Price Comovement Between Biodiesel and Natural Gas

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Abstract

We study relationship between biodiesel, as a most important biofuel in the EU, relevant feedstock commodities and fossil fuels. Our main interest is to capture relationship between biodiesel and natural gas. They are both used either directly as a fuel or indirectly in form of additives in transport. Therefore, our purpose is to find price linkage between biofuel and natural gas to support or reject the claim that they compete as alternative fuels and potential substitutes. The estimated price link between biodiesel and diesel is negative and the strongest among analysed commodities. The price transmission between biodiesel and natural gas is the weakest one.

Keywords: biofuels, shale gas
JEL Codes: Q16, Q42

1 Introduction

We study relationship between biodiesel, as a most important biofuel in the EU, relevant feedstock commodities and fossil fuels. Our main interest is to capture relationship between biodiesel and natural gas. They are both used either directly as a fuel or indirectly

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in form of additives in transport. Therefore, our purpose is to find price linkage between biofuel and natural gas to support or reject the claim that they compete as alternative fuels and potential substitutes.

2 Theoretical framework

Biofuel market is subject to substantial regulation in the EU. In fact, regulation creates biofuel market through indicative or mandatory targets and corresponding incentives such as blending mandates and production subsidies. Serra et al. (2008) described biofuel market as standard supply and demand market with technical and regulatory barriers. They used such framework to study nonlinear price transmission in corn-ethanol-oil price system in the US. This framework suits the EU biofuel market well. Blending "wall" or mandatory blending mandates can be assigned to regulatory constraint. It lays down minimum quantity of biofuel that has to be placed on the market. On the other hand, technical constraint represents production limits and technical limits of biofuel application as a fuel. In actual fact it sets maximum quantity of biofuel that can be put on the market. We can imagine them as vertical lines in standard economic supply and demand equilibrium model. These constraints may set such conditions that market equilibrium is unachievable. For example, when price of relevant fossil fuel decreases, demand for biofuel shifts which results in lower price and less quantity of biofuel on the market. Supply function behaves in a similar way when price of relevant feedstock increases, which pushes biofuel price up. However, technical and regulatory barriers can prevent market from achieving new equilibrium. Price and quantity are then determined by the barrier which results in price above the equilibrium price. Moreover, these barriers may vary over time due to regulation changes or technical innovations. That can cause demand and supply functions to follow nonlinear patterns in converging to those constraints (Krištoufek et al., 2014). Further, they claim that, as a cause of constraints, supply and demand functions will rather change their shape than perform horizontal or vertical shifts like in a standard economic framework. It is another argument for nonlinear nature of supply and demand which leads to price dependence and co-movements among commodities.

For estimation of price dependences econometrics often uses log-log model. Estimated coefficient than represents elasticity of one commodity to another. However, if we consider model of prices in logarithmic form on both sides of an equation:

$$logP_j = \alpha + \beta logP_i + \upsilon \tag{1}$$

Estimated coefficient β represent elasticity in form $e_{P_i}^{P_j} = \dfrac{\Delta P_j/P_j}{\Delta P_i/P_i}$. It is not a standard microeconomic cross-price elasticity which describes how demanded quantity of one commodity reacts to changes in price of another one. It is defined as $e_i^j = \dfrac{\Delta Q_{d_j}/Q_{d_j}}{\Delta P_i/P_i}$ and it gains positive and negative values which corresponds to their microeconomic relation, i.e. if they are gross substitutes or gross complements, respectively. However, if we lack data on demanded quantity the elasticity from log-log model serves as a good substitute. It is convenient to distinguish between them since both captures different phenomenon. Thus, we call it price transmission between commodity i and j as Krištoufek et al. (2014) do. The price transmission represents how price of a commodity j reacts to changes in price of a commodity i (Krištoufek et al., 2012). In fact, they showed that price transmission is a ratio between own price elasticity of demand and aforementioned cross price elasticity of demand for a commodity j.

$$e_{P_i}^{P_j} = \frac{\Delta P_j/P_j}{\Delta P_i/P_i} = \frac{\Delta P_j/P_j}{\Delta P_i/P_i} \times \frac{Q_{d_i}/\Delta Q_{d_i}}{Q_{d_i}/\Delta Q_{d_i}} = \frac{\Delta P_j/P_j}{\Delta Q_{d_i}/Q_{d_i}} \times \frac{\Delta Q_{d_i}/Q_{d_i}}{\Delta P_i/P_i} = \frac{1}{e_{P_j}^{d_i}} \times e_{P_i}^{d_i} = \frac{e_{P_i}^{d_i}}{e_{P_j}^{d_i}} \tag{2}$$

