Estimating fuel price volatility and spillover effects across different European countries

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Abstract. *This paper analyses the volatility of retail fuel prices in nine different EU countries and the spillover effects between fuel prices across selected countries from Central and Eastern Europe and the Eurozone over the 2008-2019 period. In particular, we use the GARCH-GJR model in order to investigate fuel price volatility and identify potential asymmetric dynamics. Moreover, in order to assess the links between fuel prices across countries, we estimate a VAR model and compute spillover measures using the Generalised Forecast Error Variance Decomposition (GFEVD) approach formulated by Diebold and Yilmaz (2009). Our results provide evidence of weak links between retail fuel prices across EU countries, with slightly higher spillovers originating from some developed economies such as France and Italy.*

Keywords: fuel price; volatility; spillover effects; contagion; oil price transmission.

Introduction

The fuel market plays a major role in any economy due to its many uses, from industry, manufacturing to transportation. An increase in fuel prices will trigger an increase in the cost of many consumer products and, further, in inflation. Products with a persistent volatility, mainly due to their dependency of crude oil price, have the potential to amplify economic fluctuations and instability. Therefore, modeling fuel prices volatility is of high importance for the energy as well as the financial markets. Moreover, it is well documented that central banks closely follow international oil prices in formulating monetary policy actions.

International crude oil prices significantly affect the evolution of retail fuel prices in the long run. However, there are many other factors that affect fuel prices, such as foreign exchange rates, local supply and market competition. Furthermore, taxes constitute an important part of the retail fuel prices and often lead to significant differences in retail prices across countries. International pressures triggered by regional pricing policies or political factors may also influence the movement in fuel prices, leading to the integration of separate geographic markets.

There is an extensive research literature on the fuel market and particularly on fuel price behavior. A relevant study is Kpodar and Abdallah (2016) which investigates the transmission of crude oil price shocks to retail fuel prices across a number of 162 countries. The study focuses on the period between January 2005 until December 2014

and finds the lowest pass-through of crude oil price changes to domestic fuel prices in the Middle East and North Africa countries as major oil producers in the region significantly subsidize retail prices, while the highest pass-through of crude oil prices takes place in advanced economies and emerging Europe. Furthermore, examining pass-through coefficients, results suggest a price asymmetry with the pass-through being higher in periods of rising oil prices than during periods when oil prices fall. Another example is Pilart et al. (2009) which investigate the retail gasoline pricing behavior in Spain over the period 1993-2004, a period partially covered by a maximum price regulation. Using multivariate error correction models, the authors find that retail gasoline prices respond symmetrically to both increases and decreases of crude oil and gasoline spot prices on the entire analysed period. However, following liberalization, since October 1998, when the maximum price was removed, the results suggest a slower rate of pass-through of the gasoline spot price in the Spanish retail prices when gasoline spot prices increased, compared with the average European pre-tax retail prices, contesting thus the market power hypothesis for market imperfections.

Some authors investigate the fuel price volatility in order to be able to discover cartel behaviors. Both theoretical and empirical literature support the idea that a low price volatility can suggest the existence of a cartel as price rigidity generally appear in the presence of such behavior (Athey et al., 2004, Harrington and Chen, 2004, Abrantes-Metz, 2006). Esposito and Ferrero (2006) test the variance screening on two already discovered cartel cases in the Italian motor fuel and personal care and baby food markets in order to verify the effectiveness of this marker. Regarding the motor fuel market, the authors examine price patterns across different markets in Europe and find that price volatility is the lowest in Italy for both gasoline and diesel prices. Furthermore, the results indicate that the average fuel prices are the second highest of EU-15 member states, also supporting the collusion scenario. Hence, the authors conclude that the variance screen would have successfully detected collusion, their results being in line with the antitrust investigations findings. To the same effect, Zlatcu et al. (2015) study the retail fuel price volatility for Romania and four other markets, namely Germany, France, Poland and Czechia over the 2008-2014 period and don't find clues of collusion in any of the investigated markets. Moreover, the authors analyse the relationship between crude oil prices and retail fuel prices in order to assess whether changes in crude oil prices are transmitted in retail fuel prices. The cointegration analysis suggests some asymmetric adjustments as the prices adjust faster to increases than to decreases in crude oil prices.

