



# The impact of oil prices on gas and electricity prices

## Abstract

The development of oil prices is usually considered a key factor in determining the energy prices – gas or electricity. The aim of this article is to quantify this relationship using econometric methods and to observe how it is changing through time. The set of applied methods includes simple regression equations, Markov-switching models, state space models and Bayesian state space models. All approaches agree that the relationship between oil prices and energy prices has a time-varying character. The elasticity between oil prices and electricity prices during the period before the crisis is estimated around 0.6 – 0.8. Between years 2009 and 2015 it falls approximately to 0.2 and after that it proceeds to grow once again reaching current values 0.4 – 0.6. Prior to the crisis, the gas prices were fully determined by long-term oil indexed contracts. Analysis of the data, which became available in the end of 2010, indicates that the relationship between oil prices and gas prices was only marginal until the first half of 2015. Starting in the second half of 2015, it gradually grows stronger and the elasticity converges to current value 0.4.

## Introduction

In order to quantify the relationship between oil prices and energy prices using econometric methods, it is first necessary to define the basic model structure. Afterwards, it is possible to apply more complex approaches that will provide further extension and depth. Since one of the challenges of this article is to determine how this relationship changes over time, it is required to specify whether these changes will be discrete or continuous and what other parameters will be time-varying.

## Methodology

A wide variety of different instruments can be used to research the impact of oil prices on electricity and gas prices and its changes over time. The most intuitive approach is based on a simple regression equation (using ordinary least squares) with commodity prices of electricity or gas as a dependent variable and oil prices, the first lagged value of dependent variable (autoregressive term of order 1 – AR(1)) and the constant as regressors. Resulting coefficients, especially elasticity of oil prices, can be then tested for structural breaks. Ideally, we would have some prior knowledge about when to expect structural breaks and therefore we could apply the test specifically to these time points. However, it is possible to utilize tests that automatically search for periods with highest probability of structural breaks as well as their overall count. Such test is for example provided by Bai, Perron (1998). Obtained results will inform us how to divide the original sample into two or more periods and then we estimate the model separately for each one of them. In case we don't have enough observations for one of these periods or we track changes over time only for one of the coefficients, it is recommended to use dummy variables indicating selected periods in time.

More sophisticated approach to these issues is provided by Markov-switching models. They assume that the variables of the model operate in two or more different regimes (states) and

the parameters of the model depend on what regime are they currently in. It is possible to switch between these states and the probability of currently being in a certain regime depends solely on the previous regime (in what regime we were during previous period). These models provide us with possibility to allow certain coefficients (including variance) to change over different states and to fixate the others. They are usually used to distinguish between periods with higher and lower volatility or recessions and expansions. Their usefulness for this article will be in differentiating between periods with stronger and weaker effect of oil prices to electricity (gas) prices<sup>1</sup>.

Up until now, the coefficients were allowed to change only in prespecified points in time or to jump between several regimes. Moving forward, we would like to grant the parameters the ability to change over the whole sample without any restrictions. Among instruments capable of such estimations can be found state space models. Generally, they are used to model unobserved variables – observation errors, cycles, trends or in our case coefficients that are subject to a random process. A state space model with time-varying coefficients can be written as follows:

$$y_t = x_t\theta_t + z_t\beta + \varepsilon_t$$

$$\theta_t = \theta_{t-1} + \eta_t .$$

The first equation is denoted as an observation equation while the second one is a state equation. Furthermore,  $y_t$  is the dependent variable (in this case the price of electricity or gas),  $x_t$  is a matrix  $n \times m_1$  of explanation variables with time-varying coefficients that are represented by a vector  $\theta_t$  of size  $m_1 \times 1$ . Variables with coefficients constant over time are in a matrix  $z_t$  ( $n \times m_2$ ) and their coefficients are represented by a vector  $\beta$  of size  $m_2 \times 1$ . Altogether, there are  $m_1 + m_2 = m$  explanation variables including the constant and  $n$  is the number of observations. The errors  $\varepsilon_t$  and  $\eta_t$  are normally distributed and independent.

