronger in the tails of the distribution than in the centre, and be characterized by asymmetries. This calls for the need to use flexible statistical instruments to represent multivariate distribution functions.

Statistical copulas provide flexibility in evaluating dependence between variables. A copula function is a multivariate distribution function defined on the unit cube $[0,\ 1]^n$, with uniformly distributed marginals. Copulas are based on the Sklar's (1959) theorem that implies that, in multivariate distribution functions, the univariate margins and the multivariate dependence structure can be separated and the dependence structure represented by a copula. The Sklar's theorem allows the researcher to focus on modeling univariate distribution functions, which usually leads to the construction of better models (Patton, 2006). The dependence structure is fully represented by the copula. Copulas allow flexible characterization of dependence between random variables and are especially useful if no obvious choice for the multivariate density function exists. The use of copulas in the economics literature is rather recent and most empirical applications are found within the financial economics literature (see, for example, Patton, 2004 and 2006; or Parra and Koodi, 2006). More recently Goodwin and coauthors have applied copula-based models to appraise systemic risk in U.S. agriculture. Serra and Gil (2012) have used copulas to study dependence between crude oil and biofuel prices. The use of copulas to assess dependency in the agricultural sector, constitutes the guiding theme of this PhD Thesis.

This thesis is composed by three main core chapters that constitute three independent scientific articles. The first article assesses how the introduction of revenue insurance in Spain will affect the cost of purchasing insurance, relative to yield insurance. A sound implementation of revenue insurance requires reliable assessment of price and yield dependency. With the launching of agricultural revenue insurance programs, which was specially relevant in the US by the end of the past century, the modeling of dependence between prices and yields has received increasing research attention within the agricultural economics field (USDA, 2001). The relevance of joint consideration of risks is manifest in that periods of low yields may be accompanied by high prices. This would lead to lower fair premium rates than if declines in both yields and prices occurred at the same time. In short, to design a revenue insurance contract it is necessary to understand the usually negative relationship between agricultural yields and prices. If this relationship is ignored, risk will likely be over-estimated. While numerous research articles have been published on the proper modeling of agricultural yield risk, the literature focusing on price and yield risk dependence is relatively new (Tejeda and Goodwin, 2008; Zhu et al., 2008; Woodard et al., 2010; Ghosh et al., 2011). The apple and orange sectors in Spain are the focus of the empirical analysis. The research is based on annual average prices and yields from the Spanish Ministry of Agriculture, Food and Environment (MAGRAMA, 2010) for the period from 1954 to 2010, which yields a total of 57 observations.

The second and third research articles focus on assessing dependency of prices along the food marketing chain, from producers to final consumers in less developed countries (LDCs). 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 LDCs due to different market characteristics such as excessive governement intervention, corruption, defficient infrastructures, etc. Price formation is usually poorly understood in these countries. 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. The interest grows if we consider the scarcity of price transmission analyses in these countries, which bears strong connection with data availability problems.

The second scientific article aims at understanding how millet prices are transmitted across millet markets in Niger. Niger agriculture is overly influenced by a harsh climate and geography. Rough climatic conditions and market price volatility bring instability to food supply, exacerbating chronic food insecurity and poverty. This has an impact on prices. Data to conduct research on Niger millet markets were made available by Intermon Oxfam (2012) and consist of monthly millet producer and consumer prices in Maradi and Tillabéri, two relevant millet markets, for the period from 1990 to 2011. While Maradi represents a region where there is excess millet production, Tillabéri is a deficit zone.

The third research article examines food price transmission along the marketing chain in Egypt. The analysis is conducted for the period around the revolution of January 25, 2011, that came to accentuate economic hardships and food price inflation in this country. The tomato market is the focus of this research article. Tomato production is a very relevant economic activity within Egypt. The analysis is based on weekly price data for tomatoes, 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, 2014).

The thesis, that is structured in a journal article format, consists of five chapters. The three scientific articles described above follow this introduction. Integrative conclusions are provided in Chapter 5, where I pull together all the work described in the core chapters of the thesis (i.e., chapter 2 to chapter 4) and relate this back to the issues raised in the Introduction. Chapter 2 (the first scientific article) entitled “Economic analysis of the introduction of agricultural revenue insurance contracts in Spain using statistical copula” is currently under third-round review in the Agricultural Economics journal. Chapter 3 (the second scientific article) entitled “Price volatility of food staples .The case of millet in Niger” is being considered for publication (second-round review) in the

Australian Journal of Agricultural and Resource Economics. Chapter 4 (third article) entitled "Vertical price transmission in the Egyptian tomato sector after the Arab Spring", is under review in the Applied Economic Perspectives & Policy journal.

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CHAPTER 2

Economic analysis of the introduction of agricultural revenue insurance contracts in Spain using statistical copulas[1]

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2.1. Introduction

The agricultural sector usually faces a combination of risks rarely found in other enterprises. Two of the major risks affecting agriculture are climatic and natural risks that influence agricultural yields, and market risks that may lead to agricultural price fluctuations. Recent dismantling of public commodity price stabilization mechanisms leading to increased dependence of prices on global markets, may have increased price risk (Antón and Kimura, 2011; Gilbert and Morgan, 2010). Since the 2008 financial crisis, changes in both food price levels and volatility are more the norm than the exception. Food price volatility is likely to persist in the upcoming years (European Commission, 2011). This has renovated the interest in risk management tools for the agricultural sector.

To develop sound risk management strategies, it is important to understand the nature of risk: its origin, distribution and correlation with other risks, and the capacity of several instruments to reduce it (Hardaker et al., 1997). A non-exhaustive list of risk management instruments that agriculture can use includes marketing contracts, derivatives, diversification, storage, or agricultural insurance. We focus on the latter. Different agricultural insurance schemes comprise: yield, price and revenue insurance. Yield insurance protects against production risks (climatic and other natural risks) and triggers indemnity payments if yields fall below a pre-defined level. Price insurance protects against agricultural price risk (KANG, 2007). Price insurance is specially useful for livestock producers who, contrary to crop producers, are more affected by price fluctuations. An example is the United States (US) livestock risk protection program.

Revenue insurance provides joint price and yield coverage, to guarantee farmers a minimum income level. The probability of loss depends on the joint probability distribution of prices and yields. Defining an actuarially fair premium rate is key to any insurance program if an efficient resource allocation is pursued. Under and overvalued premium rates will distort the demand and supply of insurance, the adoption of risk management strategies, the economic sustainability of different insurance programs, and may motivate the introduction of inefficient public policies. Undervalued premium rates are likely to bias insurance demand in favor of the most expensive programs and the highest coverage levels. It may also be detrimental to other risk management products and may compromise economic viability of insurance companies, unless inefficient public subsidies are launched to support the industry. Further, inadequate premium rates may distort farmers' production choices (Babcock, 2012; Westcott and Young, 2002), which may have implications for both the agrofood industry and food consumers.

While revenue insurance has been successfully implemented in countries such as the US (through different programs such as Crop Revenue Coverage (CRC), Income Protection (IP), Revenue Assurance (RA), or Revenue Protection (RP)),[2] Spain is considering its implementation. Agroseguro, the pool of the agricultural insurance companies in Spain, has recently funded a series of studies to assess how these insurance programs should be implemented. The main challenge of implementing revenue insur5ance is the computation of an actuarially fair insurance premium taking into consideration dependence between price and yield risks. The relevance of joint consideration of risks is manifest in that periods of low yields may be accompanied by high prices. This would lead to

[2] In 2011 the CRC, RA and IP programs in the US, were merged and updated mostly to the Revenue Protection and Revenue Protection with the Harvest Price (RP with HP) exclusion programs. The latter excludes coverage against harvest price declines.

lower fair premium rates than if declines in both yields and prices occurred at the same time. Dependence between prices and yields has received increasing research attention in the agricultural economics field (USDA, 2001). Recent research in this area has proposed the use of statistical copulas as flexible instruments that soundly capture the joint distribution function of yields and prices. Copulas are statistical instruments that combine univariate distributions to obtain a joint distribution (multivariate distribution) with a particular dependence structure. This is important given the scarcity of multivariate distributions available from the statistical literature. [3]

This research aims at evaluating the economic impacts of implementing revenue crop insurance in Spain. We study how insurance premium rates will change under such scheme, relative to yield insurance schemes. For such purpose, we apply copula modeling to assess dependence between prices and yields in the orange and apple sectors. As noted, shedding light on this issue is especially relevant for policy makers, insurance companies and farmers, but also to the food industry and consumers. This analysis is especially useful at a time where revenue insurance is being considered for its implementation in Spain.

The paper is organized as follows. In the next section, a brief description of agricultural insurance programs in the European Union (EU) and in Spain is offered. We then present the main characteristics of the orange and apple sectors in Spain. A literature review of risk modeling in agricultural insurance is offered in section 4. The methodological approach is described in the fifth section. The sixth and seventh sections are devoted to the empirical implementation and a

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[3] Other approaches to building bivariate distributions with given marginals include mixture models (Marshall and Olkin, 1988; Genest and Mackay, 1986).

Monte Carlo simulation to assess the economic consequences of implementing revenue insurance, respectively. The article closes with concluding remarks.

2.2. Agricultural insurance in the EU and in Spain

The Barometer of Agricultural Insurance (Ikerfel, 2008) identifies agricultural producer main risk concerns. Hail is the most relevant, except for viticulturists who identify frost as the most relevant risk. Price declines are placed either in the second or third position in the ranking. Livestock producers differ from agricultural producers in perceiving price drops as their main source of risk, followed by the main animal diseases (Ikerfel, 2008). Despite the relevance of price risk, EU agricultural insurance schemes mainly focus on yield protection.

Calamity funds, mutual funds and insurance contracts are the most relevant agricultural risk management tools in the EU (Bielza et al., 2009). Publicly regulated calamity funds provide aids when catastrophes are declared. Mutual funds, in contrast, are privately owned and organized by farmers. Agricultural insurance schemes are specially interesting when a country's legal framework precludes public payments (e.g. calamity funds) to damages that are subject to be insured. While yield insurance programs predominate within the EU, revenue insurance programs enjoy widespread diffusion in the US.

Different coverages lead to different premium rates, which are, on average, close to 4% in Europe and 9% in the US.[4] The US and the EU also differ in terms

[4] While yield insurance in the US is an all comprehensive insurance, a poli-risk insurance which covers just a few risks predominates in the EU. Comprehensive yield insurance exists only in a few EU countries such as Spain, Austria, and more recently also in Italy and France.

of adoption of insurance schemes: while about 80% of the major crop (corn, wheat, soybean, cotton and peanuts) values are insured in the US, this percentage (FAPRI, 2010) falls to 23% within the EU (Bielza et al., 2009).

Agricultural insurance programs in Spain have been evolving during the 20th century under public, private and mixed initiatives. Since private initiatives usually focus on specific risks and clients, universalization of agricultural insurance has required some form of government intervention. In 1978, a mixed approach was adopted in Spain that aimed at integrating all the interested parties (farmers, insurance companies and society at large). A co-insurance panel led by Agroseguro was built and opened to the participation of insurance entities willing to do so. The public administration, on the other hand, regulates insurance schemes and supports the contracting of insurance plans. Finally, an insurance compensation consortium reinsures the system (Antón and Kimura, 2011).

2.3. Orange and apple markets in Spain

To evaluate the economic consequences of revenue insurance programs, we focus on orange and apple fruit sectors in Spain, which are affected by different natural perils such as frost, hail, freeze, insects, etc., that can reduce yields, as well as by price risks. Spain is a world leading producer of fruits: by output volume, it ranks fifth after China, the US, Brazil, and Italy. Jointly with Spain, these countries represent nearly 50% of the global fruit output (MAGRAMA, 2011). Oranges, mandarins and peaches are the main fruits produced in Spain. They represent, respectively, 32%, 24% and 14% of total fruit output and are followed by lemons, apples, and pears with a share of 9%, 8% and 6%, respectively (FAOSTAT, 2010). In year 2010, the orchard area in Spain was 1.6 million hectares yielding a production of 15.6 million tons (FAOSTAT, 2010). The Spanish orchard area represents more than a fifth of the EU's fruit harvested area.

