Understanding Recent Food Price Patterns: A Time-Series Approach

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Dedication

I dedicate this thesis to my wonderful wife and my lovely daughter Rania for their patience and sacrifice in helping me to be what I am today.

FADI

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General introduction

Food price patterns have been historically characterized by considerable volatility. Market instability makes future price prediction a difficult task and creates significant uncertainty for market participants. The very large food price swings that have been registered over the last decade, have revitalized the literature on food price behavior. Proper understanding of the dynamics of price behavior is especially relevant to design adequate policies to mitigate the impacts of price shifts (Deaton, 1999). Price volatility results in large social and economic consequences (Prakash and Gilbert, 2011). Social effects are specially felt in developing countries, where the population spends a large share of its income on food, and thus suffers substantially from food price increases. At the economic level, food price instability has large impacts on farmers, market participants and consumers. While high commodity prices benefit sellers and hurt buyers, lower prices have the opposite impacts. This puts a premium to understanding the drivers of price behavior, so as to be able to anticipate and ameliorate the consequences of large price shifts.

The literature has suggested several causes that may be underlying recent food price increases. These include (Prakash and Gilbert, 2011) crude oil price increases and financialization of food commodities. Crude oil price increases have affected food supply through increasing input costs such as fertilizers, pesticides, or transportation costs. Crude oil prices have also influenced food demand by altering the competitiveness of biofuels, whose expansion caused an unprecedented increase in the demand for food commodities to produce energy. In the past decade, the magnitude of financial traders' positions in commodity markets has substantially grown. This financialization of food commodities has raised questions regarding the extent to which food prices are still driven by market fundamentals such as demand and supply, or whether financial trade has acquired a major role. Exchange rates, that alter the purchasing parity, interest rates, commodity stocks, among others, have also been highlighted by previous literature as potential influences on food price behavior.

While several causes have been suggested as possible explanations for recent food price changes, further quantitative empirical research is needed to confirm or dismiss these hypotheses. The objective of this thesis is to provide further understanding of recent food price patterns. Price 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. The approach throughout this dissertation is based on non-structural time-series models that require less data than

structural models. Data necessary to estimate structural models is usually unavailable at high frequencies. High frequency data is key to understand price instability, one of the most characteristic patterns of food price behavior. Time series models differ from mainstream econometrics because time series data often violate the most common assumptions of conventional statistical inference methods, which may lead to obtaining completely spurious results. This makes it especially relevant to use methods suited to model time series.

The empirical focus of this dissertation is twofold. First, I study price links between food and energy markets, both in Spain and Europe. As well known and up to date, agricultural commodities constitute the main feedstocks used by the biofuels industry. The outbreak of the international biofuels market has stimulated research on the impacts that biofuel demand has had on food prices. While research has mainly focused on the US and Brazilian industries that dominate the global biofuel markets, less attention has been paid to European and Spanish industries. This thesis aims at filling this gap. The analysis covers not only the first statistical moment, but also the second moment of prices, i.e., attention is paid to both price levels and price volatility. The analysis relies on flexible and innovative time-series econometric techniques. Second, I study the effect that information exerts on commodity prices. More specifically, I appraise the effect that the release of public information, containing structural data on different crops, has on their futures market prices. Time-series econometric techniques are also used to achieve this second purpose. The main contribution of this thesis is of an empirical nature and aims at understanding food price formation over the last years.

This thesis is composed by three main core chapters that constitute three independent scientific articles. The first chapter is devoted to study the impacts of the Spanish biofuels market on food prices. More specifically, the relationship between the Spanish biodiesel, refined sunflower oil and crude oil prices is modeled. Attention is paid to both the first and second moment of prices. The existence of a long-run relationship between food and energy prices in Spain is tested by means of cointegration techniques. How prices adjust to this equilibrium parity is assessed through a vector error correction model. This model also depicts short-run price-level links between the prices considered. Volatility and volatility spillovers are studied using asymmetric multivariate GARCH models. This represents a contribution to previous literature that has hardly allowed for asymmetric impacts of price increases and decreases on volatility. Hence, it is not yet well known whether an increase in biofuel prices has a stronger impact on food price volatility than a biofuel price decline. Nor is obvious whether the biofuel price becomes more volatile during crude oil price increases than crude oil price declines.

While the biofuels market in Spain has a reduced size, the biodiesel industry in the European Union occupies the first position in the worldwide ranking. Previous literature has paid little attention to study the effects of this industry on food prices, a gap that I fill in the second chapter of this thesis. More specifically, the relationship between the European biodiesel, rapeseed oil and Brent oil prices is investigated. As in the first chapter, short and long-run price level links are assessed by means of cointegration and error-correction analysis. A common characteristic of food price volatility studies is that, with few exceptions, they have usually considered price volatility interactions across related markets and volatility clustering as the sole causes of price instability. Previous research, however, has identified other possible volatility sources such as storage, food demand shocks, weather conditions, macroeconomic framework, speculation in futures markets, etc. (Cooke and Robles, 2009; Balcombe, 2011; Wright, 2011). This raises questions such as what is the impact of biofuels on food price instability relative to other volatility causes? In the second chapter of the thesis, I contribute to shed light on this question. I investigate volatility and volatility spillovers by means of the semiparametric MGARCH model proposed by Long et al. (2011), which is extended to a consideration of the influence of exogenous variables representing market fundamentals.

In the third chapter, I investigate the effect of public information in the form of USDA released crop production reports, on corn and soybean futures price levels and volatility. Futures markets have two main roles: price discovery and price risk management. The third chapter of the thesis focuses on the first, for which information on market supply and demand is vital. Since market fundamentals are crucial in explaining price movements, published forecasts on production and consumption are expected to have an effect on market prices. The value and impact of released (public and private) information on commodity prices (futures and spot) has recently received considerable attention. This thesis contributes to enlarge this literature. The influence of public information on close to close and close to open returns for corn and soybean futures prices is assessed by means of GARCH models.

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Chapter 1: Asymmetric price volatility transmission between food and energy markets: The case of Spain

1.1. Introduction

The link between biofuel and food markets is receiving growing attention within the economics literature, specially since the outbreak of the global biofuels industry in the second half of the 2000s. Increased food prices and volatilities are a major threat over food security and economic well-being, specially in developing countries, where an important portion of the population spends most of household income on food (Prakash, 2011). Many studies have assessed the impacts of biofuel prices on food prices using time series econometric techniques (Balcombe and Rapsomanikis, 2008; Zhang et al., 2009; Serra et al., 2011a and 2011b). Other methods such as general or partial equilibrium models have been used as well (Arndt et al., 2008; Rosegrant et al., 2008). In contrast to time-series econometric techniques, these other methodologies usually require a considerable amount of data that is often unavailable, specially at high frequencies, thus reducing the amount of data at hand for econometric model estimation.

While evidence on causal links from biofuels to food prices and vice-versa is mixed (Saghaian, 2010), several research results point towards the conclusion that fuel price shocks govern rising food prices. Balcombe and Rapsomanikis (2008) show that an increase in energy price levels will lead to an increase in Brazilian sugar prices, the link between the two markets being established through the ethanol industry. Similar conclusions are reached by Serra et al. (2011b) for the United States (US) corn market. Chang and Su (2010) show that during periods of high crude oil prices, crude drives US corn and soybean price levels. In contrast to the literature showing strong links between food and energy markets, Zhang et al. (2010) find no evidence of an equilibrium relationship between US fuel and agricultural commodity prices. Limited evidence, if any, of short-run price links is provided.

EU markets have received less research attention than US and Brazilian biofuel markets (Serra and Zilberman, 2013). Peri and Baldi (2010) find EU's rapeseed oil price levels to be affected by diesel prices.

Busse et al. (2011) show that agricultural commodity and energy price levels exhibit an increasing positive correlation in the EU, particularly during the 2006/08 period. This correlation not only increases during periods of high prices, but it keeps rising afterwards. Busse et al. (2012) find the German biodiesel industry to influence rapeseed oil and soy oil price levels. The German ethanol industry is found by Rajcaniova and Pokrivcak (2011) to drive agricultural price levels. Hassouneh et al. (2012) study the Spanish biodiesel industry to find evidence of sunflower oil price levels to be driven by energy prices.

Although most of the literature on energy-food price links has focused on price levels (Balcombe and Rapsomanikis, 2008; Serra et al., 2011b), multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models have started to be used to capture volatility spillover effects (Zhang et al., 2009; Serra et al., 2011a). These latter studies recognize that, if biofuel and food price levels are interrelated, volatility spillovers between these markets should also take place.

Previous research has shown that price time series are usually characterized by volatility persistence, i.e., periods of high (low) volatility tend to be followed by periods of high (low) volatility. To capture volatility clustering, Autoregressive Conditional Heteroscedastic (ARCH) models and their Generalized (GARCH) version were introduced in the time series econometrics literature. In their early versions, these models were based upon the assumption that positive and negative market shocks have a symmetric impact on volatility. However, it soon became evident, through the estimation of more flexible models, such as the asymmetric GARCH by Glosten et al. (1993) (GJR), the threshold GARCH (TGARCH) proposed by Zakoïan (1994), or Nelson's (1991) Exponential GARCH (EGARCH) models, that price volatility may respond differently to positive and negative market shocks. Previous studies assessing volatility spillovers between food and biofuel markets have not allowed for asymmetries, offering scope for further research. Asymmetric models should allow responding to questions such as: do biofuel price increases have the same impact on food price volatility than price declines?, or does biofuel price instability get worse during feedstock price increases than feedstock price declines?

This paper aims at studying price behavior in the Spanish biofuel industry. Special attention to model volatility is paid and asymmetries are

allowed for. The contribution of this work to the literature is twofold. First, it focuses on the Spanish biodiesel market. From recent literature reviews on the use of time-series methods to assess biofuel prices (Serra and Zilberman, 2013), it is clear that previous research has mainly focused on the two main ethanol markets in the world: the US and Brazil. Conversely, European Union (EU) biofuel markets have not received much research attention. Second, in contrast to the predominant literature, not only we do assess price level links, but also volatility spillovers, by means of an asymmetric MGARCH model. While a few attempts to model volatility spillovers between food and biofuel markets have been published, our work is the first in explicitly allowing for asymmetries.

The remainder of this chapter is organized as follows. Section 1.2 presents a literature review on nonlinear price behavior in energy and food markets. Section 1.3 describes the biodiesel industry in the EU and the Spanish biodiesel market. Section 1.4 presents the methodological approach. Section 1.5 reports the empirical results. Section 1.6 presents the concluding remarks and a summary of the research results.

1.2. Previous literature

Empirical studies in the food and energy economics literature have provided evidence that price transmission mechanisms are usually characterized by nonlinearities. However, attention has focused on nonlinearities in price level links. Nonlinearities in price volatility spillovers have been widely ignored. In the following lines, we focus on price-level studies, to then review some articles assessing price volatility interactions.

1.2.1. Price level studies

Serra and Gil (2012) study the link between crude oil and biodiesel blends, and crude oil and diesel prices in Spain during extreme market events, which are the most likely to have relevant economic impacts. Copula models are used to assess dependence. Results suggest asymmetric dependence between the crude oil and the biodiesel price, which protects consumers against extreme crude oil price increases. Diesel and crude oil prices, in contrast, exhibit a symmetric dependence by which both extreme crude oil price increases and decreases are equally likely to be passed on to consumers.

Busse et al. (2012) use a Markov-switching Vector Error Correction Model (VECM) to investigate the relationship between biodiesel, diesel, rapeseed oil and soy oil price-levels in Germany. Results show that two co-integration relationships characterize long-run price dynamics, one representing the relationship between biofuels and agricultural commodities and the other the biodiesel-diesel. This is compatible with Serra et al. (2011b) findings that two co-integration relationships characterize long-run price level behavior in the US ethanol industry, one representing the ethanol industry and the other the oil industry equilibrium. Strong evidence of nonlinear price adjustments is found through the use of a smooth transition VECM.

As for the literature focusing on energy price-levels, Grasso and Manera (2007) use asymmetric and threshold-type Error Correction Models (ECM) to assess gasoline - crude oil price level links in the EU. They find evidence of long-run asymmetries in Spain, France, Italy, United Kingdom and Germany. While a handful of studies support that crude oil price increases are passed on to liquid fuel prices more quickly and completely than price declines, Douglas (2010) warns that findings of asymmetry critically depend on outlying observations. He provides evidence that asymmetries in the US gasoline market may be driven by a small number of outliers, which suggests less departures of gasoline prices from traditional price theory than previously thought and minimal consumer welfare losses derived from asymmetry.

The literature on asymmetric price transmission in food markets is extensive, but focuses on price levels. Threshold autoregressive type of models (TAR) have been a useful tool to assess vertical price transmission along the value chain (Goodwin and Holt, 1999; Goodwin and Piggott, 2001; Serra and Goodwin, 2003; Hassouneh et al., 2010). By studying a wide range of products, Peltzman (2000) concludes that asymmetries are more the rule than the exception. The asymmetric price transmission literature survey conducted by Meyer and Cramon-Taubadel (2004), shows that out of 40 articles published in major journals over the last decade, 27 focus on agricultural products. They also show that 48% of the applied asymmetry tests reject symmetry.

1.2.2. Price volatility studies

In the following lines, we review the scarce price volatility literature that focuses on the links between food and energy markets. Zhang et al. (2009) study volatility spillovers between US weekly ethanol, corn, soybean, gasoline and oil prices by means of Baba-Engle-Kraft-Kroner (BEKK-GARCH) model. Price volatility links between oil and gasoline and corn and soybean characterize the markets, both during the pre-ethanol and the ethanol boom periods. Serra et al. (2011a) fit a MGARCH to weekly Brazilian ethanol, sugar and international crude oil prices. Results indicate strong bidirectional volatility spillovers between food and energy markets. Trujillo-Barrera et al. (2012) study US corn, ethanol and crude oil price volatility interactions. A MGARCH model that includes an exogenous random shock coming from the crude oil market is estimated to assess the volatility of corn and ethanol prices. Evidence of spillovers from crude to corn and, specially, to ethanol prices is found. Spillovers between corn and ethanol are also identified, being the ones from corn to ethanol much larger.

Volatility studies focusing on energy markets include Rahman and Serletis (2012) who examine the effects of oil price uncertainty on real economic activity in Canada using a bivariate vector autoregression moving-average (VARMA), GARCH-in-Mean, asymmetric (BEKK-GARCH) model specification. The conditional variance-covariance process underlying output growth and the crude oil price changes is characterized by significant non-diagonality and asymmetry. Evidence is also provided that increased crude oil price uncertainty involves lower economic activity.

The theoretical literature attempting to explain asymmetries in volatility has focused its attention on financial markets. Two main theories have been offered for this purpose: the leverage and the feedback theory (French et al., 1987; Schwert, 1989; Campbell and Hentschel, 1992). No theoretical framework however has been offered to explain possible asymmetric spillovers between food and energy markets. Our paper contributes to the literature by providing empirical evidence that asymmetries in volatility spillovers between food and biodiesel prices are relevant and should thus deserve further attention on the part of economic theory.

1.3. The Biodiesel industry in the EU and Spain

Biofuels have been promoted within the EU not only as a means of curbing down greenhouse gas (GHG) emissions and reducing dependence on fossil fuels, but to also enhance energy security and offer alternative outlets for agricultural production. Several studies (Pimentel, 2003; Pimentel and Patzek, 2005; OECD, 2007) have shown that energy output from biofuels is less than the output from fossil fuels. While opinions regarding the capacity of biofuels to reduce GHG are mixed, there seems to be a general agreement of a positive impact (US-EPA, 2007; FAO, 2013; USDA-FAS, 2012). EU policies are important for European biofuel markets to develop and acquire a critical size, and can also play a key role for second-generation biofuels to join the first generation in the fuels market.

The most common tools being used to promote biofuels in the EU include tax reductions, subsidies and blending mandates establishing minimum content of biofuels in liquid fuels sold in gas service stations. The EU 2020 targets require renewable sources to represent 20% of total EU energy use. A minimum 10% share of renewable energies should further be ensured in the transportation sector in every member state (Directive 2009/28/EC). In 2008, energy from renewable sources contributed 10.3 % to EU-27 gross final energy consumption. The highest share of consumption from renewable sources was recorded in Sweden (44.4%) and the lowest in Malta (0.2%). The Spanish share was 10.7% (Energy, transport and environment indicators, 2010). Further, in 2008, the share of biofuels in transport fuel consumption in the EU-27 was 3.29 %, which contrasts with the share ten years ago of 0.13 %. At the state-level, the highest shares of biofuel consumption in transport were observed in Slovakia 6.19 %, Germany 6.09 %, Austria 5.67 %, France 5.47% and Spain 1.80%.

In 2008, the EU transport sector was responsible for about one third (32%) of final energy consumption. Further, 79 % of total GHG emissions were energy-related. Fuel use in the energy and manufacturing industries represented 60% of these emissions, while the transport sector made up the remaining 19%. During the last 18 years, transport has been the only sector that has increased its emissions (24%), making it specially pertinent to curb them down. Most energy used in transportation comes from oil. The EU-27

is highly dependent on crude oil imports, and this dependence has been growing in the last years (Energy, Transport and Environment Indicators, 2010). Biofuels can partially replace fossil fuels and possibly reduce GHG emissions. Since biofuels are being mainly produced from agricultural crops, agriculture can thus play a role in increasing supply of renewable energy. Predominant biofuel feedstocks are currently corn in the US, sugar cane in Brazil, and rapeseed in the EU. Rapeseed cultivation in Spain is however irrelevant, being sunflower the major domestically produced feedstock.

The EU is the first world biodiesel producer, representing around 65% of the world market. In 2008, total EU-27 biodiesel production was over 7.7 million metric tons, an increase of 36% from 2007. Production reached 9 million metric tons in 2009. Biodiesel output represents around 75% of the EU's biofuel production (EBB, 2010). Germany was the first country in the EU ranking of biodiesel production in 2009, followed by France and Spain. While Spain occupied the third position in terms of production, its production capacity was the second largest among the EU countries, after Germany (EBB, 2011). The EU biodiesel industry is characterized by its relevant unused production capacity. While in 2009 biodiesel production reached 9 million tons, production capacity was 22 million tons (the latter representing a fivefold increase from 2005). In 2008, the EU-27 biodiesel production capacity represented 70% of total biofuel capacity. Production capacity in Spain in 2010 was 4.1 million tons compared to actual production of 0.925 million tons (EBB, 2011). Such large unused production capacity can be attributed to favorable expectations for biodiesel markets due to high crude oil prices and EU policies that led to investments in biodiesel plants, subsidized biodiesel imports from Argentina and the US, or the recent economic crisis that has reduced energy demand (EBB, 2010; EurObserv'ER, 2010).

Biofuel use in the EU in 2009 totaled 12 million toe,[1] representing 4% of the fuels used for transportation. Biodiesel and bioethanol consumption in Spain were on the order of 894 and 152 thousand toes in 2009, respectively (EurObserv'ER, 2010), with a growth rate of 71% from 2008. Biodiesel is usually sold blended with diesel at gas service stations and benefits from favorable tax treatments and fiscal incentives. Biodiesel

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[1] Tonne of Oil Equivalent

consumption in Spain has increased, specially after enforcement of the consumption mandates since 2009. Consumption of biodiesel has doubled since 2008 to reach 1,668 million tons in 2011 (CORES, 2012).