Since we have three regressors – the constant, the oil price and the autoregressive term – we assumed four possible model specifications, based on how many coefficients will be time-varying:

- coefficients of all regressors
- constant and oil price
- autoregressive term and oil price
- just oil price

The variance of the random errors was considered to be constant over time. The algorithm used to estimation (optimization) is known as Kalman filter. Before it can be used properly, it is necessary to assign starting values to all parameters (they can be derived from theory or previous empirical results). The robustness of the model will depend on how sensitive it is to different settings of the starting values<sup>2</sup>.

Last possible way how to expand the current model structure is to relax the assumption that the variance of random errors is constant over time. Based on Primiceri (2005), we can rewrite the state space model equations as follows:

---

<sup>1</sup> For further information see Frühwirth-Schnatter (2006).

<sup>2</sup> For more about Kalman filter see Hamilton (1994) or Koop, Korobilis (2012).

$$y_t = x_t \theta_t + e^{\frac{h_t}{2}} \varepsilon_t$$

$$\theta_t = \theta_{t-1} + \sigma_\theta \eta_t$$

$$h_t = h_{t-1} + \sigma_h \nu_t .$$

Contrary to previous specifications, we assume that all parameters, including the variance of the random errors are time-varying (the last feature is also known as stochastic volatility). Since the number of parameters to estimate now grows rapidly, it would be convenient to use Bayesian methods, in this case specifically the Gibbs sampler. In order to do so, it is first necessary to specify a prior distribution of parameters, what will be inverse Gamma distribution with following settings:

$$\sigma_\theta^2 \sim IG(5, 0.005)$$

$$\sigma_h^2 \sim IG(5, 0.5) .$$

These starting values will enable the Gibbs sampler to initiate iterative process, that in each step chooses a new set of values of parameters, conditionally on previous values, until convergence is achieved. The results may be to some extent affected by the calibration of the prior distribution.

## Data

The analysis is based on daily German electricity price data (Phelix) and daily German gas price data (NCGI), both denominated in euros and converted to monthly averages. The explanatory variable is monthly average of crude oil price Brent, in euros. All variables are transformed into year-on-year growth rates in order to ensure their stationarity. Electricity prices are provided from February of 2005 (or 2006 after transformation) till August 2018 and gas prices from November 2010 (or 2011 after transformation) till August 2018. All models are estimated on this sample minus one month because of the inclusion of the first lagged value.

## Results

### Regression equation

Estimates using ordinary least squares (OLS) and subsequent application of tests of structural breaks have shown, that the elasticity of oil prices in relation to electricity prices changed in December of 2008, while in case of gas prices it was in August 2015. Since all possible subsamples have sufficient number of observations, it was decided to estimate separate models for each period.

**Table 1 Electricity and gas prices using OLS**

Electricity	Coefficients			Gas	Coefficients		
	Full sample	until 2008M11	after 2008M12		Full sample	until 2015M7	after 2015M8
<b>Constant</b>	-0,65	-6,32	-0,91	<b>Constant</b>	0,69	-0,48	-0,73
<b>Oil</b>	0,32	0,94	0,23	<b>Oil</b>	0,24	-0,10	0,40
<b>AR(1)</b>	0,71	0,60	0,68	<b>AR(1)</b>	0,75	0,93	0,62
<b>Standard deviation of residuals</b>	20,26	29,42	15,59	<b>Standard deviation of residuals</b>	9,37	7,12	9,32

As Table 1 shows, the assumptions about structural breaks have been justified in both cases. The impact of oil prices on electricity prices fell rapidly down after 12<sup>th</sup> month of 2008, on the contrary, the impact on gas prices rose after 8<sup>th</sup> month of 2015. Same changes can be seen in almost all coefficients and even in the variance of random errors. The only coefficient unaffected by the structural break seems to be the lagged value of electricity prices. Some attention could be paid to estimated negative relationship between gas prices and oil prices during period from November 2011 till July 2015. However, this coefficient is statistically insignificant and thus we can regard it as zero and no further concern is necessary.