According to FAOSTAT (2005 and 2010) data, the orange sector is the most relevant Spanish fruit sector. After banana and apple, orange is the third most relevant fruit production in the world. Global orange production expanded from 63.1 billion tons in 2005 to 69 billion tons in 2010. In 2010, international exports and imports of oranges were estimated to be 6.5 and 6.1 million tons, respectively. In the same year, Spain was the largest orange exporter in the world, with 20% of global exports, most of which went to the EU. Worldwide orange production is distributed among more than 100 countries, being Spain the sixth most relevant one, after Brazil, USA, China, and Mexico, and the first EU producer. Spanish production represented 4.5% of global orange output in 2010. In 2005, Spanish production was 2.4 million tons and grew to be 3.1 million tons in 2010, an increase of around 131%.The orange sector is very important for EU economies that in 2010 devoted 312.5 thousand hectares to produce 6.5 million tons. EU exports (imports) of orange were estimated to be on the order of 2.4 (2.9) million tons in 2010. EU largest harvested orange area is found in Spain with 153.6 thousand hectares (representing a 110.5% growth rate since 2005). Spain concentrated 48% of all oranges produced in the EU in 2010.

The apple sector is one of the most relevant non-citrus Spanish fruits by output volume and the first fruit sector within the EU. With 533.4 thousand hectares that yield 10.7 million tons of output, apple is the most relevant fruit cultivated within the EU. It represents 9% of the EU's fruits harvested area and 18.2% of the EU's fruits production. Spain produced 646.2 thousand tons in 2010, being the per capita production the 11th highest in the world and the 4th highest in the EU (FAOSTAT, 2010). Spanish consumer preferences regarding fruit place oranges in the first position and apples in the second (11.8% of total fruit consumption). While 63.9% of apple consumption in Spain is produced nationally, 36.1% is imported. Spain exports apples especially to other EU countries, being the most relevant target markets France, Italy, Portugal and Germany. North Africa, the Persian Gulf and South America also import Spanish apples (MAGRAMA, 2010).

The Spanish fruit sector is relevant for agricultural insurers. In 2010, 60,118 insurance contracts were signed in this sector, 23 % of the agricultural insurance pool, covering around 111.2 thousand hectares of fruits area, 1.8% of total insured agricultural land. Costs of fruit insurance were 205.4 million euros (43% of total agricultural insurance costs). Fruit producers received 79.5 million euros indemnity insurance (45.56% of total Spanish farmer indemnities, MAGRAMA, 2012a, 2012b). In the Spanish citrus sector, 37 thousand insurance contracts were signed in 2011 (14.3% of total fruit insurance contracts) covering 3 million tons (56.6% of the total amount of insured fruits). Citrus farmers incurred insurance costs on the order of 57.2 million, 26.5% of total fruit insurance costs. The indemnities received were on the order of 739 thousand euros (1.27% of indemnities received by the fruits sector) (MAGRAMA, 2012a). In 2011, 998 apple insurance contracts were signed in Spain, 4.6% of total fruit insurance contracts. Insurance covered 65.7 tons of apples (1.19% of the total amount of insured fruits). Apple farmers incurred insurance costs on the order of 2.58 million, 1.19% of total fruit insurance costs. The indemnities received were on the order of 739 thousand euros (1.27% of total indemnities received by the fruits sector) (MAGRAMA, 2012b).

2.4. Literature review

Revenue insurance programs have not been popularized until recently. While numerous research articles focus on the proper modeling of agricultural yield risk, the literature on price and yield risk dependence is relatively new. Goodwin and Ker (1998) model yield risk using nonparametric methods and assess the consequences of doing so on the actuarial performance of Group-Risk Crop Insurance Contracts (GRP). Nonparametric kernel densities are more flexible than parametric specifications. Results confirm the flexibility of the non-parametric estimates and show these estimates to improve the actuarial performance of the GRP program (Goodwin and Ker, 1998). Ozaki et al. (2008) estimate yield density using both parametric (normal and beta densities) and nonparametric statistical modeling (nonparametric kernel estimator) and evaluate the implications of doing so for pricing crop insurance contracts for corn, soybean and wheat in Brazil. Rates are higher under the nonparametric approach and authors advise insurance companies to charge premium rates according to the nonparametric technique.

Tejeda and Goodwin (2008) model prices through a Burr distribution, while a Beta distribution is used to model yields. Correlation between crop prices and yields is assessed using copula method and found to be negative. Such negative correlation reduces the likelihood of indemnity payouts, relative to the case where prices and yields are assumed to be independently distributed. Zhu et al. (2008) aim at providing the necessary instruments to design an efficient whole farm insurance contract. This requires deep understanding of revenue risk that derives from changes in multi-output random prices and yields. Beta and log-normal marginals are used to model individual yields and prices, respectively, while dependency is studied using copula techniques. Pooling all farm risks within a single insurance contact is found to provide coverage at lower rates than the alternative of insuring each risk individually.

Ghosh et al. (2011) consider different copula models and their mixtures in order to assess the dependence structure between yields and prices in agriculture. Copula mixtures are construed by assigning weights to each single copula function. Results show the potential of copula mixtures to perform better than individual copulas. More specifically, results show that the mixture between Archimedean copulas is capable of improving insurance pricing. Widespread adoption of revenue insurance programs in the US explains why most of the literature on this topic focuses on US insurance markets. Our paper contributes to the preceding literature by studying the dependency between the crop prices and yields for apple and oranges fruit in Spain,[5] a country that is currently considering the introduction of revenue insurance programs.

2.5. Methodology

The use of copulas in the economics literature is recent and most empirical applications are found within the financial economics field (Patton, 2004 and 2006; Parra and Koodi, 2006). Copulas allow flexible characterization of dependence between random variables, being especially useful if no obvious choice for the multivariate density function exists. A copula function is a

[5] Estavillo et al. (2005) focus on determining reference price for revenue insurance in the Spanish potato sector. Bielza et al. (2002) assess dependency between prices and yields in the olive oil sector in Spain by using the Spearman correlation coefficient.

multivariate distribution function defined on the unit cube $\left[0,\ 1\right]^n$, with uniformly distributed marginals. Let F and G be univariate continuous distribution functions of two random variables (x, y). The unconditional copula of (x, y) is the joint distribution function of $u = F(x)$ and $v = G(y)$, where u and v are the probability integral transforms of x and y that are distributed as *Unif*(0,1) (Fisher, 1932). According to the Sklar's (1959) theorem, there exists a unique copula C that can be expressed as (Embrechts et al., 2001):

$$H(x, y) = C(F(x), G(y)) = C(u, v)\,. \qquad (1)$$

where $C(u,v) = H(F^{(-1)}(u), G^{(-1)}(v)), \forall (u,v) \in [0,1]\times[0,1]$ is a bivariate distribution function with marginal distributions F and G, being $F^{(-1)}$ and $G^{(-1)}$ the quasi-inverses of the marginal distributions. The joint bivariate density function can be expressed as:

$$h(x, y) = f(x)g(y)c(F(x), G(x))\,, \qquad (2)$$

where c is the copula density and $f(x)$ and $g(y)$ univariate density functions.

The copulas and marginal distributions are specified such that parameters can be estimated in two different stages (Patton, 2006). Appendix 2.1 discusses model specification. In the first stage of the estimation, marginal distribution parameters are obtained by optimizing the marginal log likelihoods independently of each other. In the second step, copula parameters are estimated by optimizing the corresponding copula log likelihood, conditional on the results from the first step (see Appendix 2.2 for further details).

Elliptical copulas are copulas of elliptical distributions such as the Gaussian and the Student's *t*. While being very practical, they do not have closed form expressions and are restricted to have radial symmetry. Another class of copulas includes the Archimedean, that are popular because they can be expressed in terms of a single argument generator function, the generator function depends on one or few parameters, which allows to model dependence in high dimensions with only one or a reduced set of parameters (Nelsen, 2006; Joe, 1997). Another advantage that has been attributed to Archimedean copulas is that, in contrast to Elliptical copulas, they allow assessing dependence in extreme tails of the distribution. Copulas may also be categorized as static and time-varying. A static copula implies parameter constancy over time, while a dynamic copula allows the parameters to change with changing environment (Okhrin et al., 2009).

Different copula specifications represent different dependence structures. In order to select the copulas that better fit our data, a series of time-varying dependence, model selection and goodness of fit (GoF) tests are conducted (see Appendices 2.3 and 2.4). According to time-varying dependence test results, time-varying copulas are excluded from the analysis. The range of static copulas considered is initially wide and the four copulas with the highest log-likelihood value are chosen for further detailed analysis. These are the Gaussian, the Student's *t*, the Clayton and the Plackett copula. Model selection and GoF tests are applied on these copulas in order to select the optimal. A bivariate Gaussian copula can be expressed as:

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

where R_{12} is the correlation coefficient of the bivariate normal distribution, $-1 < R_{12} < 1$, and Φ denotes the univariate normal distribution. A drawback of the Gaussian copula is that it assumes that variables u and v are independent in the extreme tails of the distribution. It thus represents dependence in the central region of the distribution. A bivariate Student's *t* copula can be expressed as:

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

where R_{12} is the correlation coefficient of the corresponding bivariate *t*-distribution with γ degrees of freedom ($\gamma > 2$ for the correlation to be defined (Embrechts et al., 2001)), and t_γ denotes the bivariate distribution function. When $\gamma > 30$, the Student's *t* copula tends to the Gaussian copula (Goodwin, 2012).

While copulas model dependence, the strength of overall dependence has been measured through robust copula-based measures such as the Kendall's tau. [6]

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[6] The use of linear correlation coefficients as a measure of dependence strength can be rather misleading if the dependence cannot be modeled through an elliptical distribution. Copula-based dependence measures are more robust (Embrechts et al., 2002; Joe, 1997).

For both the Student's *t* and the Gaussian copula, the correlation coefficient R_{12} is connected to the Kendall's tau according to: $\tau = \frac{2}{\pi} \arcsin R_{12}$. Neither the Gaussian, nor the Student t copulas allow for dependence in the extreme tails of the distribution. Such dependence may be relevant and differ from dependence in central areas of the distribution. Tail dependence may be key from a risk management point of view, i.e., insurance companies might be more interested in the dependence of yields and prices during extreme weather or market events than during more frequent and less drastic events. The Clayton copula can be expressed as:

$$C_{\phi}^{c}(u,v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta}. \tag{5}$$

This copula does not have right tail ($\lambda_r = 0$) dependence, but allows for left tail dependence which can be expressed as $\lambda_l = 2^{-1/\theta}$. Parameter θ is related to the Kendall's tau as follows $\tau = \frac{\theta}{\theta + 2}$. The Plackett copula can be defined as (Manner, 2007):

$$C_P(u,v) = \frac{1}{2(\theta-1)}\left[1 + (\theta-1)(u+v) - \sqrt{\left[(1+(\theta-1)(u+v))^2 - 4\theta(\theta-1)uv\right]}\right], \tag{6}$$

where $\theta \in (0,\infty)$. The Plackett copula covers a wide range of dependence: from perfect lower tail dependence ($\theta = 0$), to perfect upper tail dependence ($\theta = \infty$).

One of the most important features of copula functions is that marginal distributions do not necessarily have to come from the same families. Marginal models filter the information contained in univariate distributions and allow deriving *i.i.d.* residuals from the filtration. The *i.i.d.* residuals are then transformed to $Unif(0,1)$ using the non-parametric empirical cumulative distribution function (CDF). The empirical CDF method is especially convenient when the true distribution of the data is not known.

Copulas apply to stationary time-series. The augmented Dickey and Fuller (1979) and KPSS (1992) tests for unit roots support the presence of a unit root in all price and yield series. First differenced data are thus used. The following lines describe how we determine price and yield shocks. Univariate models for apple and orange prices are specified following previous research (Bollerslev and Mikkelson, 1996; Diebold, 2004; Patton, 2013; Mohammadi and Su, 2010) as an ARIMA-GARCH, According to parsimony and statistical significance an ARIMA(1,1,0)-GARCH(1,1) is used for apple prices, and an ARIMA(2,1,0)-GARCH(1,1) for orange prices. The latter can be expressed as:

$$\Delta P_{i,t} = \alpha_{ipc} + \alpha_{ip1}\Delta P_{i,t-1} + \alpha_{ip2}\Delta P_{i,t-2} + \varepsilon_{ip,t}, \tag{8}$$

$$\sigma^2_{i,t} = \omega_{ipc} + \omega_{ip1}\varepsilon^2_{i,t-1} + \omega_{ip2}\sigma^2_{i,t-1}, \tag{9}$$

where $\Delta P_i, i = a, o$ is the first differenced logged price. Subindex i takes values a and o to represent apples and oranges, respectively, α_{ipc} is the constant of the conditional mean model, α_{ip1} and α_{ip2} are the coefficients representing the autoregressive component, $\varepsilon_{ip,t}$ is normally distributed error term, ω_{ipc} is the constant in the conditional volatility model, being ω_{ip1} and ω_{ip2} the coefficients representing the lagged square residuals and variance, respectively. Log-likelihood methods assuming normally distributed errors are used in model estimation. Along the lines of Goodwin and Ker (1998), the univariate models for orange and apple yields ($Y_i, i = a, o$) adopt an ARIMA (1, 1, 0) specification:

$$\Delta Y_{i,t} = \alpha_{iyc} + \alpha_{iy1}\Delta Y_{i,t-1} + \varepsilon_{iy,t} \tag{10}$$

where $\Delta Y_{i,t}, i = a, o$ are first-differenced apple yields, α_{iyc} is the constant, α_{iy1} the coefficient of lagged yield changes and $\varepsilon_{iy,t}$ a normally distributed error term.