Nevertheless, the volatility spillover effects in fuel market has been under-researched. For example, David et al (2011) investigates the links between fuel prices among eight countries in West Africa for gasoline, diesel and kerosene. Employing vector error correction models, the IMF study indicates the existence of significant cross-country spillovers, in particular for gasoline and diesel, as smaller, non-oil producing countries tend to respond to price changes in larger producing countries. In case of kerosene products, the results suggest a weaker link between prices across the analysed countries.

Our paper examines the price behaviour of two fuel products, namely gasoline and diesel in nine European countries. Specifically, we analyse fuel price volatility using the GARCH-GJR model formulated by Glosten, Jagannathan and Runkle (1993) which allows us to capture potential asymmetric effects in volatility dynamics. Furthermore, we investigate the spillover effects between retail fuel prices across some Central and Eastern European countries and some euro area ones, in order to assess whether

consumer prices in one member state receive any influences from those in the other countries, or are based strictly on market conditions.

The rest of this paper is organized as follows. Section 2 describes the data used for the empirical analysis and section 3 provides the description of the methodologies applied. Section 4 presents the empirical results and, finally, section 5 provides the concluding remarks.

Data description

The data used for our analysis consists of the average weekly prices for gasoline and diesel, obtained from the European Commission's Oil Bulletin. The price series are expressed in euro/liter for euro area countries and national currency/litre for Central and Eastern European countries using the exchange rate indicated by the European Commission in the database in order to eliminate foreign exchange rate effects. The taxation levels for fuels differ across countries so we chose prices without taxes in order to see the different price behavior driven by market forces. The data covers the period between January 2008 and February 2019.

As mentioned above, the study is focused on two fuel products: gasoline and diesel. Nowadays, these products are the most common types of fuel used for motor vehicles. Gasoline and diesel are homogeneous products so we can easily compare the price evolution for different geographical markets. To that effect, we choose five countries from Central and Eastern Europe, namely Romania, Bulgaria, Hungary, Poland and Czechia and four countries from the euro area, namely Austria, France, Germany and Italy.

Figure 1 illustrates the evolution of gasoline fuel prices over the period 2008 to 2019 in the countries considered in this paper (results for diesel fuel prices are available in the Annex).

Figure 1. Retail gasoline prices in selected countries

Source: European Commission

Even with no formal analysis, the similarities are striking. Gasoline prices fell during the crisis along with international crude oil prices, once global demand and outlook for economic activity weakened. The rebound was slow and peaked in 2012, when crude Brent would almost reach \$130/barrel at some points, levels not seen since before the global crisis. What followed was a couple of years of relative stability, up until mid-2014 when crude prices started dropping sharply, on the back of the expansion of

fracking operations allowing access to cheaper oil, mainly across the US. Retail prices followed more slowly, embarking on a downward trend which would cut prices to almost half those of 2012 by 2016. Since then, prices have been oscillating around the 0.5 euro/litre mark with a slight ascending trajectory, mainly due to geopolitical tensions with Iran and persistent threats to the global trade.

Before estimating the links between the fuel prices, we transform price levels into percentage changes in order to estimate the GJR-GARCH model using stationary data.

Methodology

In this section we discuss the methodology used to assess the fuels price volatility and the existence of spillover effects across prices charged in different countries for gasoline and diesel.

For capturing potential asymmetric effects in volatility dynamics, we resort to the GARCH-GJR model formulated by Glosten, Jagannathan and Runkle (1993), due to its desirable characteristics which allow for a larger impact of negative excess returns on the conditional variance. Formally, we specify the following equations:

$$\begin{aligned} p_t &= \mu + \varepsilon_t \\ \sigma_t^2 &= \alpha_0 + (\alpha_1 + \delta_1 \mathbb{I}(\varepsilon_{t-1} < 0)) \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{aligned} \quad (1)$$

where $\mathbb{I}(\cdot)$ is the indicator function which takes value 1 if the condition is realized and 0 otherwise. The so-called “leverage effect” is captured by the δ_1 coefficient, a positive value indicating the fact that negative returns at time t have a positive impact on volatility at time $(t+1)$. Conversely, if the asymmetry coefficient is close to zero the model does not bring any additional information compared to the standard GARCH framework.