If absolute value of price transmission is less than one, then price of commodity i - P_i reacts more to the changes in demanded quantity Q_{d_i} of commodity i than of commodity j (Krištoufek et al., 2012). That is what one would expect. To capture introduced possible nonlinearities on biofuel market, we use approach proposed by Krištoufek et al. (2014). The standard log-log model is extended by expression that capture price dependence to second order polynomial.

$$e^{P_i}_{P_j} = \alpha + \gamma_1 P_i + \gamma_2 P_i^2 \tag{3}$$

Therefore, the model for price transmission between two commodities that allows for nonlinear relations is stated as follows:

$$logP_j = \alpha + \beta_0 logP_i + +\beta_1 P_i + \beta_2 P_i^2 + \varepsilon \tag{4}$$

According to Krištoufek et al. (2014), proposed framework is able to control for not only price dependence, but also for time dependence which is benefit over standard constant elasticity approach that assume constant elasticity over time. It enable us to analyse development of the price transmission between desired commodities over time and connect it to certain occurrences on market.

3 Data description

Our dataset consists of time series of biodiesel, related fossil fuels and feedstocks prices. Target market of this work is the EU, thus we analyse biodiesel and closely related commodities. In a previous studies German diesel was found to have price link with biodiesel and it is undoubtedly its close substitute. Further, we include prices of relevant feedstocks into our dataset. Rapeseed as the most common used feedstock for production of biodiesel in the EU and soybeans are included. Besides, we add time series of prices of Brent crude oil and the UK natural gas. Our dataset contains information on demanded quantity of some of variables. they turned out to be good instruments within 2SLS estimation. Time series range between April 2009 and January 2015. Unfortunately, our dataset does not contain year 2008 when the food crisis occurred. Since prices of biodiesel are illiquid, we use weekly data for our analysis. Summary statistics are enclosed in the Appendix. All series were obtained from the Thomson Reuters Contributed Data. Summary of commodity tickers is presented in Table 1.

Table 1: Analysed commodities

Commodity	Ticker	Contract type
Biodiesel	FAME FOB ARA	spot, ARA OTC
Diesel	ULSD10	spot, ARA FOB
Crude oil	BRENT CRUDE JU	futures, ICE
Rapeseed	RAPESEED EU MA	futures, MATIF
Soybeans	CBT SOYBEANS MAY5	futures, CBOT
Natural gas	NAT BAL PT MAY	futures, ICE

It is know from previous literature that oil and gas prices and generally series of prices of energy commodities contain unit roots, i.e. their series are non-stationary and first-order integrated (Asche et al., 2012). Since presence of unit root in time series can have substantial effect on statistical inference, we test for it. If time series is found to be highly persistent , i.e. contains unit root, cointegration analysis have to be used. However, it is convenient to detrend the series and account for seasonal cycles first, because trending series can be easily confused with highly persistent series. Appropriate detrending and seasonal adjustment of the series are not common in related literature what raises questions about their results (Krištoufek et al., 2014). Data filtering was done by Stata with use of Butterworth filter. Estimated trend and seasonality can be seen in the Appendix. We applied ADF, DF-GLS and KPSS tests on detrended series in logarithmic form thereafter. We also provide test statistics for original series. Null hypothesis of ADF and DF-GLS is that time series contain unit root. Contrary, KPSS assumes series stationary under the null. Results are depicted in Table 2. It shows test statistics and corresponding 5 percent critical values. They differ for original and detrended series, because we used tests that account for linear trend in case of original series. However, unit root is not rejected in any of original series even though that applied tests accounted for trend. Only discrepancy comes from KPSS statistic on original series of natural gas which does not reject trend stationarity. The p-value is greater than 10 percent. Whereas we apply test on properly detrended series that was purged of seasonality, the results are straightforward. Unit root is rejected in every series and stationarity is not rejected in case of the ADF, DF-GLS and KPSS, respectively. Therefore, cointegration technique can not be used and the OLS or 2SLS, alternatively, is right approach.

