Energy Economics 37 (2013) 141–151

Contents lists available at SciVerse ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Biofuel-related price transmission literature: A review☆

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ARTICLE INFO

Article history:
Received 20 June 2012
Received in revised form 16 February 2013
Accepted 18 February 2013
Available online 24 February 2013

JEL classification:
C01
Q42
Q48

Keywords:
Time series
Biofuels
Price levels
Price volatility
Literature review

ABSTRACT

In this article, an extensive review of the rapidly growing biofuel-related time-series literature is carried out. The data used, the modeling techniques and the main findings of this literature are discussed. Providing a review of this flourishing research area is relevant as a guidepost for future research. This literature concludes that energy prices drive long-run agricultural price levels and that instability in energy markets is transferred to food markets.

1. Introduction

The growth of global biofuel production during the first decade of the new millennium has been mainly led by government policies that target different objectives such as adding to domestic energy security, promoting rural economic growth, addressing global warming, or reducing fossil fuel prices (Hochman et al., 2010).[1] World ethanol production reached roughly 20 billion gallons in 2009, with the United States (US), Brazil and the European Union (EU) representing about 54%, 34% and 5% of this production, respectively (RFA, 2011). World biodiesel output is dominated by the EU that produced 9 million tons in 2009, 65% of global output (EBB, 2010).

Currently commercialized biofuels are, by and large, first-generation biofuels based on food crops.[2] Ethanol is mainly produced from coarse grains (representing 51% of global ethanol output by feedstocks in 2008–2010), specially corn, and sugarcane (accounting for 29% of global ethanol output in the same period) (OECD-FAO, 2011). Biodiesel is mainly produced from vegetable oils (rapeseed oil in Europe and soybean oil in the US). About 20 million hectares (1% of worldwide agricultural land) were committed to grow biofuel feedstocks in 2008 (Scarlat and Dallemand, 2011). In 2008–2011, around 11% of global coarse grain production, 13% of vegetable oil production and 21% of sugar cane production were used to fuel cars (OECD-FAO, 2011). These average figures however disguise significant differences across countries and commodities. The proportion of US corn production transformed into alcohol for fuel reached 40% in 2010–2011 (USDA, Economic Research Service, 2011). In Brazil, 55% of sugarcane was distilled into ethanol in the same period (Valdes, 2011).

Subject to mandates, tax exemptions, subsidizations, or technical restrictions in different countries, biofuels are usually consumed blended into gasoline and diesel, but also in pure form (Chang et al., 2011). The share of ethanol in total US gasoline consumption was 5.5% in 2009 (RITA, 2011), below the US blend wall of 10% of ethanol in gasoline.[3] In Brazil ethanol displaced around 50% of gasoline used for transportation in the same year (REN21, 2010). In the EU, biofuels represented 4% of all transportation fuels in 2009 (EurObserv'ER, 2010).

More recently, skepticism around the benefits of promoting biofuels has grown as these have been blamed for being one of the causes of the

☆ The authors gratefully acknowledge financial support from the Instituto Nacional de Investigaciones Agrícolas (INIA) and the European Regional Development Fund (ERDF), Plan Nacional de Investigación Científica, Desarrollo e Innovación Tecnológica (I + D + i), Project Reference Number RTA2009-00013-00-00.
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[1] As noted by a referee, the fact that biofuels usually require government support to be competitive, casts doubts on their actual contribution to fuel price declines.

[2] While cellulosic sources are projected to supplement biofuels from food crops sometime in the future, they are still at a research or demonstration stage and are not expected to be commercialized before 2020 (Sims et al., 2010).

[3] As explained by Abbott (2012), the blend wall has not been a binding constraint over the short-run, but it is expected to be more binding in the longer-term through its influence on investments on ethanol plants.

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http://dx.doi.org/10.1016/j.eneco.2013.02.014

2007/08 and the 2010/11 global food crises, having negative environmental and social impacts, etc. This has led many governments to reconsider support to biofuels. One of the most important effects of the growing biofuel production has been the change in the nature of the link between agricultural commodity and energy markets that has spurred the food versus fuel debate. While this link was traditionally weak (Taheripour and Tyner, 2008) and mainly supply driven (i.e., through input costs, specially through energy intensive agricultural inputs), a wide range of analyses have reported a stronger connection since the increase in the biofuel industry demand for food commodities. Though much of the interest among the press and the academic world has been on the implications of biofuels for food prices, some research papers also investigate how biofuels affect fossil fuel prices (Whistance and Thompson, 2010).

An overwhelming majority of analyses studying the biofuel impacts on food and energy prices have focused their interest on price levels. Price volatility has received much less attention. The recent 2007/08 crisis, however, has stimulated research in the area of commodity price volatility. While there is not a single definition of price volatility, it is generally characterized as a directionless price variability that cannot be predicted by market fundamentals (Prakash, 2011). Episodes of prolonged and/or relevant volatility have been shown to have important economic impacts (they can lead to reduced investments in R&D and in physical and human capital, unemployment, income fluctuations, etc.) that can bring on social and welfare costs, increased poverty, reduced social peace and cohesion, etc. (Prakash, 2011).

The academic literature has extensively relied on partial and general equilibrium models as a methodological approach to characterize the economic impacts of biofuels. These models have however been widely criticized for not being sufficiently validated against historical data and perform poorly (Beckman et al., 2011). Further, since they are usually calibrated using annual data, they are unable to assess short-run price dynamics. Given that volatility is intuitively a measure of the extent to which prices jitter, volatility assessments gain from using data at high frequencies, both because high frequency volatility is easier to predict and because it has proven useful to forecast at longer horizons (Andersen et al., 2003). The time-series econometrics literature studying the economic impacts of biofuels has been growing in parallel with the availability of biofuel time-series data.

Reviews of the literature investigating the economic impacts of biofuels have paid special attention to structural models (Kretschmer and Peterson, 2010; Rajagopal and Zilberman, 2007). Some recent articles have presented non-exhaustive reviews on the biofuel-related price transmission literature (Janda et al., forthcoming; Zilberman et al., in press). In this article, an extensive review of the time-series literature addressing the impacts of biofuels on food and/or fuel prices is carried out. The data used, the modeling techniques and the main findings are discussed. Providing a review of this rapidly growing research area is relevant as a guidepost for future research.