The model is estimated using Markov Chain Monte Carlo or MCMC algorithms, i.e. drawing samples from the posterior distributions of the coefficients in order to compute posterior means and standard deviations. Specifically, we resort to the Metropolis-Hastings algorithm used in practice for obtaining random samples from distributions for which direct sampling is not feasible. In this case, we apply the methodology described by Chan and Grant (2016), which involves grouping the standard GARCH parameters into two blocks and drawing sequentially from the posterior distributions. The priors chosen are left non-informative as we aim to extract information from the dataset, in the following manner:

$$\begin{aligned} \mu &\sim \mathcal{N}(\mu_0, V_\mu), \log \gamma \sim \mathcal{N}(\gamma_0, V_\gamma) \mathbb{I}(\alpha_1 + \beta_1 + \delta_1 < 1) \text{ where } \gamma = (\alpha_0, \alpha_1, \beta_1) \\ \delta_1 | \gamma &\sim \mathcal{U}(-\alpha_1, 1 - \alpha_1 - \beta_1) \end{aligned} \quad (2)$$

Additionally, we assume a uniform prior for the leverage parameter while at the same time ensuring that the variance process is strictly positive ($\alpha_1 + \delta_1 > 0$) and stationary ($\alpha_1 + \beta_1 + \delta_1 < 1$). The hyperparameters of the model closely follow Chan and Grant (2016), arguing the fact that the values imply relatively noninformative priors and are similar to empirical estimates obtained in practice using financial data.

For the second part of the empirical investigation, in order to measure bidirectional volatility spillovers between fuel prices we employ the Diebold-Yilmaz (2009) methodology, involving the estimation of a VAR model and computing spillover

measures using the Generalized Forecast Error Variance Decomposition (GFEVD), defined by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998):

$$\gamma_j^g(h) = \frac{1}{\sqrt{\sigma_{jj}}} A_h \sum e_j \text{ and } \theta_{ij}^g(H) = \frac{\sigma_{ii}^{-1} \sum_{h=1}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=1}^{H-1} (e_i' A_h \sum A_h' e_j)^2} \quad (3)$$

Diebold and Yilmaz propose estimating the contribution of each time series to the volatility of others by using a weighted average of the sum of all contributions:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (4)$$

Finally, we can compute an overall index by weighting all spillover contributions except each country's own to the total sum of relative contributions and recursively estimating the model in order to obtain a time-varying index:

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \cdot 100 \quad (5)$$

Empirical results

We estimate the GARCH-GJR model using the dataset for Gasoline and Diesel fuel prices for the 9 selected CEE and Eurozone countries, using 10,000 draws for the Metropolis Hastings algorithm and obtain the following results:

Table 1. Estimated posterior means and standard deviations (in brackets) for the GARCH-GJR model estimated on gasoline prices

	RO	BG	CZ	HU	PL	AT	DE	FR	IT
μ	0.093 (0.087)	0.021 (0.070)	0.106 (0.055)	0.147 (0.094)	0.069 (0.068)	0.078 (0.091)	0.036 (0.132)	0.198 (0.094)	0.133 (0.071)
α_0	0.151 (0.062)	0.042 (0.013)	0.086 (0.028)	0.357 (0.152)	0.105 (0.039)	0.182 (0.066)	0.653 (0.200)	0.710 (0.333)	0.220 (0.069)
α_1	0.015 (0.007)	0.054 (0.011)	0.119 (0.030)	0.031 (0.017)	0.034 (0.016)	0.033 (0.017)	0.076 (0.031)	0.038 (0.020)	0.131 (0.039)
β_1	0.914 (0.014)	0.904 (0.008)	0.770 (0.031)	0.859 (0.042)	0.876 (0.027)	0.879 (0.023)	0.806 (0.040)	0.729 (0.085)	0.709 (0.047)
δ_1	0.102 (0.020)	0.106 (0.024)	0.253 (0.055)	0.090 (0.029)	0.158 (0.040)	0.131 (0.031)	0.187 (0.061)	0.247 (0.090)	0.228 (0.078)

Source: authors' estimation

Table 1 shows the results for the GARCH-GJR model, indicating the posterior estimates of the parameters and the corresponding standard deviations for gasoline prices, with the results for diesel prices presented in the Appendix.