Table 2: Tests for unit root

	Original series			Detrended series		
	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
Biodiesel	-2.167	-2.293	0.152	-5.049	-3.838	0.0167
Natural Gas	-2.927	-2.727	0.116	-5.807	-3.620	0.0159
Diesel	-1.002	-0.769	0.318	-6.373	-5.812	0.0167
Brent	-0.616	-0.756	0.343	-6.276	-4.978	0.0177
Rapeseed	-2.127	-1.845	0.192	-6.145	-2.362	0.0178
Soybean	-2.316	-2.369	0.184	-6.192	-2.322	0 .0178
5% critical value	-3.410	-2.872	0.146	-2.860	-1.979	0.463

Authors computations in Stata.

4 Econometric model

Here we present our model. The model was build on relevant literature reviewed in previous sections and available dataset to capture price links between biodiesel and natural gas. Dependent variable is $BiodieselPrice$ and it occurs in the logarithmic form in the model. Set of explanatory variables consists of prices of diesel, natural gas, Brent crude oil, rapeseed and soybean. According to the section 3.1, prices occur as in the logarithmic form, level form and the second order polynomial. Additionally we used information on demanded quantity of some of commodities in the 2SLS estimation, because they turned out to be good instruments. Variables are $DieselPrice$, $NGasPrice$, $NGasVolume$, $BrentPrice$, $BrentVolume$, $RapeseedPrice$, $RapeseedVolume$, $SoybeanPrice$ and $SoybeanVolume$. The model is stated as follows:

$$logP_{B_t} = \alpha + \sum_{i=1}^{5} \beta_i logP_{it} + \sum_{i=1}^{5} \gamma_i P_{it} + \sum_{i=1}^{5} \delta_i P_{it}^2 + u_t \tag{5}$$

where P_{B_t} and P_{it} represents biodiesel price in time t and prices of aforementioned commodities, respectively. t corresponds to the week, thus t=1,2,...,522 since we have observations for that number of weeks. The error term u_t constitutes of unobserved effects which are uncorrelated with explanatory variables. We used various estimation methods to precisely estimate the price transmission between analysed commodities. Applied approaches are described in the Methodology section.

4.1 Expectation

Based on the previous research, we expect the largest price transmission effect between biodiesel and diesel, since they are undoubtedly the closest substitutes. Certainly, strong price transmission is expected among feedstocks as well. Again, such price links were found before (Krištoufek et al., 2014). However, we expect rapeseed price to have larger effect than soybean, because it is the most common feedstock for biodiesel in the EU. The price transmission among biodiesel, crude oil and natural gas is hard to forecast since their separated effect has not been estimated yet. We think that most of information on crude oil is contained in diesel prices as well and if our hypothesis of price link between natural gas and biodiesel is correct, then the price transmission should be very low in case of crude oil.

5 Methodology

In this section, we present procedures that we used to properly estimate our model. We provide description for the Prais-Winsten and the 2SLS methods. We continue with description of the Durbin-Watson test for serial correlation and the Hausman specification test. Section is based on Wooldridge (2009).

5.1 Prais-Winsten

If we find that disturbance in the model follow AR(1) process, i.e. are serially correlated, OLS inference is no longer valid and we have to correct for it. The Prais-Winsten method is one of few possibilities how to transform the data to remove the serial correlation. The AR(1) model of errors can be written as

$$u_t = \varrho u_{t-1} + e_t, t = 1, 2, ..., n \tag{6}$$

where e_t are serially uncorrelated errors. Let consider model with a single explanatory variable

$$y_t = \alpha + \beta x_t + u_t, t = 1, 2, ..., n \tag{7}$$

where u_t follows process specified in equation 6. Then the Prais-Winsten method suggests to write model 7 for time period $t-1$. Thus for $t \geq 2$, we write

$$y_{t-1} = \alpha + \beta x_{t-1} + u_{t-1} \tag{8}$$

$$y_t = \alpha + \beta x_t + u_t. \tag{9}$$

We multiply first equation by ϱ from the equation 6 and subtract it from the second one afterwards. The idea is to get serially uncorrelated errors e_t.

$$y_t - \varrho y_{t-1} = (1-\varrho)\alpha + \beta(x_t - \varrho x_{t-1}) + e_t, t \geq 2. \tag{10}$$