In 2009 (2010) biodiesel imports represented more than 40% (60%) of biodiesel consumption. Argentina and Indonesia are the primary biodiesel suppliers, representing around 50% and 20% of total Spain's imports in 2010, respectively (USDA-FAS, 2011). The biodiesel industry complains that imports have dramatically affected the profitability of the Spanish domestic industry (EBB, 2010; EBB, 2012). Recently, the EU Commission has launched anti-dumping measures against Argentina and Indonesia to protect European producers from uncompetitive imports of biodiesel (EBB, 2013).

Spain's biodiesel production depends substantially on imported feedstocks. According to Spanish CNE (2011), soybean, palm, sunflower and rapeseed oils are the major feedstocks. Soybean and palm represent 47,66% and 38,36% of the total feedstock used, respectively; frying oil, sunflower and rapeseed oil represent around 11,67%; and animal fats represent 2.31% (Spanish CNE, 2011). Of all the feedstocks currently being used to produce biofuel, the Spanish agricultural sector only produces sunflower oil, being the production of the other feedstocks residual. The domestic production of sunflower reached 1,09 million tons in October 2011, with a cultivated area of about 863.7 thousand hectares representing an increase of about 67% from 2005 (MAAMA, 2012).2 Sunflower production has traditionally been directed to food consumption. Recently, its use as an input in the biodiesel industry has increased its demand. Hence, if the biodiesel industry has any impact on Spain's agricultural prices, this should be specially evident on sunflower oil prices. The focus of this article is on sunflower prices as the major biofuel industry feedstock that is being produced in Spain.

1.4. Methodology

Most price time series data have common characteristics that need to be considered when conducting econometric analysis (Myers, 1994). Three of these characteristics are important to our research. First, commodity price time series usually have a unit root. Second, prices of related markets

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[2] The irrelevance of rapeseed, soybean and palm oil output, is the underlying reason of a lack of price statistics on these crops in Spain.

can share a tendency to co-move. Co-movements that can result from the existence of an equilibrium relationship between individual price series are known as co-integration. Third, commodity prices usually exhibit volatility that tends to change over time and to display a clustering behavior.

1.4.1. Unit roots and Vector Error Correction Model (VECM)

Well-known standard unit root tests are used in our analysis to test for non-stationarity in price series (Dickey and Fuller, 1979; KPSS, 1992; Perron, 1997). We assess co-integration using Johansen (1988) methodology. While we focus on the links between crude oil, biodiesel and sunflower oil prices, crude oil is imposed to be exogenous for both short and long-run parameters. Johansen (1988)'s approach is applied based on the following VECM:

$$\Delta P_t = \alpha_p \varepsilon_{t-1} + \sum_{i=1}^{l} \alpha_i \, \Delta P_{t-i} + \delta X_t + u_t \qquad (1)$$

where Δ represents the first differences operator, P_t and P_{t-i} are, respectively, n-dimensional vectors of the current and lagged prices being considered, with n representing the number of prices (n=2 in our analysis). Vector X_t contains exogenous variables and u_t is a n-dimensional vector of white noise residuals that may be correlated with each other. The term ε_{t-1} contains the residual from the co-integration relationship (i.e. the linear combination of the non-stationary variables that is stationary). α_i and δ are parameter matrices showing short-run price dynamics, while α_p is an n-dimensional vector containing parameters that measure the speed at which a variable adjusts to disequilibriums from the long-run equilibrium relationship.

1.4.2. Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model (MGARCH)

VECMs explain price-level behavior by explicitly allowing for non-stationarity and co-integration. These models, however, are based upon fairly simplifying assumptions on price variance: they assume that price variance is constant over time. ARCH models and their generalized version (GARCH) were introduced in the econometrics literature in order to model time-changing and clustering price volatility. The ARCH model was introduced by Engle (1982) to allow for the variance-covariance matrix of

the current model errors to be a function of the actual size of the lagged error terms. However, ARCH models have limited capacity to explain persistent volatility usually present in time-series. Later, Bollerslev (1986) proposed a generalized version of the ARCH model. In the GARCH model, the variance-covariance matrix not only depends on lagged residuals, but also on its own lags. While multivariate GARCH (MGARCH) models can be specified using different functional forms, some of the parsimonious forms proposed in the literature are too restrictive in that they do not allow for volatility spillovers across the different markets considered. Further, most of these specifications do not allow testing for volatility causality links. Our analysis will rely on the BEKK model defined in Engle and Kroner (1995) to capture patterns of volatility transmission across markets and to test for volatility causality links. While the multivariate BEKK-GARCH model is an improvement over other more restrictive specifications, it is unable to capture asymmetric volatility patterns. Our analysis will be based upon an asymmetric specification of the multivariate BEKK-GARCH model following Kroner and Ng (1998).

Previous literature on price behavior has provided evidence that linearities in price links should not be expected to hold, either because prices respond nonlinearly to market changes, or because changes in the political or economic framework can lead to structural breaks (Obstfeld and Taylor, 1997). While articles studying price-level behavior in biofuel markets have usually allowed for these nonlinearities, price volatility studies have generally not. The financial economics literature has however recognized the importance of allowing for asymmetry (or nonlinearity) in volatility transmission (Engle and Ng, 1993; Bekaert and Harvey, 1997; Brooks and Henry, 2002; and Bekaert et al., 2003). Kroner and Ng (1998) define the asymmetric volatility effect as implying that bad market shocks lead to higher volatility than good market shocks. Failure to account for asymmetry in volatility models may lead to model misspecification. The asymmetric BEKK-GARCH model has the property that the conditional covariance matrices are positive definite by structure and can be expressed as follows:

$$H_t = CC' + A'u_{t-1}u'_{t-1}A + B'H_{t-1}B + D'v_{t-1}v'_{t-1}D \qquad (2)$$

where Ht is the (n x n) variance-covariance matrix, A, B, C and D are (n x n) parameter matrices (recall that n=2 in our analysis) and C is further a lower triangular matrix. Asymmetries are captured by adding the term $D'v_{t-1}v'_{t-1}D$ to the conventional BEKK model where $v_{t-1} = u_{t-1}o\ I_{u<0}(u_{t-1})$ and o is the hadamard product of the vectors. The conditional mean (1) and variance (2) models are estimated by Seemingly Uncorrelated Regression (SUR) and standard maximum likelihood procedures, respectively. In order to estimate the asymmetric BEKK-GARCH, we assume normally distributed statistical innovations which leads to the following log likelihood function:

$$l_t = -\left(\frac{1}{2}\right)\sum_{t=t+1}^{t}\log|H_t| - \left(\frac{1}{2}\right)\sum_{t=t+1}^{t}e_t'H_t^{-1}e_t \qquad (3)$$

that is maximized with respect to the parameter matrices A, B, C, and D.

Allowing for asymmetry in our model provides valuable information to policy makers and economic agents participating in the marketing chain, on the existing differences between the impact of negative and positive news on biodiesel market price fluctuations. The fact that asymmetric effects are significant indicates potential misspecification if asymmetries are ignored. Before concluding this section, it is relevant to note that, in contrast to the theoretical models that rely on economic theory and require an important amount of data, time-series models are nonstructural models that identify empirical regularities in the data. Our results should not be interpreted beyond this point.

1.5. Empirical Results

Previous research assessing the links between food and energy prices has usually considered feedstock, crude oil and biofuel prices (Serra and Zilberman, 2013) and concluded that crude oil prices are very relevant in explaining both biofuel and feedstock prices. These results are supported theoretically by a series of conceptual models that establish a link between crude oil, biofuel and feedstock prices (de Gorter and Just, 2007 and 2008; Rajagopal and Zilberman, 2007). In our selection of data to conduct the analysis, we follow previous research and use weekly nominal Spanish biodiesel blend prices (P1t), refined Spanish sunflower oil prices (P2t) and international crude oil prices (P3t). Prices are expressed in Euros (€) per liter and observed from 07/11/2006 to 05/10/2010, yielding a total of 205

observations. The time span evaluated comprises a period of relevant price increases that occurred during 2007, reaching their maximum in 2008. Information on Spanish biodiesel blend prices was obtained from the Spanish Ministry of Industry, Tourism and Trade (2010). These prices correspond to national average biodiesel blend prices at the pump.3 In being pump prices, they are affected by policy instruments such as a blending mandate or a tax exemption. Refined sunflower oil prices were obtained from the Spanish Ministry of Environment and Marine and Rural Affairs (2010), while international crude oil prices were taken from the US Energy Information Administration (2010) dataset. The latter are a weighted average of world spot FOB crude prices using, as a weight, the estimated export volume. They are expressed in US dollars per barrel and were converted into € per liter using the European Central Bank (ECB, 2010) exchange rates. Figure 1.1 shows the evolution of the three prices over time. The analysis was carried out using the econometric software RATS 6.3. Given the relevance of imported soybean and palm oil as feedstocks used by the Spanish biodiesel industry, international prices for these two oils were considered in the analysis. However, the high correlation between feedstock prices created multicolinearity problems, recommending model simplification to a consideration of a single feedstock price. Noteworthy is the fact that price dynamics that will be identified in our analysis, are conditional upon the selection of the prices being modeled.

Logarithmic transformations of price series are used in the empirical analysis[4] and descriptive statistics are presented in table 1.1 Standard augmented Dickey and Fuller (1979), Kwiatkowski et al., (1992) and Perron (1997) tests confirm that all three series are integrated of order one I(1) (table 1.1). Long-run links between crude oil, biodiesel and sunflower oil prices are assessed using Johansen (1988) co-integration tests. Prices are found co-integrated with a co-integration rank r=1, i.e., there is a single relationship characterizing long-run price dynamics (table 1.2). Hansen and Johansen (1999) recursively calculated beta test for the null of constancy of the cointegration parameters shows that no structural breaks affect the cointegration relationship.

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[3] Noteworthy is the fact that these are the only data available on biofuel prices in Spain.

[4] Logarithmic transformations allow obtaining well behaved error terms (Bierlen et al., 1998) and facilitate the interpretation of research results. By using logged prices, the parameters of the co-integrating vectors represent elasticities and the short-run dynamic parameters represent proportionate changes.

Within the Johansen's framework, a chi square test for the null of sunflower weak exogeneity for long-run parameters, leads to the acceptance of the null (table 1.2). As will be seen below, this result is compatible with the conditional mean model results. In light of these results, the equilibrium relationship should be interpreted as the parity that biodiesel blend prices need to maintain with crude and sunflower oil prices, for the biodiesel industry to be in equilibrium. In other words, biodiesel blend prices in the long-run are influenced by crude oil and sunflower oil prices, but not the other way around. Engle and Granger (1987) tests for co-integration, taking biodiesel blend as the endogenous variable in the price system, also support the existence of a long-run relationship characterizing the biodiesel industry. Co-integration parameters (table 1.2) suggest that, in the long-run, an increase in sunflower and crude oil prices will lead to an increase in biodiesel blend prices. The positive relationship between biodiesel blend and sunflower oil prices is expected given that more than 90% of biodiesel production costs have been attributed to feedstock (IDAE, 2005). Since biodiesel is not usually commercialized in its pure form, but blended with regular diesel, a crude oil derivative, it is not surprising to find that blend prices increase with an increase in crude oil prices. Our results are compatible with Hassouneh et al. (2012) who study Spanish biodiesel industry price level behavior using both a VECM and local modeling techniques. Also, our co-integration results are in line with Balcombe and Rapsomanikis (2008), who found evidence of a price transmission hierarchy from oil to sugar to ethanol and not the other way around.

Interpretation of price elasticities from the cointegration analysis requires reliable information on average blends available in the market, as well as the share of feedstocks and crude oil in biodiesel and diesel production costs, respectively. There are no accurate statistics on average blend ratios in Spain. While the Spanish Government set a binding mandate on the order of 6,5% for 2012 (Real Decreto 459/2011), blends on the order of 10% are not rare. This makes it difficult to interpret the elasticities derived from the cointegration analysis. Assuming a blend ratio around 7% and assuming that 90% of biodiesel production costs are due to feedstock costs (IDAE, 2005), a 100% increase in feedstock prices would involve an increase in biodiesel blend prices on the order of 6.3%, the elasticity obtained in our analysis. As for the elasticity of crude oil prices, on the order of 47%, it is compatible with an approximate 50% share of crude oil

price in diesel price, a percentage in line with estimates presented in US Energy Information Administration (2013).

Results from the two-step estimation of the VECM, the conditional mean model, and the multivariate asymmetric BEKK-GARCH, the conditional covariance model, are presented in tables 1.2 and 1.3, respectively. As noted, crude oil prices are considered as exogenous in the price system (Asche et al., 2003; Trujillo- Barrera et al., 2012).[5] This assumption is reasonable, given the small size of the Spanish biodiesel industry relative to the international crude oil market, as well as given preliminary testing providing support for this specification. For ease of interpretation of MGARCH model, table 1.4 containing the nonlinear parameter functions of the conditional variance equations is presented. In the following lines, we focus on interpreting the conditional mean model.

Biodiesel blend short-run price dynamics involve that current changes in biodiesel blend price are positively related to past biodiesel price changes and to crude oil lagged price changes. Short-run sunflower oil price dynamics are driven by own lagged price changes and by lagged changes in biodiesel blend prices. Consistently with weak exogeneity testing for long-run parameters within the Johansen's (1988) framework, the biodiesel blend price is the only price in the system that responds to long-run disequilibriums. i.e., both energy and food price levels exert a relevant influence on biodiesel equilibrium prices. This confirms, once more, that the co-integration relationship represents the parity that biodiesel blend prices in Spain have to keep with sunflower and crude oil prices for the biodiesel market to be in equilibrium. Further, weak exogeneity of sunflower oil prices with respect to long run parameters suggests that, at least for the market and time-period studied, the Spanish biodiesel industry has not been able to shape agricultural prices in the long-run. It has, however, influenced these prices in the short-run.

In contrast to our results, Serra et al., (2011a), who assessed price links within the Brazilian ethanol industry, did not find sugar short-run dynamics to change as a response to past ethanol price changes. However, sugar prices were found to adjust to disequilibrium from the long-run parity. For the US ethanol market, Zhang et al. (2009) found that during the

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[5] Crude oil was considered as exogenous in both the conditional mean and volatility models, but only found to be significant in the first one. AIC and SBC criteria were used for model selection.

pre-ethanol boom period, ethanol price changes were not affected by lagged corn price changes. In contrast, short-run corn price dynamics were driven by past changes in ethanol prices. Also, Zhang et al., (2009) found evidence of co-integration between food and energy prices during the pre-ethanol boom period. However, this equilibrium was not found to be significant during the ethanol boom.

Residuals of the VECM were tested for multivariate autocorrelation following Hosking's (1981) variant of the multivariate Q statistic and results led to accept the null of no autocorrelation. Also, the multivariate ARCH LM test was conducted and evidence of ARCH effects was found, thus supporting the use of a MGARCH model. We now turn to the interpretation of the conditional volatility model. The test for the null hypothesis that parameters in matrices A, B and D in the MGARCH model are equal to zero is rejected, showing evidence of time varying volatility, additionally, an LR test for the null that parameters in D matrix in the GARCH specification are zero is conducted to test for the relevance of the asymmetric effects. Results show that asymmetric effects are statistically significant (table 3). Nyblom (1989) fluctuations test leads to accept the null of model stability.

As noted above, individual coefficients of the MGARCH parameterization cannot be directly interpreted. Instead, we draw conclusions from the nonlinear parameter functions in the conditional variance equations (table 4). We focus on statistical significance at the 5% level. Results suggest statistically significant direct and indirect volatility spillovers from sunflower oil to biodiesel prices. Past shocks to the sunflower oil market are found to have an asymmetric effect (v_{2t-1}^2) on biodiesel blend price volatility (h_{11t}), with sunflower oil price declines increasing the biodiesel price variance more than price increases. This is indicative of biodiesel blend price responses being more sensitive to sunflower price decreases than to price increases. Passing an increase in production costs on to biodiesel consumers may reduce biodiesel competitiveness in the liquid fuels market. Conversely, passing on a price decline may improve market perspectives. The sunflower oil price instability (h22t) is affected by its own lagged shocks (u_{2t-1}^2) that increase volatility independently on their sign (i.e., both good and bad news increase market instability). The parameter representing h_{12t-1} suggests that the strength of the correlation between biodiesel and sunflower oil price

volatility has an impact on sunflower oil price instability. While a positive and strong correlation will reduce instability, a negative strong correlation will enhance it. So it looks like stability is guaranteed when the prices of both the feedstock and the biofuel move together in the same direction. Statistical significance of h_{12t-1} also provides evidence of an indirect effect of biodiesel on sunflower price variability. Hence, biodiesel blend markets are not only found to influence sunflower oil price levels in the short-run, but they also show some power to affect instability in these markets.

Serra et al. (2011b) found sugarcane-based ethanol price volatility to increase with own lagged volatility, as well as by past turbulence in sugar and crude oil markets. Indirect volatility transmission through covariances was also identified. Zhang et al. (2009) found corn-based ethanol price volatility to be independent of past volatilities in corn and crude oil markets in pre and post ethanol market boom. Spillovers between agricultural markets (corn and soybean) were however found to be significant.

The MGARCH model forecast of the biodiesel blend price volatility (the only endogenous variable for long-run parameters) is presented in (figure 1.2) after being annualized. The model predicts specially high volatility during the period 2007-2009, which corresponds with a relevant increase in the demand for biodiesel, mainly as a result of public initiatives such as the EU 2020 target to ensure a minimum 10% share of renewable energies in the transportation sector. The boost in demand caused a substantial increase in biofuel price levels and volatility. This period also coincides with the global financial crisis that led to the global economic recession and to increased volatility in stock and commodity prices. The period also includes the 2008 global food crisis after which high and volatile food prices (and biofuel feedstocks) have become more the norm than the exception.

1.6. Concluding Remarks

This paper investigates price relationships in the Spanish biodiesel industry. We assess both price level links and volatility interactions. Three prices relevant to this industry are considered: the international crude oil price, the Spanish biodiesel blend price and the Spanish sunflower oil price. Prices are observed at a weekly frequency from November 2006 to October 2010. Price level relationships are studied by means of a VECM model

using SUR estimation, while price volatility behavior is analyzed through an asymmetric BEKK-GARCH model estimated by maximum likelihood procedures. Our work is the first in assessing asymmetries in biofuel-food price links, as well as in studying volatility spillovers in the Spanish biodiesel market.

We find blended biodiesel, sunflower and crude oil prices to be interrelated in the long-run by an equilibrium parity. This parity is maintained by the biodiesel industry in order to be in equilibrium. Based on co-integration analysis results, we can conclude that renewable energy plays a modest role in defining Spanish fuel prices. Blends usually commercialized in gas stations highly depend on crude oil prices, which is reflected in a high price elasticity on the order of 47%. Conversely, agricultural commodities have a limited influence on biodiesel prices at the pump, with an elasticity of around 6%. Other statistically significant short-run price interactions are also found to characterize price dynamics. While biodiesel blend prices are not found to influence sunflower oil prices in the long-run, they exert an influence in the short-run. Hence, biofuels can only cause a temporary increase in agricultural prices. Significant volatility spillovers between sunflower and biodiesel markets are found. Evidence of asymmetries in price volatility patterns is also found, with price declines causing more price instability than price increases. Asymmetries are likely due to the availability of alternative feedstocks in the market, together with reluctance of biodiesel producers to increase food prices when feedstocks become more expensive.