Firstly, the parameter μ is mostly insignificant statistically for gasoline prices (and even more so for diesel prices), meaning that the GARCH -GJR volatility manages to capture most of the movement in prices. The parameter α_0 is significant for all countries and largest in the case of France and Germany, signaling the biggest base volatility, as is also suggested in Figure 2 below. On the other hand, the coefficient is smallest for

Bulgaria, but that does not necessarily translate into a small variance, as volatility can result from the other terms. In the case of diesel prices, the largest coefficient is estimated for Bulgaria, confirming the high volatility of prices seen in Figure 1 in the Annex. The coefficient α_1 corresponds to the first lag of the GARCH process and indicates how important last period's residuals are for present volatility. For gasoline prices, such high persistence of volatility is visible in the case of Italy and Czechia, while looking at diesel prices the results are roughly similar. The posterior mean of the volatility autoregressive term β_1 is estimated to be between 0.71 for Italy and 0.91 for Romania, with a high degree of statistical significance in all cases, while for diesel prices, volatility persistence is also highest in Romania, with the lowest value recorded in the case of Bulgaria. Finally, the estimate of δ_1 is positive and statistically significant for all countries, ranging from 0.09 (Hungary) to 0.25 (Czechia) in the case of gasoline prices and 0.06 (Romania) to 0.2 (Bulgaria and Czechia) for diesel prices respectively, meaning that a negative shock at time t will always increase the conditional variance at time $t+1$.

We then plot the results of the GARCH-GJR volatilities obtained from the estimation for both gasoline and diesel fuel prices (see Annex for the results on diesel prices).

Figure 2. Estimated volatilities for gasoline fuel prices for the CEE (upper) and Eurozone (lower) countries

Source: authors' estimation

Looking at the volatility of fuel prices over the years, some common patterns across countries become apparent. In all cases for gasoline prices and almost all for diesel prices, volatility peaked in 2009, at the height of the financial crisis. The episode was associated with historically high levels of volatility in the prices of all assets, commodities

and oil being no exception. To exemplify, Brent opened 2008 around the \$97/barrel level and closed it below half that, at just \$36/barrel, while ending the following year at the \$78/barrel mark, more than double the starting price, the highest annual price swing since 1999 - naturally, this was reflected in final consumer prices. After the rapid surge in 2010 and the beginning of 2011, Brent crude prices stabilized around the \$110/barrel level for the next three and a half years, which also meant low variation in retail prices. A spike in volatility is again visible after 2014, when the expansion of hydraulic fracturing technologies and global oil output drove prices down very rapidly, the impact on final price volatility being however significantly smaller, since crude did not recover the losses, like it had done after the Great Recession.

Next we turn to the spillover methodology results – we compute the bilateral spillover measures using the entire dataset using multiple formulations in order to ensure robustness. We use several formulations for the VAR model by specifying 2 and 4 lags and computing the GFEVD on a 1- and 4-step ahead horizon.

From all four methods, we can observe that there are no significant spillover effects between gasoline prices and that generally prices move independently between different European countries. However, there are countries such as Bulgaria where we identify spillovers effects from other CEE countries and even from Eurozone countries, particularly in the one step formulation. In addition, we identify weak spillover effects in Romania and Czechia, mostly from the prices changes in the other CEE countries.