We can rewrite equation as

$$\tilde{y}_t = (1-\varrho)\alpha + \beta\tilde{x}_t + e_t, t \geq 2, \tag{11}$$

where $\tilde{y}_t$ and $\tilde{x}_t$ are so called quasi-differenced data. By application of this procedure we lose first observation. However, that can be easily fixed by multiplying equation 3.9 for $t = 1$ by $(1 - \varrho^2)^{1/2}$. It using the fact that $Var(u_t) = \dfrac{\sigma_e^2}{1 - \varrho^2} > \sigma_e^2 = Var(e_t)$ where $| \varrho | \leq 1$. Therefore, we obtain errors with same variation for first observation as well. The first observation looks as

$$\tilde{y_1} = (1 - \varrho^2)^{1/2}\alpha + \beta\tilde{x_1} + \tilde{u_1} \tag{12}$$

where $\tilde{u_1} = (1 - \varrho^2)^{1/2}u_1, \tilde{x_1} = (1 - \varrho^2)^{1/2}x_1$ and $\tilde{y_1} = (1 - \varrho^2)^{1/2}y_1$. Variation of the error in 3.12 is equal to variation of errors in 11, i.e. $Var(\tilde{u_1}) = (1 - \varrho^2)Var(u_1) = \sigma_e^2$. If we use OLS regression on model 11 and add 12 we obtain BLUE estimators of α and β. Prais-Winsten estimators are example of feasible generalised least squares (FGLS) estimators. They are asymptotically more efficient than OLS estimators when errors follow AR(1) process.

5.2 Two Stage Least Squares

When one or more explanatory variables suffer from endogeneity, OLS estimators are generally inefficient. The 2SLS method mitigates the endogeneity problem and gives us consistent estimators. Source of the endogenity can be either an omitted variable, an error-in-variables or simultaneity. Let assume model

$$y_1 = \alpha + \beta_1 y_2 + \beta_2 x + u \tag{13}$$

where variable y_2 is suspected to be endogenous, i.e. suffer from one of the mentioned problem. We call such equation structural equation. Consider further that we have variable z which satisfies these two conditions:

$$Cov(z, u) = 0;$$
$$Cov(z, y_2) \neq 0.$$

The first condition means that z is exogenous in the equation and is also referred to as instrument exogeneity. It means that after the y_2 and unobserved effect in the error u has been controlled for, z has no partial effect on y_1. The second condition is referred to as instrument relevance. It requires that variables have to be related in either positive or negative way, i.e. it has to have partial effect on the endogenous variable y_1 after x has been controlled for. In other words, coefficient π_1 in the following equation has to be different from zero.

$$y_2 = \pi_0 + \pi_1 z + \pi_2 x + v \tag{14}$$

This equation is called reduced form. The 2SLS procedure then regresses y_1 on fitted values $\widehat{y_2}$ from OLS regression 3.14 and x, in fact $\widehat{y_2}$ is used as instrument for y_2. OLS estimates $\widehat{\alpha}$, $\widehat{\beta_1}$ and $\widehat{\beta_2}$ from regression

$$y_1 = \alpha + \beta_1 \widehat{y_2} + \beta_2 x + e \tag{15}$$

are called 2SLS estimators. The error term $e = u + \beta_1 v$ is uncorrelated both with $\widehat{y_2}$ and x. It is using the fact that suspected correlation of y_2 and u is purified in regression 14. The method can be extended to the case with more endogenous variables with at least same number of exogenous variables.

5.3 Tests

To decide which econometric method suits out data best, we have to apply two crucial tests. The Durbin-Watson tests for serial correlation and we use it to decide whether we have to correct for it with Prais-Winsten method. The Haussman specification test helps us to decide between OLS and 2SLS, i.e. to find out if an endogeneity is present.