The paper is organized as follows. In the next section, a discussion of different price modeling approaches, as well as some general time-series properties and how they should be modeled is presented. The third and fourth sections are devoted to review price level and volatility studies, respectively. A summary of research results and a list of still open research questions conclude the article.

2. General modeling issues

The economics profession's ability to accurately understand and forecast commodity prices has been widely questioned (Deaton, 1999; Hamilton, 2009). Recent progressive dismantling of public commodity price stabilization mechanisms, leading to increased dependence of prices on global markets may have complicated the task. The relevance to obtain accurate forecasts cannot be understated given the influence of expected prices on the decisions taken by economic agents.

Attempts to theoretically model food-energy price links are relatively new (Ciaian and Kancs, 2011a) and mainly focus on assessing price level patterns. In contrast, price volatility interactions receive little attention (Wright, 2011). Price links have been usually defined using partial equilibrium models that differ in terms of sophistication and underlying assumptions. de Gorter and Just (2008, 2009a, 2009b) use a partial equilibrium model of corn, ethanol and oil markets to show that consumers' willingness to pay for ethanol establishes a long-run link between crude and ethanol prices, while supply forces lead to an equilibrium between feedstock and ethanol prices. Ciaian and Kancs (2011a) extend de Gorter and Just's (2008) model to allow for agricultural commodities other than feedstock and for the indirect input channel through which energy can affect agricultural prices. As opposed to the competitive structure generally assumed, Saitone et al. (2008) and Hochman et al. (2010, 2011a, 2011b) allow for market power. Hochman et al. (2011b) and Carter et al. (2012) include corn inventories in the assessment of the impacts of biofuels on corn prices. A strand of literature stresses the relevance of considering policy regulations to better understand food-energy price links (Abbott, 2012; Carter et al., 2012; de Gorter and Just, 2008, 2009a, 2009b; Tyner, 2010). While theoretical structures generally allow for energy-agricultural price causality links to flow in both directions, more attention has been paid to quantify the increase in food prices as a result of the influence of biofuel markets. Hochman et al. (2010)'s literature review places these increases between 3 and 75%.

In spite of the progress made in theoretical modeling of food–energy price relationships, there is no widely accepted model that explains food price volatility (Wright, 2011).[4] Speculation in futures markets, stocks, changes in food and fuel demand, weather conditions, changes in world population, policy regulations, or macroeconomic conditions (exchange rates, interest rates, monetary policy, etc.) can alter food and energy prices and their links (Balcombe, 2011; Cooke and Robles, 2009; Gilbert, 2010; Headey and Fan, 2008; Meyers and Meyer, 2008; Mitchell, 2008; Wright, 2011). However, no comprehensive theoretical framework embracing all these elements has been developed, which makes it difficult to predict the sign and relative magnitude of their impact.

Time-series models hardly impose any theoretical structure and mainly focus on empirical investigation of price links. They have the advantage of not requiring as much data as structural models. Many price transmission models are based on price data alone, which is usually available at relatively high frequencies that are suitable to investigate price volatility issues. In being non-structural models, however, time-series models do not allow distinguishing price patterns under alternative theories (Miller and Hayenga, 2001). Their results should thus be interpreted with care. Abbott (2012) and Headey and Fan (2010) criticize time-series analyses for being rather inconclusive regarding the influence of biofuels on commodity prices and for failing to provide substantial economic insight into price behavior patterns.

Caveats being made, time-series models are relevant instruments to characterize price behavior. When relevant market events are in place and if we, social scientists, wish to be relevant, "we do not have the luxury of waiting for the evidence needed for formal testing of hypotheses (…)" (Wright, 2011; p.42). In this regard, an empirical non-structural assessment can shed light on the patterns followed by the relevant economic indicators. Some general statistical properties of time-series dynamics such as nonstationarity, co-movements, nonlinearity and time-varying clustering volatility, should be considered to provide refined price forecasts (Deaton and Laroque, 1992; Myers, 1994; Stigler, 2011). Nonstationary time series tend to have a high degree of persistence or autocorrelation, implying that both their mean and variance change over time. While empirical proof of the presence of a unit root

[4] Alghalith (2010) developed a theoretical model assessing joint oil and food price uncertainty in a small producing country. The model, however, does not allow to a priori predict the sign of the impacts of oil price, price uncertainty and production on food prices.

in commodity price series is mixed, numerous analyses provide supporting evidence (Ghoshray, 2011; Kellard and Wohar, 2006; Maslyuk and Smyth, 2008; and Serletis and Rangel-Ruiz, 2004). Standard statistical inference methods can produce completely spurious results if applied to nonstationary stochastic variables.

Another central property of time-series is that the dynamics of a system of variables may be characterized by the existence of a long-run relationship and a built-in tendency to adjust to this equilibrium (Goodwin and Piggott, 2001; Saghaian, 2010; Serra et al., 2006). The works of Nobel laureates Clive Granger and Robert Engle (Engle and Granger, 1987) have provided the literature with vector error-correction models (VECM) that formally characterize nonstationary and cointegrated data, and inform both on the short and long-run dynamics of time series.

Times series data are usually characterized by high, time-varying and clustering volatility, which invalidates the common assumption of independently and identically distributed variables. The introduction of autoregressive conditional heteroscedastic (ARCH) models in the seminal article by Engle (1982) and their subsequent generalization to GARCH models by Bollerslev (1986) has radically changed the way volatility is modeled. While understanding the volatility of a single variable has been the main focus of attention, multivariate GARCH (MGARCH) models have been proposed and used to understand volatility interactions across related markets (Beck, 2001; Ramirez and Fadiga, 2003; Serra, 2011).

Two submodels integrate GARCH (MGARCH) specifications: the conditional mean and the conditional covariance model. The conditional mean model investigates price level behavior and its specification can range from a simple vector of constants, to more sophisticated forms including VECMs. The conditional covariance model considers heteroskedasticity as a variance that can be modeled and predicted (Engle, 2001). The variance–covariance matrix is typically expressed as a function of its own lags and the lagged square residual matrix that captures new market information.