2.6. Empirical analysis

To assess the economic impacts of implementing revenue insurance in Spain, the US RA program is used as a reference. RA schemes protect farmers against declines in yields, prices or both, leading to a decline in revenue. RA indemnities can be computed according to (Zhu et al., 2008): $\max\left[\left(\lambda_i R_i^e - R_i\right), 0\right], \; i = a, o$, where $R_i = Y_i * P_i$ is total annual revenue, $R_i^e = E(R_i)$ is the expected revenue and $\lambda_i \in (0,1)$ is the coverage level percentage, which is previously agreed between the insurer and the farmer. If $R_i \leq \lambda_i R_i^e$ the farmer will receive from the insurer the amount of $\left(\lambda_i R_i^e - R_i\right)$. An actuarially fair insurance premium, which is the cost to purchase insurance, is equal to the expected loss of the contract:

$$EL(R_i) = E\left[\left(\lambda_i R_i^e - R_i\right) I\left(R_i \leq \lambda_i R_i^e\right)\right], \tag{11}$$

being $I\left(R_i \leq \lambda_i R_i^e\right)$ an indicator equal to one if indemnities are paid, and zero otherwise.

The dataset used for the analysis includes annual Spanish average prices and yields for apple and orange for the period from 1954 to 2010, yielding 57 observations. Apple and orange prices yields are expressed in constant 2010 euros per 100 kilogram, and yields in tons per hectare (figures 2.1 and 2.2). Data were obtained from the Spanish Ministry of Agriculture, Food and Environment (MAGRAMA, 2010). Unit root tests show that none of the series is stationary (Table 2.1). Since copula modeling can only be applied to stationary data, we take the logged prices in first differences and yields in first differences. Summary statistics for first-differenced data are presented in Table 2.1. Implicit in the mean and standard deviation is a rather large fluctuation in annual yields, specially relevant in apple production: the average coefficient of variation of apple (orange) yields is 34.1 (9.3). Price volatility is much less relevant than yield volatility with a coefficient of variation of 4 and 3 for the apple and orange market, respectively. With the exception of orange yield data, skewness characterizes our data. Excess kurtosis characterizes apple yields and prices. The Doornik-Hansen (2008) normality test supports normally distributed data. The next stage consists of estimating marginal price and yield models.

The Akaike's information criterion (AIC) and Bayesian information criterion of Schwarz's (BIC) are used to choose the optimal marginal model specification (Table 2.2). Table 2.3 presents the results of estimating an ARIMA (1, 1, 0)-GARCH (1, 1) model for apple prices and an ARIMA (2, 1, 0)-GARCH

(1, 1) for orange prices. The apple price conditional mean model shows that current price changes are negatively affected by past price changes. Univariate GARCH (1, 1) model parameters are all positive, which indicates that past market shocks as well as past volatility cause higher current volatility. Since $\omega_{p1} + \omega_{p2} < 1$, we conclude that the GARCH process is weakly stationary, being the unconditional long-run variance equal to 0.057 (Engle, 2001). The orange price conditional mean model shows that current price changes respond negatively to lagged changes. The orange price volatility is affected by past market shocks, but not by past volatility. GARCH parameters lead to an unconditional variance σ_o^2 = 0.055 (or 0.074 if the non-significant parameter ω_{p2} is ignored). Table 2.4 presents the results of the model fit to apple and orange annual first-differenced yield data. Current yield changes are found to be negatively affected by past yield changes.

Time-varying dependence tests described in Appendix 2.3 recommend the use constant copulas for both apple and orange (Table 2.5). In order to select constant copulas that better fit our data, a series of model selection and goodness of fit (GoF) tests are conducted and results offered in Tables 1.6-1.7. We first present the log likelihood values for a wide range of copulas (Table 2.6). Those copulas yielding the highest log likelihood values are chosen for a more in depth analysis. These copulas are the static Gaussian copula, Student’s *t* copula, Clayton copula, and Plackett copula for both apples and oranges. The Chen and Fan (2006) model selection tests (Table 2.7) choose the Student´s *t* copula as a first choice and the Gaussian copula as the second choice for apple, and the Student´s *t* copula as a first choice and the Plackett copula as the second choice for orange (Gaussian is the third choice for orange). Results of GoF (Table 2.8) suggest selected models correctly fit the data. According to test results, our analysis focuses on the Student's *t* copula for both apples and oranges. The Gaussian copula is also considered, since it is a benchmark copula in economics. Parameter estimates for these two copulas are presented in Table 2.9.[7] By using Canonical Vine Copulas, Gaussian and Archimedean copulas, Goodwin (2012) finds that Gaussian models underprice the risk between US corn and soybean yields and their prices. By using Canonical Vine Copulas, Gaussian and Archimedean copulas, Goodwin (2012) finds that Gaussian models underprice the risk between US corn and soybean yields and their prices. Copula results show that prices and yields are negatively correlated. Hence, during good crop years, prices tend to decline, while during bad crop years, prices tend to be higher. Correlation estimated by Gaussian copula is around -0.55 and -0.32, corresponding to a kendall's tau of -0.37 and -0.21, for apple and orange, respectively. Correlation estimated by Student's *t* copula is around -0.57 and -0.36, corresponding to a kendall's tau of -0.39 and -0.23, for apple and orange, respectively. In addition, the degree of freedom for Student's *t* copula considered is 5.780 and 5.848 for apple and orange, respectively. This implies substantial joint fat tails.

2.7. Monte Carlo Simulation Study and policy Implication

A Monte Carlo exercise is conducted to simulate yields, prices and revenues, and derive the actuarially fair premium rate of implementing RA programs for apple

[7] By using Canonical Vine Copulas, Gaussian and Archimedean copulas, Goodwin (2012) finds that Gaussian models underprice the risk between US corn and soybean yields and their prices.

and for orange in Spain. This premium rate is compared with the fair rate of a yield insurance scheme. Different scenarios consisting of different coverage levels (75% and 80%, represented as λ_i in equation 11) are considered and year 2010 is taken as the reference to conduct the simulation. The 2-dimensional static Student´s *t* copula is used to draw 100,000 revenue series. These draws represent the dependence structure between prices and yields, and are used to compute the expected loss and premium rate at different coverage levels.

Simulated prices and yields can be obtained by undoing the differencing operation specified in equations (8) and (10). This produces expected yields and log prices. The exponential operator is used to derive price levels. The expected revenue is computed as the product of expected yields and prices $R^e_{i,2010} = Y^e_{i,2010} * P^e_{i,2010}$. Actual annual revenue is given by $R_{i,2010} = Y_{i,2010} * P_{i,2010}$. The expected revenue loss and premium for a revenue insurance contract can be computed according to the formula: $EL(R_{i,2010}) = E\left[\left(\lambda R^e_{i,2010} - R_{i,2010}\right) I\left(R_{i,2010} \leq \lambda R^e_{i,2010}\right)\right]$, where $I\left(R_{i,2010} \leq \lambda R^e_{i,2010}\right)$ is an indicator function that takes the value of 1 if the actual revenue is below the insured level, which will trigger insurance payments equal to $\left(\lambda_i R^e_{i,2010} - R_{i,2010}\right)$. The actuarially fair premium rate is the ratio between the expected loss and the liability. Both the expected loss and fair premiums are also computed for a yield insurance scheme. To maintain consistency, the same apple and orange yields obtained from the price revenue scheme are used and then multiplied by the predicted 2010 price to derive their euro value. The expected yield loss is given by: $EL(Y_{i,2010}) = E\left[\left(\lambda Y^e_{i,2010} - Y_{i,2010}\right) I\left(Y_{i,2010} \leq \lambda Y^e_{i,2010}\right)\right] * P^e_{2010}$ (see Goodwin and Ker 1998).

As can be appreciated in Table 2.10, and compatible with our expectations and previous research, revenue insurance programs result in lower expected losses and lower premium rates than yield insurance programs. At a 75% coverage level, the actuarially fair premium rate for a revenue (yield) program for apple is 1.4% (2.8%). The actuarially fair premium rate for a revenue (yield) program for orange is 5.2% (5.4%).When coverage levels increase to 85%, premium rates for apple become 3.2% for revenue and 6.3% for yield insurance, and premium rates for orange become 8.7% for revenue and 9% for yield insurance. These rates are among the ranges provided in Bielza et al. (2009) for European agricultural insurance. From these results, we conclude that when shifting from yield insurance to a revenue insurance contract, the price of insurance will decline. Hence, launching revenue insurance programs in Spain may result in higher acceptance and demand of agricultural insurance programs.

2.8. Concluding remarks

While Spain is one of the EU countries with more advanced agricultural insurance schemes, it has not yet promoted revenue insurance that protects against revenue losses due to either yield or price declines. This article studies the economic consequences of launching agricultural revenue insurance contracts in Spain. Specifically it assesses whether agricultural revenue assurance (RA) contracts are likely to reduce the cost of purchasing insurance relative to yield insurance schemes. We focus our empirical analysis on the apple and orange sectors.

Determining the actuarially fair insurance premium for any revenue insurance program requires joint modeling of the perils covered, i.e. price and yield risks. In this article, yields and price distributions are modeled independently, and the Student´s-*t* and Gaussian copulas are used to capture the dependence structure between the two. Research results show a negative correlation between yields and prices. Monte Carlo Simulation allows deriving simulated yields, prices, expected losses and premium rates. Revenue insurance premium rates are compared to those of yield insurance. At the same coverage level, the former is found to be cheaper than the latter. Hence, launching revenue insurance programs in Spain may result in higher acceptance and demand for agricultural insurance programs.

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Table 2.1. Unit root testing and summary statistics for first differenced logged price and yield series

Unit root testing				
	Apple		Orange	
	Prices	Yields	Prices	Yields
Augmented Dickey-Fuller test	-2.045	-2.109	-1.424	-2.837*
(p-value)	(0.977)	(0.980)	(0.920)	(0.996)
KPSS test	2.531***	1.624***	2.505***	1.740***
(p-value)	(0.010)	(0.054)	(0.011)	(0.044)
Summary statistics for first-differenced data				
	Apple		Orange	
	Prices	Yields	Prices	Yields
Mean	-0.019	0.081	-0.015	0.013
Variance	0.077	2.760	0.045	0.121
Standard Deviation	0.277	1.661	0.028	0.046
Skewness	0.363	0.657*	0.621*	0.014
(p-value)	(0.280)	(0.051)	(0.099)	(0.966)
Excess kurtosis	1.049	1.243*	0.459	0.365
(p-value)	(0.132)	(0.075)	(0.863)	(0.600)
Doornik-Hansen test	4.260	4.996	3.314	1.288
(p-value)	(0.119)	(0.082)	(0.191)	(0.525)
Number of observations				57

Note: *(**) (***) denotes statistical significance at the 10% (5%) (1%) level. The skewness and kurtosis and their significance tests are from Kendall and Stuart (1958). The Doornik–Hansen (2008) is the well-known test for normality, based on the skewness and kurtosis of univariate data.