The Durbin-Watson tests for AR(1) serial correlation. Its statistic (DW) is based on the OLS residuals and it is defined as:

$$DW = \frac{\sum_{t=2}^{n} (\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=2}^{n} \hat{u}_t^2} \tag{16}$$

The DW statistic is closely related to $\hat{\varrho}$ from regression of OLS residuals on its lagged values.

$$u_t = \alpha + \varrho u_{t-1} + e_t \tag{17}$$

Even for small sample sizes, DW statistic is close to

$$DW \approx 2(1 - \hat{\varrho}). \tag{18}$$

The DW distribution is derived under full set of classical linear assumptions. Since ϱ is predominantly positive, hypothesis are stated as follows,

$$H_0 : \varrho \neq 0 \tag{19}$$

against alternative

$$H_1 : \varrho > 0. \tag{20}$$

Therefore, rejection of the null hypothesis requires DW to be statistically less than two. Since the relation to the ϱ is only approximation, the DW statistic has to be compared with two critical values d_U and d_L upper and lower, respectively. If $DW < d_L$, then we choose to reject the null in favour of alternative. If $DW > d_U$, we fail to reject the null hypothesis of serial correlation. Finally, if the DW statistic lays between upper and lower critical value, the test is inconclusive.

The Hausman specification test directly compares estimated coefficients from OLS and 2SLS regression and evaluates whether the differences between them are statistically significant. Following scheme summarizes consistency of procedures under both hypothesis. Hypothesis are:

$$H_0 : \text{difference in coefficients is not systematic}$$
$$H_1 : \text{difference in coefficients is systematic}$$

	H_0	H_1
OLS	consistent & efficient	inconsistent
2SLS	consistent	consistent

If we reject H_0, we choose 2SLS. However, if we fail to reject H_0, we choose OLS since it is more efficient than 2SLS.

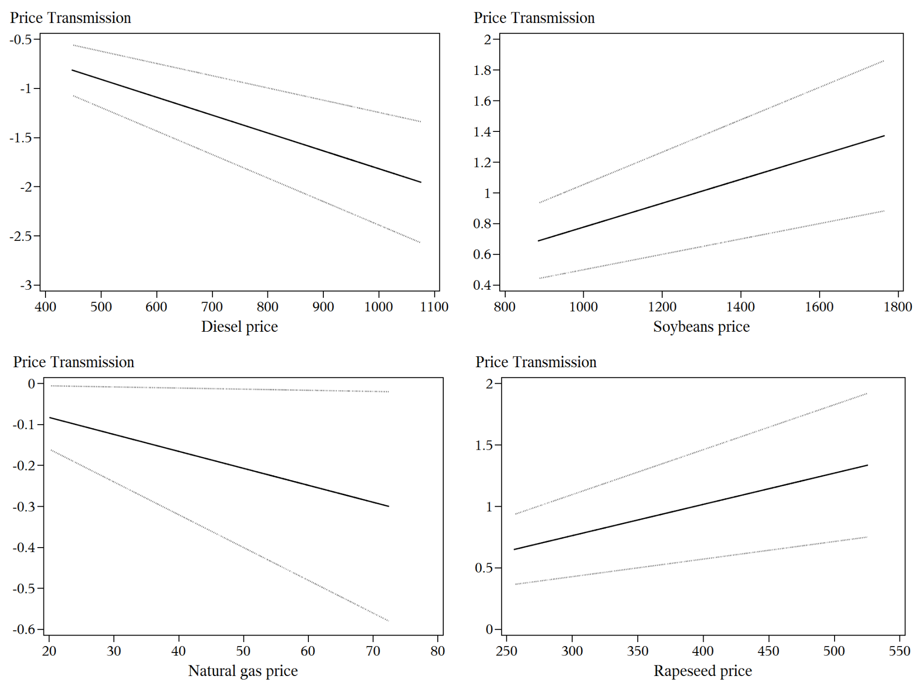
6 Results

Since we confirmed the data does not contain unit roots, thus cointegration analysis is not valid approach and we applied OLS estimation. The Breusch-pagan test confirmed presence of heteroskedasticity with chi-square statistic $\chi^2 = 108.51$ with p-value practically zero. Therefore, we accounted for it by using heteroskedasticity robust standard errors. We verified assumption about serial correlation then. The Durbin-Watson test produced statistic $DW = 1.105$. Lower critical value for 1 percent significance level is 1.691. Consequently, we concluded that our errors follow AR(1) process and we had to use the FGLS estimation, since the usual OLS inference is no longer valid under presence of serially correlated errors. More precisely, we used the Prais-Winsten method that accounts for the first observation and makes the FGLS more efficient in finite sample sizes. We estimated the model by the 2SLS procedure and we used serial correlation robust standard errors to account for the serial correlation. The Hausman specification test yielded statistic 9.65 which corresponds to p-value 0.29. Thus, we chose to not reject the H_0 which means that there is not enough evidence for presence of endogeneity and Prais-Winsten procedure is consistent. Estimated regressions are depicted in the Appendix. We left only significant variables in the final model. The model meets assumptions. We accounted for time trend and seasonalities. Serial correlation of errors is corrected by the FGLS estimation and we control for heteroskedasticity by using robust standard errors.