Changes in market fundamentals, different market and commodity characteristics, or nonlinear responses of prices to changes to explanatory variables can lead to nonlinear price behavior.[5] Such nonlinearities have been found to characterize both nonenergy and energy commodity prices (Balcombe and Rapsomanikis, 2008; Holt and Craig, 2006; Honarvar, 2009; Nazlioglu, 2011; Peri and Baldi, 2010; Radchenko, 2005; Serra et al., 2011a). A wide array of models have been proposed that generalize linear specifications to allow for nonlinear price behavior both in error correction and volatility models. Generalizations of the traditional VECMs that have gained popularity in the price transmission literature include asymmetric vector error correction models (AVECM) by Granger and Lee (1989), threshold vector error correction models (TVECM) (Balke and Fomby, 1997), smooth transition vector error correction models (STVECM) (Teräsvirta, 1994), or Markov-switching VECM (MS-VECM) (Hamilton, 1989). These generalizations usually permit different price responses to different signs and magnitudes of the error correction term. ARCH and GARCH models have also been generalized to accommodate different price volatility responses to positive and negative market shocks. Some popular specifications include the multivariate extension of the model by Glosten et al. (1993) proposed by McAleer et al. (2009), the matrix-exponential GARCH (Kawakatsu, 2006), or the asymmetric Baba–Engle–Kraft–Kroner (BEKK) model (Engle and Kroner, 1995) proposed by Kroner and Ng (1998).

The biofuel-related price transmission literature has focused on studying price level links using VECM-type of models. More recently, price volatility interactions have also been assessed by means of multivariate versions of ARCH or GARCH models. Our literature review classifies research papers according to whether they allow for price volatility links, or they only focus on price level interactions. A summary of the papers reviewed, their modeling approach, data used and main research conclusions is presented in Tables 1 and 2.

[5] Meyer and von Cramon-Taubadel (2004) and Frey and Manera (2007) have provided reviews of the causes and estimation of nonlinearities in price transmission.

3. Price level link interactions among biofuel-related markets

While the literature addressing price volatility interactions in biofuel-related markets is rather thin, assessments of price-level links are more numerous. In the following lines, thirty-four articles devoted to study this issue are reviewed. Out of these, ten focus on the US biofuel market (Campiche et al., 2007; Cha and Bae, 2011; Chang and Su, 2010; Mallory et al., 2012; McPhail, 2011; Qiu et al., 2012; Saghaian, 2010; Serra et al., 2011a; Wixson and Katchova, 2012; Zhang et al., 2010). Different data are used in US studies. Saghaian (2010), Zhang et al. (2010), Serra et al. (2011a), Mallory et al. (2012), Qiu et al. (2012) and Wixson and Katchova (2012) study dependency between fossil fuel, biofuel and feedstock prices. McPhail (2011) focuses on fossil fuel and biofuel price links, while the rest of the articles consider fossil fuel and feedstock prices. Data availability issues are usually behind the decision to ignore biofuel prices. Studies ignoring biofuel prices generally rely on the hypothesis that a change in the food–fuel price relationship after the outbreak of the biofuels industry can be reasonably attributed to the impact of biofuels.

Predominant methodological approaches in the US literature consist of cointegration analysis and/or estimation of a VECM, or one of its generalized nonlinear versions. Causality is assessed by different means (Granger causality tests, directed acyclic graphs, etc.). Sample splitting is sometimes used to allow for shifts in price patterns due to structural changes such as the outbreak of the biofuels industry.

A wide majority of error correction models conclude that energy prices drive feedstock price equilibrium levels in the US. Campiche et al. (2007) find corn and soybean prices to be cointegrated with crude oil prices after the eruption of the biofuels market, with crude prices driving feedstock prices. Saghaian (2010) supports cointegration between crude oil, ethanol, wheat, corn and soybean prices. Crude oil drives corn, soybean, wheat and ethanol equilibrium prices, while ethanol affects long-run corn prices. Serra et al. (2011a) provide evidence of two cointegration relationships: crude oil–gasoline (representing the gasoline market equilibrium) and ethanol–corn–gasoline (representing the ethanol market equilibrium). Corn responds to ethanol market disequilibriums, but not to gasoline market disequilibriums, which suggests that energy–agricultural price links occur through the biofuels market. Wixson and Katchova (2012) find soybean prices to be influenced by crude oil prices in the long-run. In contrast with previous studies, Zhang et al. (2010) find no evidence of cointegration between energy and agricultural commodity prices. Saghaian (2010), Serra et al. (2011a), Mallory et al. (2012) and Wixson and Katchova (2012) support the thesis that long-run biofuel prices are influenced by feedstock prices. Evidence of biofuel markets being able to shape fossil fuel prices is only provided by Serra et al. (2011a) and Rajcaniova and Pokrivcak (2011).

While the leading methodological approach among US studies is the error correction model, Chang and Su (2010) and Cha and Bae (2011) rely on vector autoregressive (VAR) models that restrict inferences to short-run causality. They identify short-run impacts of crude on feedstock prices. McPhail (2011) and Qiu et al. (2012) use a structural VAR model. McPhail (2011) supports bidirectional causality links between crude oil and ethanol prices. Along the lines of Zhang et al. (2010) and Mallory et al. (2012), Qiu et al. (2012) provide evidence that fossil fuel and biofuel market shocks do not spill over grain prices.

The international market has attracted the attention of fourteen research articles (Chen et al., 2010; Ciaian and Kancs, 2011a, 2011b; Cooke and Robles, 2009; Esmaeili and Shokoohi, 2010; Gilbert, 2010; Kristoufek et al., 2012a, 2012b; Natalenov et al., 2011; Nazlioglu, 2011; Nazlioglu and Soytas, 2011a; Rosa and Vasciaevo, 2012; Vacha et al., 2012; Yu et al., 2006). Only Kristoufek et al. (2012a, 2012b) and Vacha et al. (2012) use biofuel prices. Half of these studies rely on methodological approaches that preclude

Table 1
Summary of the time-series literature on biofuel markets. Price level models.

