Modeling and Analysis

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Price transmission between biofuels, fuels, and food commodities

Ladislav Kristoufek, Academy of Sciences of the Czech Republic, Prague, Czech Republic, and Charles University, Prague, Czech Republic
Karel Janda, Charles University, Prague, Czech Republic and University of Economics, Prague, Czech Republic
David Zilberman, University of California, Berkeley, CA, USA

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Abstract: For the biofuel markets and related commodities, we study their price transmission, which is in fact equivalent to studying price cross-elasticities. Importantly, we focus on the price dependence of the non-linear price transmission mechanism. We discuss several methodological caveats. Specifically, we combine the memory robust feasible generalized least squares estimation with two-stage least squares to control for endogenity bias and inconsistency. We find that both ethanol and biodiesel prices are responsive to their production factors (ethanol to corn, and biodiesel to German diesel). The strength of transmission between both significant pairs increased remarkably during the food crisis of 2007/2008. © 2013 Society of Chemical Industry and John Wiley & Sons, Ltd

Keywords: biofuels; price transmission; non-linearity; elasticity

Introduction

The development of biofuels is key to tackling the interrelated problems of climate change and food and energy security. Early economic research of biofuels[1] was very much concerned with engineering-like calculations of transformation ratios among basic food commodities used for the production of biofuels, with energy and greenhouse gas (GHG) emission comparisons between biofuels and fossil fuels, and with the evaluation of the economic effects of biofuel mandates and subsidies. The most important economic research questions related to the current development of biofuels are far more concerned with their price characteristics and cross-relationships as basic building blocks for economic modeling of indirect land use changes (iLUCs) related to biofuel production and consumption.[2,3]

Price linkages between the food, energy, and biofuel markets have therefore become one of the most discussed topics for energy, environmental, and agricultural economists interested in the question of sustainable development of biofuels.[4–8] A unique feature of our paper is that we consider price transmission in both major biofuel production lines and that we include all of the most relevant commodities (crude oil, fossil fuels, biofuels, agricultural feedstock) in our econometric analysis. This is a major step forward as compared to the literature dealing only with crude oil and agricultural commodities,[9–14] only with fossil fuels and biofuels,[15,16] only with biofuels and agricultural commodities,[17,18] or only with one type of biofuel.[19,20] It is especially common that fossil fuels (gasoline or diesel) are not directly included in the analysis.[21] A further advantage is that our paper is not restricted to one particular country like the USA, which receives major attention in the biofuel

Correspondence to: Ladislavl Kristoufek, Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Pod Vodarenskou vezi 4, 182 08, Prague, Czech Republic, and Institute of Economic Studies, Faculty of Social Sciences, Charles University in Prague, Opletalova 26, 110 00, Prague, Czech Republic. E-mail: kristouf@utia.cas.cz

time series literature. Besides the US market, we focus also on the European market as represented by the EU's most advanced biofuel economy – Germany. We analyze price transmission between prices of the two most-used biofuels (ethanol and biodiesel), related feedstock, and fossil fuels. Moreover, we focus on potential price dependencies of the transmission mechanism, i.e. whether the connections and effects between specific pairs of commodities change with the price level of one of them.

An important novelty of our approach lies in its methodology. We show that the prices of ethanol and biodiesel are strongly trending in time and are seasonal. After controlling for these effects, the series neither contain a unit root nor are fractionally integrated, implying that neither cointegration nor fractional cointegration should be used for their analysis as is frequently done in the literature.[15,22–24] Obviously these studies used a different data set than our paper. Our empirical results therefore do not imply that these studies were wrong, but they emphasize the need for checking the validity of assumptions allowing the use of cointegration techniques after controlling for time trends and seasonality. As the series remain weakly dependent, we apply Prais-Winsten methodology to control for such dependence. Moreover, the biofuel system is suspected to include at least several endogenous variables. To control for this, we apply a combination of Prais-Winsten methodology and a two-stage least squares approach. Such an approach is very novel in the biofuels-related literature. Controlling for all the mentioned effects, we find that ethanol is significantly connected to corn and crude oil, while biodiesel is mainly connected to German diesel. Other transmission effects are either economically (with a low practical impact) or statistically insignificant. We also find that the significant price transmission is price-dependent. The price dependence is most visible for the ethanol-corn pair; it is close to zero for average prices of corn but can climb up to almost unity for high historical prices. As the price of commodities evolves over time, we are able to transform the price-dependent transmission effects into time-dependent ones. By doing so, we show that the price transmission mechanism between the analyzed commodities varies over time while the most interesting dynamics was observed for the year 2008, which is considered the year of the global food crisis.

Our paper is solely concerned with price analysis. This is consistent with a large literature which aims to understand linkages between the prices of different fuels. But prices are the outcome of a system that includes factors of quantity, supply, and demand, etc. Therefore, prices are affected by all of these variables and to some extent they provide an understanding of how different related markets operate. This is very important for the construction of economic models of iLUC[25,26] caused by biofuels. As opposed to early models of direct LUCs, which were typically based on energy and biology related transformation processes, iLUC is a complex process driven by the economic (price) effects on demand and supply and as such may be estimated through detailed economic models. As explained for example by Finkbeiner,[27] the economic equilibrium approach and cause-effect deterministic approach are two main approaches currently used in life cycle assessment studies dealing with iLUC.

Our results suggest that economic models of iLUC should not assume constant cross-price elasticities (price transmissions) among various elements of the biofuel production and consumption cycles. We also confirm that iLUC models should take into account the dynamics of the transmission mechanism related to extreme price changes during food crises. More generally, our price- and time-dependent price transmissions are very appropriate for modeling the effects of biofuels in the era of general commodity price increase, commonly reflected since the start of the 2007/2008 food crisis, as opposed to the long period of a relative commodity price stability which was characteristic for the earlier period.