Both the EU and the US advocate for an increase in the role of renewable energies as instruments to reduce dependence on fossil fuels, as well as to reduce GHG emissions. Biofuels are a relevant renewable energy source. Up to date, marketed biofuels are mainly first generation biofuels that rely on agricultural commodities as feedstock. Policies promoting renewable energies have had a relevant effect on the agricultural sector, altering the pattern of the global agricultural land use and production, as well as agricultural price behavior. Our analysis shows that the biodiesel industry in Spain has had an impact on both short-run sunflower oil price levels and price volatility. The long-run sunflower oil price levels, however, are not found to depend on the energy market. This conclusion is compatible with Serra (2011) and with a small size of the biodiesel industry in Spain. In any case, long-run effects are likely to appear in the future as

the biofuel industry expands. Promotion of second-generation biofuels can prevent energy price instability being spread to agricultural markets.

MGARCH models have been found to be affected by several limitations. Among them it is noteworthy the assumption of normally distributed errors. Longin and Solnik (2001) and Richardson and Smith (1993), among others, have rejected the normality assumption. This suggests a possible extension of our analysis to a consideration of conditional volatility models that are robust to misspecifications of the error distribution. This may include the use of nonparametric specifications such as the ones proposed by Long et al. (2011). Further, nonlinearities in volatility behavior may also be captured by more flexible models such as Threshold-GARCH and Smooth Transition Conditional Correlation (STCC-GARCH) models that are based upon the assumption that conditional volatility correlations change depending on the prevailing economic regime. These models are more flexible than the asymmetric MGARCH models used in this analysis because they not only allow for two price behavior regimes, but for an unlimited number of regimes.

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Table 1.1. Descriptive statistics for weekly prices

	Biodiesel price	Sunflower price	Crude oil price
Mean	1.005	0.894	0.333
Standard deviation	0.113	0.275	0.079
Maximum	1.314	1.686	0.550
Minimum	0.823	0.619	0.156
Skewness	0.820**	1.215**	0.421**
Kurtosis	0.262	0.391	0.235
Jarque-Bera	23.572**	51.776**	6.547**
ADF	1.483	1.424	1.240
Perron	-5.586	-5.365	-6.524
KPSS	0.395**	0.573**	0.339**

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level

Note: the deterministic component used in conducting unit root tests is a constant

Table 1.2. Biodiesel - sunflower oil - crude oil: conditional mean equations

Co-integration relationship $P_{1t} = 0.536^{***} + 0.063^{**}P_{2t} + 0.468^{***}P_{3t}$
$\qquad\qquad\qquad\qquad\qquad (0.044) \qquad (0.031) \qquad\quad (0.043)$

Conditional mean equations $\begin{pmatrix} \Delta P_{1t} \\ \Delta P_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \varepsilon_{t-1} + \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \begin{pmatrix} \Delta P_{1t-1} \\ \Delta P_{2t-1} \end{pmatrix} + \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix} \Delta P_{3t-1} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$

	$i=1$	$i=2$
α_i	-0.057***(0.014)	0.025(0.048)
α_{1i}	0.277***(0.046)	0.010(0.019)
α_{2i}	0.384**(0.152)	0.431***(0.064)
δ_i	0.160***(0.014)	0.040 (0.045)

Chi square test for the null of weak exogeneity of Sunflower oil price within
Johansen's framework = 0.165
Hosking multivariate Q(12) Statistic = 48.875
Multivariate ARCH LM test = 36.04***
AIC = -3487.270
SBC = -3447.512

P_{1t} biodiesel, P_{2t} refined sunflower oil price, P_{3t} crude oil price
*** (**) [*] denotes statistical significance at the 1 (5) [10] % level
Standard errors in parenthesis

Table 1.3. Biodiesel - sunflower oil - crude oil : conditional variance equations

Conditional volatility equations

$$\Omega = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}\begin{pmatrix} c_{11} & c_{21} \\ 0 & c_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{pmatrix}\begin{pmatrix} u_{1t-1}^2 \\ u_{2t-1}^2 \end{pmatrix}\begin{pmatrix} u_{1t-1}^2 & u_{2t-1}^2 \end{pmatrix}\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{pmatrix}\begin{pmatrix} h_{11t-1} & h_{12t-1} \\ h_{21t-1} & h_{22t-1} \end{pmatrix}\begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} +$$

$$\begin{pmatrix} d_{11} & d_{21} \\ d_{12} & d_{22} \end{pmatrix}\begin{pmatrix} v_{1t-1}^2 \\ v_{2t-1}^2 \end{pmatrix}\begin{pmatrix} v_{1t-1}^2 & v_{2t-1}^2 \end{pmatrix}\begin{pmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{pmatrix}$$

	$i=1$	$i=2$
c_{1i}	0.003** (0.001)	
c_{2i}	0.004(0.006)	0.007***(0.002)
a_{1i}	0.152 (0.121)	0.520*(0.263)
a_{2i}	2.786e-02 (0.021)	0.470***(0.072)
b_{1i}	-0.333(0.222)	-1.602***(0. 483)
b_{2i}	-0.220***(0.064)	0.523*** (0.180)
d_{1i}	-0.436***(0.147)	-2.000***(0.555)
d_{2i}	0.196***(0.051)	0.543***(0.174)

LR test for the null that parameters in matrices A, B and D are zero =
1200.881***
LR test for the null that parameters in matrix D is zero = 40.511***
Nyblom (1989) fluctuation joint test   = 2.556(0.420)

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level

Standard errors in parenthesis

¨e¨ refers to exponential operator

Table 1.4. Biodiesel - sunflower oil - crude oil : conditional variance equations

$$h_{11} = 2.916e - 05 + 0.111\ h_{11t-1} + 0.050^*\ h_{22t-1} + 0.147^*\ h_{12t-1} + 0.023\ u_{1t-1}^2 + 7.765e - 08\ u_{2t-1}^2 + 8.482e$$

$$- 05\ u_{12t-1} + 0.190\ v_{1t-1}^2 + 0.040^{**}\ v_{2t-1}^2 - 0.171^*v_{12t-1}$$

$$h_{22} = 4.823e - 05 + 2.566^*\ h_{11t-1} + 0.274\ h_{22t-1} - 1.677^{**}\ h_{12t-1} + 0.270\ u_{1t-1}^2 + 0.220^{***}\ u_{2t-1}^2 + 0.488^*\ u_{12t-1}$$

$$+ 3.997^*\ v_{1t-1}^2 + 0.295\ v_{2t-1}^2 - 2.172^*\ v_{12t-1}$$

h_{11} biodiesel, h_{22} refined sunflower oil price variance. The standard errors of the estimated parameters are obtained by means of first order Taylor series expansion of the function around its mean (the so called delta method)
*** (**) [*] denotes statistical significance at the 1 (5) [10] % level
¨e¨ refers to exponential operator

Figure 1.1. Evolution of Price series
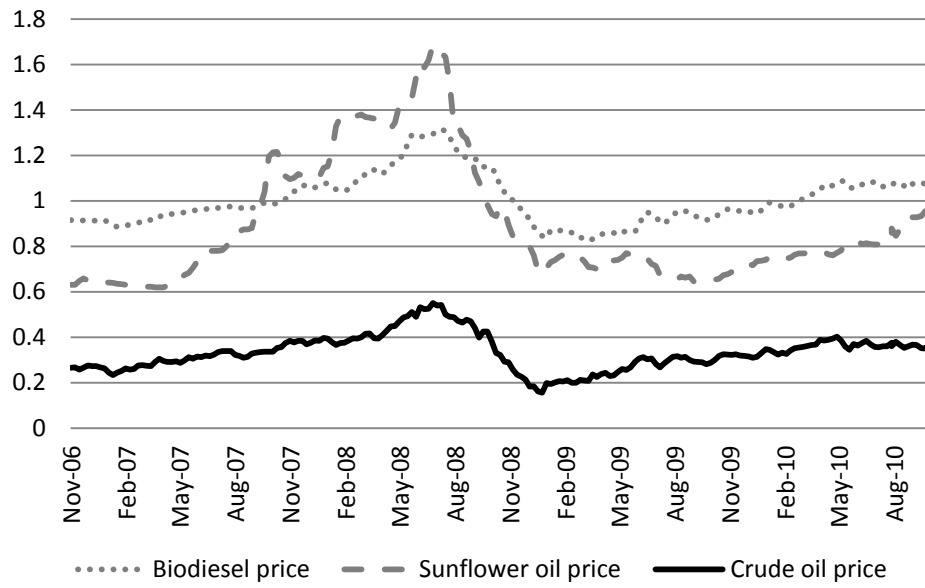
Figure 1.2. Predicted annualized volatility of blended biodiesel price

Predicted annualized volatility of blended biodiesel
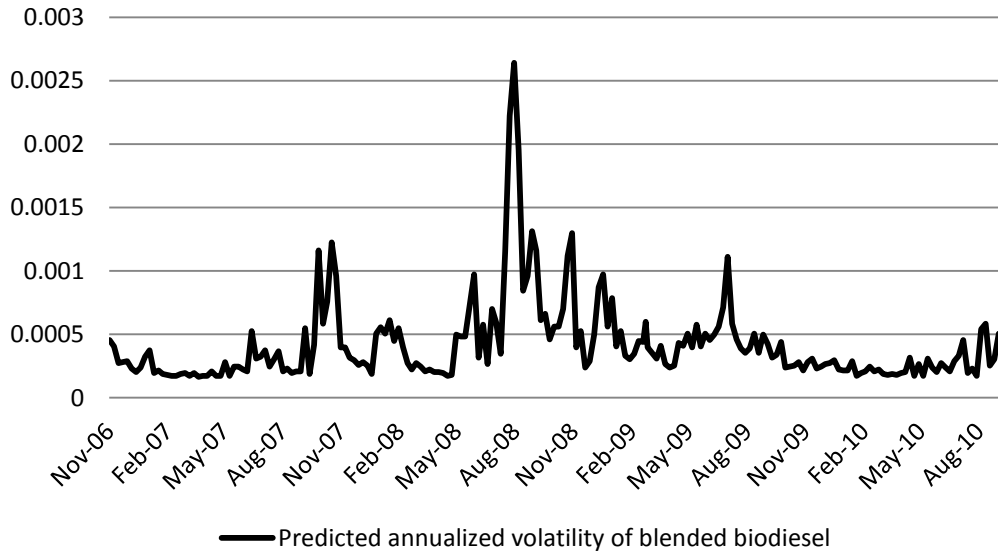
Chapter 2: Asymmetric volatility spillovers between food and energy markets in Europe: A semi-parametric approach

2.1. Introduction

Since the outbreak of the global biofuels industry in the second half of the 2000s, considerable research has been devoted to investigate biofuel markets. The expansion of biofuels has coincided with the increase in food prices. First generation biofuels are produced from agricultural commodities, implying competition with agricultural production for land use. Many studies have investigated the economic nature of this interesting time period from different perspectives such as agricultural land allocation (Banse et al, 2008; Timilsina and Beghin, 2012), or the relationship between agricultural commodity and energy prices (Zhang, 2009; Serra 2011; Trujillo et al, 2012). According to Busse et al. (2011), there has been an increasing positive correlation between agricultural commodity and energy prices, particularly during the 2006/08 period. This correlation not only increases during periods of high prices, but it keeps rising afterwards. High food price levels and volatilities are a major risk over food security and economic welfare in developing countries, where an important portion of the population spends most of household income on food (Prakash, 2011; Rapsomanikis, 2011).

While the literature on food-energy price relationships has focused on price levels (Serra and Goodwin, 2003; Serra et al., 2011b; Hassouneh et al., 2012) and found that nonlinearities usually characterize price transmission mechanisms, more recently a few studies have concentrated on modeling price volatility spillovers between different energy-food markets (Zhang et al., 2009; Serra et al., 2011a). Volatility is usually studied using time-series econometric methods that generally model current price volatility as a function of past volatility and past market shocks. Less attention has been paid to volatility studies allowing for the influence of exogenous variables in the conditional variance equation. Additionally, nonlinearities in price volatilities are usually ignored. Nonlinear patterns, including asymmetries, in the conditional covariance matrix have been

widely observed, specially in the financial economics literature (Long et al., 2011). Prakash and Gilbert (2011) note that there are many factors prone to affect price volatilities, including rising energy prices, the rapid expansion of biofuel production, inventory supplies, international trade and other macroeconomic factors like interest rates and exchange rates. Low inventories can inflate prices. A low carryover from the past will reduce the possibility of using inventories in order to meet positive demand or negative supply shocks (Gilbert and Morgan, 2010; Balcombe, 2011). Exchange rates were considered and found to have an impact on food price volatilities (Balcombe, 2011). Mitchell (2008) concluded in his paper that the major factor causing food prices to increase was the large increase in biofuel production in the United States (US) and the European Union (EU). The use of food commodities to produce first generation biofuels has implied a shock to food markets, and is thus likely to have increased price instability. Expansion of biofuels has been so quick that it has overtaken the ability of many economies to keep up with it, which has led to extreme price increases in response to unpredictable demand shifts (Wright, 2010).

The objective of this study is to investigate food-energy price relationships, allowing for both asymmetric volatility spillovers and the influence of exogenous variables in the conditional variance. We focus on the European biodiesel industry, which is the largest in the world. Rapeseed oil is the main EU's biodiesel feedstock industry, representing around 62% of total 2013 feedstock use, as forecasted by USDA-FAS (2012), which explains our decision to assess the links between biodiesel and rapeseed oil prices. The influence of exogenous variables that can exert an influence on European biodiesel industry's price instability is considered.

To address our objective, we adopt a multivariate generalized auto-regressive conditional heterscedasticity (MGARCH) model with exogenous variables, that allows for asymmetry in the variance-covariance matrix (Kroner and Ng, 1998). The contribution of this work to the literature is double. First, it focuses on the European biodiesel market. Recent literature reviews on the use of time-series methods to assess biofuel market prices (Serra and Zilberman, 2013), show that previous research has mainly concentrated on major ethanol markets: US and Brazil, while the EU has not received much research attention. Second, in comparison to the predominant literature, not only we study price level links. Instead, we adopt a MGARCH model to estimate price volatility spillovers allowing for

asymmetric effects and exogenous variables in the conditional variance. We further use a semi-parametric approach following Long et al.'s (2011) to capture the remaining information that is not reflected by the parametric estimation.

The remainder of this chapter is organized as follows. Section 2.1 presents a review of the literature assessing nonlinear price links between energy and food markets. Section 2.2 describes the biodiesel industry in the EU. Section 2.3 presents the methodological approach. Section 2.4. reports and analyzes the empirical results. Section 2.5. offers the concluding remarks.

2.1. Previous literature

Previous research has found ample evidence that biofuel and food price levels are strongly interrelated (Balcombe and Rapsomanikis, 2008; Serra et al., 2011b; Hassouneh et al, 2012). As a result, volatility spillovers should also take place. However, not until recently has this question started to be assessed. Multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models have been used to characterize not only price links but also price volatility interactions (Serra, 2011; Serra et al., 2011a; Zhang et al., 2009; Trujillo-Barrera et al., 2012).

2.1.1. Price levels studies

In the following lines, we review some of the articles that study food-energy price level links. Serra et al. (2011b) adopted a smooth transition vector error correction model to investigate the relationship among corn, ethanol, oil and gasoline prices in the US. Results show that two co-integration relationships characterize long-run price level dynamics, one representing the ethanol industry and the other the oil industry equilibrium. Results also suggest that the strong link between food and energy markets occurs mainly through the ethanol market and contributes to explain relevant corn price increases during the ethanol boom in the second half of the 2000s. Hassouneh et al. (2012) study the Spanish biodiesel price and its relationship with sunflower oil price. A vector error correction model (VECM) and local modeling techniques are fit to weekly data observed between 2006 and 2008. They find a long-run link to characterize biodiesel, sunflower oil and crude oil prices. Biodiesel is the only variable that adjusts to disequilibrium from the long-run parity. The estimation of

the model using local linear regression techniques allows refining results and shows that the speed of adjustment to this parity is faster when biodiesel is relatively cheap than relatively expensive.

Busse et al. (2012) use a Markov-switching VECM to investigate the relationship between biodiesel, diesel, rapeseed oil and soy oil price-levels in Germany. Results show that two co-integration relationships characterize long-run price dynamics, one representing the relationship between biofuels and agricultural commodities and the other the biodiesel-diesel. The relationship between biodiesel-diesel price levels is characterized by two different regimes. In the first regime, from 2005 to 2007 when the biodiesel expansion took place, biodiesel price was independent from diesel market. In the second regime, after 2007, biodiesel shows a marked response to diesel price changes, motivated by blending mandates.

2.1.2. Price volatility studies

Studies investigating the relationship between food and energy price volatility interactions are scarce and include Zhang et al. (2009), Serra et al. (2011a), Du et al. (2011), or Trujillo-Barrera et al. (2012). Trujillo-Barrera et al. (2012) study US corn, ethanol and crude oil price interactions. A MGARCH model that includes an exogenous random shock coming from the crude oil market is estimated to assess corn and ethanol price volatility. Evidence of spillovers from crude to corn and, specially, to ethanol prices is found. Spillovers between corn and ethanol are also identified, being the ones from corn to ethanol much larger.

Du et al. (2011) adopted stochastic volatility models to study the impact of crude oil on corn and wheat futures prices during the period from November 1998 to January 2009. Consistent with Zhang et al. (2009), no evidence of spillover effect before the biofuels boom is found. Nevertheless, between October 2006 and January 2009, results show strong volatility spillovers from crude oil to corn markets. Wu et al. (2011), who fit a volatility spillover model to corn spot and Crude oil futures prices using data from January 1992 to June 2009, obtain results consistent with Du et al. (2011).

2.1.3. Price volatility studies with exogenous variables

Most of the literature on price volatility has explained current volatility as a function of past volatility and past market shocks. Empirical

studies considering exogenous variables in the conditional variance-covariance model have been scarce (Balcombe, 2011; Serra and Gil, 2012b). The impact of commodity stocks on food price volatility has received considerable theoretical debate (Gustafson, 1958; Samuelson, 1971; Scheinkman and Schechtman, 1983; William and Wright, 1991; Deaton and Laroque, 1992). This debate is based on the competitive storage model that, under the assumption that economic agents are rational, finds stocks to be a major factor affecting commodity price behavior. When the current price is below the expected price, sales will be delayed and the commodity stored. On the other hand, when prices are higher than the expected price, there will be no incentive to store and stock-out will be the case. The impact of macroeconomic factors is also found to be relevant in the literature on price volatility (Roache, 2010; Balcombe, 2011). During the period 2006 to 2010, EU's blending mandates spurred an increase in domestic demand and production of biofuels, creating a demand for imports. Around a fifth of biofuel domestic use is imported from the outside the EU (USDA-FAS, 2012), which contributes to reduce internal biofuel and feedstock price pressures, thus reducing their volatility.

Balcombe (2011) adopted a random parameter model with time varying volatility that was fit to different food products including cereals, vegetable oils, dairy products, or meat products. The author allowed for exogenous variables in the conditional variance equation and found that crude oil price volatility has a positive impact on food price volatilities. Yields and stock levels were also found to have a strong impact on price volatility. Exchange rates and interest rates were also pointed to be important volatility determinants.

Serra and Gil (2012b) used a bivariate GARCH model to investigate price volatilities of corn and ethanol markets. They allowed time-varying volatilities to depend on corn stocks to disappearance ratio and interest rate volatilities. They found that both exogenous variables have a significant effect on corn price volatility and no effect on ethanol price volatility. While stocks are found to reduce price fluctuations, interest rate volatility contributes to higher corn price instability. Serra and Gil (2012b) further apply Long et al.'s (2011) approach which is essentially a nonparametric correction of the parametric MGARCH model, that uses the information still remaining in the residuals of the model. They concluded that the

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semiparametric model, which is more flexible than the parametric one, is specially suited to capture high volatility periods.