Reference	Time-series modeling approach	Time-series variables used	Are biofuel prices used?	Data frequency	Period of study	Do biofuel or energy prices affect feedstock prices in the long run?			Do biofuel prices affect fossil fuel prices in the long-run?			Do biofuel or energy prices transmit volatility to feedstock prices?			Do biofuel prices transmit volatility to fossil fuel prices?		
						Yes	No	Not studied	Yes	No	Not studied	Yes	No	Not studied	Yes	No	Not studied
Balcombe and Rapsomanikis (2008)	Taylor series expansion of VECM; AVECM; TVECM	Brazilian ethanol and sugar prices, world crude oil prices	Yes	Weekly	July 2000–May 2006	x				x				x			X
Busse et al. (2012)	MS-VECM	German diesel, biodiesel, rapeseed oil and soy oil prices	Yes	Weekly	July 2002–July 2008	x				x				x			x
Campiche et al. (2007)	VECM	Corn, sorghum, soybeans, soybean oil, palm oil, world sugar and crude oil prices	No	Weekly	2003–2007	x					x			x			x
Cha and Bae (2011)	Reduced-form VAR	WTI crude oil price; US bioethanol, feed, other residual and export demand for corn, and corn prices	No	Quarterly	1986–2008			x			x			x			x
Chang and Su (2010)	VAR-EGARCH	WTI crude oil, US corn, US soybean futures prices	No	Daily	January 2000–July 2008			x			x			x			x
Chen et al. (2010)	ARDL	Corn, soybeans, wheat and crude oil futures prices	No	Weekly	March 1983–February 2010			x			x			x			x
Ciaian and Kancs (2011a)	VECM	World corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum tea, crude oil	No	Weekly	January 1993–December 2010	x					x			x			x
Ciaian and Kancs (2011b)	VECM	World crude oil, wheat, corn, rice, sugar, soybeans, cotton, banana, sorghum and tea prices	No	Weekly	January 1994–December 2008	x					x			x			x
Cooke and Robles (2009)	VAR	World corn, wheat, rice, soybean, crude oil and fertilizer prices; US ethanol and biodiesel production; USD/euro exchange rate; world demand; grain exports and different proxies for speculation in futures prices	No	Monthly	2002–2009			x			x			x			x
Esmaeili and Shokoohi (2010)	VAR; PCA	World eggs, meat, milk, oilseeds, rice, sugar, wheat and crude oil prices; world consumer price index, food production index, GDP.	No	Monthly	1961–2005			x			x			x			x
Gilbert (2010)	ARDL	Agricultural food, grain and vegetable oil price indices, world GDP growth, crude oil prices, USD exchange rate, world money supply and futures market open interest	No	Quarterly	1971–2008			x			x			x			x
Hassouneh et al. (2011)	VECM and MLPR	World crude oil, Spanish biodiesel and sunflower oil prices	Yes	Weekly	November 2006–October 2010		x			x				x			x
Kristoufek et al. (2012a)	Minimal spanning and hierarchical trees	Crude oil, ethanol, corn, wheat, sugarcane, soybeans, sugar beets, biodiesel, German diesel and gasoline, US diesel and gasoline.	Yes	Weekly/monthly	November 2003–February 2011			x			x			x			x
Kristoufek et al. (2012b)	VAR	Crude oil, ethanol, corn, wheat, sugarcane, soybeans, consumer diesel, German diesel, US gasoline	Yes	Weekly	November 2003–February 2011			x			x			x			x
Mallory et al. (2012)	VECM	Nearby and 1-year to expiration futures prices of ethanol, corn and natural gas	Yes	Daily	January 2007–February 2012		x			x				x			x

McPhail (2011)	Structural VAR	Growth rate in global crude oil production, global economic activity, crude and US gasoline and US ethanol price, US gasoline consumption growth rate, change in US ethanol production	Yes	Monthly	January 1994–February 2010			x			x	x	x
Natalenov et al. (2011)	VECM; TVECM	Crude oil, cocoa, coffee, corn, soybeans, soybean oil, wheat, rice, sugar and gold futures prices	No	Monthly	July 1989–February 2010	x					x	x	x
Nazlioglu (2011)	TY and DP causality tests	World corn, soybean, wheat and oil prices	No	Weekly	January 1994–July 2010	x					x	x	x
Nazlioglu and Soytas (2011a)	Panel cointegration; VECM	World prices for 24 agricultural commodities (grains, oils, meats, beverages and other food prices), world crude oil price and USD exchange rates	No	Monthly	January 1980–February 2010	x					x	x	x
Nazlioglu and Soytas (2011b)	TY causality	World crude oil prices, Turkish lira–USD exchange rate, Turkish wheat, maize, cotton, soybeans and sunflower prices	No	Monthly	January 1994–March 2010	x					x	x	x
Peri and Baldi (2010)	TVECM	European sunflower oil, rapeseed oil, soybean oil and diesel prices	No	Weekly	January 2005–November 2007	x					x	x	x
Pokrivcak and Rajcaniova (2011)	Cointegration; VAR	German ethanol and gasoline and Europe Brent crude oil prices	Yes	Weekly	January 2000–October 2009			x		x		x	x
Qiu et al. (2012)	Structural VAR	US crude oil, gasoline ethanol and corn prices, world oil supply, US ethanol and corn supply, US gasoline consumption, Consumer Price Index and Baltic Exchange Dry Index.	Yes	Monthly	January 1994–October 2010		x			x		x	x
Rajcaniova and Pokrivcak (2011)	VECM	EU oil and gasoline prices, German bioethanol, maize, wheat and sugar prices	Yes	Weekly	April 2005–August 2010	x			x			x	x
Rapsomanikis and Hallam (2006)	TVECM	Brazilian ethanol and sugar prices, world crude oil prices	Yes	Weekly	July 2000–May 2006	x				x		x	x
Rosa and Vasciaevo (2012)	VECM	US and Italian wheat, corn, soybean prices, crude oil price	No	Weekly	January 2002–December 2010	x					x	x	x
Saghaian (2010)	VECM	US crude oil, ethanol, wheat, corn and soybean prices	Yes	Monthly	January 1996–December 2008	x				x		x	x
Serra et al. (2011a)	STVECM	US ethanol, corn, gasoline and world crude oil prices	Yes	Monthly	January 1990–December 2008	x			x			x	x
Vacha et al. (2012)	Wavelet transform, coherence and phase	US gasoline, German diesel, crude oil, corn, wheat, soybeans, sugarcane, rapeseed oil, ethanol and biodiesel prices.	Yes	Weekly	November 2003–February 2011	x					x	x	x
Wixson and Katchova (2012)	TVECM	US soybean corn, wheat, oil, ethanol prices	Yes	Monthly	January 1995–December 2010	x				x		x	x
Yu et al. (2006)	Cointegration	World soybean oil, sunflower oil, rapeseed oil, palm oil and crude oil prices	No	Weekly	January 1999–March 2006		x				x	x	x
Zhang and Reed (2008)	VARMA	World crude oil, China corn, soy meal and pork prices	No	Monthly	January 2000–October 2007		x				x	x	x
Zhang et al. (2010)	VECM	US prices for ethanol, gasoline, corn, soybeans and wheat; free market sugar price; Thailand rice price; international crude oil price	Yes	Monthly	March 1989–July 2008		x			x		x	x
Ziegelback and Kastner (2011)	TVECM	European rapeseed and heating oil futures prices	No	Daily	January 2005–December 2010	x					x	x	x