The paper is organized as follows. Next we describe our methodology in some detail. This is followed by a detailed description of the data set as well as comments on its trending and seasonality. We then present the results for the price transmission mechanism and finally conclude.

Methodology

Theoretical framework

The biofuel market can be treated as a standard economic market with a market-clearing price determined by a supply and a demand for the commodity. In a partial equilibrium framework based on Serra *et al.*,[21] the basic characteristics of the biofuel markets – technological and regulation constraints – are included. In the standard equilibrium without constraints, biofuel prices are set at the intersection E of the biofuel demand curve $D(P_B, P_G)$ and the biofuel supply curve $S(P_B, P_F)$ in Fig. 1, where P_B, P_F, P_G are the prices of relevant biofuel, its feedstock, and an appropriate fossil fuel, respectively. The price of biofuel increases with a demand curve shift caused by the increasing price of the relevant fossil fuel, eventually reaching a new equilibrium level E_1 with a higher price and quantity. A supply curve shifts with an increasing feedstock price

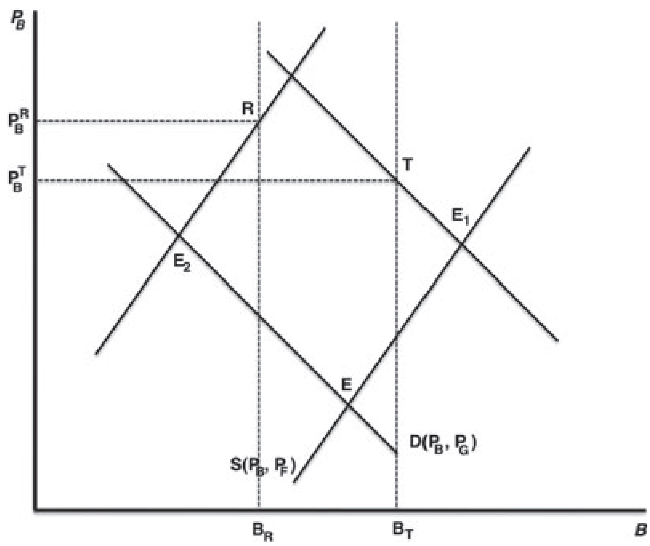

Figure 1. Determination of price of biofuel. Equilibria E_1 and E_2 are unattainable under active regulations B_R and technological constraints B_T when supply and demand functions *S* and *D* move from the original attainable equilibrium *E*.

leading to a new equilibrium E_2 with a higher price and a lower quantity. This simple unrestricted equilibrium analysis implies that at least in the long term, the movements in prices of biofuels, fossil fuels and feedstock are strongly positively correlated and the changes in biofuel prices are caused by the behavior of the feedstock and fossil fuels.

However, important drivers of biofuel development are regulatory supports like mandates, blending obligations, subsidies, technological feasibility (production capacities and technological possibilities of biofuel utilization), etc.[28,29] Accounting for this, the description of supply and demand in Fig. 1 includes regulatory and technological constraints denoted by vertical straight lines through points B_R and B_T, respectively. Taking these constraints into account, we obtain minimum and maximum possible quantity of a specific biofuel on the market. Therefore, equilibria E_1 and E_2 are no longer attainable. Resulting non-equilibrium market situations *T* or *R* are associated with biofuel prices P_B^T or P_B^R, respectively, which are higher than for the equilibrium situations E_1 and E_2.

In effect, the technological and regulatory constraints influence the shape of the supply and demand curve, respectively. The demand curve is a vertical line overlapping with the line of the constraint down to the intersection with the unrestricted demand curve and then behaves just as a standard decreasing demand function. In a similar way, the supply curve is increasing with quantity up to the intersection with the technological constraint where it becomes a vertical. When the constraints are taken as fixed, both the demand and supply functions change their shape when the prices of relevant fossil fuels or feedstock, respectively, increase or decrease, i.e. they are not just shifted one way or another. Moreover, we can consider the constraints as being variable (either in time, or for individual market agents so that they change on an aggregate level) or not precisely definable. This may lead to demand and supply functions which are not just broken linear functions but rather non-linear functions converging to the constraint. One way or another, there is a strong possibility that the demand and supply functions are not linear and are likely to change their shape, which leads to possibly price-dependent links and co-movements between commodities. This non-linear time-evolving dynamics of biofuel prices is investigated in our paper. In our econometric model, we explicitly control for prices P_F and P_G while assuming that efficiently functioning commodity markets incorporate the institutional features of biofuel markets like mandates and blending walls, which we introduced in Fig. 1, into the prices P_B, P_B, and P_G.

Generally, the literature may have some locational emphasis (i.e. considering Brazilian ethanol when looking at sugarcane and US ethanol when looking at corn) but the real underlying assumption is that the global markets are considered implicitly. Yet, in reality, our results suggest that by using data on more markets (US and German markets in our case), we may identify linkages at the commodity level, linkages at the input level, and most importantly, linkages due to time and space. Namely, it is not only substitution in the final use that matters, but the production location and the related substitution of use of inputs among activities matter as well. Furthermore, the time and cost of moving commodities across locations play an important role, too. This is why we find a strong correlation between European and American prices and a low correlation across the world. Even though modern economics speaks about globalized modern markets, there are transaction costs that cause location to matter and affect prices. Location not only means distances: different locations may have different regulations and these result in different patterns of price linkages between biofuel, fossil fuel, and agricultural commodities. Furthermore, another important element is that time-different data tell a different story, and in the long run, relationships between markets are stronger than in the short run.