From the literature review presented above, we can conclude that asymmetries have not been explicitly modeled in the literature assessing volatility spillovers between food and biofuel prices. This paper contributes to the literature by providing empirical evidence of asymmetric volatility spillovers by means of a parametric GARCH model. Following Serra and Gil (2012b), the parametric model is then flexibilized by means of the semiparametric technique proposed by Long et al. (2011), so that information remaining in the model residuals can be used.

2.2. The biodiesel industry in the EU

The EU is considered the largest biodiesel producer in the world. In 2011, biodiesel represented 70% of total EU biofuel production, being the share of bioethanol on the order of 28%. Use and production of biofuels within the EU was pushed forward by Directive 2003/30/EC, which established that Member States should define national mandates ensuring that biofuels and renewable fuels represent a minimum proportion of the fuels market. This Directive led to introduction of tax incentives in several member states and a considerable expansion of the biodiesel industry, mainly in Germany and France (USDA-FAS, 2012). Biofuels have been promoted within the EU not only as a means of reducing greenhouse gas emissions, but also to enhance energy security by reducing dependence on fossil fuels (USDA-FAS, 2012). Several studies (Pimentel, 2003; Pimentel and Patzek, 2005; OECD, 2007) have shown that energy output from biofuels is less than the output from fossil fuels. While opinions regarding the capacity of biofuels to reduce GHG are mixed, there seems to be a general agreement of a positive impact (US-EPA, 2007; FAO, 2013; USDA-FAS, 2012). Competition of first-generation biofuels with the use of agricultural commodities to produce food, has led EU policies to encourage second-generation biofuels to join first generation biofuels in the fuels market. For this purpose, the food-based biofuels share to meet the 10% renewable energy target in the transportation sector has been limited to 5% (EC press release, 2012).

Biodiesel is currently the major biofuel used in the EU's transportation sector. The transportation sector alone consumed one third (33%) of the EU27 final energy consumption in 2009. The share of

renewable energy consumption in transport was about 3% in 2009. Biofuel promotion, however, is likely to bring this share to higher levels. Consumption of biofuels experienced a 26-fold increase in 2009 relative to 1999. Further, while EU's total fuel consumption declined between 2008 and 2009, biofuel use increased (Energy, transport and environment indicators, 2011). The EU's biofuel industry is characterized by an important unused production capacity. In 2010, biodiesel production in the EU reached 9.57 million tons, being the production capacity on the order of 22 million tons. In terms of production capacity, Germany was followed by Spain and France (EBB, 2013). The idled production capacity is partly due to investments responding to the expectations created by public promotion of biofuels. These expectations, however, were recently curbed down by both the recent economic crisis, by heavily subsidized biodiesel imports from Argentina, Indonesia, the US and other countries, as well as by increasing feedstock costs resulting from a global increase in agricultural commodity prices.

Largest EU biofuel consumers in 2011 were Germany, France, Spain, Italy and the UK. The top three producers were Germany, France and Spain, that accounted together for about 57.66% of total production. This production share decreased from a 75% in 2006 (EBB, 2013). Hence, increased production came at the hand of other Member States. Excess production capacity has dramatically lowered annual increases in this figure: while between 2006-09 the increase was of 360%, increases on the order of 2-3% were registered between 2010-11. Slowdowns in production capacity increases are expected to continue in the future (USDA-FAS, 2012).

Major biofuel feedstocks used worldwide are currently corn in the US, sugar cane in Brazil, and rapeseed oil in the EU. Rapeseed oil is the major EU biodiesel industry input and represents almost two thirds of total feedstocks. Soybean and palm oil are conversely used in limited amounts (USDA-FAS, 2012). Most soybean oil is used in Spain, France, Italy and Portugal. Recycled vegetable oils and animal fats are not used extensively; however, they provide an alternative to the use of food commodities to produce biofuels (USDA-FAS, 2012). Our article focuses on studying price links within the EU's biodiesel industry and for such purpose, it considers the biodiesel, the Brent oil and the rapeseed oil prices.

2.3. Methodology

Previous research has shown that price time series usually display time-changing and clustering volatility. The latter property implies that periods of high volatility are followed by periods of high volatility and vice versa (Myers, 1994). GARCH models, that have been devised to capture such volatility behavior, express current volatility as a function of lagged volatilities and past market shocks. Our specification also allows for exogenous variables (the exchange rate and global rapeseed oil stocks[6]) to affect price volatilities.

2.3.1. Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model (MGARCH) with exogenous effects

GARCH models are usually composed of two sub-models. The conditional mean that captures prices in levels and the conditional volatility that represents price volatility patterns. The conditional mean and variance models are estimated separately using standard procedures.[7] The conditional mean is specified as a VECM, which characterizes both short-run and long-run price dynamics of nonstationary and cointegrated data (equation 1). The conditional variance model follows the specification of Baba-Engle-Kraft-Kroner (BEKK) model defined in Engle and Kroner (1995), but allows for asymmetry and exogenous influences as presented in equation (2). While the multivariate BEKK-GARCH model is an improvement over other more restrictive specifications, it is unable to capture asymmetric volatility patterns. We adopt the Kroner and Ng (1998) asymmetric specification of the multivariate BEKK-GARCH.

$$\Delta P_t = \alpha_p \varepsilon_{t-1} + \sum_{i=1}^{l} \beta_i \Delta P_{t-i} + u_{t-1} \tag{1}$$

$$H_t = CC' + A' u_{t-1} u'_{t-1} A + B' H_{t-1} B + D' v_{t-1} v'_{t-1} D \tag{2}$$

where Δ represents the first differences operator, P_t and P_{t-i} are, respectively, n-dimensional vectors of the current and lagged prices. The term ε_{t-1} is the lagged residual from the long-run (co-integration)

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[6] The influence of other possible exogenous variables was considered, but not found to be statistically significant.
[7] Joint estimation was attempted, but did not converge.

relationship, and α_p is an *n*-dimensional vector containing parameters that measure the speed at which a variable adjusts to disequilibrium from the long-run equilibrium relationship. Matrix β_i represents the short-run price dynamics. Vector u_t contains *n* white noise residuals that may be correlated with each other. Model (1) is estimated by seemingly unrelated regressions (SUR) techniques.

A, B, C and D are (2x2) parameter matrices that capture the volatility process. Matrix A represents the ARCH effect, i.e., the impact of market innovations on the volatility process. Matrix B contains the GARCH effect, i.e., the impact past volatility on current volatility. The C matrix is a 2x2 lower triangular matrix containing the exogenous variables in the model. It is specified following Moschini an Myers (2002) as: $C_{ij} = x_t \delta_{ij}$, being x_t a vector of exogenous variables in the variance equations and δ_{ij} a vector of parameters. The specification of C does not restrict the sign of the influence of the exogenous variables on price volatility. Asymmetries are captured by adding the term $D' v_{t-1} v'_{t-1} D$ to the conventional BEKK model where $v_{t-1} = u_{t-1} \circ I_{u<0}(u_{t-1})$, I is the indicator function and o is the hadamard product of the vectors. We assume normally distributed statistical innovations which leads to the following log likelihood function:

$$l_t = -\left(\frac{1}{2}\right) \sum_{t=t+1}^{t} \log |H_t| - \left(\frac{1}{2}\right) \sum_{t=t+1}^{t} e'_t H_t^{-1} e_t \qquad (3)$$

Multivariate parametric GARCH models have several limitations, among them the assumption of normally distributed errors. Another limitation is the rather common assumption of parameter constancy, which restricts the ability to capture changing price behavior. Longin and Solnik (2001) and Richardson and Smith (1993), among others, have found ample evidence against both normality and parameter constancy.

2.3.2. The semi-parametric model

To overcome the above mentioned restrictions, flexible parametric specifications have been proposed (Capiello et al., 2003; Silvennoinen and Terasvirta, 2005). Asymmetric volatility models are an example of such attempt to move towards more flexible parametric specifications. While our parametric model partially overcomes the assumption of parameter constancy by allowing for a different effect of negative and positive past errors on current volatility, this flexibility is limited. Nonparametric and

semi-parametric specifications usually offer increased flexibility. To benefit from this increased flexibility, we apply the nonparametric correction to the parametric MGARCH as proposed by Long et al. (2011).

Assume that the conditional mean model vector of errors $u_t = (u_{1t}, u_{2t})'$ follows the stochastic process $u_t|\mathcal{F}_{t-1} \sim P(\mu_t, H_t; \theta)$, where $\mathcal{F}_{t-1}$ is the information set at time $t-1$, $E(u_t|\mathcal{F}_{t-1}) = \mu_t$, $E(u_t u_t'|\mathcal{F}_{t-1}) = H_t$, P is the joint cumulative distribution function of u_t and θ are the distribution parameters. Vector e_t is the standardized u_t vector: $e_t = H_t^{-1/2} u_t$, $E(e_t|\mathcal{F}_{t-1}) = 0$, $E(e_t e_t'|\mathcal{F}_{t-1}) = I_k$, being $H_t^{1/2}$ the symmetric square root of H_t. No distributional assumption on e_t is required to obtain the semi-parametric estimator. Let $H_{p,t}(\theta) \in \mathcal{F}_{t-1}$ be the parametric estimation of the variance-covariance matrix. The semiparametric estimator of this matrix can be expressed as follows:

$$H_t = H_{p,t}(\theta)^{1/2} \, E[e_t(\theta)e_t(\theta)'|\mathcal{F}_{t-1}] H_{p,t}(\theta)^{1/2} \tag{4}$$

where $H_{p,t}(\theta)^{1/2}$ is the symmetric square root of $H_{p,t}(\theta)$, and $e_t(\theta) = H_{p,t}(\theta)^{-1/2} u_t$ the vector of the standardized residuals from the parametric model. $E[e_t(\theta)e_t(\theta)'|\mathcal{F}_{t-1}]$ is the nonparametric component of H_t. This component is defined by assuming that the conditional expectation of $e_t e_t'$ depends on the current information set $\mathcal{F}_{t-1}$ only through a q x 1 vector $x_t = (x_{t1}, \ldots, x_{qt})'$ (see equation 5). By substituting (5) into (4), the semiparametric estimate of H_t is obtained (equation 6). $G_{np}(x_t)$ is derived through the Nadaraya-Watson non-parametric estimator as presented in equation (7),

$$E[e_t e_t'|\mathcal{F}_{t-1}] = G_{np}(x_t) \tag{5}$$

$$H_t = H_{p,t}(\theta)^{1/2} \, G_{np}(x_t) \, H_{p,t}(\theta)^{1/2} \tag{6}$$

$$\widehat{G}_{np,t}(x) = \frac{\sum_{s=1}^{T} \hat{e}_t \hat{e}_t' K_h(x_s - x)}{\sum_{s=1}^{T} K_h(x_s - x)} \tag{7}$$

$$\widehat{H}_{sp,t} = \widehat{H}_{p,t}^{1/2} \widehat{G}_{np} \, \widehat{H}_{p,t}^{1/2} \tag{8}$$

where $K_h(x_s - x) = \prod_{l=1}^{q} h_l^{-1} k((x_{ls} - x_l)/h_l)$ is a multiplicative kernel, k is a univariate Gaussian kernel function: $k(u) = \exp(-u^2/2)/\sqrt{2\pi}$, and $h = (h_1, \ldots, h_q)$ is a vector of bandwidth parameters defined as

$h_i = m_j \widehat{\sigma}_i T^{-1/6}$, being T the number of observations, $\widehat{\sigma}_i$ the sample standard deviation and m_j a parameter selected through a grid search. The grid search minimizes the difference between the true conditional covariance matrix and its estimates. Since the true conditional covariance matrix is not known, the squared u_t vector is used as an approximation (Zangari, 1997; Awartani and Corradi, 2005; Pelletier, 2006; Long et al, 2011). The semi-parametric estimator is presented in equation (8).

2.4. Empirical Results

The empirical application aims at assessing the links between weekly pure biodiesel price (P_{1t}), rapeseed oil price (P_{2t}) both expressed in US dollars per metric tons, and the Brent spot price (P_{3t}) expressed in dollars per barrel. The study period is between 06/11/2008 to 14/06/2012, yielding a total of 189 observations. Biodiesel and rapeseed oil prices were obtained from Mer-7 (http://www.mer-7.com) and are based on indications provided by market players including traded prices, firm bids and offers. Brent spot prices were taken from the US Energy Information Administration (2010) dataset. Two variables were considered as exogenous in the volatility model[8]: the euro-dollar exchange rate (Z_1) that was obtained from Mer-7; and international rapeseed oil stocks (Z_2) that were obtained from the Foreign Agricultural Service of the U.S Department of Agriculture on a monthly basis, and converted to weekly frequency through cubic spline methods. The period of analysis is of interest, as it includes the food price spike in 2010/2011 and is likely to reflect the impacts of the EU biofuels Directive (2003/30/EC) and mandatory goals for increased use of biodiesel (Directive 2009/28/EC). Figure 1 shows the evolution of the three price series, as well as rapeseed oil inventories and the exchange rate over time. We used RATS 8.0 to carry out our analysis.

Logarithmic transformations of the prices are used in the empirical analysis[9]. A preliminary analysis of the prices is conducted to assess their time-series properties. Standard augmented Dickey and Fuller (1979),

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[8] Other exogenous variables such as crude oil prices were considered, but found to be non-significant. The Exchange rate and the rapeseed oil inventories variables are used in first differences in the conditional variance model.

[9] Logarithmic transformations allow obtaining well behaved error terms (Bierlen et al., 1998) and facilitate the interpretation of research results. By using logged prices, the parameters of the co-integrating vectors represent elasticities and the short-run dynamic parameters represent proportionate changes.

Kwiatkowski et al., (1992) and Perron (1997) tests confirm that all three series have a unit root, descriptive statistics and unit root results are presented in table 2.1., long-run links between the three prices are assessed using the co-integration tests proposed by Johansen (1988). Test results provide evidence that the prices considered are co-integrated with a co-integration rank r=1, i.e., there is a single long-run relationship characterizing price behavior as shown in table 2.2.[10] We follow previous research that has considered crude oil as an exogenous influence within the food-energy price system (see, for example, Amano and Norden, 1998; Asche et al., 2003; Trujillo- Barrera et al., 2012). This assumption is reasonable given that the European biodiesel industry is very small compared with the Brent oil market. A chi square test for the null of Rapeseed oil price weak exogeneity for long-run parameters, against the alternative hypothesis of being endogenous, leads to the acceptance of the null (table 2.2). This result is compatible with the conditional mean model results.

The cointegration relationship presented in table 2.2 shows that the increase in rapeseed oil and Brent spot prices has a positive impact on pure biodiesel price. The positive relationship between rapeseed oil and biodiesel prices is expected since rapeseed represents the highest biodiesel production cost (IISD, 2013). Brent positive influence on biodiesel may point towards a substitute relationship between the two fuels. Our results are compatible with Balcombe and Rapsomanikis (2008), whose results suggest a price transmission hierarchy from crude oil to sugar and finally to ethanol for the Brazilian industry. Results from the maximum likelihood estimation of the conditional variance-covariance model are presented in table 2.3. MGARCH model parameter estimates can't be directly interpreted, but we draw inferences from the nonlinear parameter functions in the conditional variance equations (table 2.4). Conditional mean model results are discussed in the following lines. While cointegration tests confirm the existence of a long-run parity between the prices considered, only biodiesel price dynamics react to disequilibriums and move to reequilibrate the market. In contrast, EU rapeseed oil prices do not respond to deviations from the biodiesel market equilibrium parity. Short-run price dynamics

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[10] Engle and Granger (1987) tests for co-integration, taking pure biodiesel as the endogenous variable in the price system, also support the presence of a long-run relationship.

confirm rapeseed oil price exogeneity within the price system. While crude oil prices are found to influence biodiesel prices through the long-run price dynamics, they do not seem to influence these prices through short-run dynamics Our results are compatible with Serra (2011), who found that short-run dynamics of sugar prices are not affected by ethanol and that sugar prices do not respond to deviations from the ethanol market equilibrium parity.

The VECM residuals were tested for multivariate autocorrelation following Hosking's (1981) variant of the multivariate Q statistic and results led to accept the null of no autocorrelation. Also, the multivariate ARCH LM test was conducted and evidence of ARCH effects was found, thus supporting the use of a MGARCH model. The test for the null hypothesis that parameters in matrices A, B and D in the MGARCH specification are equal to zero is rejected, showing evidence of time varying volatility. Additionally, an LR test for the null that parameters in D matrix are zero is conducted to test for the relevance of the asymmetric effects, being the null hypothesis of symmetry rejected. As noted, for an easier interpretation of MGARCH model parameter estimates, we rely on the nonlinear parameter functions of the conditional variance equations presented in table 2.4. Biodiesel price volatility is found to be positively affected by its own past volatility and past shocks to the pure biodiesel market. Past shocks to the rapeseed oil market are found to have an asymmetric effect on biodiesel price volatility: negative residuals increase variance more than positive ones, which indicates that negative news have a greater impact on pure biodiesel price instability than positive news. Results also show that while biofuels cannot influence rapeseed price levels, they can bring instability into this market: past volatility in the biodiesel market tends to increase current rapeseed price volatility.

The marginal impacts of euro-dollar exchange rate variations (Z_1) and the international rapeseed oil inventories (Z_2) are computed at the data means and presented in table 2.5. Exchange rate variations reduce biodiesel and rapeseed oil price volatilities. Blending mandates between 2006 and 2007 spurred an increase in domestic demand and production of biofuels and created a demand for imports (EU biofuels annual, 2012). Our results suggest that the appreciation of the euro against the dollar facilitates imports and reduces price volatility. Our results are compatible with Balcombe (2011) who found exchange rates to be a relevant variable in

explaining price volatility. International rapeseed oil inventories have an expected negative and significant effect on h_{11} and h_{22}, which is in line with Balcombe (2011), Stigler and Prakash (2011), Serra and Gil (2012b) and compatible with the theory that stock building usually reduces price volatilities and the dependence of prices on market shocks (Williams and Wright, 1991; Wright, 2011).

As noted above, the non-parametric correction of the conditional variance-covariance equation proposed by Long et al. (2011) allows capturing the information that still remains in the residuals of the model. Parametric and semi-parametric predicted volatilities are shown in figure 2. While predictions during low-volatility periods are quite similar, the semiparametric model deviates from the parametric one for periods of specially relevant volatility. This suggests that the semi-parametric approach may have greater flexibility in capturing erratic behavior. Volatility is specially high at the beginning and middle of our sample period. Blending mandate objectives defined by the EU and the impacts of food crises in the second half of the 2000s may explain increased price instability. Long et al.'s (2011) method further allows correcting the nonlinear parameter functions in the conditional variance equations for each observation in sample. The benefits of adopting Long et al.'s (2011) methodology are confirmed by the variation in the localized nonlinear parameters in the biodiesel and rapeseed volatility equations (figures 2.3 and 2.4). The parametric marginal effects of the exogenous variables can also be corrected under the Long et al.'s (2011) approach to get better inferences of the estimates. In figure 2.5, we compare the predicted parametric and semi-parametric marginal effects of rapeseed oil stocks and exchange rate variations on pure biodiesel price volatility. We find the impacts of these exogenous variables to change notably over time, and specifically to grow during high volatility periods. It is thus precisely when volatility is the highest that a policy intervention aiming at calming down the markets by means of managing public stocks or seeking currency appreciation will be more effective.