Table 2. Bilateral spillovers using multiple formulations (lags and horizons) for gasoline fuel prices

2 lags											From others
4 steps	RO	BG	CZ	HU	PL	AT	DE	FR	IT		
RO	55%	1%	2%	9%	4%	6%	4%	11%	8%		45%
BG	1%	47%	0%	7%	0%	5%	13%	11%	16%		53%
CZ	8%	3%	27%	7%	4%	10%	8%	13%	19%		73%
HU	5%	4%	1%	36%	4%	13%	8%	16%	13%		64%
PL	5%	0%	4%	13%	37%	10%	5%	15%	11%		63%
AT	2%	2%	1%	7%	7%	43%	9%	15%	14%		57%
DE	1%	7%	0%	4%	1%	10%	57%	9%	10%		43%
FR	3%	4%	0%	11%	4%	15%	10%	36%	17%		64%
IT	3%	8%	1%	9%	4%	15%	9%	17%	35%		65%
To others	28%	30%	9%	66%	27%	85%	66%	108%	108%		
incl. own	83%	77%	36%	102%	65%	128%	123%	144%	144%		

2 lags											From others
1 step	RO	BG	CZ	HU	PL	AT	DE	FR	IT		
RO	75%	1%	6%	4%	1%	3%	2%	4%	5%		25%
BG	24%	42%	2%	5%	0%	4%	7%	7%	10%		58%
CZ	19%	31%	26%	4%	0%	3%	5%	5%	7%		74%
HU	17%	27%	23%	10%	1%	3%	5%	6%	7%		90%
PL	16%	26%	21%	10%	5%	3%	5%	6%	7%		95%
AT	13%	22%	17%	9%	5%	13%	5%	8%	8%		87%
DE	7%	15%	9%	7%	2%	10%	34%	8%	8%		66%
FR	6%	13%	7%	8%	3%	10%	28%	16%	10%		84%
IT	6%	12%	6%	7%	2%	10%	24%	16%	16%		84%
To others	108%	147%	90%	54%	15%	45%	82%	59%	63%		
incl. own	183%	189%	116%	64%	21%	58%	116%	74%	80%		

4 lags											From others
4 steps	RO	BG	CZ	HU	PL	AT	DE	FR	IT		
RO	53%	1%	2%	6%	2%	8%	5%	13%	9%		47%
BG	0%	47%	0%	6%	0%	6%	12%	13%	15%		53%
CZ	6%	4%	28%	5%	4%	11%	8%	16%	19%		72%
HU	4%	4%	1%	33%	4%	14%	8%	18%	13%		67%
PL	8%	0%	5%	13%	37%	11%	3%	14%	8%		63%
AT	3%	3%	1%	6%	6%	46%	7%	14%	13%		54%
DE	1%	8%	0%	4%	0%	12%	55%	9%	10%		45%
FR	4%	4%	0%	11%	3%	18%	9%	36%	14%		64%
IT	3%	8%	1%	8%	3%	17%	7%	18%	35%		65%
To others	30%	34%	10%	60%	23%	96%	60%	115%	101%		
incl. own	83%	81%	39%	94%	60%	142%	115%	151%	137%		

4 lags											From others
1 step	RO	BG	CZ	HU	PL	AT	DE	FR	IT		
RO	76%	0%	4%	3%	1%	4%	2%	5%	5%		24%
BG	22%	43%	1%	4%	0%	4%	7%	8%	10%		57%
CZ	18%	32%	24%	3%	0%	3%	5%	6%	7%		76%
HU	16%	28%	21%	10%	1%	4%	5%	7%	7%		90%
PL	15%	27%	20%	10%	5%	4%	5%	7%	7%		95%
AT	13%	23%	16%	9%	4%	13%	5%	8%	8%		87%
DE	7%	16%	8%	7%	2%	10%	35%	8%	8%		65%
FR	6%	14%	6%	8%	2%	11%	29%	15%	10%		85%
IT	5%	13%	5%	7%	2%	11%	25%	16%	16%		84%
To others	102%	152%	83%	51%	14%	50%	84%	63%	62%		
incl. own	178%	195%	107%	61%	19%	64%	119%	79%	78%		

Source: authors' estimation

Likewise, for diesel prices, the results show small spillover effects from prices changes in other countries. Nevertheless, diesel prices in Bulgaria seem to be significantly influenced by prices changes in other countries, such as Czechia, Hungary, Poland, Austria, Germany, France and Italy.