Price transmission

Econometric estimation of elasticity is often based on an approximation in a log-log specification of a linear regression. When we have variables X and Y and we estimate the model

$$\log Y = \alpha + \beta \log X + \varepsilon, \quad (1)$$

parameter β is then taken as an approximation to elasticity as $\beta = \frac{\delta Y/Y}{\delta X/X}$ which is the definition of the point elasticity of Y with respect to X. In microeconomic demand analysis,[30,31] we usually deal with the elasticity of a demanded quantity with respect to a price, $e_p^d = \frac{\delta Q_d/Q_d}{\delta P/P}$. To analyze whether the relevant pair of goods is a pair of substitutes or complements, we are interested in cross-price elasticities of demand, $e_{pi}^{dj} = \frac{\delta Q_{dj}/Q_{dj}}{\delta P_i/P_i}$. In cases when we have no information about demanded quantities, we might be interested in price elasticities e_{pi}^{pj} defined as $e_{pi}^{pj} = \frac{\delta P_j/P_j}{\delta P_i/P_i}$. To avoid confusion, we call this elasticity a price transmission between assets i and j. This price transmission specifies how the price of a good j reacts to the change in the price of a good i. It can be easily shown[32] that the price transmission parameter is actually a ratio between own-price elasticity of demand and cross-price elasticity of demand for a good j. In words, if $e_{pi}^{pj} > 1$, i.e. the price of a good i reacts more than proportionally to a change in the price of a good j, then the demanded quantity Q_{d_i} is more sensitive to changes in P_i than in P_j.

In the standard framework, all mentioned elasticities are assumed to be constant for all price levels. However, constant elasticities are a strong simplification. Returning to Fig. 1, there is no such restriction on the effect of P_F and P_G on P_B. The effect of P_F on the supply $S(P_B, P_F)$ and the effect of P_G on the demand $D(P_B, P_G)$ may take various forms. The expectations are that the price transmission effect between P_F and P_B is increasing in prices. This might reflect the situation in which the substitution effect between fossil fuels and biofuels is low when the prices of fossil fuels are low as well as the effect of increasing costs which is low when the prices of feedstock are low (and are likely to be offset by subsidies). To analyze such a price dependence of the transmission mechanism, we need to generalize the expression of the elasticity from the original log-log regression in Eqn (1). To obtain the price dependence, we aim to arrive at

$$e_X^Y = \beta + \gamma X + \delta X^2 \quad (2)$$

which captures price dependence to the second-order polynomial (the second-order polynomial is arbitrary here and can be easily generalized to higher orders). This form of the price transmission leads to the following model:

$$\log Y = \alpha + \beta \log X + \gamma X + \frac{\delta}{2} X^2 + \varepsilon \quad (3)$$

The introduced concept of price transmission has an additional advantage over standard constant elasticities in its ability to control for price and, mainly, time dependence. Analyzing the transmission thus enables us to comment on the evolution of the relationship between two price series in time and its connection to relevant events on the corresponding markets. Obviously, the proposed methodology is not restricted only to biofuel markets, as we use it, but can be used on any portfolio of assets. In most cases, we expect that the absolute value of the price transmission effect is lower than one, i.e. that the price of i reacts more to the changes in demanded quantity of asset i than of asset j. However, it might happen that an asset reacts more to the changes of demanded quantity of the other asset, which could be associated with over-reaction of market participants or explosiveness of the prices. Indeed, we find that for biofuel markets, the absolute value of the transmission effects remains below unity and there is not a single period where it is higher than unity on a statistical basis.

To obtain the price transmission effect for ethanol and biodiesel with respect to other commodities, we need to construct models according to Eqn (3) and include the variables of interest in set X. Since we are analyzing time series of the logarithmic prices, we need to carefully check the assumptions of OLS estimation as well as stationarity and possible trending and/or seasonalities. Especially for the time series, the assumption of no auto-correlation in the residuals is crucial. If we find that the auto-correlation in residuals is strongly significant and the detrended/deseasonalized explanatory variables are strongly auto-correlated as well (yet both remain far from a unit-root), OLS becomes inefficient.[33] In such a case, we need to switch to feasible GLS (FGLS) estimation – either Cochrane-Orcutt [34] or Prais-Winsten[35] estimation. Both methods are based on quasi-differencing of the original series (see Kristoufek *et al.*[32] for details). We stick to the Prais-Winsten version as it is more efficient for finite samples. Moreover, the analyzed biofuel system contains variables which are highly interconnected and affected by one another. Therefore, some of the variables might be endogenous, causing the estimates to be inefficient. To control for this, we also apply the two-stage least squares (2SLS) procedure.

To summarize the applied procedures and possibilities of estimation: if the series are stationary after detrending and the residuals of the estimated models are not highly autocorrelated, we apply standard OLS; if the residuals are autocorrelated and the variables are not endogenous, we utilize FGLS; if the residuals are autocorrelated and some variables are endogenous, we apply 2SLS combined with FGLS to obtain consistent estimates. Eventually, we apply the last procedure and the results are presented later, which distinguishes our work from other studies analyzing the price transmission between biofuels and related commodities.

Data description and model specifications

In this section, we carefully describe the dataset and follow with the model specification used for the estimation of the price transmission in the analyzed biofuel system.