The model is by definition linear in parameters. The $R^2 = 0.2865$ which means that the model explains 29 percent of the variation in the data.

The model predicts that largest price transmission pertains to diesel. According to the model, the price-dependent transmission between biodiesel and diesel is linear and for our data on price of diesel, which ranges between \$447 and \$1075, the price-dependent transmission reaches almost -2 for the the highest prices. Estimated price transmission for soybeans and rapeseed is comparable. It ranges between 0.6 and 1.3 for both commodities. The estimate for natural gas is still statistically significant with p-value 0.036. The price transmission between biodiesel and natural gas is predicted to be the lowest among analysed commodities. However, is reaches -0.3 for higher prices of natural gas which can be considered economically significant as well.

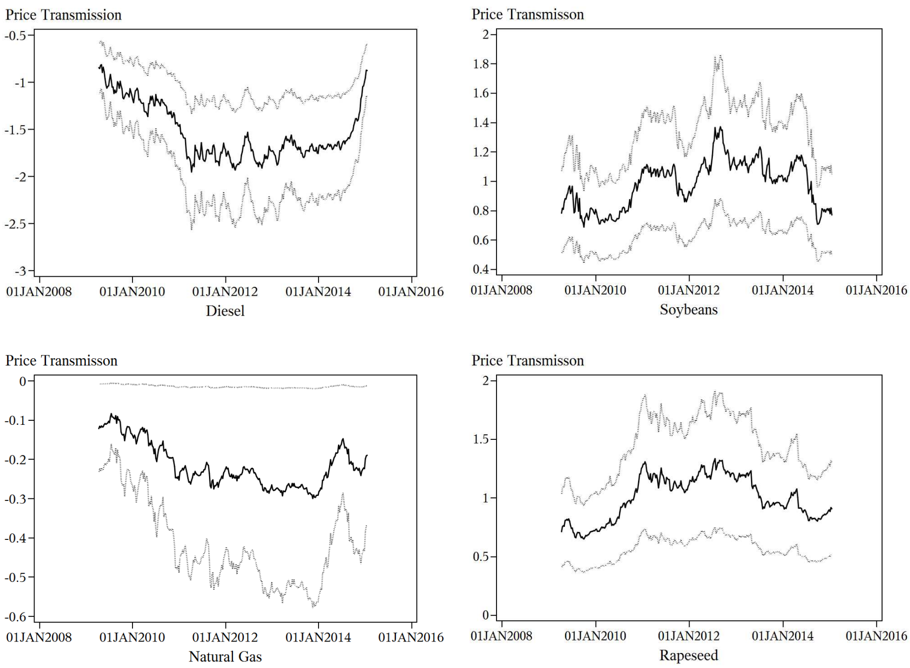
Figure 1: Estimated price-dependent price transmission with 95% confidence boundaries



Authors computations.

Furthermore, with our model we are able to comment on development of the price transmission over time. The figure 2 shows steadily growth of the absolute value of price transmission for the biodiesel-diesel pair from 0.8 and peaks approximately at 2 in the first half of 2011. The following years are represented by fluctuations between values 1.5 and 2. The effect plummets sharply at the end of 2014 when oil prices dropped. The development of the price transmission over time among soybeans, rapeseed and biodiesel is again comparable. Their development can be described by three spikes in 2011, than in summer of 2012 and last in the first half of 2014. Most of the time the price transmission stays around value 1, however in the end of a tracked period it substantially dropped in case of soybeans and followed by resurgence in case of rapeseed. We present development for natural gas price transmission as well, even thought it attains much lower magnitude. We again present it in absolute value since the relation is estimated to be negative. The relation gradually grows from 2009 with fluctuations around its trend. It decreases sharply in 2014 together with price of natural gas.

Figure 2: Development of the price transmission over time with 95% confidence boundaries



Authors computations.