### Markov-switching models

A wide variety of different model specifications was provided by the second presented method. It was required to identify coefficients that will have time-varying character (and those that will be fixated) and whether the variance of random errors will be allowed to change over time. Out of all possible combinations the one most suitable was chosen for each dependent variable, regardless of results obtained from first method. The factors that determined the choice were robustness and minimalization of information criteria. The number of regimes was in both cases set to two.

**Table 2 Estimates from Markov-switching models**

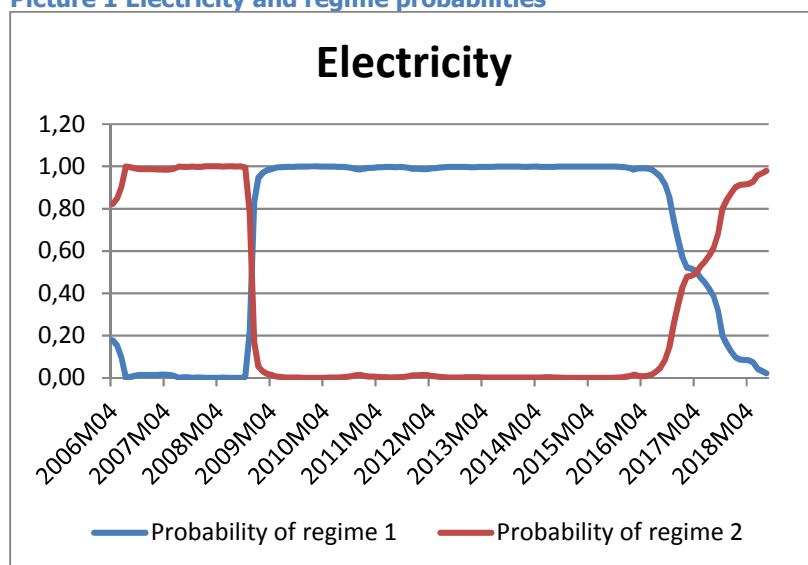
Electricity	Coefficients		Gas	Coefficients	
	Regime 1	Regime 2		Regime 1	Regime 2
<b>Constant</b>	-1,91	-5,43	<b>Constant</b>	-0,70	
<b>Oil</b>	0,20	0,76	<b>Oil</b>	-0,09	0,40
<b>AR(1)</b>	0,65		<b>AR(1)</b>	0,93	0,62
<b>Standard deviation of residuals</b>	14,23	25,91	<b>Standard deviation of residuals</b>	7,91	

Table 2 shows, that in the model chosen for electricity prices are all parameters, except the autoregressive term, time-varying. These results are similar to those obtained by separate regression equations, what is also validated by picture 1, containing the probabilities of individual regimes. The first regime corresponds to the period of lower effect of oil prices on electricity prices while the second regime represents the opposite. The transition between these two states happens at the end of 2008. More interestingly, the model considers the time period at the end of the sample (approximately from the start of 2017) to be a period of gradual return to the second regime. This indicates that the relationship between oil prices and electricity prices is becoming stronger again during the last year and a half. However, the tests of structural breaks from previous passage were unable to detect this behavior.

Results related to gas prices are showing many similarities with the first approach as well. Both the constant and the standard deviation of random errors are fixated over time in the chosen Markov-switching model. Although the standard deviations differ in separate regression equations, these differences do not seem to be essential. The rest of coefficients are almost exactly copying their counterparts estimated using the first approach. The time period of transition from the first regime (lower effect of oil prices, statistically indistinguishable from zero) to the second regime (stronger effect) is consistent as well. It happens around 7<sup>th</sup> or 8<sup>th</sup> month of 2015, exactly as indicated by the tests of structural