2.5. Conclusions

This study analyzes price behavior in the EU biodiesel market. Special attention is paid to modeling price volatility interactions. Since price volatility has been found to have important negative economic

consequences, it is particularly interesting to identify those variables that can contribute to calm down the markets. This is why we consider the influence of exogenous variables in the conditional variance-covariance model. Our analysis is based on a parametric MGARCH model and results from this parametric exercise are refined using the semi-parametric approach by Long et al. (2011). Our empirical application focuses on the biodiesel, rapeseed oil and crude oil prices. International rapeseed oil stocks and exchange rates are considered as exogenous variables in the conditional volatility equation. Results suggest that the three prices have a long-run equilibrium relationship that is maintained by the pure biodiesel price. Crude oil and rapeseed oil prices are found to be exogenous. Pure biodiesel price volatility is affected by its own past volatility and past biodiesel and rapeseed market shocks. The latter have a nonlinear influence, with negative market news having a greater impact than positive ones. While biodiesel prices cannot affect rapeseed price levels, they can cause instability in this market by means of increasing rapeseed price volatility. Stock building and the euro-dollar exchange rate can reduce biodiesel and rapeseed oil price volatilities.

The importance of using the semi-parametric approach by Long et al. (2011) is confirmed through the identified heterogeneity in the localized nonlinear parameters in the conditional variance equations. Predicted variances from the parametric and semi-parametric models suggest that the semi-parametric estimator may better capture price fluctuations during convulsive times. We further find evidence of the capacity of stocks and exchange rates to reduce price volatility. Our results have important policy implications. They suggest that biodiesel markets in Europe have been unable to generate long-lasting impacts on agricultural feedstock prices. Hence, the EU biofuel industry has been incapable of causing long-run increases in food prices. Conversely, biodiesel prices strongly depend on rapeseed prices. Biodiesel price volatility can be managed by increasing rapeseed oil stock levels. By altering biodiesel foreign trade, the euro-dollar exchange rates are also found to exert significant influence on price fluctuations.

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Table 2.1. Descriptive statistics for weekly prices

	Pure biodiesel price	**Rapeseed oil price**	**Brent price**
Mean	7.044	6.975	4.412
Standard deviation	0.204	0.216	0.317
Maximum	7.365	7.293	4.841
Minimum	6.633	6.536	3.566
Skewness	-0.050	-0.040	-0.651**
Kurtosis	-1.364**	-1.465**	-0.342
Jarque-Bera	14.737**	16.966**	14.281**
ADF	-1.050	-0.938	-1.464
Perron	-4.641	-5.239	-3.787
KPSS	2.881**	3.045**	3.465**

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level
Note: the deterministic component used in conducting unit root tests is a constant

Table 2.2. Brent oil – Biodiesel – rapeseed oil conditional mean model

Co-integration relationship

$$P_{1t} = 0.930^{**} + 0.804^{**}P_{2t} + 0.113^{*}P_{3t}$$

$$(0.400) \qquad (0.090) \qquad (0.062)$$

Conditional mean equations

$$\begin{pmatrix} \Delta P_{1t} \\ \Delta P_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \varepsilon_{t-1} + \begin{pmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \end{pmatrix} \begin{pmatrix} \Delta P_{1t-1} \\ \Delta P_{2t-1} \\ \Delta P_{3t-1} \end{pmatrix}$$

	$i=1$	$i=2$	$i=3$
α_i	-0.206***(-0.061)	-0.070(0.062)	
α_{1i}	-0.313***(0.105)	0.254**(0.103)	0.008(0.065)
α_{2i}	0.016(0.107)	-0.028(0.105)	-0.016(0.066)

Chi square test for the null of weak exogeneity of rapeseed oil price within Johansen's framework= 0.599

Hosking multivariate Q(12) Statistic = 46.095

Multivariate ARCH LM test = 24.70**

AIC = -2706.139

SBC = -2660.903

P_{1t} biodiesel, P_{2t} rapeseed oil, P_{3t} Brent oil
*** (**) [*] denotes statistical significance at the 1 (5) [10] % level
Standard errors in parenthesis

Table 2.3. Brent oil – biodiesel – rapesed oil MGARCH model: conditional variance equations

$$
\begin{aligned}
\Omega = \Bigg[&\begin{pmatrix} c_{111} & 0 \\ c_{211} & c_{221} \end{pmatrix} + \begin{pmatrix} c_{112}z_1 & 0 \\ c_{212}z_1 & c_{222}z_1 \end{pmatrix} \\
&+ \begin{pmatrix} c_{113}z_2 & 0 \\ c_{213}z_2 & c_{223}z_2 \end{pmatrix} \Bigg] \Bigg[\begin{pmatrix} c_{111} & c_{211} \\ 0 & c_{221} \end{pmatrix} + \begin{pmatrix} c_{112}z_1 & c_{212}z_1 \\ 0 & c_{222}z_1 \end{pmatrix} \\
&+ \begin{pmatrix} c_{113}z_2 & c_{213}z_2 \\ 0 & c_{223}z_2 \end{pmatrix} \Bigg] \\
&+ \begin{pmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{pmatrix} \begin{pmatrix} u_{1t-1}^2 \\ u_{2t-1}^2 \end{pmatrix} \begin{pmatrix} u_{1t-1}^2 & u_{2t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \\
&+ \begin{pmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{pmatrix} \begin{pmatrix} h_{11t-1} & h_{12t-1} \\ h_{21t-1} & h_{22t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \\
&+ \begin{pmatrix} d_{11} & d_{21} \\ d_{12} & d_{22} \end{pmatrix} \begin{pmatrix} v_{1t-1}^2 \\ v_{2t-1}^2 \end{pmatrix} \begin{pmatrix} v_{1t-1}^2 & v_{2t-1}^2 \end{pmatrix} \begin{pmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{pmatrix}
\end{aligned}
$$

	$i=1$	$i=2$
c1i1	0.010***(0.002)	
c2i1	-0.004**(0.002)	-0.001(0.004)
c1i2	-0.051(0.036)	
c2i2	-0.072(0.068)	-0.185**(0.071)
c1i3	0.157**(0.077)	
c2i3	0.347**(0.153)	-0.109 (0.149)
a1i	0.504 (0.127)	-0.102(0.127)
a2i	-0.403***(0.109)	0.360**(0.165)
b1i	0.709***(0.153)	0.657***(0.110)
b2i	0.183(0.153)	0.305(0.221)
d1i	-0.150(0.180)	0.195(0.200)
d2i	0.368**(0.129)	0.084(0.217)

LR test for the null that parameters in matrices A, B and D are zero = 15731.448***

LR test for the null that parameters in matrix D is zero = 18.682***

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level
Standard errors in parenthesis

Table 2.4. Brent oil – biodiesel – rapesed oil MGARCH model: conditional variance equations

$h_{11} = 1.27e - 03^{***} + 0.168\,z_1^2 + 0.017\,z_2^2 - 0.551e - 03\,z_1 - 0.490\,e - 03\,z_2 - 0.105^{***}z_1z_2 + 0.500^{**}\,h_{11t-1}$
$\qquad + 0.029\,h_{22t-1} + 0.240\,h_{12t-1} + 0.197^*\,u_{1t-1}^2 + 0.110\,u_{2t-1}^2 - 0.295\,u_{1t-1}u_{2t-1} + 0.045\,v_{1t-1}^2$
$\qquad + 0.271^{**}\,v_{2t-1}^2 - 0.110\,v_{1t-1}v_{2t-1}$

$h_{22} = 0.000 + 0.133\,z_1^2 + 0.037^*\,z_2^2 - 1.209e - 03\,z_1 - 0.641e - 03\,z_2 + 0.140^*z_1z_2 + 0.483^{**}\,h_{11t-1}$
$\qquad + 0.051\,h_{22t-1} + 0.315\,h_{12t-1} + 0.002\,u_{1t-1}^2 + 0.103\,u_{2t-1}^2 - 0.030\,u_{1t-1}u_{2t-1} + 0.075\,v_{1t-1}^2$
$\qquad + 0.013\,v_{2t-1}^2 + 0.032\,v_{1t-1}v_{2t-1}$

h_{11} pure biodiesel variance, h_{22} rapeseed oil variance

z_1 exchange rate variations, z_2 rapeseed oil feedstocks variations

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level

¨e¨ refers to exponential operator

Table 2.5. Marginal effects of the exogenous variables on price volatility at data means

$\partial h_{11}/\partial z_1$	0.336 Z_1	-0.551e-03	0.105*** Z_2	= -1.186e-03
$\partial h_{11}/\partial z_2$	0.034 Z_2	-0.490e-03	0.105*** Z_1	= -2.816e-04
$\partial h_{22}/\partial z_1$	0.133 Z_1	1.209e-03	0.140* Z_2	= -4.550e-04
$\partial h_{22}/\partial z_2$	0.074 Z_2	-0.641e-03	0.140* Z_1	= -2.415e-04

h_{11} pure biodiesel variance, h_{22} rapeseed oil variance

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level

¨e¨ refers to exponential operator

Figure 2.1. Time series data

Pure Biodiesel Price USD/MT

BRENT Price USD/Barrel

Rapeseed oil Price USD/MT
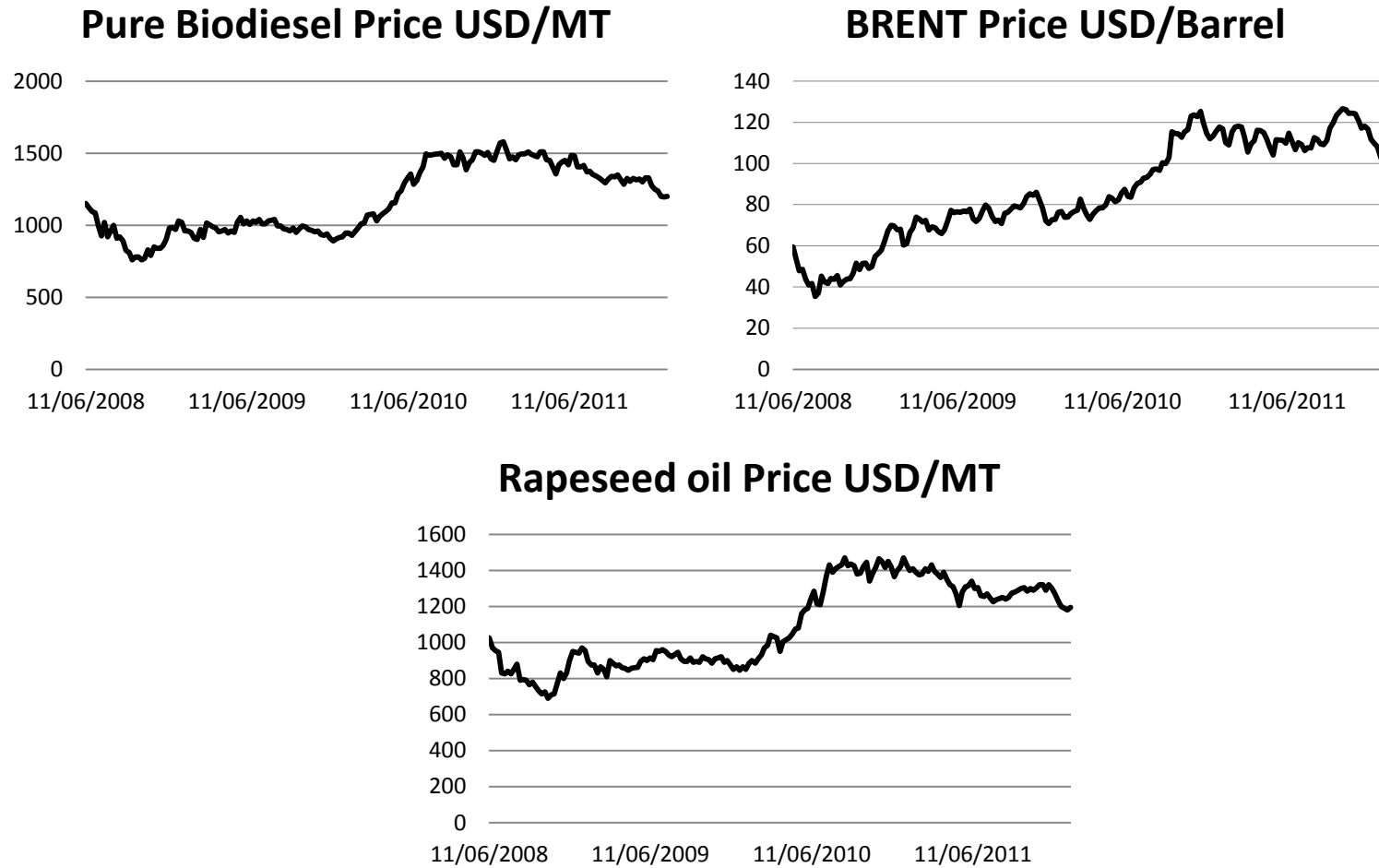
Figure 2.1. (Continued) Time series data

Rapeseed oil Inventories MT

Exchange rate
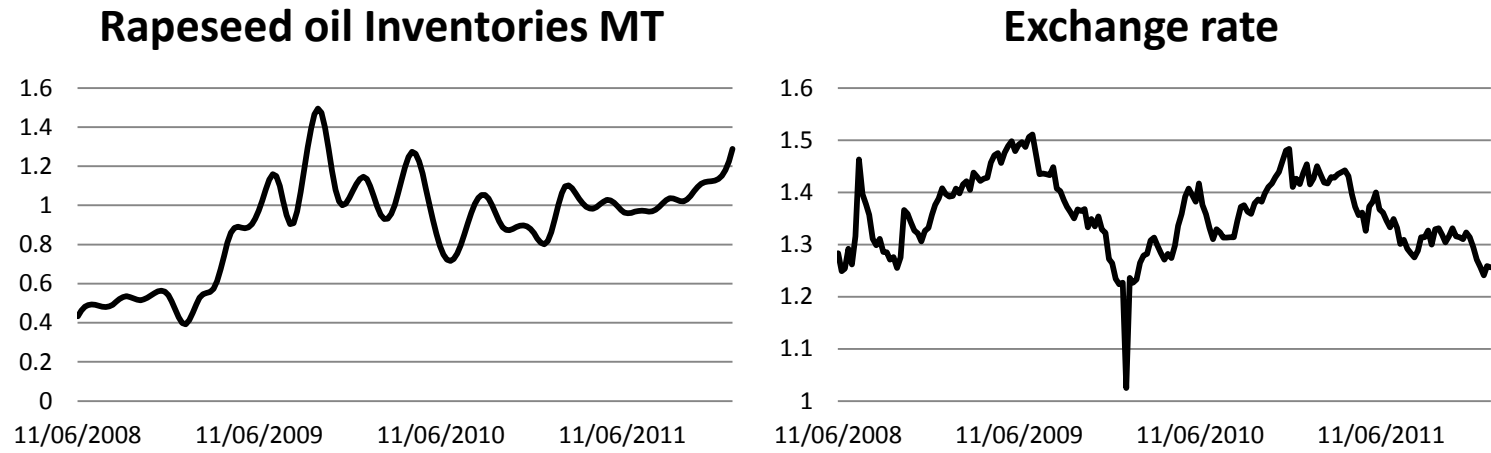
Figure 2.2. Predicted volatilities for pure biodiesel (h_{11}) and rapeseed oil (h_{22}) under parametric and semi-parametric approaches
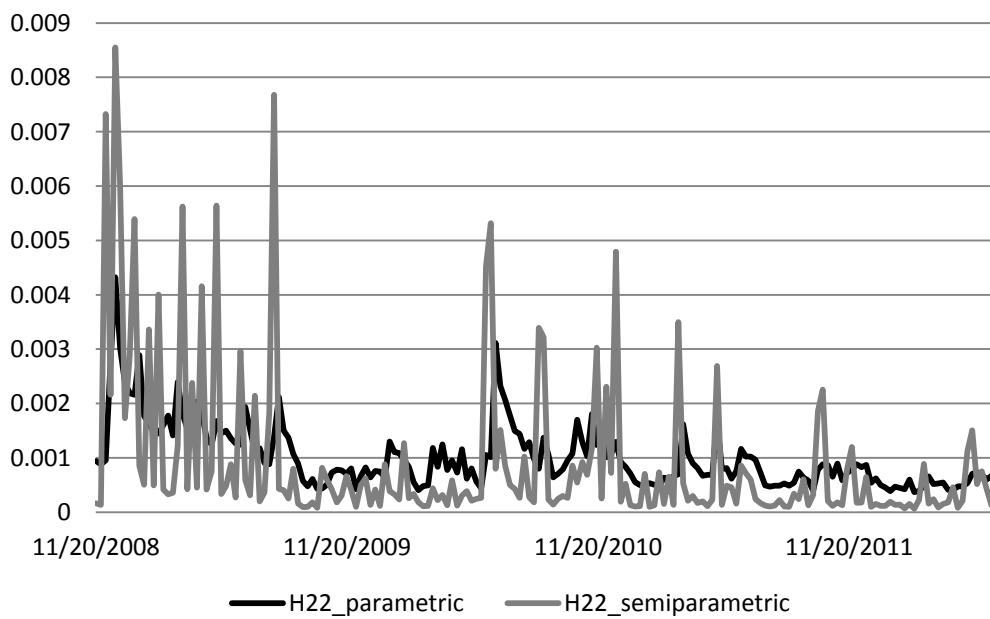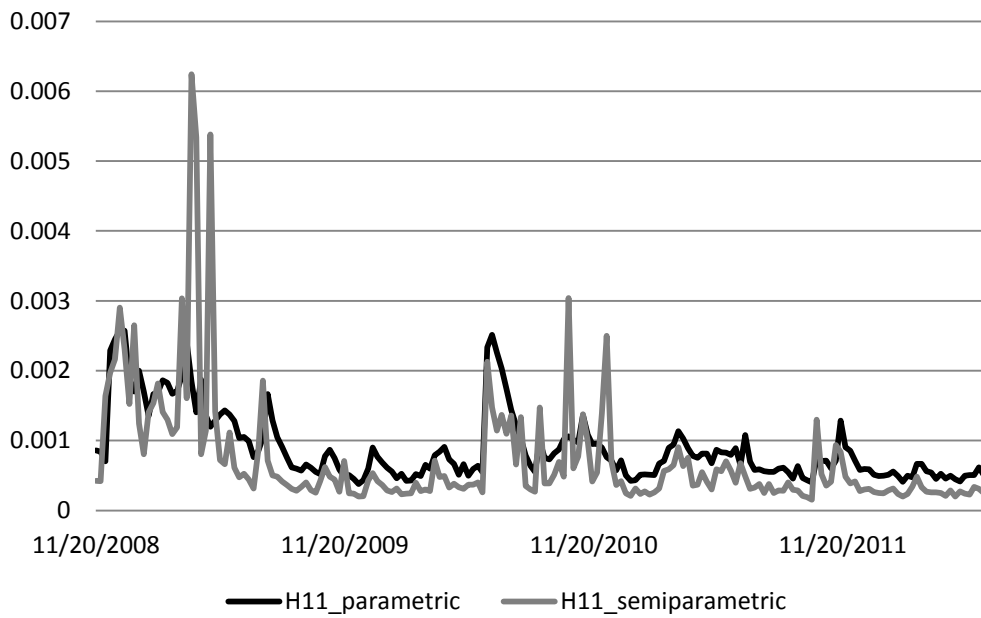
Figure 2.3. Distribution of the localized parameters of the pure biodiesel conditional variance equation
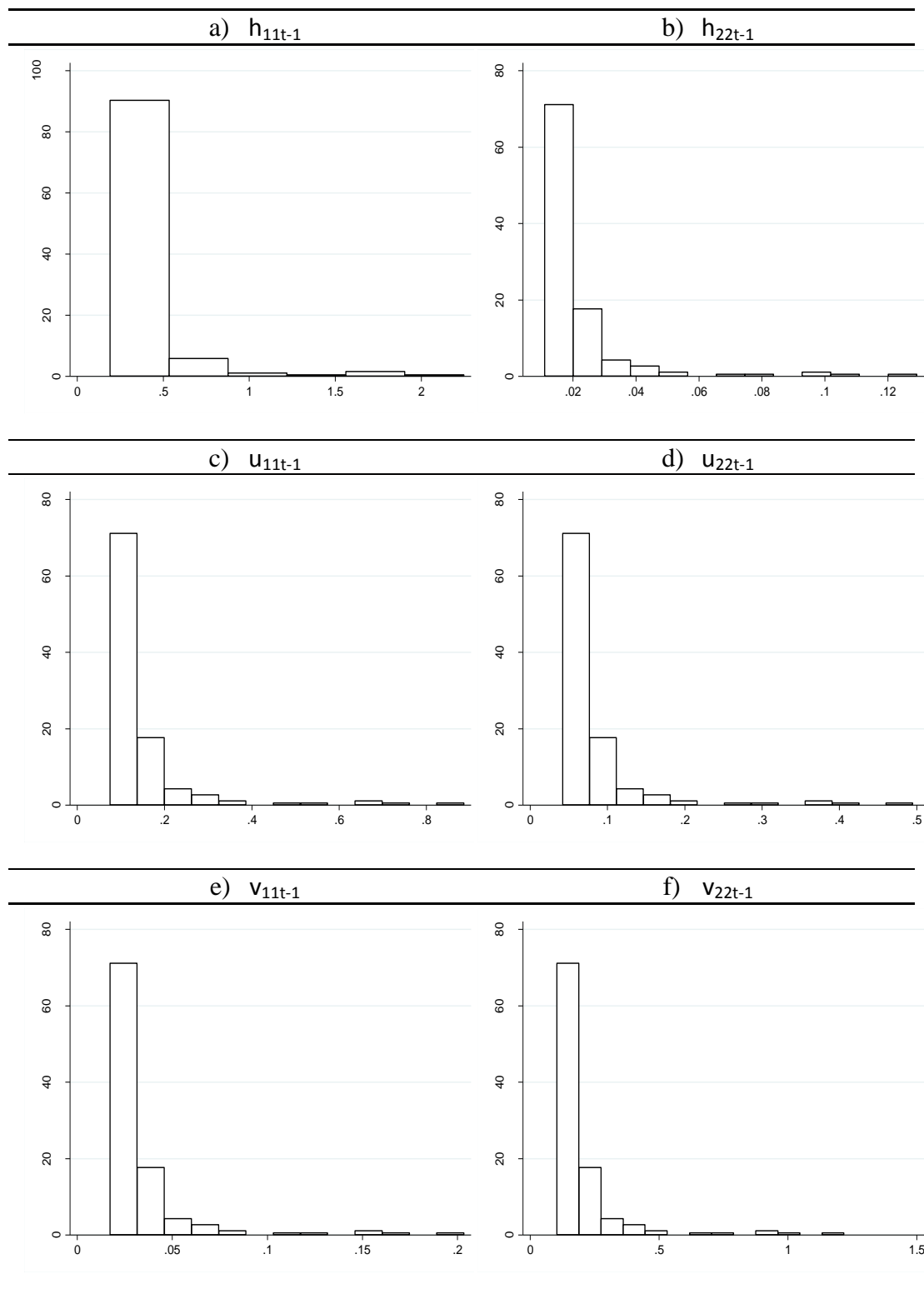
Figure 2.4. Distribution of the localized parameters of the rapeseed oil conditional variance equation