Dataset

The main aim of this paper is to analyze the price transmission mechanism between biofuels, their related production factors, and related fossil fuels. Since our focus is on biodiesel and ethanol, we include only relevant agricultural commodities which are used for their production, and only relevant fossil fuels, which are their respective natural substitutes. Our dataset thus contains consumer biodiesel (*BD*), ethanol (*E*), corn (*C*), wheat (*W*), soybeans (*S*), sugarcane (*SC*), crude oil (*CO*), German diesel (*GD*), and US gasoline (*USG*). Corn, wheat, and sugarcane are the feedstock for ethanol; soybeans are the feedstock for biodiesel. As ethanol is mainly the US domain and its natural substitute is gasoline, we include US gasoline. In a similar way, biodiesel is predominantly the EU domain and its substitute is diesel, thence German (as the biggest EU economy) diesel is included. Crude oil (Brent) is included as well because it serves as a production factor for all fuels in our dataset, at least indirectly. A majority of the dataset was obtained from the Bloomberg database (Table 1), the two fossil fuels were obtained from the US Energy Information Administration and they are formed

Table 1. Analyzed Bloomberg commodities.

Commodity	Ticker	Contract type
Crude oil	CO1 Comdty	1st month futures, ICE
Ethanol	ETHNNYPR Index	Spot, FOB
Corn	C1 Comdty	1st month futures, CBOT
Wheat	W1 Comdty	1st month futures, CBOT
Sugarcane	SB1 Comdty	1st month futures, ICE
Soybeans	S1 Comdty	1st month futures, CBOT
Biodiesel	BIOCEUGE Index	Spot, Germany

of the countries' average price. As the price series of the biofuels are very illiquid, we analyze weekly data for the period between November 24, 2003 and February 28, 2011 (Monday closing prices).

Logarithmic prices of the biofuels of interest – ethanol and biodiesel – are shown in Fig. 2. In the charts, we also present the fitted values based on time trend and seasonality. Since weekly data are analyzed, we can work with fact that a year has 52 weeks, which in turn enables us to include various seasonalities (cycles) into the time-trend filtering. We pick an 8-year cycle as the longest (one year longer than the actual length of the dataset due to evenness) and the shortest cycle is taken as 13 weeks, i.e. a quarter of a year. The filtering model looks as follows

$$\log BF_t = \alpha + \sum_{i=1}^{4} \beta_i t^i + \sum_{j=1}^{2} \gamma_j \sin\left(\frac{2\pi t}{13 j}\right) + \sum_{k=1}^{8} \delta_k \sin\left(\frac{2\pi t}{52 k}\right) + \varepsilon_t \quad (4)$$

where $\log BF_t$ is the logarithmic price of the biofuel in time *t*. The first sum represents the polynomial trend, the second and the third sums control for the cyclical components. The insignificant trend and seasonal variables were omitted to arrive at more efficient estimates and thus more accurate

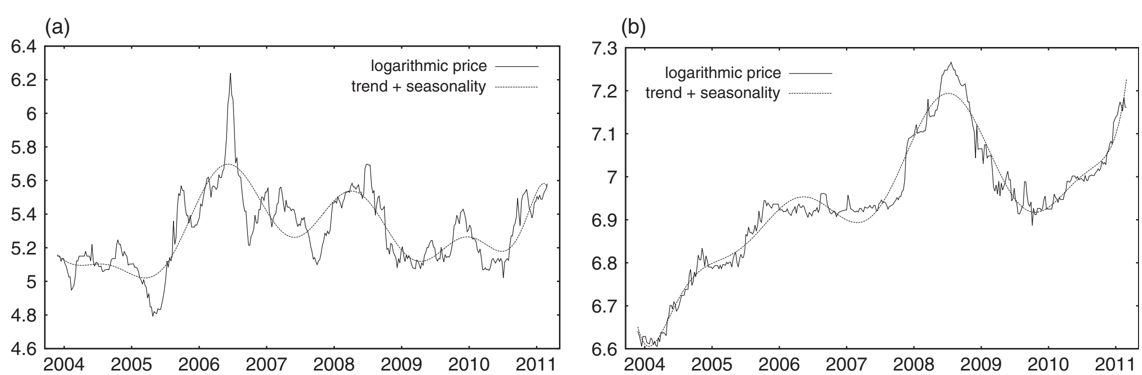

Figure 2. **Logarithmic prices of ethanol (a) and biodiesel (b).** Time trends and seasonal effects are covered in the fitted values shown by the dashed lines.

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Table 2. Unit-root and stationarity Tests.

Series	ADF	p-value	ADF-GLS	p-value	KPSS	p-value
Ethanol log-prices	–2.3265	>0.1	–1.8437	0.0622	1.9377	0.0000
Biodiesel log-prices	–1.5075	>0.1	0.9759	>0.1	11.2302	0.0000
Ethanol detrended	–4.4399	0.0001	–4.4390	0.0000	0.0653	>0.1
Biodiesel detrended	–4.5714	0.0001	–4.3329	0.0000	0.0961	>0.1

Note: the null hypotheses are: 'a unit root series' for ADF and ADF-GLS, 'stationary series' for KPSS.

fitted values. Nevertheless, it is clearly visible that both the time trend and seasonality effects are significant for both biofuels. Therefore, these time and seasonal variables should be included in the final regression estimating the price transmission. Such a procedure is important for correct selection of an appropriate modeling procedure since we need to separate the potential unit roots from the time trend and seasonality effects. On the one hand, if a unit root is found in the variable of interest, it leads to either cointegration techniques (and vector error-correction models) or vector autoregression (VAR) models with differenced series. On the other hand, if a unit root is incorrectly not taken into consideration, the results will be strongly biased, inconsistent, and will very likely lead to the spurious regression which is characteristic by identifying non-existing relationships as statistically significant ones. Therefore, testing for stationarity and unit roots becomes crucial (note that we are predominantly interested in showing that the specific series is or is not unit root so that homoskedasticity is not important in this case). The results for ADF,[36] ADF-GLS,[37] and KPSS,[38] are summarized in Table 2. The results* are straightforward – unit root is not rejected for the original series but is strongly rejected when the series are appropriately detrended and deseasonalized. Even though the detrended series are strongly autocorrelated (the sample first-order autocorrelations are 0.9218 and 0.8354 for ethanol and biodiesel, respectively), they do not contain a unit root. Therefore, standard cointegration and VAR with differences methods cannot be used. Note that detrending and seasonality effects are usually not taken into consideration in the relevant literature, which raises serious questions about correctness of the results and following implications. Therefore, we can proceed with standard least squares estimation. If OLS estimation is found inefficient and inconsistent, which is the case for strongly dependent residuals, we will switch to Prais-Winsten regression. If the estimated models do not pass the Hausman specification test,[39] we apply the 2SLS estimation to additionally control for endogenity. The procedure is thus robust to both strong memory in the disturbances and to endogenous variables.