7 Conclusions

The estimated price link between biodiesel and diesel is negative and the strongest among analysed commodities. While we expected strong relation within this pair, the negative price link is opposed to previous studies. The positive relation was quantified between German biodiesel and diesel. However, we use different time series in our work. Our dataset contains time series for ARA biodiesel and diesel. Their prices are created by trading in three ports the Antwerp, the Rotterdam and the Amsterdam. It suggests that prices of our commodities have different mutual responsiveness than German consumer biodiesel and diesel. The price transmission represents how price of one commodity reacts to changes in price of another. According to results, if price of diesel increases, the price of biodiesel decreases. Therefore, we can refer to them as so called "price substitutes." Another explanation can be that commodities in ports yield to speculations. The relation with soybeans and rapeseed price is strong as we expected. Again, the price transmission is estimated in different direction in case of soybeans price compared to the previous studies. However, according to the results when price of corresponding feedstock rises, the price of biodiesel rises as well. This is what one could expect. The price transmission between biodiesel and natural gas is the weakest one. We can still denote it as significant. Their relation is negative similar to the diesel, however in a much smaller size. From the figure 2 we see that the price transmission gradually grows over 5 years. Since, introduction of different technologies into transportation takes a while, the price transmission would rise gradually rather in a long term. That is in conformity with the fact that natural gas as an alternative fuel has experienced boom only recently, thus our dataset may not capture such phenomenon so far. However, we think that as the number of NGVs and consequently consumption of natural gas based fuels will grow, the price link may strengthen in a long term.

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8 Appendix – Tables

Table 3: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
BiodieselPrice	278.212	108.044	87.5	535	302
DieselPrice	840.950	162.667	447.75	1075.5	302
NGasPrice	51.77	13.645	20.1	72.38	302
NGasVolume	37316.142	17378.408	9325	94160	302
BrentPrice	97.455	18.472	50.11	126.65	302
BrentVolume	831664.036	229455.232	246497	1476185	302
RapeseedPrice	393.383	73.932	255.75	525.25	302
RapeseedVolume	14909.235	6771.067	2525	36841	302
SoybeanPrice	1264.598	206.616	885	1764.5	302
SoybeanVolume	293426.642	224660.41	401	914977	302

Authors computations in Stata.

Table 4: OLS Estimation

Variable	**Coefficient**	**(Std. Err.)**
$\log(Diesel)$	-3.66063†	(2.07831)
$\log(NaturalGas)$	0.37457	(0.28929)
$\log(Brent)$	3.64236*	(1.80789)
$\log(Rapeseed)$	3.44126**	(1.08391)
$\log(Soybean)$	-1.76576†	(1.04036)
$Diesel$	0.00255	(0.00260)
$NaturalGas$	-0.01668*	(0.00680)
$Brent$	-0.04039*	(0.01862)
$Rapeseed$	-0.00556*	(0.00265)
$Soybean$	0.00223*	(0.00088)
$NaturalGas^2$	-0.00015	(0.00039)
$Brent^2$	-0.00024	(0.00051)
$Diesel^2$	0.00001	(0.00001)
$Rapeseed^2$	-0.00002	(0.00002)
$Soybean^2$	0.00000	(0.00000)
Intercept	-0.00219	(0.01050)
N	302	
R^2	0.54935	
$F_{(15,286)}$	33.29298	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Authors computations in Stata.

Table 5: 2SLS Estimation

Variable	Coefficient	(Std. Err.)
log($Diesel$)	0.70005	(0.73333)
$Diesel$	-0.00308	(0.00093)
$Diesel^2$	0.00001	(0.00000)
log($NaturalGas$)	0.12306	(0.30967)
log($Rapeseed$)	4.04527	(1.28732)
log($Soybean$)	-1.97956	(1.04493)
$NaturalGas$	-0.01013	(0.00711)
$Rapeseed$	-0.00710	(0.00324)
$Soybean$	0.00239	(0.00084)
$NaturalGas^2$	-0.00031	(0.00048)
$Rapeseed^2$	-0.00002	(0.00002)
$Soybean^2$	0.00000	(0.00000)
Intercept	0.00354	(0.01335)
N	302	
R^2	0.53658	
$F_{(12,.)}$	20.21911	

Significance levels : † : 10% $*$: 5% $**$: 1%

Authors computations in Stata.