a) h_{11t-1}

b) h_{22t-1}

c) u_{11t-1}

d) u_{22t-1}

e) v_{11t-1}

f) v_{22t-1}
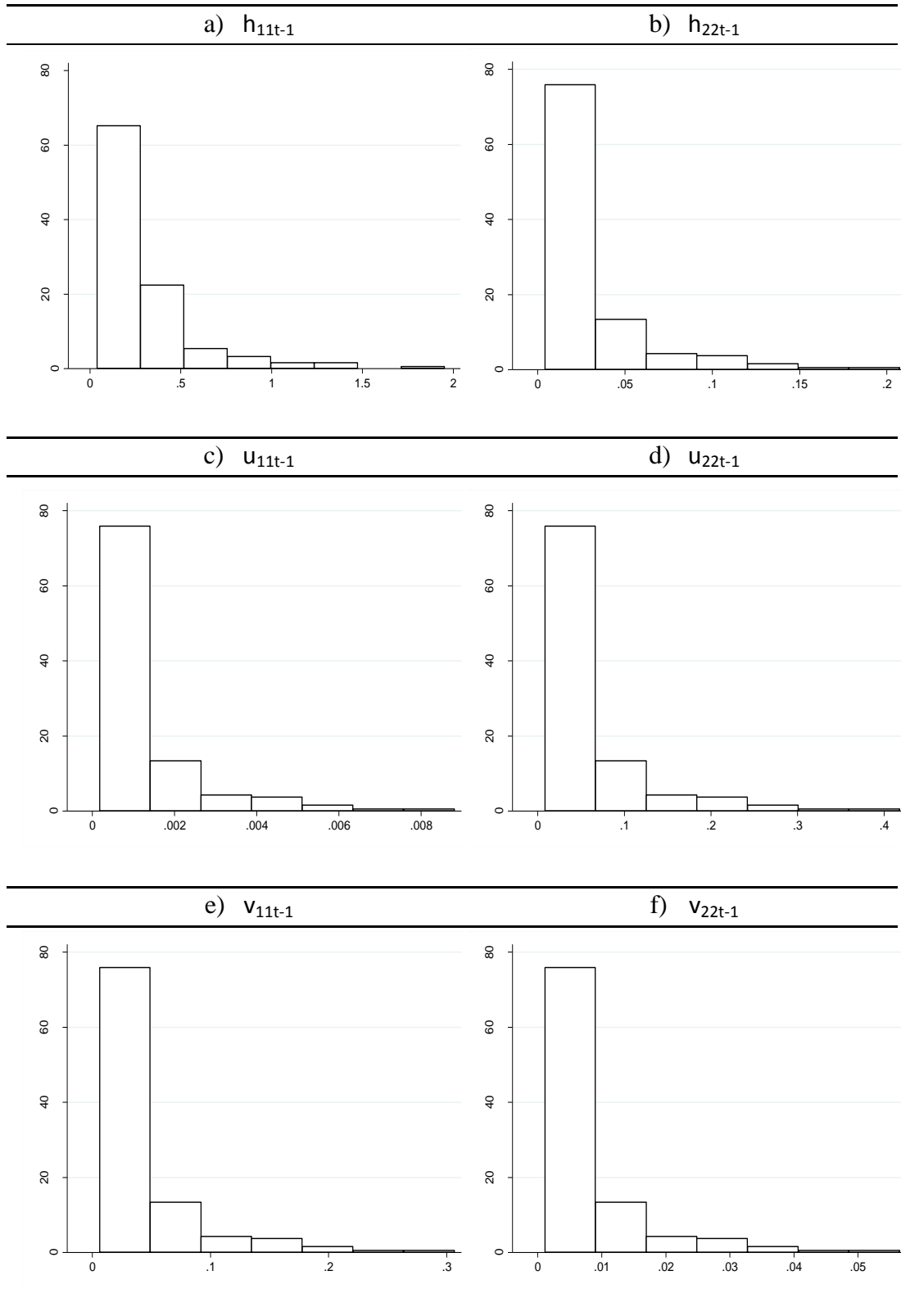
Figure 2.5. Parametric and semi-parametric marginal effects of exchange rate variations (Z_1) and Rapeseed oil stocks variations (Z_2) on Biodiesel volatility
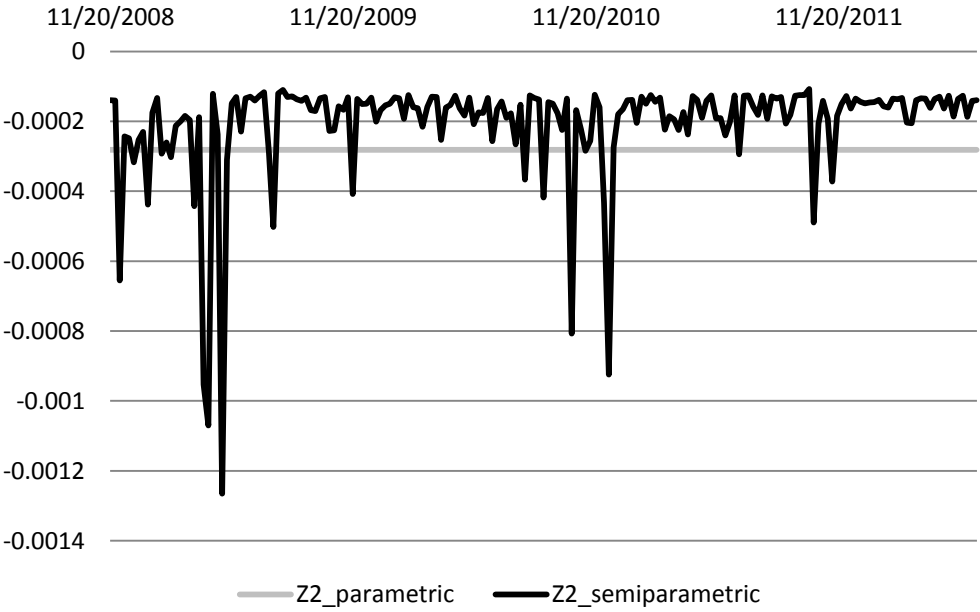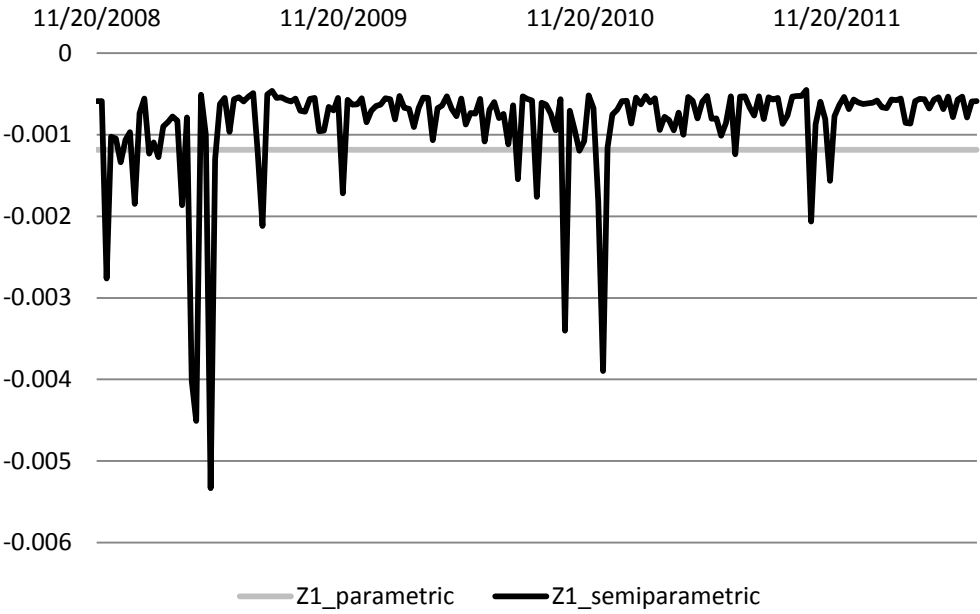
Chapter 3: The impact of news on Corn and Soybeans futures markets

3.1. Introduction

Since the global food price increase in the second half of the 2000s, substantial research has been devoted to investigate food price levels and volatility. Several factors have been identified that explain recent food price patterns, including rising energy prices, the rapid expansion of biofuel production, inventory supplies, international trade and other macroeconomic factors like interest rates and exchange rates (Prakash and Gilbert, 2011). Futures markets have two main roles: price discovery and price risk management. This article focuses on the first, for which information on market supply and demand is vital. Since market fundamentals are crucial in explaining price movements, published forecasts on production and consumption are expected to have an effect on market prices. The value and impact of released (public and private) information on commodity prices (futures and spot) has recently received considerable attention. A body of literature has been developed to address this matter (Taylor, 2012).

One of the major sources of information used by economic agents participating in the United States (US) agricultural commodity futures markets are the United States Department of Agriculture (USDA) crop production reports (Makenzi and Singh, 2011). According to the Efficient Market Hypothesis (EMH), as new fundamental information becomes available, futures markets should immediately react to reflect the change in rational traders' price expectations. Several research results confirm this hypothesis for agricultural commodity markets. Adjemian (2012), Lehecka (2013) and Makenzi (2008) have proved the effect of information on grain markets like corn, soybean and wheat. The impact of information on livestock prices has also been assessed and demonstrated by Isengildina-Massa et al. (2006), Mckenzie and Thomsen (2001), Schaefer et al. (2004). The cotton market was studied by Adjemian (2012) and the lumber market by Rucker (2005). Although most of the literature on the effect of

information on food price behavior has focused on price levels (Mckenzie and Thomsen, 2001; Rucker et al., 2005; Lehecka, 2013), more recently generalized autoregressive conditional heteroskedasticity (GARCH) models have started to be used to capture volatility responses (Isengildina-Massa et al., 2006; Karali, 2012; Karali and Park, 2010).

Our analysis studies corn and soybean futures price responses to USDA production forecasts for these two crops. More specifically, we assess the market response to production forecasts released on August, September, October, and November.[11] The literature has proposed several methods to convert information released into a quantitative variable that can be used in numerical models. These methods range from the use of dummy to continuous variables (Andersen et al., 2003; Steiner et al., 2009; Hassouneh and Serra, 2010; Isengildina-Massa et al., 2006; Karali, 2012). Compared to dummy variables, continuous variables have a richer nature as they allow capturing not only whether information is available or not, but also the intensity of the information. Following Andersen et al. (2003), in this article a "news surprises" variable is defined as the difference between private market's production expectations and USDA production forecasts. This implies that the market impact of USDA reports is measured by considering the response to how well the market anticipates the public forecasts. If private agents expectations agree with USDA forecasts, then, under EMH, prices will not change. However, if market expectations diverge from USDA forecasts, market prices will respond to the degree of the surprise.

While studies assessing the impacts of news on price volatility are scarce, those that focus on news surprises effects have mainly restricted their attention to the conditional variance only (Adjemian, 2012; Isengildina-Massa et al., 2006; Karali, 2012; Karali and Park, 2010) without considering its effects on the conditional mean. The assumption that either price levels or price volatility are not affected by the news surprises may imply model misspecification issues and lead to biased results. The objective of this paper is to study the impact of public information on Chicago Board of Trade (CBOT) corn and soybean daily futures prices. A twofold contribution is made to the literature. First, in contrast to previous

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[11] Instead of a forecast, the January report, published after harvest, is considered to contain the final production estimates. We do not consider the January report in our analysis.

research that has usually measured information through a dummy variable on the release day, we consider the magnitude of information through the news surprises variable. Second, since changes in price levels can involve changes in price volatility and the other way around, and in contrast to the predominant literature that has either focused on the effects of news on price levels or on price volatility, we consider both types of impacts.

The remainder of the paper is organized as follows. Section 3.2 presents a literature review on the effect of public information on prices. Section 3.3 presents the methodological approach. Section 3.4 presents a description of the corn and soybeans markets. Section 3.5 offers a description of the corn and soybean sectors in the US. Section 6 provides details on the data used and reports the empirical results. Finally, section 3.6 presents the concluding remarks and a summary of the research results.

3.2. Literature review

The economic value and impact of public information has long been subject to debate. The changing structure of the agricultural sector, the growth of private firms that provide relatively low-cost information and evolving priorities within the USDA (Isengildina-Massa et al., 2006) have increased, over the last decade, the interest in assessing the effect of release of information on the agricultural sector (Karali, 2012). Taylor (2012) has grouped the literature into three main areas, depending on the subject of analysis: accuracy, value and market effect literature. While our interest will be on the later, the following lines briefly discuss the first two types of analyses.

3.2.1. Public information accuracy studies

Previous research has raised questions on the accuracy of public information. While public reports have been generally found to be better than private agency forecasts (Kastens et al, 1998; Bailey and Brorsen, 1998; Sanders and Manfredo, 2002, 2003; Isengildina-Massa et al., 2004, 2006), USDA report forecasts have been shown to contain, to some extent, biased farm-level data (Bailey and Brorsen, 1998; Isenglidina et al, 2004, 2006). Bailey and Brorsen (1998) investigate the accuracy of USDA report production and supply forecasts, by computing trends for mean and variance of percentage forecast errors. Forecast errors are defined as the difference between USDA's production estimate and actual production.

Evidence is found of a significant decreasing bias for both beef and pork production and supply forecasts over the period studied (1982-1996). Good and Irwin (2004) assess the accuracy of the USDA production forecasts for corn and soybeans, by comparing the monthly forecasts with the final post-harvest January forecast and find that the August report is the one with the largest forecasting error. The August report is the first within the crop year and coincides with the start of the harvest time. The forecasting error becomes smaller in the subsequent reports, showing an improvement in the information of the real crop size as the crop year progresses.

3.2.2. Public information value studies

The literature on the value of the USDA reports for the society concludes, in general, that these reports are vital and ignoring them would have negative consequences for relevant industries (Hyami and Peterson, 1972; Just, 1983, Garcia et al., 1997). Some farmers and agribusinesses, however, choose not to share their data with USDA because they consider these reports to push commodity prices down (Hoffman, 1980). Gerling et al. (2008) argue that this is the third most important reason for farmers declining to take part in the survey conducted by the USDA, in order to collect information on production practices and elaborate estimates of crops, livestock and economic trends.

3.2.3. Public information impact studies

Most of the literature on the market effect of public information has focused on the impact of information on price levels and has used non-structural models. Miller (1979) investigates the effect of USDA's Hogs and Pigs reports on futures prices of hogs, to test the basic hypothesis of market efficiency. The author uses partial adjustment models. Colling and Irwin (1990) asses the same issue using two-limit tobit models. Results suggest a significant impact of unanticipated changes in reported information on market prices. Hoffman (1980) studied the effect of USDA reports on cattle and hog prices through different regression specifications that compare cash and futures prices just before and after the report release. While cash prices can either increase or decrease after the release of information, futures prices are more prone to rise. Relative to cash markets, the futures market seems to be more efficient in predicting the underlying market conditions. Summer and Mueller (1989) use several statistical tests

(t-tests, F-tests and non-parametric chi-square tests) and find evidence that USDA information release on harvest forecasts, impacts on corn and soybean futures markets daily price changes. Releases in August, September and October are found to be specially influential.

Mckenzie and Singh (2011) study daily cash and closing futures prices around report release time using two-stage estimation methods. First, authors estimate the value at risk by Monte Carlo simulation to identify hedging effectiveness. Second, factors affecting the estimated value at risk are identified using ordinary least squares. The analysis is conducted for the period 1992-2008 on daily futures and cash returns for soybean and corn. Dummy variables are used to represent and capture the information impact. Results indicate that hedging stored grain during USDA report days (five days before and six days after report release) is vital from a risk management point of view. Un-hedged corn and soybean losses are larger during event days compared with non-event days. Additionally, release of other information, location, crop type and storage strategy are found to have an effect on value at risk losses.