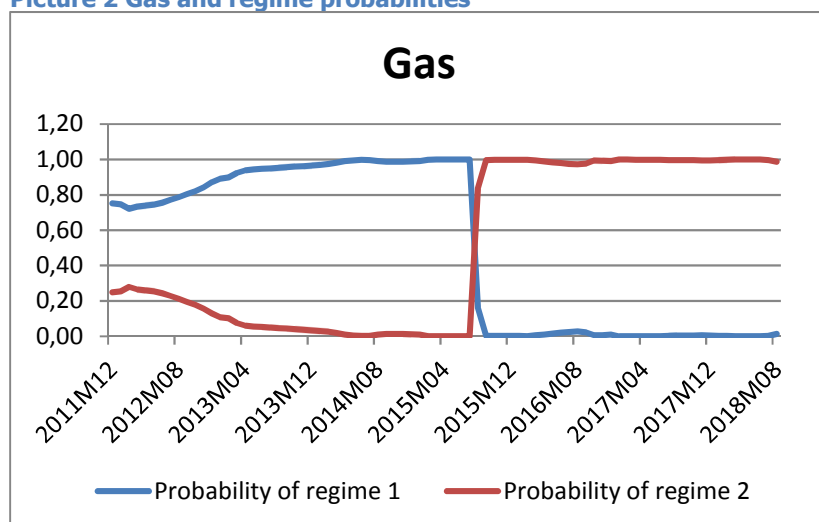
breaks. Contrary to the case of electricity prices, the data does not implicate any returns to the original regime.

Picture 1 Electricity and regime probabilities



Source: own calculations

Picture 2 Gas and regime probabilities



Source: own calculations

### State space model

Estimation using state space models provided four possible model specifications. Similarly to previous approach, the factors that determined the choice of the model were robustness (sensitivity to initial conditions<sup>3</sup>) and minimalization of information criteria. The most suitable specification for both dependent variables was the one, where the only time-varying

<sup>3</sup> Starting values of coefficients that were needed to estimate individual models were calibrated based on results of basic regression equations, estimated on full sample. Afterwards, these models were estimated another 1000 times using randomly generated starting values from uniform distribution. The robustness of the model was then determined by the consistency of these results.

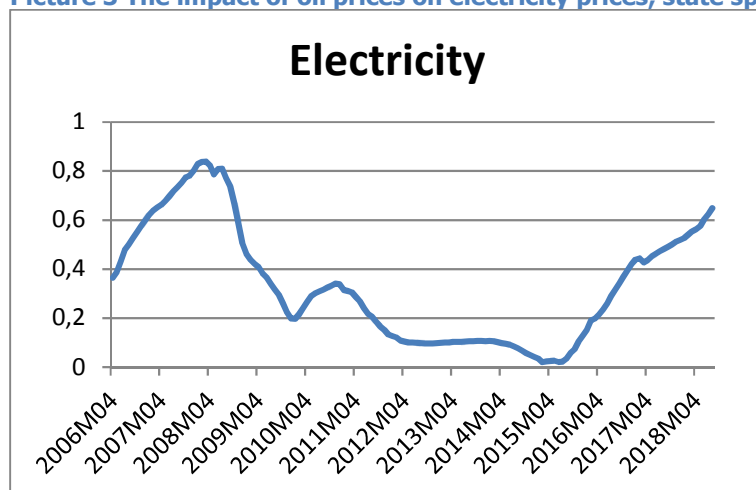
coefficient was related to oil prices. Table 3 contains coefficients and standard deviations, that are fixated over time.

**Table 3 State space model estimates**

	Electricity	Gas
<b>Constant</b>	-2,91	-0,62
<b>AR(1)</b>	0,61	0,71
<b>Standard deviation of residuals</b>	18,51	8,66

The constant in the case of electricity prices together with autoregressive term and standard deviation of residuals in the case of gas prices are in accordance with previous results. However, the main focus of this article is on oil prices. Contrary to previous approaches, there is not a set of several discrete values but a whole time series of coefficients (as shown in Picture 3 and 4).