Table 2.2.AIC and BIC information criteria for univariate model selection for first differenced logged price and yield series

	Yields Apple		Yields Orange			Price Apple		Price Orange	
	AIC	*BIC*	*AIC*	*BIC*		*AIC*	*BIC*	*AIC*	*BIC*
ARIMA(1,1,0)	203.239*	207.289*	11.437*	17.488*	ARIMA(1,1,0)-GARCH(1,1)	475.088*	479.139*	429.607*	433.658*
ARIMA(2,1,0)	204.575	210.651	11.969	18.045	ARIMA(2,1,0)-GARCH(1,1)	476.295	482.371	430.474	436.550
ARIMA(3,1,0)	205.383	213.484	12.490	20.592	ARIMA(3,1,0)-GARCH(1,1)	475.719	483.820	432.466	440.568
ARIMA(4,1,0)	207.354	217.480	14.222	24.349	ARIMA(4,1,0)-GARCH(1,1)	477.0039	487.130	433.522	443.649
ARIMA(5,1,0)	206.546	218.698	12.605	24.757	ARIMA(5,1,0)-GARCH(1,1)	478.67890	490.830	434.819	446.972

Note: *indicates the optimal model selected by the AIC and BIC criterion

Table 2.3. Parameter estimates for the univariate price models for apples and oranges

Parameter	Coefficient	Standard error	*t*-statistic
	Apple - ARIMA(1,1,0)-GARCH(1,1)		
α_{apc}	-0.015	0.029	-0.587
α_{ap1}	-0.380	0.099	-3.806**
ω_{apc}	0.024	0.006	3.702**
ω_{ap1}	0.222	0.112	1.967*
ω_{ap2}	0.358	0.108	3.297**
Log Likelihood			1.207
	Orange - ARIMA(2,1,0)-GARCH(1,1)		
α_{opc}	-0.039	0.024	-1.666
α_{op1}	-0.191	0.141	-1.355
α_{op2}	-0.161	0.027	-5.915**
ω_{opc}	0.040	0.016	2.576**
ω_{op1}	0.460	0.262	1.759*
ω_{op2}	-0.182	0.142	-1.284
Log Likelihood			7.393

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

Table 2.4. Parameter estimates for the univariate yield models for apple, and oranges

Parameter	Coefficient	Standard error	*t*-statistic
	Apple - ARIMA(1,1,0)		
α_{yc}	0.109	0.200	0.545
α_{y1}	-0.493	0.121	-4.072**
Log Likelihood			-99.619
	Orange - ARIMA(1,1,0)		
α_{yc}	0.017	0.037	0.462
α_{y1}	-0.615	0.102	-6.014**
Log Likelihood			-6.363

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

Table 2.5. Tests for time-varying dependence between differenced logged prices and differenced yields

Sup test for rank correlation break	ARCH LM test		
Anywhere	p=1	p=5	p=10
	Apple		
0.099	0.310	0.776	0.862
	Orange		
0.741	0.507	0.683	0.236

Note: This Table presents p-values from one-time break correlations and autocorrelation (AR) tests for time-varying dependence using 1000 bootstrap replications. The left panel test focuses on rank correlation breaks between u and v at some unknown date. The right panel is the ARCH LM test for time-varying volatility proposed by Engle (1982) that focuses on autocorrelation in dependence.

Table 2.6. Log likelihood values for static copulas

	Apple	Orange
	Log Likelihood	*Log Likelihood*
Gaussian	10.051	2.943
Clayton	-0.002	-0.001
Rotated Clayton	-0.002	-0.001
Plackett	8.536	3.141
Frank	-0.004	-0.001
Gumbel	-3.659	-2.695
Rotated Gumbel	-3.543	-2.206
Student´s t	10.409	3.282
Symmetrised Joe–Clayton	-0.964	-0.591

Table 2.7. Chen and Fan model comparison tests for Copula models

	Gaussian	*Clayton*	*Plackett*	*Student´s t*
		Apple		
Gaussian	_			
Clayton	-2.359	_	_	_
Plackett	-2.459	-4.618	_	_
Student´s t	0.421	2.139	2.236	_
Copula log *likelihood*	10.051	-0.002	8.536	10.409
Rank	2	4	3	1
		Orange		
Gaussian	_			
Clayton	-1.239	_		
Plackett	-1.359	-2.601	_	
Student´s t	0.321	1.067	1.178	_
Copula log *likelihood*	2.943	-0.001	3.141	3.282
Rank	3	4	2	1

Note: This Table presents *t*-statistics from Chen and Fan (2006) model comparison tests for Copula models.

Table 2.8. The results from goodness of fit tests for copula models

	KS_C	CvM_C
	Apple	
Gaussian	0.270	0.310
Student´s t	0.250	0.250
Clayton	0.030	0.000
Plackett	0.260	0.550
	Orange	
Gaussian	0.960	0.930
Student´s t	0.970	0.860
Clayton	0.190	0.060
Plackett	0.980	0.710

Note: this Table presents *p*-values from GoF tests using 100 bootstrap replications. KS_C and CvM_C tests refer to the Kolmogorov-Smirnov and Cramer-von-Mises tests, respectively applied to the empirical copula of the standardized residuals.

Table 2.9. Gaussian and Student´s t copulas parameter estimates

Parameter	Coefficient	Standard error	t-statistic
		Apple	
Gaussian	-0.553	0.099	-5.600**
log likelihood			10.051
Student´s t	-0.570	0.101	-5.645**
γ	5.780	1.517	3.810**
log likelihood			10.409
		Orange	
Gaussian	-0.319	0.144	-2.204**
log likelihood			2.943
Student´s t	-0.359	0.132	-2.716**
γ	5.848	1.298	4.505**
log likelihood			3.282

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

Table 2.10. Actuarially fair premium rate at 75% and 80% coverage. Student´s *t* copula.

	75% coverage		80% coverage	
	Expected loss (Premium rate) (€ per ton)	Premium rate (%)	Expected loss (Premium rate) (€ per ton)	Premium rate (%)
Apple Yields	58.224	2.777	132.042	6.294
Apple Revenue	55.594	1.424	126.706	3.245
Orange Yields	56.324	5.364	94.948	9.044
Orange Revenue	40.772	5.203	68.352	8.723

A B

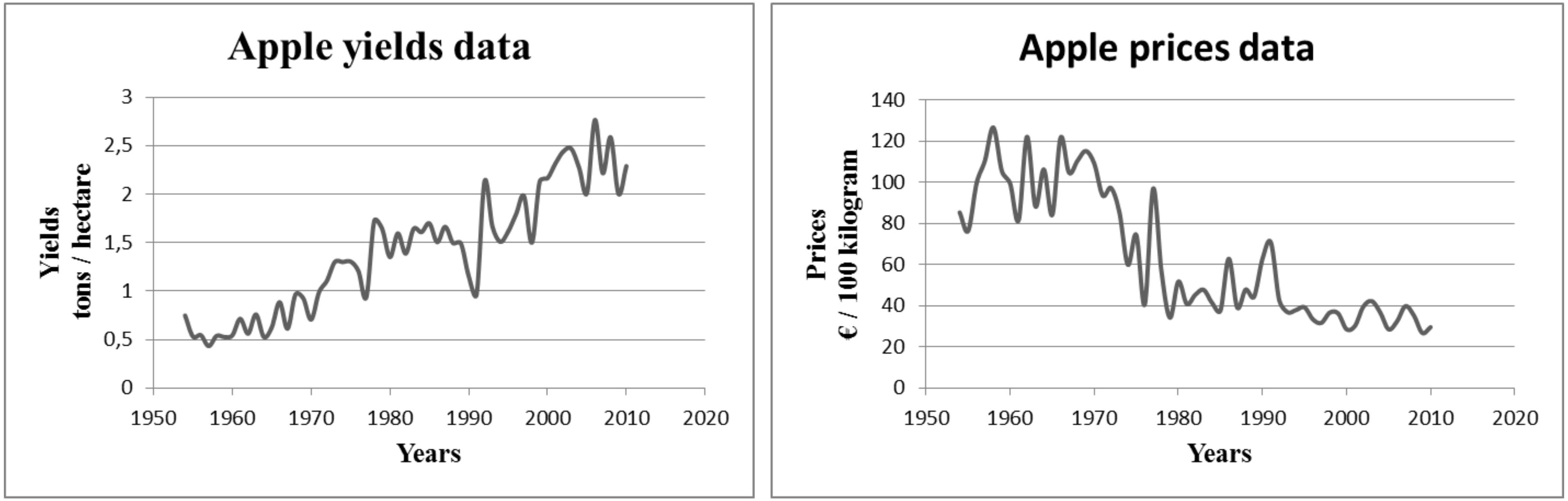

Figure 2.1. Annual apple yield expresssed in tons per hectare and price data expressed in constant 2010 € per 100 kilogram (fig.A. Yield data; fig.B. Price data)

A B

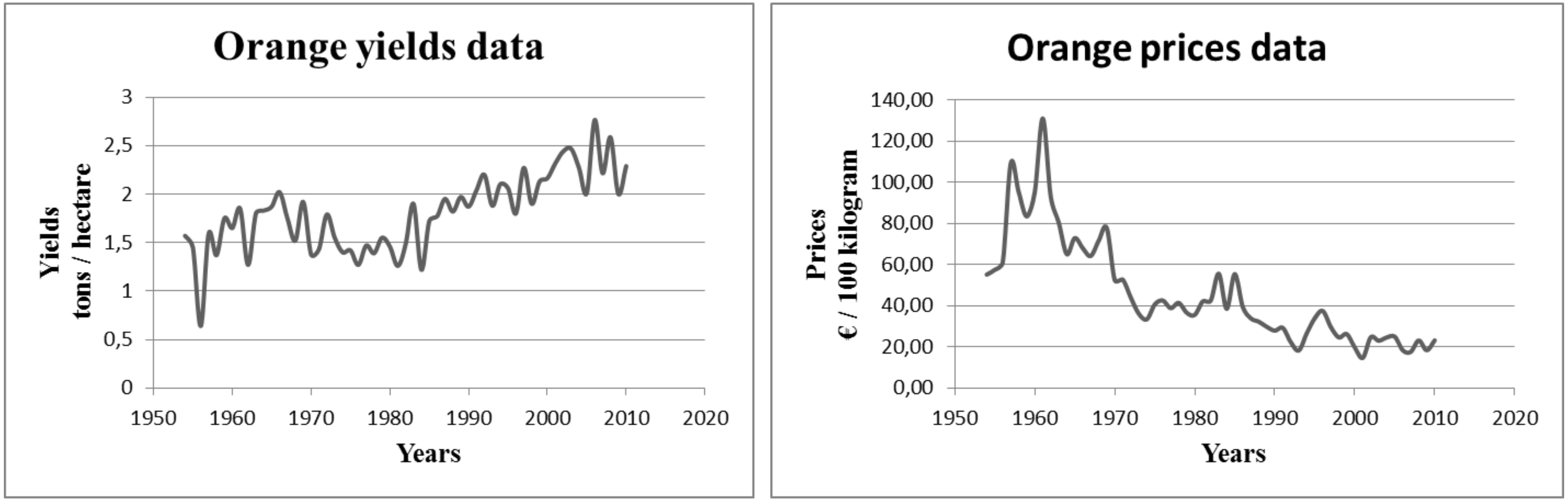

Figure 2.2. Annual orange yield expresssed in tons per hectare and price data expressed in constant 2010 € per 100 kilogram (fig.A. Yield data; fig.B. Price data)

Appendix 2.1. Specification of the copula and marginal distributions

We specify the copula and marginal distributions in such a way that the parameters are estimated in different stages (Patton, 2006). This requires first, that parameters in one marginal distribution do not appear in another marginal distribution. Second, no cross-equations can be imposed on these parameters. Under these assumptions, parameter estimation proceeds in two stages. Marginal distribution models are estimated in a first stage and the copula model in the second stage. Let's parameterize the joint distribution function as follows: $H(\xi) = C(F(\phi_x), G(\phi_y); \theta)$, where $\xi = (\phi_x, \phi_y, \theta)$ is the vector that contains both the marginal parameters (ϕ_x, ϕ_y), and the parameters characterizing dependence θ. The parameterized joint density can be expressed as: $h(x, y; \xi) = f(x; \phi_x) g(y; \phi_y)\, c(F(x; \phi_x), G(y; \phi_y); \theta)$. The log likelihood function can be derived by taking logarithms of expression $h(x, y; \xi)$ and summing across observations ($j = 1, ..., T$):

$$\ell(x, y; \xi) = \frac{1}{T} \sum_{t=1}^{T} \Big(\log f(x_t; \phi_x) + \log g(y_t; \phi_y) + \log(c(F(x_t; \phi_x), G(y_t; \phi_y); \theta)) \Big). \qquad \text{(A1.1)}$$

If parameters are indeed separable for the first and second margins and the copula, (A1.1) can be decomposed into marginal log likelihoods and the copula likelihood (Patton, 2006):

$$\ell(x, y; \xi) = \ell(\phi_x) + \ell(\phi_y) + \ell(\phi_x, \phi_y; \theta), \qquad \text{(A1.2)}$$

where $\ell(\phi_x) \equiv \frac{1}{T} \sum_{t=1}^{T} \log f(x_t; \phi_x)$, $\ell(\phi_y) \equiv \frac{1}{T} \sum_{t=1}^{T} \log g(y_t; \phi_y)$, and $\ell(\phi_x, \phi_y; \theta) \equiv \frac{1}{T} \sum_{t=1}^{T} \log(c(F(x_t; \phi_x), G(y_t; \phi_y); \theta))$.