*We select the set of stationarity tests specifically to have different types of the null hypotheses (ADF tests and KPSS) as well as to have more robust results in case of unknown deterministic trends (ADF and ADF-GLS).

Model specification

As we have shown in the previous section, both the time trend and seasonal effects are significant in the dynamics of the logarithmic prices of ethanol and biodiesel. Therefore, these need to be included in the final model. The general form of the model estimating the price-dependent price transmission while controlling for time and seasonal effects is

$$\log BF_t = \alpha + \sum_{i=1}^{4}\beta_i t^i + \sum_{j=1}^{2}\gamma_j \sin\left(\frac{2\pi t}{13j}\right) + \sum_{k=1}^{8}\delta_k \sin\left(\frac{2\pi t}{52k}\right) + \sum_{l=1}^{I}\xi_l \log P_l + \sum_{m=1}^{I}\varphi_m P_m + \sum_{n=1}^{I}\nu_n P_n^2 + \varepsilon_t$$

where $\log BF_t$ is the logarithmic price of either ethanol or biodiesel in time t and I is the number of impulse variables. In the sums with parameters ξ, φ and ν, the relevant impulse variables are included. Logarithmic, linear and quadratic forms should uncover potential price-dependent relationships between the specific biofuel and relevant commodities and/or other fuels (with reference to Eqn (3)). For ethanol, the set of impulse variables includes corn, wheat, sugarcane, soybeans, crude oil and US gasoline. And for biodiesel, we include corn, wheat, sugarcane, soybeans, crude oil and German diesel. We keep all agricultural commodities of the dataset in both models because we are mainly interested in the possible effect of biofuels on their prices (or vice versa). A single fossil fuel is kept in each regression to avoid collinearity problems as these are highly correlated. From a technological point of view, we expect corn, wheat, sugarcane and US gasoline to influence the dynamics of the ethanol prices, and only soybeans and German diesel to affect biodiesel.

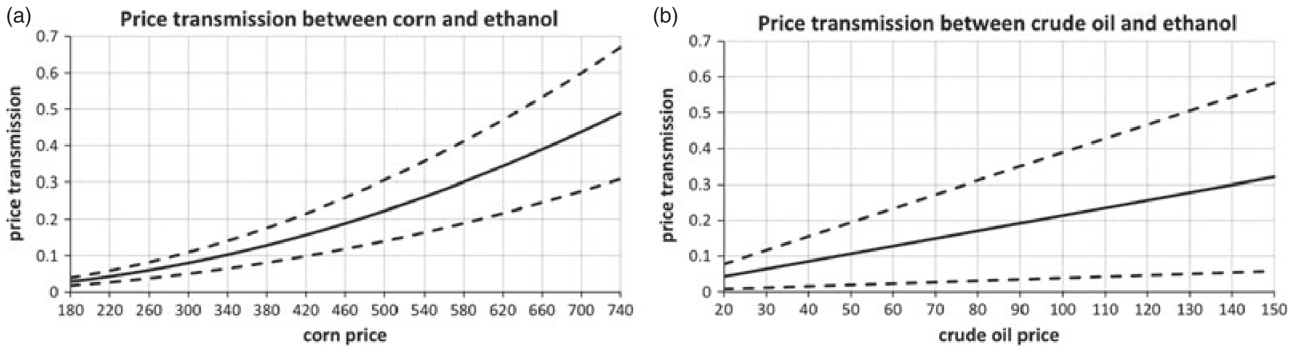

Figure 3. **Price-dependent transmission between ethanol and corn (a) and crude oil (b).** Transmission itself is represented by the black solid line while the 95% confidence intervals are shown in the dashed line.

Results

After running the OLS regression for ethanol price transmission, we arrived at the first-order autocorrelation coefficient of the residuals equal to 0.7609 with the Durbin–Watson statistic equal to 0.4758. The residuals are thus highly positively autocorrelated as suspected, which leads us to more efficient FGLS methodologies. However, the Hausman test statistic comparing FGLS and 2SLS yields 50.99 with a p-value of 0.0236, thus rejecting that the FGLS estimation is consistent, and leading us to the 2SLS procedure.† The estimates for the reduced‡ ethanol model based on 2SLS–FGLS regression are summarized in Table 3. We first observe that the model includes only two impulse variables – corn and crude oil. Price transmission from crude oil to ethanol is linear in prices and from corn to ethanol, it is non-linear. We thus find significantly non-constant cross-price elasticities. Note that the final model explains the behavior of ethanol very well ($R^2 = 0.9574$ for the quasi-differenced variables). The estimated price-dependent price transmission effects are shown in Fig. 3. Here, only corn shows interesting results. Note that the price of corn ranges approximately between $200 and $700. Therefore, most of the time, the elasticity between corn and ethanol is close to zero, and becomes both statistically and economically significant for high prices of corn and attains values up to 0.7. The price dependence of ethanol–crude oil transmission shows a linear dependence on the price of crude oil, but the confidence intervals remain very wide so that for all realistic values of the crude oil price, we remain very close to the zero price transmission.