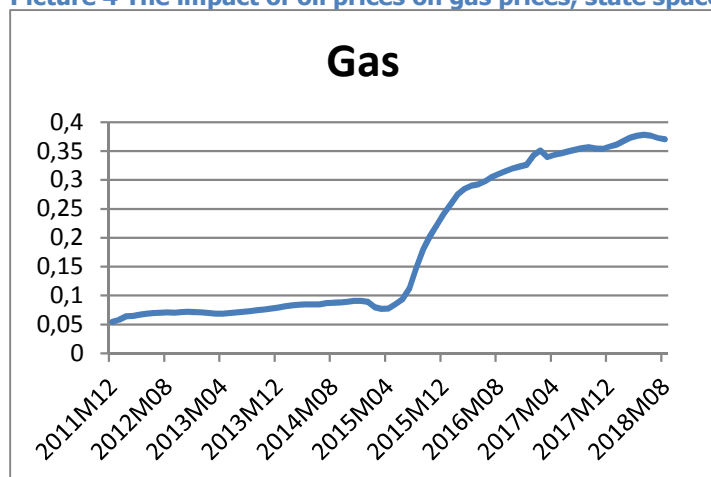
**Picture 3 The impact of oil prices on electricity prices, state space model**



Source: own calculations

The impact of oil prices on electricity prices estimated with the stated space model is, to some extent, consistent with previous findings. The connection is strong at the start of the sample, around values 0.7 – 0.8. However, a strong fall takes place at the end of 2008 and the effect converges over time almost to zero. During years 2016 and 2017 is the impact growing gradually back to values from 2007. This development is very similar to the transition between regimes in Markov-switching model, although it is continuous and smoother.

Picture 4 The impact of oil prices on gas prices, state space model



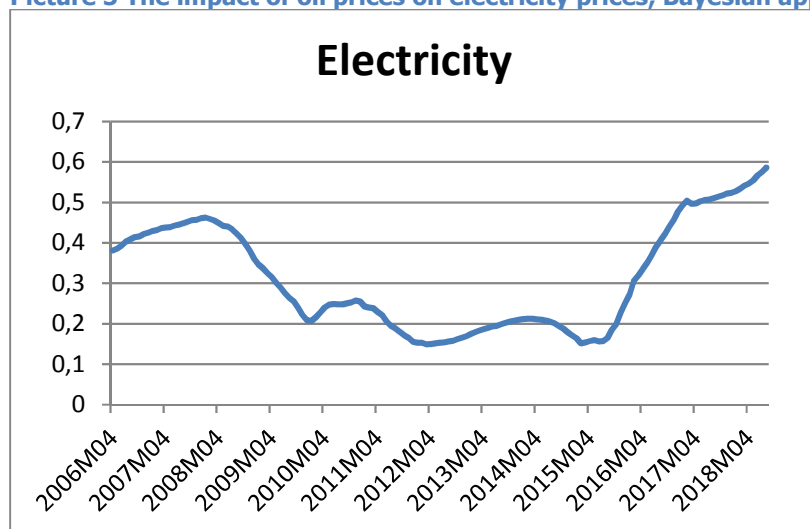
Source: own calculations

The consistency among results from different approaches regarding the effect of oil prices on gas prices, still holds. In the second half of 2015 the strength of this impact rapidly grows and afterwards remains within the higher values. Contrary to previous approaches, the value of the coefficient stays always above zero, what is more in agreement with theoretical assumptions.