Using a rolling-window estimation with a size of 96 weeks (2 years of data), we compute the overall Spillover Index, using 2-4 lags for the VAR model. The results are

plotted in Figure 3 for gasoline prices (results for diesel fuel prices are available in the Annex).

Figure 3. Spillover Index computed for gasoline fuel prices

Source: authors' estimation

Finally, we plot the overall Spillover Index together with the median fuel price volatility among countries. What we find is a positive correlation between the two, as can be seen in Figure 4 below. Periods of high volatility in fuel prices, such as during the Great Recession and the 2015 oil glut, tend to be associated with increased overall spillovers between countries. This is the expected result, as the model is unable to perfectly distinguish between the influence of a common factor (in this case the price of crude oil) and the co-movement caused by price spillovers between countries. As such, periods of calm in the markets, like 2011-2013, will be interpreted as having little in the way of cross-country spillovers in fuel price movements, as there is very limited movement to be explained.

Figure 4. Median volatility for all the countries included in the dataset and the Spillover Index for gasoline fuel prices

Source: authors' estimation

On the other hand, when consumer price volatility is high, part of it will be connected to the long-run equilibrium relationship between fuels and crude oil, while another part will be interpreted as the result of cross-country influences and reflected in the overall Spillover Index.

Conclusions

In this paper, we have attempted to analyze the path followed by final prices paid by consumers for fuels in eight European countries, while studying their volatility through a specification of the GARCH model formulated by Glosten, Jagannathan and Runkle (1993). We find two episodes of volatility surge for most countries, the largest one being in the aftermath of the Great Recession, when oil prices recovered relatively swiftly following the drop suffered mid-2008 at the onset of the global crisis, with a second one appearing in 2015-2016, when substantial improvements in shale fracking technologies and a global slowdown of economic growth sent crude prices plunging sharply.

Next, we try to measure bidirectional volatility spillovers between fuel prices, by employing the Diebold-Yilmaz (2009) methodology, involving the estimation of a VAR model, and computing spillover measures using the Generalized Forecast Error Variance Decomposition (GFEVD), defined by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998). With some small exceptions, we fail to find conclusive evidence of cross-country spillovers, the spikes in the overall Spillover Index mostly coinciding with periods of high volatility of crude prices globally, which led to closer co-movement of fuel prices.

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Annexes

Figure A. 1. Retail diesel prices in selected countries

Source: European Commission

Table A.1. Estimated posterior means and standard deviations (in brackets) for the GARCH-GJR model estimated on diesel fuel prices

	RO	BG	CZ	HU	PL	AT	DE	FR	IT
μ	0.069 (0.076)	0.048 (0.097)	0.059 (0.050)	0.098 (0.082)	0.015 (0.061)	0.046 (0.079)	-0.003 (0.117)	0.048 (0.085)	0.061 (0.063)
α_0	0.059 (0.030)	0.973 (0.213)	0.052 (0.023)	0.297 (0.145)	0.028 (0.019)	0.175 (0.062)	0.643 (0.209)	0.095 (0.044)	0.107 (0.046)
α_1	0.019 (0.008)	0.135 (0.046)	0.120 (0.028)	0.029 (0.014)	0.028 (0.010)	0.046 (0.020)	0.061 (0.033)	0.039 (0.016)	0.115 (0.035)
β_1	0.942 (0.014)	0.658 (0.061)	0.801 (0.032)	0.845 (0.052)	0.934 (0.019)	0.844 (0.028)	0.796 (0.041)	0.904 (0.020)	0.797 (0.044)
δ_1	0.055 (0.016)	0.196 (0.083)	0.196 (0.055)	0.113 (0.045)	0.075 (0.019)	0.186 (0.047)	0.190 (0.056)	0.087 (0.026)	0.129 (0.051)