Adjemian (2012) investigated the effect of USDA World Agricultural Supply and Demand Estimate (WASDE) announcements on cotton, soybean and hard winter wheat close-to-open (CTO) and close-to-close (CTC) future price differences for the study period of 1980-2010 using a two-stage GLS model. WASDE reports are found to have an impact on cotton, soybean, and hard winter wheat futures prices. The impact is on the order of $140 per contract, which represents around ±5% return on collateral for a trader in a single day.

Taylor (2012) studies the effect of USDA reports on corn prices in different US markets. The analysis uses Maximum Likelihood parameter estimates to test for the significance of the reaction of the corn basis to the report. Dummy variables and other control variables are used to measure the effect of reports at time of release, being the study period: 1949-2011. Results support the hypothesis that the reports affect corn markets at the national level and in Illinois, Iowa, and Nebraska. No effect is found on North Carolina and Wisconsin corn markets.

Although most of the literature studying public information impact on agricultural commodity futures prices has focused on price level impacts, more recently multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models have started to be used to capture

the volatility spillover effect (Isengildina-Massa et al., 2006; Karali, 2012). Isengildina-Massa et al. (2006) investigate the effects of USDA reports (measured through dummy variables) on hogs and cattle CTO futures returns' conditional variance for the period 1985-2004. Following Zakoian (1994), the authors use a threshold autoregressive conditional heteroskedasticity (TARCH)-in-mean model, which considers two types of news: positive and negative. Dummy variables are introduced in the conditional mean and volatility models to account for USDA reports' impact, days of the week effect and seasonality. Results show that there is a statistically significant positive effect of USDA reports on live/lean hogs futures price volatilities. Isengildina-Massa et al. (2008a) studied the impact of WASDE reports on the implied volatility of corn and soybean futures prices for the period of 1985-2002, using three statistical tests (Z-test, paired t-test and a nonparametric matched-sample test called the Wilcoxon signed rank test). Results indicate that WASDE reports have a statistically significant effect on implied volatility, which is reduced by 0.7 percentage points for corn and 0.8 percentage points for soybeans, on average. Reduction in volatility is interpreted as a sign that WASDE reports resolve uncertainty. Those WASDE reports that contain both domestic and international situation and outlook information are the ones with the strongest effects.

Karali and Park (2010) use a bivariate GARCH model to investigate the effect of USDA reports (captured through dummy variables) on the conditional variances and covariances of futures price returns. Results show that USDA reports have both positive and negative impacts on related markets, as covariances and correlations are found to react to announcement days. Karali (2012) studies the effect of selected USDA reports on the conditional variance and covariances of returns of agricultural commodities like corn, soybean and lean hog futures contracts using multivariate GARCH models. Results show that the biggest effect is registered on the report release days (measured through dummy variables) and consists of an increase in volatility.

Isengildina-Massa et al. (2008b) examined the impact of WASDE reports on corn and soybean price return variance for the period from 1985 to 2008 using parametric statistical tests (two-tailed F-test, Bartlett test, Levene test and Brown-Forsythe test). Results show WASDE reports containing National Agricultural Statistics Service (NASS) crop production

estimates and other domestic and international data and outlook information, are the more influential, being the impact of other WASDE reports less relevant. Information release causes return variance on report sessions to be 7.38 times greater than normal return variance in corn futures and 6.87 times greater than normal return variance in soybean futures. Results also show that the effect of WASDE reports has increased over time. Lehecka (2013) investigates the response of corn and soybean futures price return variability to USDA's crop progress reports for the period 1986-2012, using statistical tests. The Kruskal-Wallis chi-square test shows evidence of return variability increase on report day, while Wilcoxon-test results suggest that prices respond quickly to the crop progress report.

3.3. Methodology

Our analysis aims at studying the impacts of USDA reports on both the first and the second moments of commodity futures prices. This requires specification of a conditional mean and a conditional volatility model. Previous research has shown that price time series usually display time-changing and clustering volatility. Such property implies that periods of high volatility are followed by periods of high volatility and vice versa. GARCH models, that have been designed to capture such volatility behavior, express current volatility as a function of past volatilities and past market shocks. We focus on corn and soybean futures markets, which may be related as a result of the substitute or complement relationship that can characterize the two crops. Time series data are used in the analysis and their properties are assessed by means of well known unit root and cointegration tests. Since our time series have a unit root (Myers, 1994), the conditional mean model is based on first-differenced data. No cointegration relationship is found to characterize corn and soybean prices, which provides evidence against a long-run parity between the two prices studied. Univariate conditional mean and variance models are estimated separately using standard maximum likelihood procedures.

Price returns are defined as the difference between the logged price and its lag. The conditional mean of price returns R_{kt}, where k indexes crops and t the time periods, is assumed to depend on its own lags. Cross effects from related markets are also allowed for. R_{kt} is also considered to be function of news published on the crop and on other related crops. The conditional variance is specified as a Student's t Generalized

Autoregressive Heteroscedasticity model (GARCH) (Bollerslev, 1986) with exogenous variables (information release). To measure the impact of information releases, we follow Andersen et al. (2003) and compute the announcement surprises variable S_{kmt}, which is the difference between announced A_{kmt} and expected E_{kmt} news $S_{kmt} = A_{kmt} - E_{kmt}$, with m indexing the information release time. [12] Equations (1) through (3) represent the conditional mean and variance models.

$$R_{kt} = \alpha_k + \sum_k \sum_j \beta_{kj} R_{kt-j} + \sum_k \sum_m \gamma_{km} S_{kmt} + u_{kt} \tag{1}$$

$$u_{kt} = z_{kt} h_{kt}^{1/2}, \ z_{kt} \ iid(0,1) \tag{2}$$

$$h_{kt} = \eta_k + \sum_j \lambda_{kj} u_{kt-j}^2 + \sum_j \theta_{kj} h_{kt-j} + \sum_k \sum_m \upsilon_{km} S_{kmt} \quad \text{for each } k \tag{3}$$

Results from model estimation, as well as details on the data used are presented in the empirical implementation section. In the following section, a brief description of the markets studied is offered.

3.4. The US corn and soybean markets

The US is the largest world producer and consumer of corn and soybeans. In the late 2000s, it accounted for 32% and 50% of the world production of corn and soybeans, respectively (US-EPA, 2013). Corn production reached 13.9 billion bushels and soybean production reached 3.29 billion bushels in 2013 (USDA-NASS, 2014a). Corn and soybeans are used for different purposes including animal feed, biofuel production, among others. In 2013, the US represented 31.1% of global corn consumption, ranking first ahead of China (22.3%). US use of soybean meal represented 16% of world consumption, occupying the third position after China and the European Union (EU). Further, US soybean oil and crushed soybeans consumption reached 18,7% and 20.26% of global demand in 2013, respectively, placing the US second in global consumption, after China. In 2013, the US was the largest exporter of corn, soybeans, soybean oil and soybean meal with a share of 40%, 44.6%,

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[12] We don't standardize the surprise variable like Andersen et al(2003) as we only use one indicator

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15.2%, and 16% of global exports, respectively (USDA-FAS, 2014a; USDA-FAS, 2014b).

Corn and soybean futures contracts are the two most heavily traded agricultural contracts in the CBOT. In 2013, the CBOT registered a trade of corn, soybean, soybean meal and soybean oil futures contracts of 64,322 million, 46,721 million, 20,237 million , and 23,805 million, respectively, being the contract size of 5 thousand bushels (FIA annual volume survey, 2013). Corn futures contracts traded in July 2013, represented 9.7% of total agricultural commodity futures trade. The share of soybean products (soybeans, soybean oil, soybean meal) was 14.4% (CBOT Exchange Volume Report, 2014). Price limits have been applied that confine the changes that futures prices can undergo in order to control trading when markets become too volatile, and to prevent market manipulation. When applied, price limits may affect equilibrium prices. This may in turn affect price responses to NASS reports. Corn price changes were limited to 0.08 cent/bushel till November 1972, 0.10 cent/bushel (expandable to 0.15 cent/bushel) till November 1992, 0.12 cent/bushel (expandable to 0.18 cent/bushel) till august 2000 and 0.20 cent/bushel since September 2000. Soybean futures price changes were limited to 0.30 cent/bushel (expandable to 0.45 cent/bushel) till August 2000 and 0.50 cent/bushel since then. Isengildina-Massa et al. (2008a) suggest that price responses to information release are hardly affected by price limits when these are barely applied.

3.5. Empirical Application

The NASS-USDA public reports are a critical component of the US agricultural public information system. NASS reports provide comprehensive forecasts on supply and demand for the major US and world crops and livestock. These reports are mainly fed by data from farm surveys and objective surveys. Through the farmer-reported surveys, farmers located in the main producing states are asked to provide a subjective prediction for their final production. Objective surveys are conducted in the biggest corn and soybean-producing states, whose corn and soybean joint production represents about 70% of the US total. Objective surveys are based on area-frame sampling methods, where cultivated areas of a given crop are randomly selected. Farmer surveys and objective surveys are pooled in a multistage process through applying judgmental and statistical

techniques. All indications are then reviewed before the final look up the night before the release day (Good and Irwin, 2004).

The objective of this article is to assess the impact of NASS-USDA crop production public forecasts on corn and soybean futures prices. We focus on NASS production forecasts that, for corn and soybeans, are released monthly from August through November, which coincides with the corn and soybean harvest period. To achieve our objective, daily corn and soybean futures prices are studied during the five days following the NASS-USDA report release for the period starting from 1970 to 2004, yielding a total of 700 observations. Price data are obtained from the Commodity Research Bureau (http://www.crbtrader.com/). Specifically, prices for the following two contracts are used. First, the CBOT corn No. 2 with contract months including September, December, March, May and July and with a contract size of 5 thousand bushels. Second, the CBOT soybeans No. 1 with contract months including January, March, May, July, August, September, and November and contract size 5 thousand bushels. Futures prices are transformed into price returns by computing the logged changes in first differences.[13] We follow Isengildina-Massa et al. (2008a) who suggest relying on nearby futures contracts in research analysis. Nearby contracts benefit from the highest trade and liquidity. Also, nearby contracts for storable goods shall reflect both old and new crop information released.

NASS-USDA reports are released during non-trading time (either before trading begins or after trading stops). Specifically, NASS-USDA reports were released at 3 PM for the period from 1970 to 1993 and at 08:30 AM from 1994 till the end of the sample period. To capture their impact, CTC and CTO returns are derived. Karali (2012) shows that CTC returns have the advantage of being more conservative than CTO returns, if the effects of news are disseminated instantaneously when the market opens. CTC returns do not capture instantaneous reactions to releases. Further, CTC returns also capture the impacts of other information released during the trading day (Isengildina-Massa et al., 2006). Figures 1 and 2 show the CTC and CTO prices returns for corn and soybeans.

In order to define news surprises, the difference between the USDA production forecast and market expectations is taken. USDA forecasts are obtained from the NASS crop production reports (USDA-NASS, 2014b).

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[13] Price limits were applied during the period of our analysis, representing less than 7% of our sample of 700 observations.

Market expectations on production are obtained as in Good and Irwin (2004). For the 1970-2000 period, an average of the forecasts made by Conrad Leslie and Sparks Companies, Inc. is taken as a proxy for the market expectations. An average of Sparks Companies, Inc. (now Informa Economics, Inc.) and Oster/Dow Jones (ODJ) forecasts are used as a proxy for the private market expectations from 2001 onwards.[14]

Figures 3 and 4 show corn and soybean production forecasts news surprises. The analysis was carried out using the econometric software RATS 6.3. Descriptive statistics for the CTC, CTO futures price returns and news surprises are presented in table 1. Test statistics suggest futures price returns follow a non-normal distribution with the presence of fat tails. We thus assume that the errors in the conditional variance model follow a student-t distribution. News surprises are also non-normally distributed.

Results from the estimation of the conditional mean and variance models are presented in tables 2 and 3, respectively, for both the CTC and the CTO models. Lags of price returns in equation (1) were discarded as they were not statistically significant. According to economic theory, we expect that a positive surprise will cause a decrease in price returns (bearish trend), as USDA-NASS production forecasts cause an upward correction of production market estimates. A negative surprise will cause an increase in price returns (bullish trend) as private agents will update their output expectations downward. Hence, the parameter measuring the effect of (own) news surprises on price levels shall be negative. Since corn and soybeans can be substitutes and complements, both on the production and consumption side, cross effects of news surprises are likely to be observed, being their sign dependent on the relationship between the two commodities. While a negative cross-news surprises sign will be an indicator of complementarity, a positive sign would suggest a substitution relationship. As explained, USDA production forecasts for corn and soybeans, are released monthly from August to November. In the next lines a discussion on the release months that are expected to be more influential is presented. Uncertainty regarding crop production shall be highest on September, at the beginning of the harvest season, and lowest in November, at the end of the harvest season. At the beginning of the harvest season, uncertainties are higher and markets may be more sensitive to information releases. Hence, September news surprises are likely to exert a significant

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[14] Logarithmic transformation is applied on private market forecasts.

impact. As the harvest season ends, uncertainties are clearing and NASS forecasts shall increase in accuracy. This makes these forecasts more valuable and markets may be highly sensitive to them. Hence, those reports published in the extremes of the harvest season are expected to be more influential.

Conditional mean model results suggest that corn news surprises exert a negative and statistically significant effect on CTC and CTO corn price returns. Statistical significance is specially relevant in the CTO equation. This implies immediate opening time impacts of news. While all report releases are relevant to CTO returns, only the August and September news surprises are found to be statistically significant in the CTC equation, which is compatible with the hypothesis that releases at the beginning of the harvest season are relevant. Soybean news surprises are statistically significant on both CTO and CTC soybean returns, but differ in both their magnitude and the release dates that are found to be significant. Statistical significance supports, once more, the idea that releases at the extremes of the harvest period tend to be more influential. Cross effects from soybean news surprises on corn price returns are mainly significant in the extreme points of the harvest period. A similar pattern is followed by the cross effects from corn news surprises on soybean price returns. The sign of cross-effects suggest a complement relationship between the two crops considered. Our results are compatible with Taylor (2012) who studied the effects of USDA crop production reports on corn price levels and found evidence that report releases at the extreme points of the harvest season are the most important.

ARCH LM tests were applied on the residuals of the conditional mean model and evidence of ARCH effects was found, thus supporting the use of a GARCH model. We now turn to the interpretation of the conditional volatility model. While both corn and soybean price volatility are positively influenced by past volatility and past market shocks, volatilities do not respond to NASS production forecasts. The significant positive effect of September soybean news surprises on soybeans volatility is the only exception. Hence, while information release causes a change in price levels, price volatility is left almost untouched. This is indicative of a very gradual change in price levels, as opposed to abrupt changes. In contrast to our results, Isengildina-Massa et al. (2006) who only considered the impact of USDA reports on live/lean hogs futures price conditional

variance, found a statistically significant positive effect of USDA reports on price volatility.

3.6. Conclusions

This paper investigates the impact of USDA-NASS crop production reports on corn and soybean futures prices. We assess both the first and the second moments of price returns during the five days following the release of a NASS report. Our period of analysis goes from August 1970 to November 2005. Price conditional means are modeled as a function of news surprises. Price volatility behavior is analyzed through a Student's t GARCH model that allows for news surprises as exogenous variables. The model is estimated by maximum likelihood procedures. Our work is the first in assessing the effect of public information measured as news surprises on both price levels and volatility.

Our results allow deriving two main conclusions. First, USDA-NASS reports affect price levels. Both own and cross-price effects are found to be relevant. The releases of information at the beginning and at the end of the harvest season are usually the ones exerting a stronger impact. Hence, market responses seem to be specially relevant when market uncertainty is highest and when pubic production forecasts are more reliable. Second, price volatility is not affected by news surprises, which is indicative of gradual price-level changes. Cross-effects of news are also found to be significant.

In short, results suggest that private agents do not always agree with NASS when forming their output expectations. When USDA report releases evidence this expectation bias, market prices respond smoothly without increasing price instability. Our results thus suggest that public information release may contribute to increase market efficiency, to improve stock management decisions and might smooth the price formation process, relative to a situation in which public forecasts were unavailable. In this latter context, price behavior may be more erratic and market shocks may be more sizeable.

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Table 3.1. Descriptive statistics for daily price returns

	Close to close		Close to open		Corn news	Soybeans news
	Corn	**soybeans**	**Corn**	**Soybeans**		
Mean	-4.560e-4	-5.060e-4	3.120e-4	5.400e-5	1,900e-4	1,491e-3
Standard deviation	0.015	0.017	0.011	0.012	0.015	0.017
Maximum	0.055	0.074	0.061	0.083	0.046	0.044
Minimum	-0.052	-0.063	-0.052	-0.062	-0.061	-0.048
Skewness	0.264***	0.076	0.922***	0.422***	-0.311***	-0.209**
Kurtosis	0.876***	1.013***	7.209***	9.800***	1.331***	0.340*
Jarque-Bera	30.422***	30.003***	1610.484***	2769.863***	62.929***	8.463**

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level

¨e¨ refers to exponential operator

Table 3.2. The conditional mean equations for corn and soybean price

returns

	Close to close		Close to open	
	Corn	**Soybeans**	**Corn**	**Soybeans**
$S_{Corn,August}$	-0.127**	-0.022	-0.165**	-0.099**
$S_{Corn,September}$	-0.237**	0.011	-0.138**	-0.032
$S_{Corn,October}$	-0.081	-0.056	-0.121*	-0.094
$S_{Corn,November}$	-0.090	0.172	-0.238**	-0.012
$S_{Soybeans,August}$	-0.107**	-0.055	-0.068*	-0.063
$S_{Soybeans,September}$	0.071	-0.090	0.019	-0.022
$S_{Soybeans,October}$	0.015	-0.146*	-0.047	-0.120**
$S_{Soybeans,November}$	-0.326**	-0.398**	-0.045	-0.126
ARCH test	6.859**	4.948**	8.765**	3.719**
Log-Likelihood	1957.958	1829.517	2188.291	2099.082

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level

**Table 3.3.** The conditional variance equations for corn and soybean price

returns

|	Close to close		Close to open	
	Corn	**soybeans**	**Corn**	**Soybeans**
α_i	3,290e-5*	2,295e-5**	1,869e-5	2,657e-5*
u_{t-j}^2	0.078**	0.110**	0.233	0,200**
h_{t-j}^2	0.762***	0.810**	0.750**	0.715**
$S_{Corn,August}$	-6,202e-4	-1,139e-4	-4,443e-4	-4,075-e4
$S_{Corn,September}$	-3,565e-4	1,391e-4	-5,670e-4	-6,808e-4
$S_{Corn,October}$	-3,091e-4	2,350e-4	-6,610e-4	-4,118e-5
$S_{Corn,November}$	1,054e-3	-4,402e-5	1,047e-3	1,052e-3
$S_{Soybeans,August}$	6,916e-5	-3,502e-4	4,104e-4	1,179e-4
$S_{Soybeans,September}$	2,099e-3	9,281e-4*	5,637e-4	8,204e-4**
$S_{Soybeans,October}$	-6,417e-4	1,296e-4	4,327e-4	-2,226e-4
$S_{Soybeans,November}$	-7,560e-4	-2,850e-4	-5,358e-4	5,653e-4
Log-Likelihood	1984.375	1886.110	2362.431	2316.516