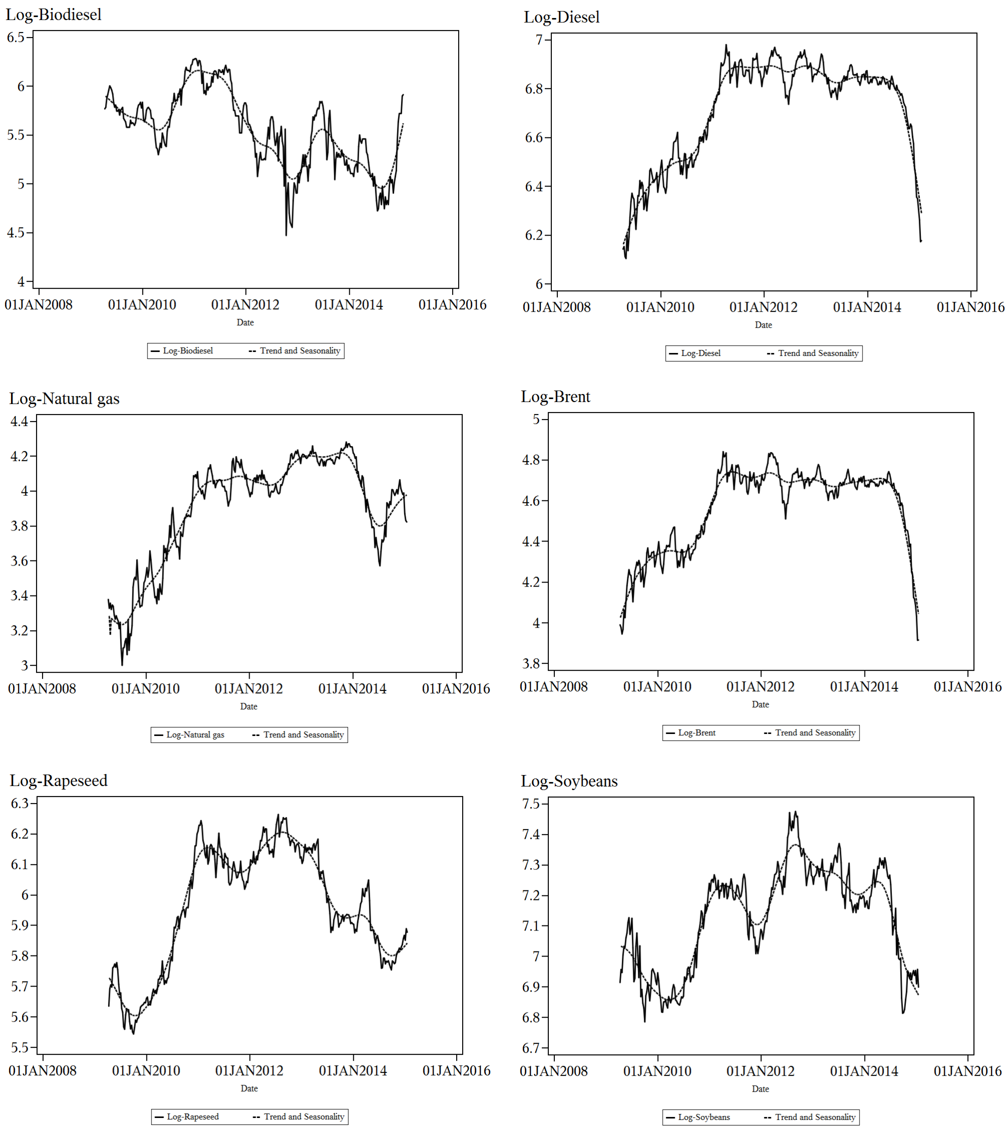
Table 6: Prais-Winsten Estimation

Variable	Coefficient	(Std. Err.)
$Diesel$	-0.00182**	(0.00029)
$NaturalGas$	-0.00414*	(0.00196)
$Rapeseed$	0.00254**	(0.00057)
$Soybean$	0.00078**	(0.00014)
Intercept	-0.00115	(0.01214)
N	302	
R^2	0.2865	
$F_{(4,297)}$	18.62163	

Significance levels : † : 10% $*$: 5% $**$: 1%

Authors computations in Stata.

Figure 3: Log-prices vs. trend and seasonality



Authors computations.