Appendix 2.2. The two-stage copula estimation

The optimization processes corresponding to the first and second stages are presented as follows:

$$\widehat{\phi}_x = \arg\max_{\phi_x} \frac{1}{T}\sum_{t=1}^{T} \log f(x_t;\phi_x),$$

$$\widehat{\phi}_y = \arg\max_{\phi_y} \frac{1}{T}\sum_{t=1}^{T} \log g(y_t;\phi_y), \tag{A2.1}$$

$$\widehat{\theta} = \arg\max_{\theta} \frac{1}{T}\sum_{t=1}^{T} \log c(F(x_t;\phi_x), G(y_t;\phi_y);\theta). \tag{A2.2}$$

where $\widehat{\phi}_x$, $\widehat{\phi}_y$ are the parameter estimates of the marginal distributions of the variables x and y, respectively. $\widehat{\theta}$ is the copula estimated parameter vector. Following Patton (2013), Chen and Fan (2006) method is used to derive standard errors for our semiparametric copula models.

Appendix 2.3. Time-varying dependence tests

Two types of time-varying dependence tests are considered (Patton, 2013). The first type focuses on rank correlation breaks between *u* and *v* at some unknown date. We use the “sup” test statistic as recommended by Patton (2013), which can be computed as:

$$\tilde{B}_{\sup} = \max_{t^* \in [t_L^*, t_U^*]} \left| \vartheta_{1,t} - \vartheta_{2,t} \right|, \tag{A3.1}$$

where $\vartheta_{1,t^*} \equiv \frac{12}{t^*}\sum_{t=1}^{t^*} {}_{1t}u_t - v_t - 3$ and $\vartheta_{2,t^*} \equiv \frac{12}{T-t^*}\sum_{t=1}^{t^*} {}_{1t}u_t - v_t - 3$. 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 time-varying dependence test that we apply is the ARCH LM test for time-varying volatility proposed by Engle (1982). This test focuses on autocorrelation in dependence, captured by an autoregressive model such as the following: $u_t v_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i} v_{t-i} + e_t$, 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. $\hat{A}_p = \hat{\alpha} R' \left(R \hat{V}_\alpha R' \right)^{-1} R \hat{\alpha}$, 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.

Appendix 2.4. The CvM and KS Goodness of Fit tests

GoF tests assess to what extent an estimated copula model is different from the unknown true copula. Following Genest and Rémillard (2008), Genest et al. (2009) and Rémillard (2010), the Kolmogorov-Smirnov (*KSc*) and the Cramer-von-Mises (*CvMc*) tests are used in order to compare the estimated with the unknown copula. These tests can be expressed as follows:

$$KSc = \max_t \left| C(u,v;\hat{\theta}_T) - \hat{C}_T(u,v) \right|, \tag{A4.1}$$

$$CvMc = \sum_{t=1}^{T} \left\{ C(u,v;\hat{\theta}_T) - \hat{C}_T(u,v) \right\}^2 . \tag{A4.2}$$

CHAPTER 3

Price volatility of food staples. The case of millet in Niger[8]

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3.1. Introduction

The 2012 Human Development Index (HDI) ranked Niger 186 out of 187 countries (UNDP, 2013). In 2010, subsistence rain-fed agriculture and stock rearing represented 41% of the Niger Gross Domestic Product (GDP), being the second most relevant economic activity after services and employing more than 80% of working-age adults (World Bank, 2013). FAO (2012) food security indicators suggest severe food security issues in Niger. The World Bank (2013) ranking of sources affecting Niger food production and security places drought and locus pests in the first instance, and price spikes in the second. The abandonment, during the 1980s, of interventionist policies that regulated cereal prices in Niger, jointly with severe market imperfections, worsened price stability and food security (Cornia et al., 2012).

This article analyzes monthly millet producer and consumer price behavior in two relevant Niger millet markets: Maradi and Tilláberi for the period from 1990 to 2011. Millet has strategic relevance for both food security and Niger economy. It represents almost one-third of Niger cultivated land and around 40% of total Niger food supply (Cornia and Deotti, 2008), being thus a very relevant crop for food security in one of the poorest economies of the world (Brown et al., 2006). Millet is also key to household economies, since most Niger farm households are net buyers of millet and rely on their own production to partially meet their consumption needs. Hence, the impacts of millet price spikes on poor households can be relevant.

Since price behavior can affect food producers and consumers differently, we assess how millet price changes are transmitted along the food marketing chain, from farmers to food consumers. While changes at the producer price level will affect farm household income, consumer price changes will impact on consumers' purchasing capacity. The relevance of information on market price behavior has been shown both at the theoretical (Stigler, 1961; MacMinn, 1980) and at the empirical level for grain markets in Niger (Aker, 2008a). Since Sen's (1981) seminal work, scholars have devoted substantial attention to provide an explanation of how food crises can be prevented or mitigated by means of a better knowledge of the functioning of the markets.

Guaranteeing availability and access to food is vital in less developed country (LDC) economies, and can be enhanced in a number of different ways. Local food reserves, for example, have been promoted by different organizations and small producer federations with the objectives of increasing farm income and food security. Despite their potential to promote food security, there is an important failure rate of local food reserve initiatives in LDCs. Guaranteeing sustainability of these reserves requires profound knowledge of producer and consumer markets, which are indicative of the purchase and sale prices of food reserves (Oxfam, 2012). This information is also key to different socio-economic agents such as producer and consumer associations, policy makers, or non-governmental organizations (NGOs).

The World Bank (2013) and Cornia et al. (2012) distinguish between two different time frames, characterized by different Niger millet price behavior. Interannual millet price changes are found to be relatively small. In contrast, price changes are substantial within a crop year. Relevant millet price spikes occur in the short-term and in a sequence of two to three years. Distinguishing between short and long term price behavior is thus relevant from a public policy and private management perspectives. Some economic and political instruments allow coping with short-run price fluctuations, but have limited applicablity as a long-term solution: seasonal export controls, food distribution by agencies and public reserves. In contrast, other more systematic and far-reaching mechanisms are more suited to influence long-run price patterns. These include supply side policies such as land reform policies that change land availability and distribution; promotion of high -yield varieties, fertilizers or irrigation mechanisms; commodity trade agreements; or buffer stocks. Demand-side interventions such as transfers to food consumers and other policies to increase the incomes of social groups, also shape log-run prices.

Our price transmission analysis assesses dependence between producer and consumer markets both in the long and in the short-term. Inter-annual millet price stability in Niger (World Bank, 2013; Cornia et al., 2012) suggests the existence of a long-run parity between the prices. Well known cointegration and error-correction techniques are used to identify this equilibrium, to assess response to disequilibriums from this parity, and to study weak exogeneity with respect to the long-run equilibrium in order to identify price leaders and followers. Through error-correction modeling, the deviation of the current prices from their long-run relationship is fed into the short-run dynamic models. Short-run millet price instability recommends the use of flexible analysis instruments that soundly capture the joint distribution function of producer and consumer prices. Correlation techniques such as the Spearman's rank and Kendall's tau correlation coefficients have been widely used to study dependence. An important limitation intrinsic to these techniques is that a single correlation coefficient is not usually enough to characterize dependence over the whole range of the distribution. For example, dependence in the extreme tails of the distribution may be different from dependence in the central areas and may be more relevant from en economic management point of view, i.e., economic agents and policy makers might be more interested in the dependence of prices during extreme weather or market events than during more frequent and less drastic changes.

Recent research has suggested the use of statistical copulas to assess dependence. 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. These multivariate distributions include the normal and the t-Student and have been shown as inappropriate to assess behavior of the type of data we intend to study.

This paper is organized as follows. In the next section, a brief description of the millet market in Niger 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 consumer prices. The last section in this article offers the concluding remarks.

3.2. Millet market in Niger

The global financial crisis has led to a global economic recession and to increased and unsTable commodity prices. This has exacerbated food security problems that have hit poor countries specially hard. Around 60 % of Niger population lives below the poverty line (Geesing and Djibo, 2006). Niger population relies on subsistence agriculture which has deteriorated in recent years and that satisfies 30 % of the country's needs (WHO, 2006). Food purchases represent 63 % of total household expenses (SANOGO, 2009). In 2012 about 40 % (6.4 million people) of Niger's population was food insecure (UNOCHA, 2013) and undernourishment affected 12.6 % of the population (FAO, 2012).

Cereals constitute the most relevant world food staple. World production of cereals in 2010 was 2.5 billion tons on an extension of land of 693 million hectares. In the same year, global cereal exports and imports were on the order of 340.3 and 336.3 million tons, respectively (FAOSTAT, 2010). In 2010, Africa produced 163 million tons, representing an increase on the order of 15 % relative to 2005 and less than 7 % of worldwide production. In the same year, African cereal exports and imports were 4 and 66.4 million tons, respectively, evidencing the continent’s deficit in food production (FAOSTAT, 2010). Among the African countries, Niger cereal production expanded from 3.7 million tons in 2005 (FAOSTAT, 2005) to 5.2 million tons in 2010, representing an increase of around 71 % (FAOSTAT, 2010) and around 3 % of all cereals produced in Africa.

Millet is the staple food for more than one-third of the world's population, and the sixth most relevant cereal in world production (FAOSTAT, 2012). Global millet production expanded from 31 million tons in 2005 (FAOSTAT, 2005) to 32.5 million tons in 2010 (FAOSTAT, 2010). In 2010, international exports and imports of millet were estimated to be 357.3 and 470 thousand tons, respectively (FAOSTAT, 2010). Millet is extremely important for African economies that in 2010 devoted 21.5 million hectares to produce 16.7 million tons (FAOSTAT, 2010). Millet production is distributed among 37 countries, being Niger the third largest global producer after India and Nigeria. These three countries represent around 12 % of total world millet production (FAOSTAT, 2010). The largest African producers are Nigeria (31.3 %), Niger (23.3 %) and Mali (8.3 %) (FAOSTAT, 2010). The largest harvested millet area is found in Niger with 7.3 million hectares (representing 24 % growth rate since 2005), Nigeria with 4.4 million hectares and Sudan with 2.0 million hectares. African exports (imports) of millet were estimated to be on the order of 4.4 (141.3) thousand tons in 2010 (FAOSTAT, 2010).

Millet represents the most relevant food staple for Niger's population of more than 16 million people. It is further the largest cereal crop produced in the country, representing 73 % of all cereals in 2010 (FAOSTAT, 2010). In 2005, Niger production was 2.7 million tons and grew to be 3.8 million tons in 2010, an increase of around 69 %. In the same year, millet consumption was around 3.8 million tons as well (USDA, 2010). Niger is the third largest world importer of millet, after Sudan and Philippines, with around 43 thousand tons.

Our study focuses on millet price behavior in two Niger markets: Maradi and Tillabéri. While Maradi represents a region where there is excess millet production, Tillabéri is a consumption zone (Oxfam, 2013). Maradi's population is around 3.3 million people (MAE, 2012), 16.2 % of which suffers from acute malnutrition (UNWFP, 2012). Maradi market is the first largest producer and consumer market of cereals in Niger, with 1.2 million tons and 767 thousand tons, respectively (MAE, 2012). Millet, the first cereal in terms of Maradi production, reached 807 thousand tons (68 % of total cereal production) and 1.5 million hectares in 2012 (MAE, 2012). Tillabéri has a population of 2.7 million people (MAE, 2012) and around 16.6 % of the population suffers from acute malnutrition (UNWFP, 2012). Tillabéri production of cereals is 821 thousand tons. Millet production in Tillabéri reached 692 thousand tons in 2012, grown on an area of 1.4 million hectares (MAE, 2012).