*** (**) [*] denotes statistical significance at the 1 (5) [10] % level
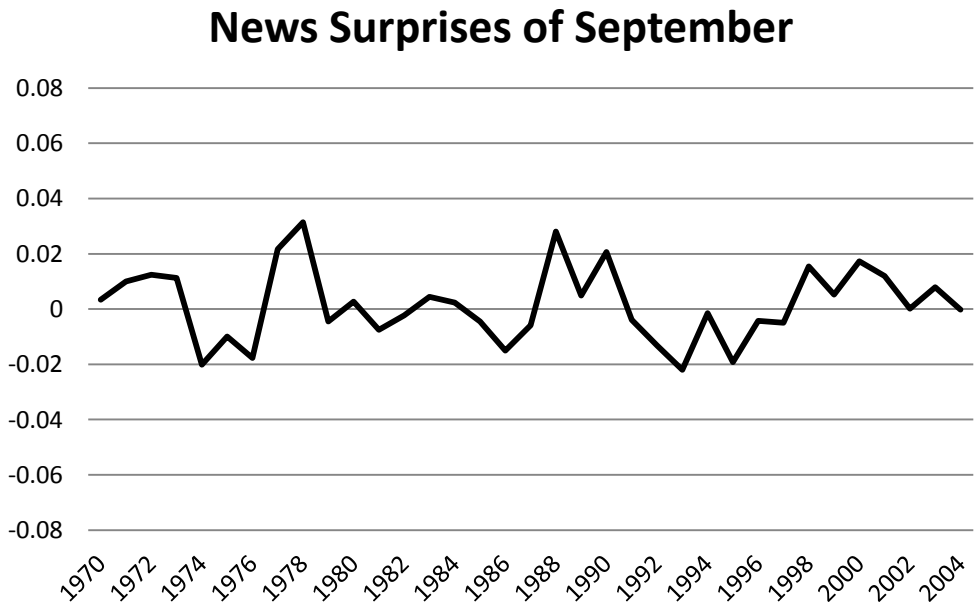¨e¨ refers to scientific notation (with exponent)

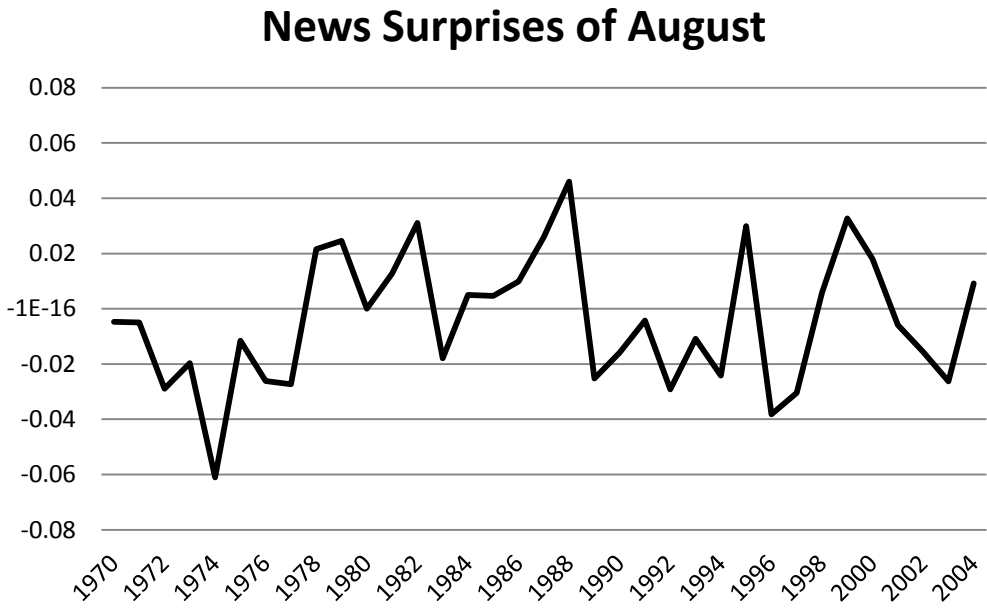**Figure 3.1.** Close to Close price returns for corn and soybeans
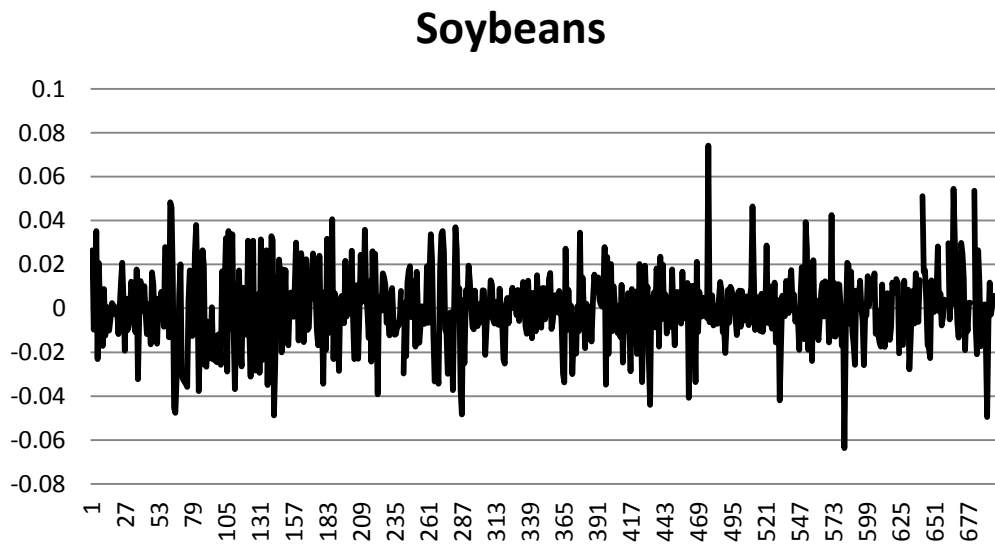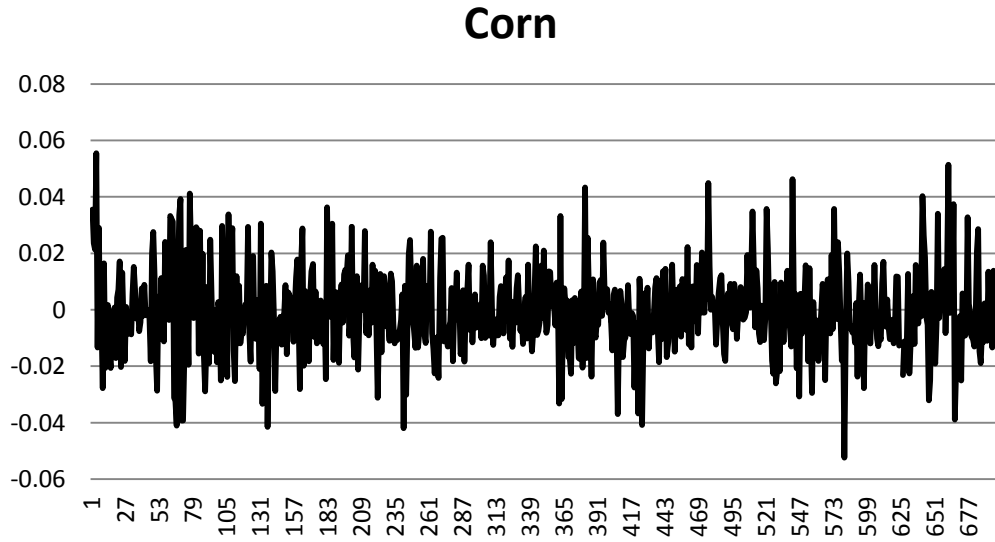
Corn

Soybeans

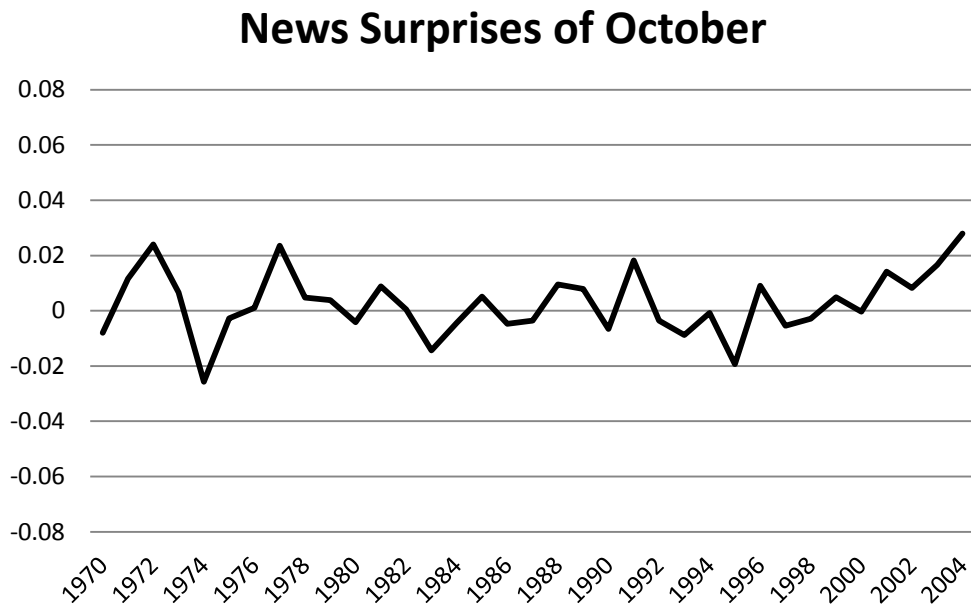**Figure 3.2.** Close to Open price returns for corn and soybeans

Corn

Soybeans
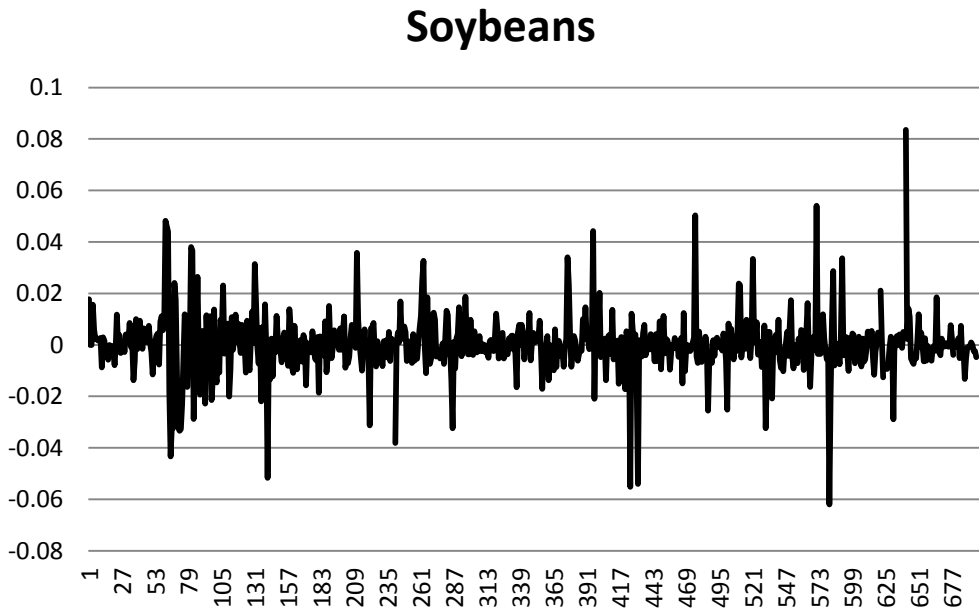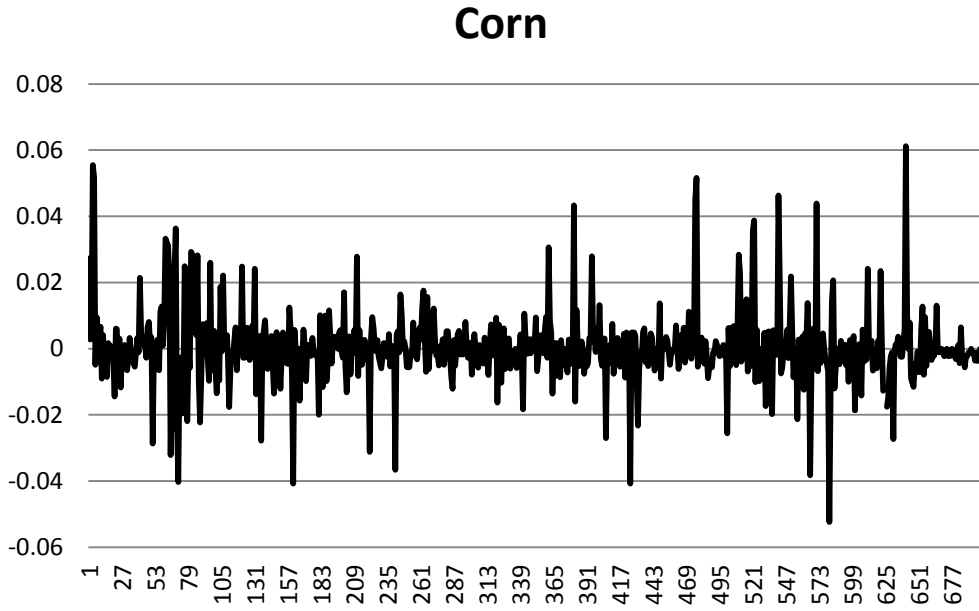
Figure 3.3. News Surprises for corn production forecasts

News Surprises of August

News Surprises of September

Figure 3.3. (continued) News Surprises for corn production forecasts

News Surprises of October

News Surprises of November
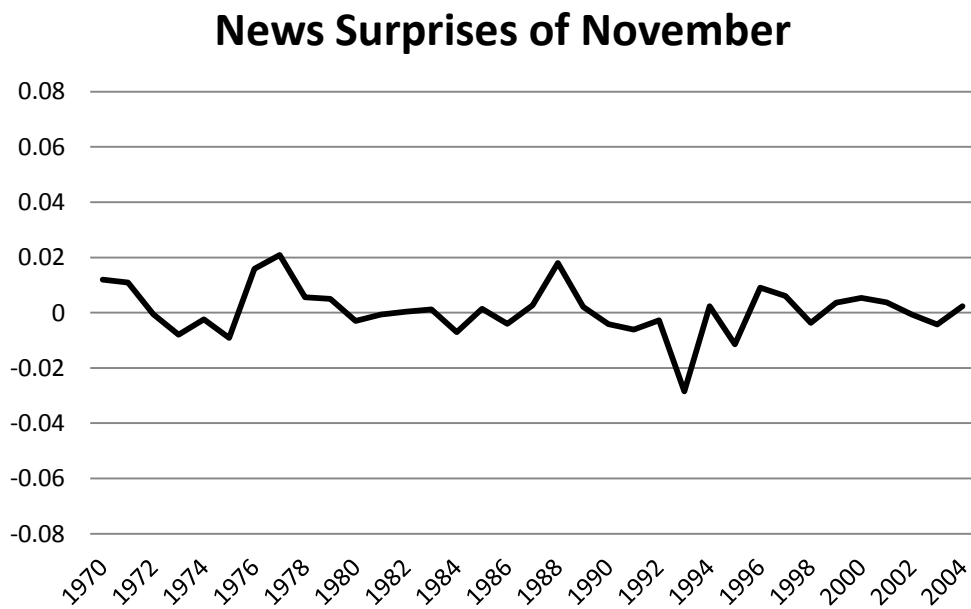
Chapter 4: General conclusions and future research

The guiding theme of this thesis is the empirical analysis of recent food price behavior. It is composed of three applied studies that address the impacts of energy prices on both food price levels and volatility, as well as the impact of public information release on futures markets of major agricultural commodities. Non-structural time series econometric techniques are applied for such purpose.

In the first chapter, the impact of the Spanish biodiesel industry on agricultural feedstock prices is investigated. Both price level and volatility interactions are evaluated. Three relevant prices are considered: the international crude oil price, the Spanish biodiesel blend price and the Spanish sunflower oil price. Weekly Prices are observed from November 2006 to October 2010, yielding a total of 205 observations. Blended biodiesel, sunflower and crude oil prices are found to be interrelated in the long-run. This parity is preserved by the biodiesel industry in order to be in equilibrium. The impact of biodiesel on sunflower oil price levels is found to be very modest, which is reasonable given the small size of the Spanish biodiesel industry. Volatility spillovers between sunflower and biodiesel markets are found to be significant. Evidence of asymmetries in price volatility patterns is also found, with price declines causing more price instability than price increases. Asymmetries can be triggered by the availability of alternative feedstocks in the market, as well as by the unwillingness of biodiesel producers to increase food prices when feedstocks become more expensive.

In the second chapter, the impact of the EU biodiesel market on agricultural feedstock prices is analyzed. The study comprises the period between 06/11/2008 to 14/06/2012, and is based on 189 weekly prices. Cointegration analysis suggests that the three prices have a long-run equilibrium relationship that is preserved by the pure biodiesel price. Biodiesel prices are not found to have an effect on rapeseed oil prices. Volatility of pure biodiesel price is affected by its own past volatility and past pure biodiesel and rapeseed market shocks. Also, evidence is found of asymmetries in price volatility, with negative market shocks having a greater impact than positive ones. While pure biodiesel prices cannot affect rapeseed oil price-levels, they can bring instability to these prices. Inventory building and the euro-dollar exchange rate are found to be

relevant risk management instruments that can be used to mitigate the biodiesel and rapeseed oil price volatilities.

In the third chapter, the impact of public information in the form of USDA-NASS crop production reports on daily corn and soybeans futures prices is evaluated. The study period is between 1970 to 2004, with a total of 700 observations. Results show that USDA-NASS crop production reports significantly affect futures price levels. Report releases at the beginning and at the end of the harvest season are usually the ones exerting a stronger impact. Report releases are not however found to have an effect on price volatility, which suggests gradual price-level changes as a response to published information. Cross-market effects of news are also found to be significant.

This thesis contributes to previous literature by shedding light on recent food price behavior. While different causes have been pointed as responsible for recent food price patterns, further empirical research is needed to confirm or dismiss such causes. This constitutes the main scientific contribution of this dissertation. More specifically, this thesis addresses three important topics that have not been considered by previous research. First, it assesses whether asymmetries do characterize price volatility links between food and energy markets. Second, it extends the specification of food price volatility models to a consideration of the impact of exogenous variables such as commodity stock building, or exchange rates. Third, it sheds light on a very recent research topic that aims at determining to what extent information release and financialization of food commodity markets can have an effect on food price behavior.

The research conducted in this thesis may be extended from different perspectives. Time-series econometric techniques are usually based upon specific assumptions on the multivariate distribution function characterizing price dependence. Conventional analyses of dependency between multiple random variables are constrained by statistical tool availability and mainly rely on multivariate normal or student's t distributions. These distributions have been shown to usually misrepresent food price patterns. This calls for the need to use flexible statistical instruments to represent multivariate distribution functions.

Statistical copulas provide flexibility in evaluating dependence between variables. Copulas are based on the Sklar's (1959) theorem that shows 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; Patton, 2012).

Future research paths not only include the use of more flexible methodologies such as copulas, but also the selection of the topics being studied. At the time of writing this concluding remarks chapter, the literature on the links between food and energy prices has grown substantially (Serra and Zilberman, 2013). A topic that still remains rather unexplored are the consequences of the financialization of food markets. Hence, the effects of speculation, the introduction of electronic trading, etc. remain very appealing areas for future analysis.

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