Table 3. Reduced 2SLS-FGLS model for ethanol.

	Estimate	SE	t-statistic	p-value
const	5.0167	0.1138	44.0982	0.0000
CO	0.0021	0.0009	2.3927	0.0172
C^2	$4.47{*}10^{-7}$	$1.68{*}10^{-7}$	2.3927	0.0083
period	.	.	25.9425	0.0002
time	0.0030	0.0011	2.6385	0.0087
R^2	0.9574		Adjusted R^2	0.9564
$F(9,370)$	128.9732		p-value(F)	0.0000
$\hat{\rho}$	0.0770		Durbin–Watson	1.8453

The results for biodiesel are in general quite similar to those of ethanol. Most importantly, the OLS estimation procedure again yields highly autocorrelated residuals (with the first-order autocorrelation coefficient of residuals of 0.5664 and the Durbin-Watson statistic of 0.8693), which leads to Prais-Winsten regression. However, the Hausman specification test yields a test statistic of 948.79 which implies a p-value of practically zero, which again leads us to the 2SLS-FGLS estimation procedure. The reduced model (Table 4) gives us four statistically significant commodities – corn, wheat, soybean, and German diesel. In Fig. 4, we observe that the price transmissions of corn and soybeans with respect to biodiesel show the same behavior as for the crude oil-ethanol pair, i.e. the

†For the 2SLS procedure, all variables (except for the time and periodic components as well as German diesel for the ethanol equation and the US gasoline for the ethanol equation) are treated as endogenous. The remaining ones are used as exogenous.

‡We follow a step-wise elimination of covariates which are insignificant at the 5% level, i.e. the ones with a p-value above 0.05. This procedure is also applied for the biodiesel model. The *period* and *time* represent the set of significant time trend and periodic components remaining in the reduced model. We report only the summary statistics for all *time* and *period* components for better legibility, i.e. we report the F-statistics for the joint significance rather than the t-statistics for the separate significance.

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Table 4. Reduced 2SLS-FGLS model for biodiesel.

	Estimate	SE	*t*-statistic	*p*-value
const	5.1134	0.4530	11.2877	0.0000
C	0.0001	0.0001	2.4858	0.0134
S	–0.0001	0.0000	–2.6291	0.0147
GD	0.0563	0.0083	6.7616	0.0000
W	–0.0013	0.0003	–4.4844	0.0000
W^2	$5.64*10^{-7}$	$1.23*10^{-7}$	4.5746	0.0000
log*W*	0.3152	0.0909	3.4680	0.0006
time	.	.	287.811	0.0000
period	.	.	216.405	0.0000
R^2	0.9911	Adjusted R^2		0.9907
$F(15,364)$	2493.103	P-value(*F*)		0.0000
$\hat{\rho}$	–0.0605	D–W statistic		2.1157

values of price transmission are statistically very close to zero for all feasible price levels. For wheat-biodiesel price transmission, we observe a non-zero effect only for very extreme prices of wheat. Therefore, the only statistically and economically significant price transmission effect is the biodiesel-German diesel pair. The effect is again price-dependent and reaches values around 0.3 for high prices of German diesel.

By obtaining the estimates of β, γ and δ, we are now able to comment on the time dependence of the price transmission between biofuels and related commodities. With the use of Eqn (2), we are able to construct the time-dependent price transmission controlling for the effects of other variables, time trends, seasonality, autocorrelation and endogenity in the biofuel network. The results for the pairs with statistically and economically significant price transmission effects are summarized in Fig. 5.

Both pairs (ethanol-corn and biodiesel-German diesel) share one main feature – the price transmissions both increase remarkably during the food crisis of 2007/2008. The most evident is the situation for corn and ethanol where we observe a very low price transmission effect, which is very close to zero, between 2003 and the end of 2007, followed by a rapid increase up to values around 0.5 in the middle of 2008 and dropping to nearly zero elasticity from 2009 till the middle of 2010. The price transmission between biodiesel and German diesel reaches lower values than the previous case. Nevertheless, the dynamics shows interesting behavior as well. The values of the price transmission between biodiesel and German diesel start at around 0.1 and grow slowly from the end of 2003 till the first half of 2007. From the second half of 2007, the transmission rockets upwards and reaches its peak in the middle of 2008 with values around