The most relevant actors in the Niger cereal marketing chain are: farmers and traders (including retailers, intermediaries, wholesalers and semi-wholesalers), transporters and consumers. Local food supply is usually transferred from farmers to intermediaries and to local wholesalers. Through a system of traditional markets, production is then sold to wholesalers, retailers and consumers (Aker and Fafchamps, 2013). Around April, local supplies are depleted and traders usually start importing from neighboring countries such as Nigeria, Mali, Burkina Faso and Benin, at prices usually above Niger domestic prices. Only during the pre-harvest period import prices can be cheaper than the domestic prices (Aker, 2008b). Defficient infrastructures, costly export procedures and scarce product availability for export, explain the meager relevance of the international millet market and the scarce influence of this market on Niger millet prices.

Grain traders usually trade outputs, not inputs, and only store for short periods of time (less than a month). Costly search, information asymmetries and price dispersion across markets characterize the millet market in Niger (Aker, 2008a). Based on a survey of traders in Niger, Aker (2008a) computes the four-firm concentration ratio (CR4). Results suggest a rather competitive structure of Niger grain markets, with most markets having CR4 below 25%.

3.3. Literature review

Many empirical analyses have studied how prices are transmitted from producers to final consumers. Two main methodological approaches have been followed for such purpose: structural analyses that rely on economic theory, and time-series empirical analyses that identify empirical regularities in the data. Our work will follow the second methodological approach. Sound econometric analysis of time series data requires investigating their statistical properties. Empirical research has found that these data often violate the most common assumptions of conventional statistical inference methods, which may lead to obtaining completely spurious results. Time-series data have usually been found to be non-stationary and, when related, to share a tendency to co-move in the long-run (Myers, 1994). 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 dynamics. 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 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 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 assess 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 in response to positive and negative price shocks. Asymmetries are apparent both in terms of speed and magnitude of the adjustment.

Evidence of asymmetric price transmission along the food marketing chain is 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 price dynamics within a cointegration framework. 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.

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 four 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 dynamic copula models to the empirical study of links between farm-retail and retail-wholesale prices for US hog/pork markets. Results indicate that farm and wholesale markets are more 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 dynamic and asymmetric behavior in price co-movements between the 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 on to consumers. Our paper contributes to the literature by examining the dependence between producer and consumer markets in Niger, a country characterized by its insufficient food production and where food security issues are very relevant, using statistical copulas. To our knowledge, this is the first attempt to study vertical price transmission in LCD countries using this methodology.

3.4. Methodology

This analysis uses statistical copulas to characterize dependency along the food marketing chain in Niger millet markets. While the use of copula functions is common within the financial economics literature (see, for example, Patton, 2006 and 2012; or Parra and Koodi, 2006), empirical studies that use copulas to assess dependency along the food marketing chain are very scarce. Copulas provide a natural way to measure dependency between two or more variables. A copula function is a multivariate distribution function defined on the unit cube $[0,\ 1]^n$, with uniformly distributed marginals. Copulas are based on the Sklar's (1959) theorem that shows that 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. This contrasts with the use of correlation coefficients between random variables as a measure of dependence. While correlations are highly popular due to the ease with which they can be calculated, they can be very misleading if random variables are not jointly elliptically distributed.

By focusing on modeling univariate distributions, the Sklar's theorem usually leads to the formulation of better models (Patton, 2006). Let F_x and F_y be the univariate distribution functions of 2 random variables (x, y). H 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 an 2-dimensional distribution function with uniformly distributed margins $u_i \sim Unif(0,1),\ i = 1,...,n$. 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 specifications represent different dependence structures. Our analysis will consider both elliptical (Gaussian copula) and Archimedean (Symmetrized Joe-Clayton-SJC copula) 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 dynamic 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.

Tests for time-varying dependence are used to determine whether time-varying copulas need to be considered. Two types of time-varying dependence tests are applied (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):

$$\tilde{B}_{\text{sup}} = \max_{t^* \in \left[t_L^*, t_U^*\right]} \left| \vartheta_{1,t} - \vartheta_{2,t} \right|, \tag{3}$$

where $\vartheta_{1,t^*} \equiv \frac{12}{t^*} \sum_{t=1}^{t^*} {}_{1t} u_t - v_t - 3$ and $\vartheta_{2,t^*} \equiv \frac{12}{T - t^*} \sum_{t=1}^{t^*} {}_{1t} u_t - v_t - 3$. 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 $\tilde{B}_{\text{sup}}$ 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: $u_t v_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i} v_{t-i} + e_t$, 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: $\hat{A}_p = \hat{\alpha} R' \left(R \hat{V}_\alpha R' \right)^{-1} R \hat{\alpha}$, where $\hat{\alpha} \equiv \left[\alpha_0, ..., \alpha_p \right]'$, $R = \left[0_{p\times1} \vdots I_p \right]$ 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.

Copulas considered in our empirical analysis are restricted by the time-varying dependence test results, providing evidence in favor of static copulas. To model price dependency along the food marketing chain, the Gaussian copula, the benchmark copula in economics, is considered. As noted in the literature review above, many authors have suggested the presence of asymmetries in vertical price transmission within the food marketing chain. 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. SJC allows for asymmetric dependence in any direction and nests symmetry as a special case (Ning, 2010).

Since our analysis is based on price pairs (producer and consumer Niger millet markets), $n = 2$. A bivariate Gaussian copula can be expressed as:

$$C_R^{Ga}(u, v; R_{12}) = \int_{-\infty}^{\Phi^{-1}_{(u)}} \int_{-\infty}^{\Phi^{-1}_{(v)}} \frac{1}{2\pi\sqrt{\left(1 - R_{12}^2\right)}} \exp\left\{ \frac{-(r^2 - 2R_{12}rs + s^2)}{2\left(1 - R_{12}^2\right)} \right\} drds, \tag{4}$$

where R_{12} is the correlation coefficient of the corresponding bivariate normal distribution, $-1 < R_{12} < 1$, and Φ 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 have lower and upper tail dependence. It thus represents dependence in the central region of the distribution.

The Symmetrized Joe-Clayton (SJC) copula is an extension of the Joe-Clayton copula which can be expressed as

$$C^{jc}_{\tau^U,\tau^L}(u,v)=1-\left(1-\left\{\left[1-(1-u)^k\right]^{-\gamma}+\left[1-(1-v)^k\right]^{-\gamma}-1\right\}^{-1/\gamma}\right)^{1/k} \tag{5}$$

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, τ^U and τ^L, that measure the upper and lower tail dependence, respectively. This copula characterizes tail dependency, i.e., it models price behavior during extreme events. More specifically, it models the probability that relevant increases (declines) in the prices studied occur together. The Joe-Clayton copula implies an 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:

$$C^{sjc}_{\tau^U,\tau^L}(u,v)=0.5\left(C^{jc}_{\tau^U,\tau^L}(u,v)+C^{jc}_{\tau^U,\tau^L}(1-u,1-v)+u+v-1\right). \tag{6}$$

Patton (2006) shows that consistent and asymptotically normal copula parameters can be obtained through a two-stage estimation procedure. In the first stage, marginal distribution models are specified and estimated. In the second stage, parameters of the copula model are estimated conditional upon the results from the first step. The two-stage estimation technique can be formalized as follows (Patton, 2012b):

$$\widehat{\phi}_x = \arg\max_{\phi_x} \frac{1}{T}\sum_{j=1}^{T} \log f_i(x_j;\phi_x), \tag{7}$$
$$\widehat{\phi}_y = \arg\max_{\phi_y} \frac{1}{T}\sum_{j=1}^{T} \log f_i(y_j;\phi_y),$$

$$\widehat{\theta} = \arg\max_{\theta} \frac{1}{T}\sum_{j=1}^{T} \log c\,(F(x_j;\phi_x), F(y_j;\phi_y);\theta). \tag{8}$$

where $\widehat{\phi}_x$ and $\widehat{\phi}_y$ represent the parameter estimates of marginal distributions. $\widehat{\theta}$ is the copula estimated parameter vector. The most attractive feature of copula functions is that the marginal distributions do not necessarily have to come from the same families. Marginal models allow deriving standardized, independent and identically distributed $(i.i.d)$ residuals from the filtration. The $i.i.d$ residuals are then transformed to $Unif\,(0,1)$ using the non-parametric empirical cumulative distribution function (CDF). The empirical CDF method is specially convenient when the true distribution of the data is not known.

The theory of copula applies to stationary time-series. The Dickey and Fuller (1979), Perron (1997) and KPSS (1992) tests used to test for unit roots are run on our data. Results support the presence of a unit root in both millet producer and consumer prices. The price pairs considered are also found to maintain equilibrium parity by implementing the Johansen (1988) cointegration test. The univariate models for the producer and consumer price pairs considered (P_p, P_c) are consequently specified as an error-correction type of model (ECM) (equations 9 and 11). Model residuals are modeled by means of a GARCH (1,1) specification in order to allow for time-varying and clustering volatility (equations 10 and 12).

$$\Delta P_{x,t} = \alpha_x + \lambda_x \delta_{t-1} + \sum_{i=1}^{2} \alpha_{xxi} \Delta P_{x,t-i} + \sum_{i=1}^{2} \alpha_{xyi} \Delta P_{y,t-i} + \varepsilon_{x,t} \tag{9}$$

$$\sigma_{x,t}^2 = \omega_x + \omega_{x1} \varepsilon_{x,t-1}^2 + \omega_{x2} \sigma_{x,t-1}^2 \tag{10}$$

$$\Delta P_{y,t} = \alpha_y + \lambda_y \delta_{t-1} + \sum_{i=1}^{2} \alpha_{yxi} \Delta P_{x,t-i} + \sum_{i=1}^{2} \alpha_{yyi} \Delta P_{y,t-i} + \varepsilon_{y,t} \tag{11}$$

$$\sigma_{y,t}^2 = \omega_y + \omega_{y1} \varepsilon_{y,t-1}^2 + \omega_{y2} \sigma_{y,t-1}^2 \tag{12}$$

where $\Delta P_{jt}, j = x, y$ is the first difference of logged consumer and producer prices, $\alpha_{j,n,i}, j, n = x, y$ are short-run dynamic parameters that measure the influence of past price differences on current differences. The error correction term derived from the long-run equilibrium relationship is represented by δ_t, thus $\lambda_j, j = x, y$ measures the long-run price dynamics. $\varepsilon_{jt}, j = x, y$ are normally distributed error terms.

Conducting goodness of fit tests on the marginal models is essential for copula model estimation. 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 $Unif\,(0,1)$.

3.5. Empirical analysis

Intermon Oxfam made available monthly millet producer prices in Maradi (P_{My}) and consumer prices in Maradi and Tillabéri (P_{Mx}, P_{Tx}, respectively) for the period from January 1990 to December 2010, yielding a total of 252 observations. Consumer prices for millet are available for both markets, given their economic relevance as consumption centers. However, producer price data are only available for the Maradi market. Conversations with Oxfam experts in Niger economy, recommended to take the Maradi producer price as representative of producer prices in both Maradi and Tillabéri, and asses the links between two pairs of prices: Maradi producer price – Maradi consumer price (P_{My}, P_{Mx}) and Maradi producer price – Tillabéri consumer price (P_{My}, P_{Tx}). We follow this recommendation. Prices are expressed in Central African Francs (CFA) per kilo and studied in pairs. Logarithmic transformations of price series are used in the empirical analysis. Table 3.1 presents summary statistics for first differenced logged prices series. Standard unit roots tests were carried out and results, available from authors upon request, show that price time series are non-stationary.