Table 2
Summary of the time-series literature on biofuel markets. Price volatility models.

Reference	Time-series modeling approach	Time-series variables used	Are biofuel prices used?	Data frequency	Period of study	Do biofuel or energy prices affect feedstock prices in the long run?			Do biofuel prices affect fossil fuel prices in the long-run?			Do biofuel or energy prices transmit volatility to feedstock prices?			Do biofuel prices transmit volatility to fossil fuel prices?		
						Yes	No	Not studied	Yes	No	Not studied	Yes	No	Not studied	Yes	No	Not studied
Alom et al. (2011a)	VAR; GARCH; ARMA-GARCH; BEKK-MGARCH	World crude oil; Asia and Pacific food producer price indexes	No	Daily	January 1995–April 2010		x				x	x					x
Bailis et al. (2011)	GARCH; VECH-MGARCH	US ethanol and gasoline; corn production	Yes	Monthly	January 2000–January 2010			x			x			x			x
Balcombe (2011)	Random parameter model	Cereals, vegetable oils, meat, dairy, cocoa, coffee, tea, sugar, cotton, crude oil world prices; US interest and exchange rates, stocks, agricultural yields and exports of agricultural commodities	No	Monthly, quarterly, annual	Variable, depending on commodity			x			x	x					x
Busse et al. (2010)	DCC-MGARCH	Brent crude oil, EU rapeseed and rapeseed oil, EU soybean and soybean oil prices	No	Daily	1999–2009			x			x	x[a]					x
Du et al. (2011)	SVMJ	Crude oil, US corn, US wheat futures prices; crude oil inventories; a proxy for speculation and a proxy for scalping	No	Weekly	November 1998–January 2009			x			x		x				x
Du and McPhail (2012)	DCC-MGARCH; Structural VAR	US ethanol, corn and crude oil futures	Yes	Daily	March 2005–March 2011		x			x		x[a]			x[a]		
Harri and Hudson (2009)	VECM-MGARCH; VAR-MGARCH; Chung and Ng test	US corn, soybean, soybean oil, cotton, wheat, futures prices, crude oil futures prices, USD exchange rate.	No	Daily	April 2003–March 2009	x					x	x					x
Nazlioglu et al. (2012)	Univariate GARCH; Hafner and Herwartz test	World oil, wheat, corn, soybean and sugar prices	No	Daily	Jan 1986–March 2011			x			x	x					x
Onour and Sergi (2011)	BEKK-MGARCH	World crude oil, fertilizer, wheat and corn prices	No	Monthly	January 1992–February 2011			x			x	x					x
Serra (2011)	VECM-BEKK-MGARCH	International crude oil, Brazilian ethanol and sugar prices	Yes	Weekly	July 2000–November 2009		x			x		x			x		
Serra et al. (2011b)	VECM-BEKK-MGARCH	International crude oil, Brazilian ethanol and sugar prices	Yes	Weekly	July 2000–February 2008		x			x		x			x		
Serra and Gil (2012a)	BEKK-MGARCH	Spanish diesel and biodiesel prices; crude oil international price	Yes	Weekly	November 2006–October 2010			x		x				x			x
Serra and Gil (2012b)	VECM-BEKK-MGARCH	US corn, US ethanol prices; US corn stocks; US interest rate	Yes	Monthly	January 1990 – December 2010	x					x	x					x
Trujillo-Barrera et al. (2012)	Univariate TGARCH; Bivariate VECM-BEKK-MGARCH	WTI crude oil, US ethanol, US corn futures prices	Yes	Daily	July 2006–January 2011		x			x		x					x
Wu et al. (2011)	Univariate TGARCH; Bivariate VECM-BEKK-MGARCH	Crude oil, US corn cash, US corn futures prices; US fuel consumption	No	Weekly	January 1992–June 2009		x				x	x					x
Zhang et al. (2008)	BEKK-MGARCH	Brazil ethanol, US ethanol, US gasoline prices	Yes	Monthly	May 1998–March 2007			x			x			x			Not discussed
Zhang et al. (2009)	VECM-BEKK-MGARCH	WTI crude oil, US gasoline, US ethanol, US corn, US soybean prices	Yes	Weekly	March 1989–December 2007		x		x				x			x	

[a] The conclusion is based on volatility correlations.

long-run causality inferences. The rest study long-run causality either through error-correction models (or a generalized version) or Toda and Yamamoto (TY) (1995) and Diks and Panchenko (DP) (2006) causality tests. Besides nonlinear VECM specifications, sample splitting is also used to allow the parameters of the model to change over time. Vacha et al. (2012) and Kristoufek et al. (2012a) are innovative in borrowing methodologies from other research areas to study price links. While the first uses wavelet methods, the second relies on minimal spanning trees and hierarchical trees.