### Bayesian state space model with stochastic volatility

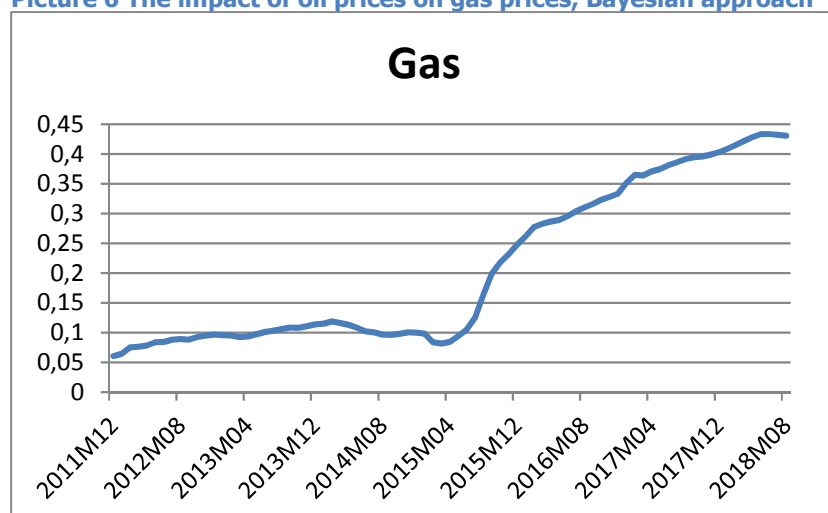
Estimation using state space models might be to some extent affected by fixing the standard deviation of residuals over time. This could possibly explain why both chosen models allowed only one variable to act as time-varying – the oil prices. Another explanation might be provided by high number of parameters required to be estimated – versions of models with more time-varying coefficients showed problems with convergence. Should the assumption about constant character of variance be relaxed, this would only multiply the problem. All these factors represent the motivation for using Bayesian methods, capable of better handling of estimations having large number of parameters or small sample. For clarity, only results regarding the oil prices will be presented in this passage.

Picture 5 The impact of oil prices on electricity prices, Bayesian approach



Source: own calculations

Picture 6 The impact of oil prices on gas prices, Bayesian approach



Source: own calculations

The relationship between oil prices and electricity prices is showing development similar to the previous approach. The main difference can be spotted in amplitude – during periods of stronger impact of oil prices, the coefficient can be found around values 0.4 – 0.5, at the end of the sample even higher, whilst the minimal values are near 0.2. In the case of gas prices, the development of coefficient over time is almost identical with previous results.

To conclude, it would seem that relaxing the assumptions about unchangeability of constant, autoregressive term and standard deviation of random errors over time did not bring any major changes in the path of the relationship between oil prices and gas prices (see picture 6 vs. picture 4, where are the mentioned coefficients fixed). On the other hand, the effect of oil prices on electricity prices was influenced by this change – the amplitude is lower and less volatile (see picture 5 vs. picture 3).

### Comparison

The aim of this article was to analyze the impact of oil prices on electricity and gas prices and to assess changes of this impact over time. In order to do so, four different instruments were utilized – regression equations divided in points of structural breaks (OLS), Markov-switching models (MS), state space models with time-varying coefficients (SS) and Bayesian state space models with stochastic volatility (BSV). The second and third approach delivered a whole set of models, from which only the most suitable model (for each dependent variable) was chosen for further examination.

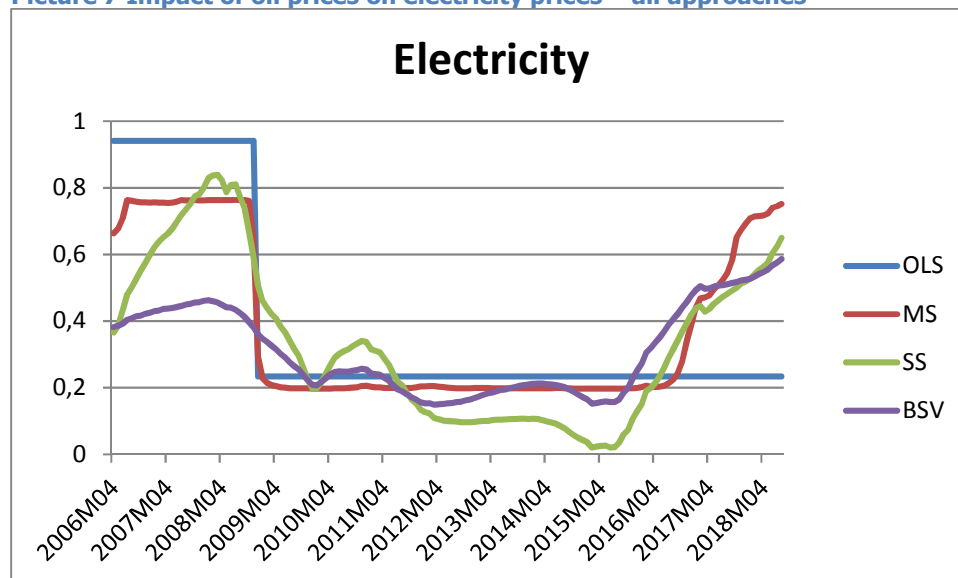
Picture 7 summarizes results of individual approaches regarding electricity prices, picture 8 regarding gas prices<sup>4</sup>. Basic trends in the development of coefficients over time are consistent across all models in both cases. The most notable difference can be attributed to results from separate regression equations in the case of electricity – contrary to all other approaches, they were unable to capture the growth of coefficient since the end of 2016. Among other differences, the most remarkable is the amplitude in the period before 2009. Especially the method BSV delivers considerably lower estimates than the alternatives.