Johansen's (1988) cointegration tests are used to assess the existence of an equilibrium relationship between the pairs of prices studied. Test results suggest that there is a long-run relationship between producer prices in the Maradi millet market, with Maradi and Tillabéri consumer prices (see Table 3.2). This is compatible with Aker 2008b) who found high integration levels among Niger cereal markets. Existence of cointegration suggests the existence of trade flows from producing areas to consumption markets, or from surplus to deficit markets, which helps combating food security. Since prices are expressed in logarithms, cointegration parameters can be interpreted as price elasticities. Price transmission elasticities are specially strong in the

Maradi market (0.96). The price transmission elasticity between the Maradi producer and Tillabéri consumer markets is lower and equal to 0.73. It is not surprising to find higher correlation when producer and consumer markets coincide geographically. In such a scenario, transaction costs (including transportation costs) are likely to be lower, facilitating price transmission. Hence, consumers in surplus areas are more likely to be affected by long-run supply shifts causing price-level changes, than consumers located in deficit areas. A chi-square test of weak exogeneity for long-run parameters within the Johansen's framework, shows that consumer prices are responsible for maintaining such equilibrium by responding to the deviations that can occur (results are available from authors upon request). The fact that Maradi producer price causes Tillabéri consumer price is also compatible with Aker (2008b) and Araujo et al. (2010) findings that markets located in surplus regions are useful for predicting price changes in other markets. As a result, producer prices may be considered as price leaders and consumer markets should be classified as price-followers. This is indicative that the estimated models are useful to predict consumer price behavior, but not producer price patterns. These results also suggest that supply enhancing policies are likely to be more effective in mitigating food security and price instability issues than demand policies. This is in contrast with the functioning of most developed country food markets, where producer prices are usually found to be endogenous, while consumer prices are weakly exogenous (Goodwin and Holt, 1999; Heien, 1980; Ward, 1982; Lloyd et al., 2001; 2006; Serra and Goodwin, 2003).

Marginal models are specified as univariate error-correction type of models. Results from univariate ECM-GARCH model estimation are presented in Tables 3.3 and 3.4 for the pairs of prices considered. Short-run parameters show that current changes in Maradi producer prices have a relevant autoregressive component. As noted above, Maradi producer prices are exogenous for long-run parameters. The conditional variance equation shows that past market shocks contribute to increase Maradi producer price volatility. GARCH(1,1) model parameters are all positive, which indicates that in–sample and out–sample variance estimates are positive. Since $\omega_{Mp1} + \omega_{Mp2} < 1$, we can conclude that the GARCH process is stationary, being the unconditional long-run variance $\left(\sigma^2_{Mp} = \omega_{Mp} / (1 - \omega_{Mp1} - \omega_{Mp2})\right)$ around 0.015.

Current changes in the Maradi consumer prices are explained by past changes in the Maradi producer market, as well as by the deviations from the long - run equilibrium (Table 3). It is thus the retail market that makes the necessary short-run price adjustments so that the millet market is in equilibrium. The conditional variance equation shows that both past market shocks and volatility contribute to destabilize the consumer market in Maradi. The univariate GARCH (1,1) model process provides evidence of a stationary volatility process, and GARCH parameters lead to an unconditional variance σ^2_{Mc} = 0.013. Price volatilities in producer and consumer markets are thus very similar.

In the next lines, we discuss Tillabéri millet price behavior derived from the (P_{My}, P_{Mx}) price pair analysis, presented in Table 3.4 Tillabéri consumer price level changes depend on their own lags, as well as on disequilibrium from the long-run parity. Relative to Maradi consumer price adjustment, Tillabéri consumer price changes show a slow adjustment to disequilibrium, which is again indicative that geographical distance slows price transmission. Supply shortage characterizing Tillabéri market is probably the underlying reason of high consumer price instability: the unconditional long-run variance for Tillabéri consumer prices is σ^2_{Tc} = 0.025.

The Ljung-Box test results presented in Tables 3.3 and 3.4 allow accepting the null of no autocorrelated residuals. The LM tests (Table 3.5) implemented to test for the independence of the first four moments of the transformed variables provide evidence that the models are well specified. We also applied the Kolmogorov–Smirnov (KS) test that confirms that the transformed series are *Unif* (0,1) (Patton, 2006). Table 3.6 presents results of the two time-varying dependence tests described above, which recommend the use constant copulas for both pairs of prices. Parameters estimated for the constant copulas are presented in Tables 3.7 and 3.8.

Copulas are a flexible modeling alternative to assess short-run dependency among the two pairs of prices considered. The parameters from static Gaussian copula (Table 3.7) measure dependency in the central region of the bivariate distribution. They provide evidence that there is a positive short-run correlation between prices at different market levels. As a result, an increase in Maradi producer prices leads to an increase in Maradi and Tillabéri consumer prices, being the link specially relevant when the two markets are geographically close. This is compatible with cointegration and error-correction model results.

Previous research on vertical price transmission shows that retailers tend to pass price increases on to consumers more quickly and completely than price declines, specially when the magnitude of the changes is relevant. The SJC studies dependency in the extreme tails of the distribution and allows for asymmetric price behavior. The upper and lower tail dependence parameters show dependency during extreme increases and extreme decreases of prices. (P_{My}, P_{Mx}) price pair shows a stronger dependence during market price increases (the correlation coefficient is 10 % higher for market upturns, relative to downturns), i.e., price increases are more likely to occur together than price declines. Hence, retailers are more likely to increase prices than to reduce them. Upper and lower tail dependence displayed by the (P_{My}, P_{Tx}) price pair are both statistically significant (see Table 3.8), being the lower tail 36 % higher than the upper tail. Hence, increases in Maradi producer prices will be passed on to Tillabéri consumers more slowly than price declines. Geographical distance is further found to increase the size of the asymmetries.

3.6. Concluding remarks

Developing countries' population suffers from poverty, food insecurity and nutritional deficiencies. While food price-level transmission along the marketing chain in developing economies has been widely assessed by previous research, less attention has been paid on less developed countries, mainly due to a lack of price data. Since the food price crisis in 2007/2008, economic research has paid substantial attention to food price behavior, given the significant impacts that it has at the political, economic and social levels. Our work focuses on characterizing millet price behavior along the Niger food marketing chain.

The contribution of this paper to the literature is twofold. On the one hand, it studies price behavior of food staples in less developed countries, thus enlarging a literature that is rather scarce due to data limitations. Second, it does so by using statistical copulas, a method that has just started to be used in vertical price analysis. An attractive feature of copula models is that they are specially suited when no obvious choice for the multivariate density characterizing price dependence exists. Copulas allow researchers to focus on modeling univariate distributions instead of the multivariate ones, which usually leads to the construction of better models.

The analysis focuses on the dependence between two pairs of prices: Maradi producer and consumer markets, and Maradi producer and Tillabéri consumer markets.

While Maradi represents a region where there is excess millet production, Tillabéri is a deficit zone. Results from the long-run price behavior analysis show that Niger millet markets are dominated by producer markets instead of consumer prices. Retail prices are the prices that guarantee maintenance of the long-run equilibrium relationship. This contrasts with market price behavior in developed countries, usually found to be dominated by retail chains. These results also suggest that supply enhancing policies are likely to be more effective in mitigating food security and price instability issues than demand policies. Geographical distance between producer and consumer markets may however reduce the effectiveness of the adopted policies. Price dependency in the short-run is also positive and declines with geographical distance. While consumers in Maradi face price increases more quickly than price declines, consumers in Tillabéri benefit from an asymmetry that favors quicker price declines. The already high food prices in non-producing areas are likely to underlie this behavior. Results also show that asymmetries affect short-run price dependencies, with the characteristics of these asymmetries depending on the markets studied.

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Table 3.1. Summary statistic for first log-differences prices series.

	Maradi producer	**Maradi consumer**	**Tillabéri consumer**
Mean	0.005	0.004	0.002
Standard Deviation	0.007	0.008	0.008
T-statistic	0.617	0.582	0.256
Skewness	-1.126	-1.014	-0.247
Kutosis (excess)	3.271**	3.122**	4.777**
Jarque-Bera statistic	164.936**	144.986**	241.268**
ARCH LM statistic	8.109**	17.977**	17.661**
Number of observations			251

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 Jarque-Bera is the well known test for normality. The ARCH LM test of Engel (1982) is conducted using 2 lags**.**

Table 3.2. Johansen λ_{trace} test for cointegration and cointegration relationship

Maradi producer - Maradi consumer				**Maradi producer - Tillabéri consumer**			
H_0	Ha	λ_{trace}	$P-value$	H_0	Ha	λ_{trace}	$P-value$
$r=0$	$r>0$	52.791	0.000	$r=0$	$r>0$	37.870	0.000
$r\leq 1$	$r>1$	6.034	0.195	$r\leq 1$	$r>1$	4.828	0.313
Cointegration : Maradi producer - Maradi consumer				**Cointegration: Maradi producer - Tillabéri consumer**			
$P_{Mx} - \underset{(-47.098)}{0.963^{**}} P_{My} - \underset{(-2.751)}{0.256^{**}} = \nu_{MxMy,t}$				$P_{Tx} - \underset{(-17.330)}{0.732^{**}} P_{My} - \underset{(-8.573)}{1.657^{**}} = \nu_{TxMy,t}$			

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

Table 3.3. Result for the univariate ECM-GARCH (1, 1) model for price pair (P_{My} , P_{Mx})

Variable	Maradi producer	Maradi consumer
$\Delta P_{My,t-1}$	0.329**	0.211**
	(0.060)	(0.062)
$\Delta P_{Mx,t-1}$	-0.117**	-0.079
	(0.042)	(0.066)
$\delta_{MxMy,t}$	0.015	-0.481**
	(0.057)	(0.072)
ω_i	0.008**	0.009**
	(0.001)	(0.001)
ω_{i1}	0.421**	0.086**
	(0.131)	(0.049)
ω_{i2}	0.059	0.215**
	(0.055)	(0.044)
Ljung-Box Q(10)	12.689	11.677

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

Table 3.4.Result for the univariate ECM-GARCH (1, 1) model for price pair (P_{My} , P_{Tx})

Variable	Maradi producer	Tillabéri consumer
$\Delta P_{Tx,t-1}$	0.223**	0.434**
	(0.076)	(0.025)
$\Delta P_{My,t-1}$	-0.016	-0.029
	(0.065)	(0.041)
$\delta_{TxMy,t}$	-0.045	-0.240 **
	(0.051)	(0.036)
ω_i	0.008**	0.005**
	(0.002)	(0.001)
ω_{i1}	0.377**	0.650**
	(0.127)	(0.069)
ω_{i2}	0.055	0.155**
	(0.118)	(0.039)
Ljung-Box Q(10)	13.047	27.547

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

Table 3.5. Results for tests on the transformed variables

	Maradi producer - Maradi consumer	
	Maradi producer	**Maradi consumer**
First moment LM test	0.561	0.924
Second moment LM test	0.215	0.390
Third moment LM test	0.371	0.570
Fourth moment LM test	0.421	0.731
KS test	0.809	0.871
	Maradi producer - Tillabéri consumer	
	Maradi producer	**Tillabéri consumer**
First moment LM test	0.116	0.417
Second moment LM test	0.124	0.712
Third moment LM test	0.222	0.874
Fourth moment LM test	0.349	0.853
KS test	0.401	0.535

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 3.6. Tests for time-varying dependence between differenced logged prices and differenced yields

Sup test for rank correlation break	ARCH LM test		
Anywhere	*p*=1	*p*=5	*p*=10
Maradi producer - Maradi consumer			
0.384	0.257	0.287	0.106
Maradi producer - Tillabéri consumer			
0.487	0.352	0.297	0.272

Note: This Table presents *p*-values from one-time break correlations and autocorrelation (AR) tests for time-varying dependence using 1000 bootstrap replications. The left panel test focuses on rank correlation breaks between *u* and *v* at some unknown date. The right panel is the ARCH LM test for time-varying volatility proposed by Engle (1982) that focuses on autocorrelation in dependence.

Table 3.7. Results for static Gaussian copula

	Maradi producer - Maradi consumer	**Maradi producer - Tillabéri consumer**
$\overline{\rho}$	0.765**	0.361**
	(0.011)	(0.058)
Copula log likelihood	110.192	17.425

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

Table 3.8. Results for static SJC copula

	Maradi producer - Maradi consumer	**Maradi producer - Tillabéri consumer**
$\bar{\tau}^U$	0.710**	0.139**
	(0.044)	(0.080)
$\bar{\tau}^L$	0.640**	0.218**
	(0.072)	(0.081)
Copula log likelihood	140.907	17.290

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

CHAPTER 4

Vertical price transmission in the Egyptian tomato sector after the Arab Spring[9]

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4.1. 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.

4.2. 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).

4.3. 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.