Overwhelming support for the hypothesis that energy prices drive long-run world agricultural price levels is found. Ciaian and Kancs (2011a, 2011b) find cointegration between crude oil and a range of food commodities that grows over time. This is compatible with the increasing relevance of the biofuel price transmission channel in establishing a link between energy and food markets. Granger causality supports unidirectional causality from crude to agricultural prices. While crude oil drives US feedstock prices, it does not drive these prices in Italy (Rosa and Vasciaevo, 2012). A binding blend wall has been shown to weaken the relationship between feedstocks and fossil fuel prices (Abbott, 2012; Tyner, 2010). Consistently, Natalenov et al. (2011) find crude oil cointegration with soybeans, soybean oil and corn to have vanished in recent years. A rather puzzling result in Natalenov et al. (2011) is that long-run causality is generally found to flow from food commodities towards crude oil.

Nazlioglu and Soytas (2011a) appraise the link between world crude oil prices, USD exchange rates and a long list of world agricultural commodity prices. Both crude oil prices and exchange rates are found to determine agricultural prices, being the impact of exchange rates stronger. Nazlioglu (2011) finds evidence of cointegration between corn, soybean and wheat with oil prices, specially in recent years. DP tests provide evidence of nonlinear causality running from oil to agricultural prices. Yu et al. (2006), who focus on the relationship between crude oil and edible oil prices, do not find evidence of energy prices driving food prices.

Cooke and Robles (2009), Chen et al. (2010), Esmaeili and Shokoohi (2010), Gilbert (2010) and Kristoufek et al. (2012b) analyses are based upon autoregressive models (VAR and autoregressive distributed lag models — ARDL) that only allow drawing short-run causality inferences. Cooke and Robles (2009) explain recent increases in world corn, wheat, rice and soybean prices as a function of oil prices and a series of economic indicators (exchange rates, speculation in futures markets, demand, exports, etc.). While speculation in futures markets is always found to be relevant, other variables are only influential for a particular case or not influential at all. Chen et al. (2010) find evidence of positive short-run links between crude oil and grain prices, which are attributed to the influence of biofuels (the links are specially relevant during high crude oil price periods). Esmaeili and Shokoohi (2010) investigate co-movement of world food prices, oil prices and different macroeconomic variables. Crude oil prices are found to influence food prices only indirectly through the food production index. Gilbert (2010) explains the evolution of different International Monetary Fund (IMF) food price indices as a function of crude oil and different economic indicators. Correlation between oil and food prices results from common causation and not from a direct causal link, which involves that biofuels' influence on recent price spikes may not have been relevant. Vacha et al. (2012) and Kristoufek et al. (2012a, 2012b) study US and German biofuel markets. Though a generalization of their results is difficult to make, they find biodiesel prices to be more connected to fuel prices, while ethanol is more related to food prices.

Rapsomanikis and Hallam (2006) and Balcombe and Rapsomanikis (2008) use ethanol, sugar and crude oil prices to investigate the Brazilian ethanol industry. Both articles rely on generalized (non-linear) versions of error-correction models. While sugar–oil and ethanol–oil are found to be nonlinearly cointegrated, ethanol–sugar prices are linearly cointegrated. Both articles provide evidence that crude oil prices drive long-run feedstock price levels, while the latter drive long-run biofuel prices. The Brazilian ethanol industry is not found able to influence crude oil long-run price levels.

The German biodiesel market is analyzed in Busse et al. (2012), while the German ethanol industry focuses the attention of Rajcaniova and Pokrivcak (2011) and Pokrivcak and Rajcaniova (2011). Methodological approaches include a regime-dependent MS-VECM (specially adequate when market or policy changes make parameter constancy not plausible) (Busse et al., 2012), a VECM and a VAR, the latter being estimated after discarding cointegration. Equilibrium feedstock prices are usually found to be influenced by energy prices. No evidence that feedstock prices drive long-run biofuel price levels is found. Two out of the three studies depicts biofuel prices as unable to affect equilibrium fossil fuel prices.

Busse et al. (2012) find evidence of cointegration between diesel and biodiesel prices, the latter being the endogenous variable, as well as between biodiesel, soybean and rapeseed prices, being the latter the endogenous variable. Rajcaniova and Pokrivcak (2011) confirm the existence of cointegration between the following pairs of prices after 2008: bioethanol–oil; bioethanol–maize; oil–maize; oil–wheat; oil–sugar. There is long-run unidirectional causality from energy to agricultural commodity prices and a bidirectional link between bioethanol and oil. Pokrivcak and Rajcaniova (2011) study the links between ethanol and fossil fuel prices and find no evidence of cointegration.

Other countries or geographic areas studied include the EU, Turkey, China and Spain. Of these studies, only the Spanish paper uses biofuel prices. Methodological approaches comprise nonlinear versions of VECM (Hassouneh et al., 2011; Peri and Baldi, 2010; Ziegelback and Kastner, 2011), TY long-run causality (Nazlioglu and Soytas, 2011b), and vector autoregression moving-average (VARMA) models (Zhang and Reed, 2008). Peri and Baldi (2010) appraise the links between biodiesel feedstock prices and diesel prices within the EU. Only rapeseed oil prices are found to be cointegrated with diesel prices, being the latter exogenous for long-run parameters.

Nazlioglu and Soytas (2011b) study the relationship between crude oil and Turkish prices for energy-intensive crops and conclude that oil prices do not generally Granger cause Turkish food prices. Zhang and Reed (2008) study how crude oil prices influence food prices in China. Cointegration analysis depicts crude oil prices as unable to trigger long-run responses in food prices. Hassouneh et al. (2011) study the Spanish biodiesel industry. Evidence of a single cointegration relationship among crude oil, biodiesel and sunflower oil prices is found, being biodiesel the only endogenous variable for long-run parameters. Ziegelback and Kastner (2011) study dynamic price adjustment of rapeseed and heating oil in the EU by allowing for asymmetries. Rapeseed and oil prices maintain a long-run equilibrium relationship. Rapeseed adjusts to this parity only when its level is too low. Rather puzzling is however the result that the oil price also adjusts to this parity when it is too cheap relative to rapeseed.