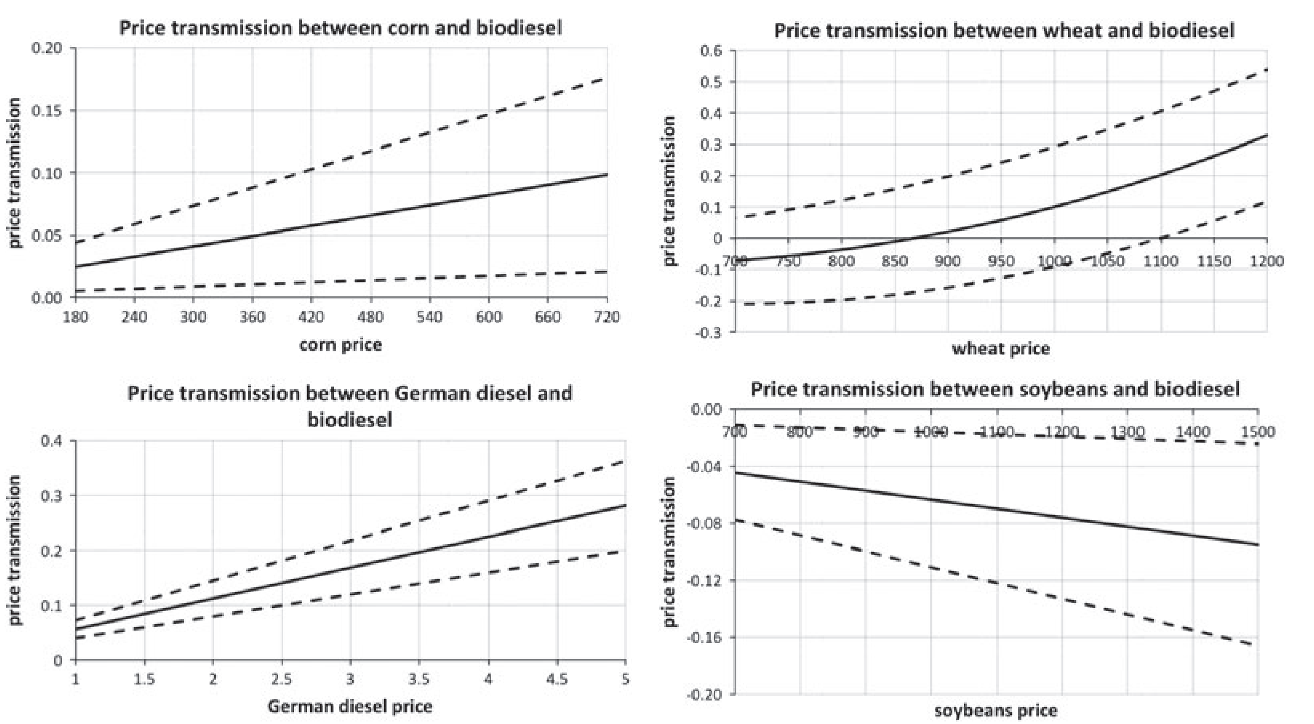

Figure 4. **Price-dependent transmission between biodiesel and corn, wheat, soybeans, and German diesel.** Transmission itself is represented by the black solid line while the 95% confidence intervals are shown in the dashed line.

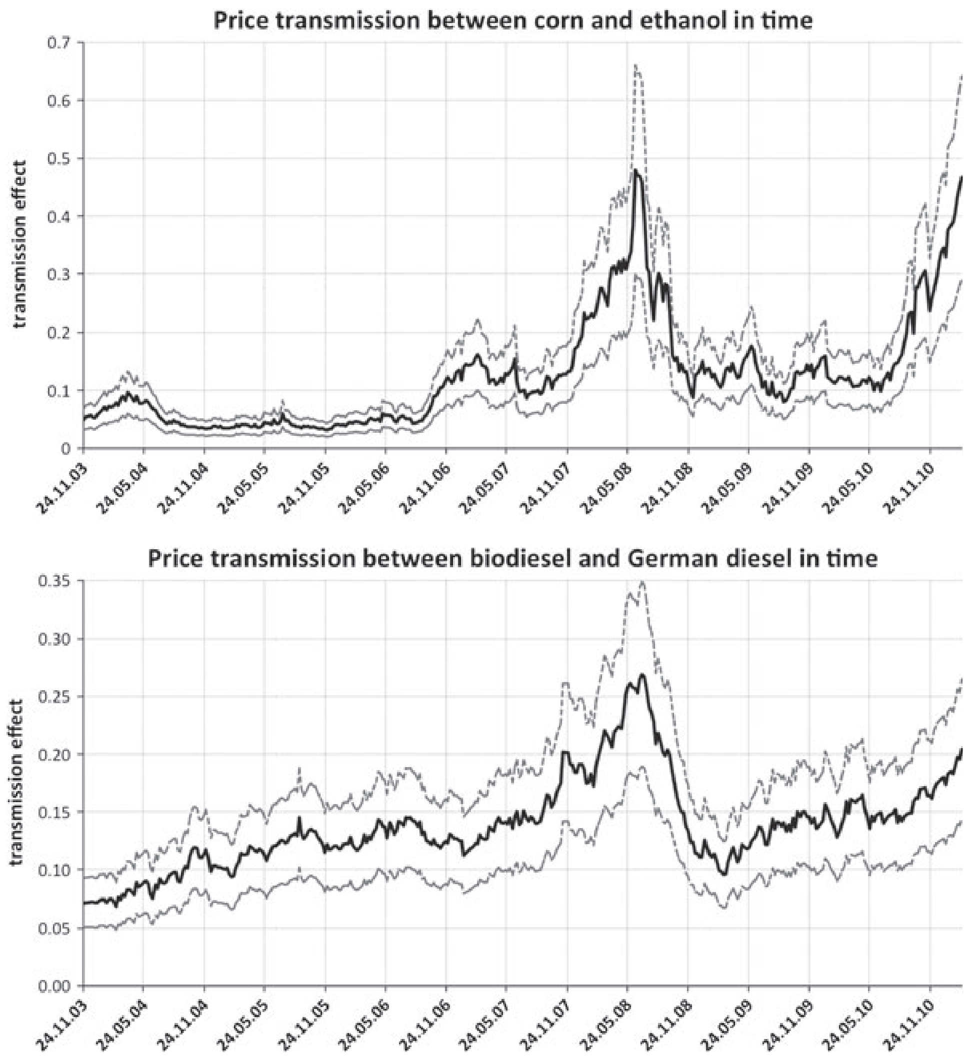

Figure 5. **Price transmission and its evolution in time.** Transmission is represented by the black line and the 95% confidence intervals are shown by the dashed grey lines.

0.3. Similar to the previous pair, it falls back to relatively low values by the end of 2008. Afterwards, the price transmission begins another, rather slow, growing trend.