4.4. 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 $C\left(.\right)$ 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 $C\left(.\right)$ 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 Φ 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:

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

where R_{12} is the correlation coefficient of the corresponding bivariate *t*-distribution with γ degrees of freedom (as explained by Embrechts et al. 2001, $\gamma > 2$ for the correlation to be defined), and t_γ 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:

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

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, τ^U and τ^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:

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

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_γ^{-1} is the inverse of the *t* distribution of ε_t with γ 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 (τ_t^U, τ_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):

$$\widehat{\phi}_u = \arg\max_{\phi_u} \frac{1}{T}\sum_{j=1}^{T} \log f_i(u_j;\phi_u), \tag{11}$$
$$\widehat{\phi}_v = \arg\max_{\phi_v} \frac{1}{T}\sum_{j=1}^{T} \log f_i(v_j;\phi_v),$$

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

where $\widehat{\phi}_u$ and $\widehat{\phi}_v$ represent parameter estimates of marginal distributions and $\widehat{\theta}$ 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, η_{1i} is the coefficient representing the autoregressive component, η_{2i} is the coefficient representing the moving average component, being ε_t a normally distributed error term, ω_i is the constant in the conditional volatility model, being ω_{i1} and ω_{i2} the coefficients representing the lagged square residuals and variance, respectively.[10] 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):

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

where $\vartheta_{1,t^*} \equiv \frac{12}{t^*} \sum_{t=1}^{t^*} {}_{1t} u_t - v_t - 3$ and $\vartheta_{2,t^*} \equiv \frac{12}{T - t^*} \sum_{t=1}^{t^*} {}_{1t} u_t - v_t - 3$. 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 $\tilde{B}_{\text{sup}}$ 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:

[10] 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 $\hat{\alpha} \equiv \left[\alpha_0, \ldots\ldots, \alpha_p \right]'$, $R = \left[0_{p\times 1} \vdots I_p \right]$ 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).

4.5. 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 4.1). Table 4.2 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 4.3. 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 4.3, allow accepting the null of no autocorrelated residuals. The LM tests (Table 4.4) 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 4.5 support the use of time varying copulas for both pairs of prices. In Table 4.6, 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 4.7) 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 4.8 and dynamic copula findings in Table 4.9, respectively.

Results of Gaussian and Student´s t copula presented in Table 4.8 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 4.9 and graphed in Figure 4.1 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 4.2 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.

4.6. 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 4.1. 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 4.2. 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 4.3. 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)
ϕ_1	0.621**	0.629 **	1.781**
	(0.099)	(0.071)	(0.059)
ϕ_2	___	___	-0.826**
			(0.051)
θ_1	0.291**	0.046**	-0.574**
	(0.106)	(0.098)	(0.095)
θ_2	0.054	0.232**	-0.296**
	(0.085)	(0.087)	(0.089)
θ_3	0.440**	0.067**	___
	(0.078)	(0.084)	
θ_4	0.380**	0.282**	___
	(0.088)	(0.081)	
	Conditional variance		
ω_i	0.002**	0.005**	0.041**
	(2.509e-07)	(1.439e-06)	(0.001)
ω_{i1}	0.325**	0.413**	0.437
	(0.026)	(0.017)	(0.031)
ω_{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 4.4. 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 4.5. 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 4.6. 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 4.7. 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 4.8. Results from static copulas

Producer - Wholesaler		
Gaussian		0.381**
		(0.074)
Log likelihood		12.151
SJC(τ^L, τ^U)	0.141**	0.297**
	(0.081)	(0.095)
Log likelihood		14.662
Student's t (ρ, ν^{-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(τ^L, τ^U)	0.002	0.174**
	(0.002)	(0.089)
Log likelihood		4.919
Student's t (ρ, ν^{-1})	0.191**	0.216**
	(0.091)	(0.108)
Log likelihood		4.919

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

Table 4.9. Time varying Student's t copula

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

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

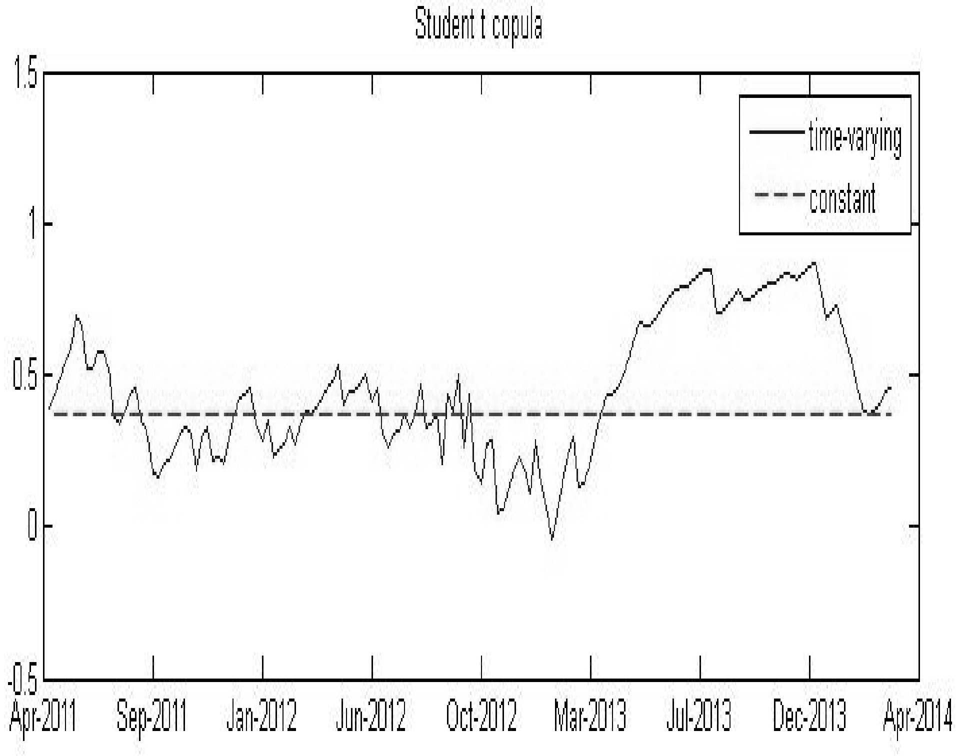

Figure 4.1. Time varying Student t copula for Producer - Wholesaler price pair

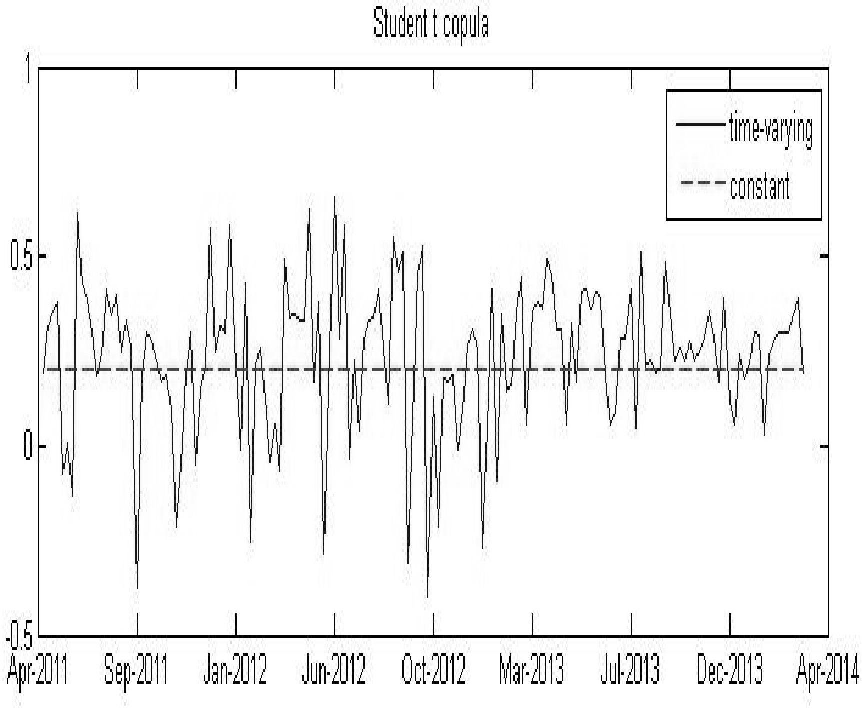

Figure 4.2. Time varying Student t copula for Wholesaler - Retailer price pair

CHAPTER 5

Conclusion

The guiding theme of this thesis is the use of statistical copulas as an instrument to model dependence between variables in the agrofood sector. While widely used in the financial economics literature, copulas have been rarely applied in the food economics field. Statistical copulas are applied to three different case studies, each constituting one of the three key chapters of the thesis. Each of these analyses addresses dependence between variables whose univariate distribution cannot be satisfactorily represented by a Gaussian or a Student *t* distribution. Hence, their joint distribution function cannot be easily characterized by any of the existing multivariate distribution functions. Under this framework, it is recommendable to use alternative statistical tools to assess dependence. One of the main advantages of copulas is that they rely on univariate distributions and do not require specification of a multivariate distribution. Further, and relative to non-parametric techniques, copulas have the advantage to produce parameters that summarize dependence between the variables considered.

The objective of the first analysis is to evaluate whether the introduction of agricultural revenue assurance (RA) contracts in Spain will imply a reduction in the price of purchasing agricultural insurance. The work focuses on the apple and orange sectors in Spain. In order to define a fair price of purchasing insurance, one needs to characterize dependence between prices and yields, which is done using statistical copulas. Monte Carlo simulation methods are used to simulate premium rates under revenue and yield insurance. Empirical results show a negative correlation between these two variables. This implies that revenue insurance is likely to reduce the price of agricultural insurance in Spain, which may result in higher acceptance and demand for agricultural insurance programs.

The second and third research articles focus on assessing price transmission along the food marketing chain, from producers to final consumers, in less developed countries (LDCs). After the food price crisis in 2007/2008, food prices increased significantly, specially in (LDCs) countries. Given the significant impacts that expensive food has at the political, economic and social levels, price analyses have proliferated since then, aiming at providing a better understanding of the causes and consequences of recent food price increases. Continued food price increases will worsen poverty rates, food insecurity and nutritional deficiencies, especially in poor countries.

In this regard, the second article contributes to the assessment of vertical price transmission from producers to consumers in Niger millet markets. Two markets are considered: Maradi and Tillabéri. While Maradi represents a region where there is excess millet production, Tillabéri is a deficit zone. Cointegration analysis is considered to examine the long-run relationship between producer and consumer millet prices. Copulas are used to examine short-run dependence. Results show that Niger millet markets are dominated by producer markets. Positive correlation is found to characterize producer and consumer price dependence, a correlation that declines with an increase in the physical distance between producer and consumer markets. Further, research results suggest an asymmetric dependence between the prices considered. For the Maradi market, this dependence involves that producer price increases are more likely to be transferred along the food market chain than price declines. In contrast, results for the Tillabéri market imply that extreme price increases will not be passed along the chain, which protects consumers in Tillabéri against price increases in the producer market. Evidence of asymmetric price behavior may point to non-competitive behavior.

Our third study focuses on vertical price transmission in the Egyptian tomato sector after the Arab Spring. Results show that, given the tumultuous period covered by the analysis, dependence changes over time, which requires the use of time-varying copulas. Positive dependence is found to characterize the link between producer and consumer prices. Dependence is less strong when it comes to wholesaler – retailer prices. Research results also suggest an asymmetric dependence between wholesaler – retailer prices, whereby 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.

In conclusion, statistical copulas assess dependence between variables in a much more flexible form than other well known statistical tools. This thesis shows how statistical copulas can become a relevant instrument in the food economics field. When drawing policy implications based on copula results, one should however be cautious since copulas are non-structural models. While structural models are founded on economic theory, non-structural analyses identify empirical regularities in the data.

This work could be extended in a number of different ways. A systematic comparison of the results derived from copulas and other conventional methods such as parametric and non-parametric time-series econometric techniques would shed light on the differences between the two. Recent research has combined pure copulas using finite mixture models, in order to increase statistical modeling flexibility. Mixture copulas have been shown to perform better than pure copulas in applied analyses (Melanie and Volker, 2012; Vrac et al., 2012; Ghosh et al., 2011; Ouyang et al., 2009). Comparison of our results with the ones produced through mixture copulas offers scope for further research. Pure and mixture copulas, however, are difficult to apply to multivariate data. A bivariate approach has been adopted in this thesis to overcome this shortcoming. Vine copulas have been devised to appraise multivariate dependence. D-vine copulas, for example, have multiple parameters to study the dependence through iterative construction of pair copulas (Kim et al., 2013). Vine copulas have accelerated the use of copulas as an instrument to depict dependence for multivariate data. The use of vine copulas would allow assessing dependence, for example, between consumer, wholesaler and producer prices, which is another path to extend the analysis presented in this thesis.

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