Most of the articles reviewed in this section rely on spot prices, being the use of futures prices less common.[6] Analyses using futures prices are: Zhang and Reed (2008), Chang and Su (2010), Chen et al. (2010), Zhang et al. (2010), Natalenov et al. (2011) and Ziegelback and Kastner (2011). The Chicago Board of Trade (CBOT) usually serves as a source for agricultural (and occasionally for ethanol) futures prices. Crude oil futures prices are frequently obtained from the New York Mercantile Exchange (NYMEX). The US Energy Information Administration (EIA) is a source for crude oil cash prices and the Nebraska Energy Office and the Renewable Fuels Association (RFA) for US ethanol cash price data. Brazilian ethanol cash prices are usually obtained from the Centre for Advanced Studies on Applied Economics (CEPEA). Agricultural cash prices are often obtained from the US Department of

[6] A new strand of literature is however paying attention to the links between grain cash prices and energy futures prices (see, for example, Chang et al., 2012 or Demirer et al., 2012).

Agriculture (USDA), CEPEA and the Food and Agriculture Organization (FAO) of the United Nations for US, Brazil and international studies, respectively.

Most of the analyses reviewed in this section provide evidence that biofuel and/or crude oil prices affect agricultural price levels in the long-run. Further, a majority of the studies based on biofuel prices support that biofuels do not have a long-lasting impact on fossil fuel energy prices, which is compatible with the small size of the biofuels market relative to the fossil fuels market.

4. Price volatility interactions among biofuel-related markets

The commodity price boom that took place in the second-half of the 2000s decade has drawn considerable interest among academics. The outbreak of the biofuels market has been pointed as one of the reasons for increased price levels and volatility (Gilbert, 2010; Meyers and Meyer, 2008). The following lines review seventeen recent empirical research articles shedding light on volatility in biofuel markets (Alom et al., 2011a; Bailis et al., 2011; Balcombe, 2011; Busse et al., 2010; Du and McPhail, 2012; Du et al., 2011; Harri and Hudson, 2009; Nazlioglu et al., 2012; Onour and Sergi, 2011; Serra, 2011; Serra and Gil, 2012, in press; Serra et al., 2011b; Trujillo-Barrera et al., 2012; Wu et al., 2011; Zhang et al., 2008, 2009).[7]

The reviewed literature can be classified on the basis of the data used into two categories, depending on whether the empirical analysis relies on biofuel prices or not. Another classification can be established on the basis of whether data are representative of US, Brazil, EU or world markets. Out of the reviewed articles, five investigate the links between biofuel, gasoline and/or crude oil and biofuel feedstock prices (Du and McPhail, 2012; Serra, 2011; Serra et al., 2011b; Trujillo-Barrera et al., 2012; Zhang et al., 2009). Serra and Gil (2012a) focus on biofuel-feedstock price links. Zhang et al. (2008), Bailis et al. (2011) and Serra and Gil (2012b) restrict their empirical study to biofuel–fossil fuel price interactions. The remaining authors narrow their research focus on the relationship between fossil fuel and biofuel feedstock prices. The US biofuel industry has attracted attention of more than half of the reviewed studies (Bailis et al., 2011; Du and McPhail, 2012; Du et al., 2011; Harri and Hudson, 2009; Serra and Gil, in press; Trujillo-Barrera et al., 2012; Wu et al., 2011; Zhang et al., 2008, 2009). In terms of research interest, the US market is followed by international markets (Alom et al., 2011a; Balcombe, 2011; Nazlioglu et al., 2012; Onour and Sergi, 2011) and the Brazilian market (Serra, 2011; Serra et al. 2011b). EU markets are assessed by Busse et al. (2010). The use of futures prices is more relevant in volatility studies than in price level analyses (see Busse et al., 2010; Du and McPhail, 2012; Du et al., 2011; Harri and Hudson, 2009; Trujillo-Barrera et al., 2012; Wu et al., 2011), but cash prices continue to predominate. Data sources in volatility studies do not differ from the ones summarized above for price level analyses.

The most common methodological approach adopted by volatility articles is the VECM-BEKK-MGARCH model. While, relative to BEKK, there are more parsimonious specifications of the conditional covariance function, these rarely fully capture price volatility dynamics (Silvennoinen and Teräsvirta, 2008). The DCC-GARCH model used in Busse et al. (2010) and Du and McPhail (2012) measures correlation between price volatilities, but does not allow drawing inferences regarding volatility causality links. Bailis et al. (2011) use a diagonal VECH-MGARCH specification to measure volatility correlation. Harri and Hudson (2009) rely on the Cheung and Ng (1996) test for causality in variance based on the sample cross-correlation function. Nazlioglu et al. (2012) use the Hafner and Herwartz (2006) causality in variance test based on the Lagranger multiplier test. Balcombe (2011) estimates a random parameters model, Du et al. (2011) rely on a stochastic volatility model with Merton jumps (SVMJ), while Serra and Gil (2012b) use copula modeling. Although BEKK models are generally flexible enough to allow volatility causality links to flow in any direction, Alom et al. (2011a), Wu et al. (2011) and Trujillo-Barrera et al. (2012) force unidirectional spillovers from crude oil to food and biofuel markets.

The following lines discuss research results. Since most of the articles not only investigate price volatility, but also price level behavior, results regarding price level links are also commented. Papers studying long-run causality from biofuel (or crude oil) to feedstock price levels conclude that feedstocks are not driven by energy markets (Alom et al., 2011a; Du and McPhail, 2012; Serra, 2011; Serra et al., 2011b; Trujillo-Barrera et al., 2012; Wu et al., 2011; Zhang et al., 2009). An exception is Serra and Gil (2012a). Few studies are able to inform on long-run causality flowing from biofuel to crude oil price levels. They conclude that neither the US, nor the Brazilian biofuel markets shape crude oil prices (Du and McPhail, 2012; Serra, 2011; Serra et al., 2011b; Trujillo-Barrera et al., 2012). Equilibrium biofuel price levels are usually found to be driven by feedstock prices. While most of the price-transmission literature focusing solely on price levels concludes that energy prices drive long-run agricultural price levels (see previous section), volatility analyses fail to provide evidence of this fact. Previous work has shown that linearities in price level links should not be expected to hold. Failure to allow for nonlinearities may lead to failure to identify long-run causality. While articles focusing on price level behavior have allowed for nonlinearities, price volatility studies have not.