Source: authors' estimation

Figure A.2. Estimated volatilities for diesel fuel prices the CEE (upper) and Eurozone (lower) countries

Source: authors' estimation

Table A.2. Bilateral spillovers using multiple formulations (lags and horizons) for diesel fuel prices

2 lags											2 lags										
4 steps											1 step										
RO	BG	CZ	HU	PL	AT	DE	FR	IT	From others	RO	BG	CZ	HU	PL	AT	DE	FR	IT	From others		
RO	57%	1%	3%	6%	3%	9%	4%	10%	8%	43%	RO	72%	0%	4%	5%	2%	3%	5%	5%	28%	
BG	0%	57%	1%	2%	1%	4%	16%	7%	12%	43%	BG	3%	65%	0%	1%	4%	16%	5%	5%	35%	
CZ	5%	2%	31%	6%	7%	12%	4%	15%	17%	69%	CZ	3%	60%	7%	1%	4%	14%	5%	5%	93%	
HU	6%	1%	1%	34%	6%	18%	7%	16%	11%	66%	HU	3%	56%	7%	4%	1%	4%	5%	5%	96%	
PL	5%	0%	4%	11%	42%	11%	3%	15%	10%	58%	PL	3%	56%	7%	4%	2%	4%	5%	5%	98%	
AT	2%	2%	1%	8%	4%	47%	9%	13%	12%	53%	AT	3%	48%	6%	5%	2%	11%	6%	6%	89%	
DE	2%	12%	0%	3%	2%	11%	54%	7%	9%	46%	DE	3%	37%	4%	4%	2%	10%	6%	7%	73%	
FR	4%	2%	1%	9%	7%	15%	8%	34%	20%	66%	FR	3%	36%	4%	4%	2%	10%	8%	7%	92%	
IT	3%	2%	2%	8%	6%	15%	8%	20%	36%	64%	IT	3%	32%	4%	4%	2%	10%	12%	88%		
To others										27%	22%	12%	52%	36%	95%	58%	105%	100%			
incl. own										84%	79%	43%	86%	79%	142%	112%	139%	136%			

4 lags											4 lags										
4 steps											1 step										
RO	BG	CZ	HU	PL	AT	DE	FR	IT	From others	RO	BG	CZ	HU	PL	AT	DE	FR	IT	From others		
RO	55%	1%	2%	4%	3%	10%	4%	12%	9%	45%	RO	74%	0%	3%	4%	2%	4%	5%	26%		
BG	0%	58%	1%	2%	0%	5%	16%	8%	11%	42%	BG	3%	66%	0%	1%	4%	15%	5%	34%		
CZ	4%	3%	31%	5%	7%	15%	4%	16%	16%	69%	CZ	3%	61%	7%	1%	4%	14%	5%	93%		
HU	5%	1%	0%	34%	6%	18%	7%	17%	11%	66%	HU	3%	57%	7%	4%	1%	4%	5%	96%		
PL	5%	0%	5%	12%	41%	12%	3%	14%	10%	59%	PL	3%	57%	7%	4%	1%	4%	5%	99%		
AT	2%	2%	1%	10%	5%	48%	8%	13%	12%	52%	AT	3%	48%	6%	5%	2%	12%	6%	88%		
DE	2%	12%	0%	4%	1%	12%	53%	8%	9%	47%	DE	2%	37%	4%	4%	1%	11%	7%	72%		
FR	4%	2%	1%	9%	7%	17%	7%	35%	19%	65%	FR	3%	35%	4%	4%	1%	11%	8%	92%		
IT	3%	2%	2%	9%	6%	15%	7%	20%	35%	65%	IT	3%	32%	3%	4%	2%	11%	12%	88%		
To others										24%	23%	12%	54%	36%	103%	54%	108%	96%			
incl. own										79%	81%	43%	88%	76%	151%	107%	142%	132%			

Source: authors' estimation

Figure A.3. Spillover index computed for Diesel fuel prices

Source: authors' estimation

Figure A.4. Median volatility for all the countries included in the dataset and the spillover index for Diesel fuel prices

Source: authors' estimation