Conclusions

The main focus of the paper was to analyze potential price and time dependence in price transmission (cross-price elasticities) between series. We found that ethanol prices are elastic with respect to corn and the effect is price dependent. For biodiesel, the only significant price transmission effect was found with German diesel, which is again price dependent. When converting the price dependence into time dependence, we showed that the food crisis of 2007/2008 had a huge effect on the price transmission levels – for both significant pairs (ethanol-corn and biodiesel-German diesel), the transmission increased markedly – starting at the beginning of 2008, reaching its peak in the middle of the year and returning back to pre-crisis values at the end of the same year. The food crisis thus had an enormous, yet short-lived, effect on elasticities between biofuels and related commodities. These results are quite robust compared to previous studies as we take time trends, seasonality, autocorrelation and endogenity of the series into consideration. Our econometric results highlight the need for policymakers to use the appropriate models, not only from the geographical and commodity coverage perspective, but also from the point of view of employing the best applicable estimation techniques and carefully utilizing the appropriate testing and diagnostic tools.

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In this paper, we investigated the linkages between the prices of fuels and related commodities not only as a mechanism to quantitatively understand these markets *per se*, but also to provide a different way of looking at price transmission. A price transmission analysis (e.g. GARCH) that is based on assuming complex multivariate relationships with many lags provides good insight on some aspects, for example the time pattern of the impacts of certain shocks, but at the same time it may conceal other important knowledge. For instance a shock to the price of ethanol in Brazil may differ considerably from a shock to the ethanol price in the USA, and there may be a stronger link between biodiesel and fossil fuel prices in Germany that is greater than one would expect if considering fossil fuels and biofuels generically.

An important general implication of our results is that policymakers in any individual country have to be aware that biofuels are a broad phenomenon, with three leading players – the USA, the EU and Brazil (two of them being covered in this paper). This obviously complicates the analysis, adding new contexts and dimensions to the mere US corn-ethanol dynamics. Any extrapolation of findings from one market to another is difficult, and potentially misleading, as shown in our paper, which displays clear qualitative and quantitative differences between these markets. The challenge for policymakers then comes from a clear imbalance between available literature on biofuels and food prices (overwhelmingly focusing on the US corn-based ethanol, and associated policy and institutional framework with significant country differences even inside seemingly single markets like the US or the EU markets) with respect to the extent of the biofuels question, both in geographic terms and in terms of feedstock and markets, which were all covered in this paper.

Our major result of consistently different price transmission dynamics over the time and market conditions highlights the challenge for policymakers to assess jointly short-term and long-term effects. While the joint occurrence of the 2007/2008 food price spike with the steep rise in biofuel production was pointing to short-term, almost instantaneous price effects (these are mostly negative effects for food security, which is currently the major short-term policy concern connected with biofuels), policymakers should keep in mind that a range of other effects can possibly manifest in the longer term, including more positive effects. While short-term sharp price increments may have severe negative food-security effects, over the long term they may stimulate agricultural investment, improve farm incomes and strengthen rural employment. Feedback mechanisms, therefore, may be positive or negative, and they may also change sign over time. The scientific community is still unevenly equipped to enable a thorough and comprehensive confrontation of short- and long-term effects within the same analytical framework.

For considering policy impacts of any changes in agricultural commodities, policymakers have to distinguish between different effects of food price increases on urban consumers (demand side) and farmers (the bulk of world's poor, who are often on the supply side of agricultural commodities). With respect to price-influencing policies, policymakers have to be aware that winners and losers are not only between rich and poor but also among poor (net buyers or net sellers). Sharply changing price transmissions shown in this article also underline the importance of timeliness in policy responses – policy response to past price increase may come with a lag into a situation with very different conditions. Therefore, quick market interventions may be a preferred tool in the time of food crises, especially since we show in this article that during the food crisis time the price transmission is markedly stronger. This points policymakers toward the long-term importance of appropriate food and fuel storage policies and facilities so that a sufficient mass of stored commodity would be available for quick price-influencing interventions during the times of crises. These storage policies have to be adequate for modern markets with high volatilities where the crisis is not a unique event but it may be recurring in relative short intervals, which do not provide sufficient time for replenishing storage capacities used during previous market interventions.

Our price-dependent framework may be applied to understand linkages between fuel and commodity prices around the world, since the question of understanding the relationship of fuel and food prices between various developing countries, China, the West, etc., is one of the key aspects of food and energy security issues. Our analysis also emphasizes that the price transmission between commodities and causal relationship will change over time. While our approach of concentrating on price linkages is much easier to understand and interpret than the complex linkages between quantities, especially because of data reliability and availability, the more detailed biofuel price analysis at the level of all biofuels important countries will help us to understand how food and fuel security are linked through biofuel prices at the global level.

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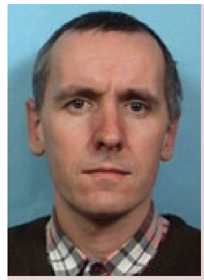
Ladislav Kristoufek

Ladislav Kristoufek is an Assistant Professor at Charles University in Prague and a Postdoctoral Fellow at Academy of Sciences of the Czech Republic. He is mainly interested in interdisciplinary approaches in economics and finance, in financial econometrics and econophysics, with a special focus on financial and energy markets.



Karel Janda

Professor Karel Janda is interested in microeconomic and econometric analysis of agricultural and natural resources. He is working on the economics of energy resources, especially the renewable ones like biofuels and photovoltaics. He is a coordinator of the EU 7FP project on climate change and energy.

Zilberman

Professor Zilberman's areas of expertise include agricultural and environmental policy, biotechnology, bioenergy and climate change, and the economics of innovation, risk, marketing, water, and pest control. He is a fellow of the American Agricultural Economics Association and the Association of Environmental and Resource Economists.