Energy markets are found able to induce volatility into feedstock markets (Alom et al., 2011a; Balcombe, 2011; Du and McPhail, 2012; Harri and Hudson, 2009; Nazlioglu et al., 2012; Onour and Sergi, 2011; Serra, 2011; Serra and Gil, in press; Serra et al., 2011b; Trujillo-Barrera et al., 2012; Wu et al., 2011). Volatility spillovers from energy to food markets are found to have increased since the outbreak of the biofuels industry in the second half of the 2000s. Some studies however show that volatility effects are small and do not last long in time. Evidence of causality in the opposite direction, implying that feedstock price turbulences are passed on to energy prices is also provided both for Brazilian, world and US biofuel markets (Alom et al., 2011a; Du and McPhail, 2012; Harri and Hudson, 2009; Nazlioglu et al., 2012; Onour and Sergi, 2011; Serra, 2011; Serra and Gil, in press; Serra et al., 2011b; Trujillo-Barrera et al., 2012; Zhang et al., 2009). Mild evidence of biofuel markets bringing on instability in crude oil prices is found (Du and McPhail, 2012; Serra, 2011; Serra et al., 2011b).

5. Summary of the literature and proposals for further research

The biofuel-related time-series literature has devoted much attention to the analysis of price-levels and has mainly concluded that energy prices drive long-run agricultural price levels. A minority of studies that have explicitly modeled price volatility and volatility interactions, have provided evidence that instability in energy markets is transferred to food markets, and that spillovers are specially intensive since the second-half of the 2000s decade, due to the outbreak of the global biofuels industry. These results have important policy implications. Policies promoting biofuel production and use may drive agricultural commodity prices up. While this may stimulate rural economic growth, it can be specially harmful for consumers that spend a high percentage of income on food. An increase in feedstock prices is also likely to harm biofuel competitiveness in the liquid fuels market, increasing the need for subsidization and other protectionist policies. The food industry might see its economic results diminished. In this regard, promotion of second generation biofuels not based on food crops, will reduce competition for agricultural land and crops, reducing the impact on agricultural prices. Another implication of research results is that the influence of energy prices on feedstock prices should be explicitly considered for the purpose of forecasting food prices and designing food policies (Alom et al., 2011a). Recent research has recognized that the

[7] Other recent articles on price volatility spillovers not specifically addressing the food versus fuel debate include Dahl and Iglesias (2009), Alom et al. (2011b) and Gallo and Otranto (2008).

second moment of price variables is very likely to have relevant economic impacts (Prakash, 2011). Energy price volatility is likely to be transferred to feedstock price. This may harm food producers and consumers, specially in developing economies, where risk coping strategies are scarce. Biofuel promotion policies are thus non-trivial and are very likely to have impacts that extend beyond the biofuel industry.

Since the biofuel-related price transmission literature, and specially the price volatility literature, is still very young, a number of research questions are still open. Some of these gaps are reviewed here. Derivation of empirical results not compatible with economic fundamentals is not rare within the time-series literature. Zhang et al. (2009) for example, find that corn drives crude oil prices.[8] Integrating economics into econometric time-series analyses is a major theme for further research. Some attempts are noteworthy, such as the work by Wu et al. (2011) that specifies volatility spillovers from crude oil to corn as a function of the ratio of fuel ethanol consumption to gasoline consumption, or the work by Carter et al. (2012).

While price level studies that allow for nonlinearities in price patterns are not rare, previous volatility research papers have relied upon the assumption that positive and negative market shocks have a symmetric impact on volatility. Hence, we still don't know whether biofuel price increases have the same impacts on agricultural price volatility than price declines, or whether biofuel price volatility gets worse during crude oil price increases than during crude oil price declines. Asymmetric MGARCH modeling approaches could be used to shed light on this question. Introducing nonlinearities in the conditional mean equation of GARCH models is also an unresolved matter.

Another characteristic common to previous price transmission studies is that they are generally focused on the biofuel marketing chain (by investigating how prices are transmitted between biofuels, crude oil and biofuel feedstock markets). Since biofuel feedstocks are not only used to produce energy, but also food products such as meat or flour, a biofuel-induced change in feedstock price behavior may eventually influence agricultural prices. It would thus be interesting to assess how price level changes and volatility are transmitted along the food market chain. This could be simply achieved by increasing the range of prices considered in the analysis.

Another research question worth answering is the relative impact of biofuels on agricultural price levels and volatility, compared to other price behavior influences that have been pointed out by previous research such as increased speculation in agricultural commodity futures markets, storage behavior, macroeconomic conditions, etc. (Balcombe, 2011; Cooke and Robles, 2009; Wright, 2011).

While biofuel policies target different objectives, one objective that merits further research is the capacity of biofuels to reduce the exposure of national economies to extreme energy price fluctuations that can harm the whole economy (Ferderer, 1996; Vedenov et al., 2006). Assessing this issue is specially relevant in light of the evolution of energy prices since the second half of the 2000s. Future research should thus aim at investigating to what extent biofuels have the capacity, relative to fossil fuels such as diesel or gasoline, to soften the impact of extreme crude oil price changes. This could be easily accomplished, for example, through the use of copula modeling (Patton, 2006). Serra and Gil (2012) represent a first attempt to move along these lines.

To our knowledge, no comparative studies have been conducted that provide a scientific assessment of the reasons underlying result differences across different approaches. Differences in methodology, data types and markets being studied do not allow comparison across different papers. Comparative analyses are thus needed to shed light on the impacts of policy instruments or market characteristics on research results.

[8] It is also true that theoretical models are based on assumptions that may not be satisfied with high frequency data.

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