<sup>4</sup> In the case of Markov-switching models, the time series was composited as a sum of products of estimated coefficients and regime probabilities.



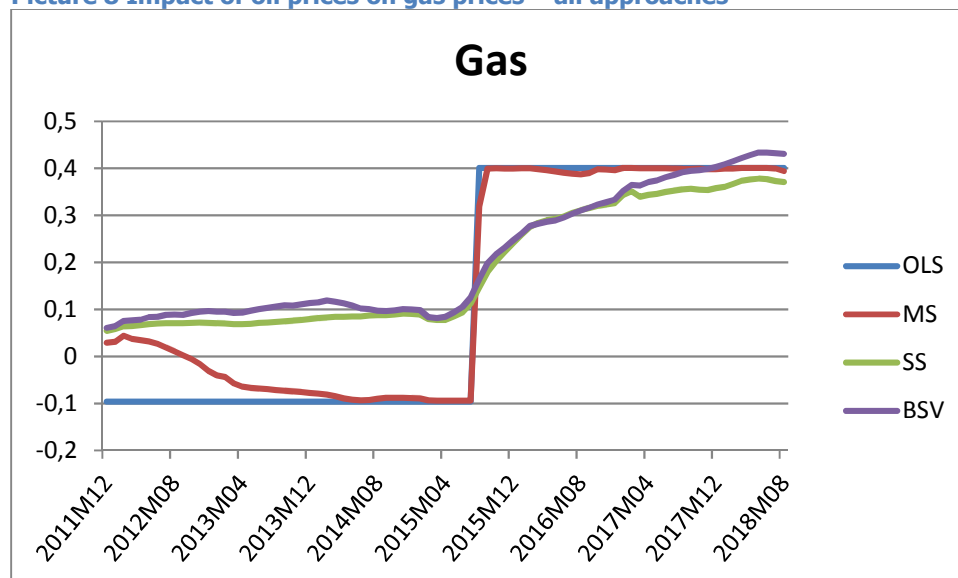
In the case of gas prices, all four approaches agree that major change of the coefficient takes place in the second half of 2015. The main difference is in the smoothness of this change, what is mainly attributed to the fact, that the first two approaches (MS and OLS) consider changes over time to be discrete, while the other two view them as continuous. Furthermore, MS and OLS estimated the value of the coefficient measuring the impact of oil prices on gas prices with negative sign until July 2015. Models that allow for a continuous change over time (SS and BSV) managed to resolve this flaw.

Picture 7 Impact of oil prices on electricity prices – all approaches



Source: own calculations

Picture 8 Impact of oil prices on gas prices – all approaches



Source: own calculations

All approaches agree on the time-varying character of the impact of oil prices on both electricity and gas prices. Additionally, they agree on considerable growth of the impact on gas prices in the second half of 2015. The effect of oil prices on electricity is falling down at the end of 2008. Apart from the first method (OLS), all the other approaches show the recovery of the impact in the period starting approximately in 2016. Subsequently, the values at the end of the sample are very similar to those at the end of 2008.

Three distinct periods can be defined in the relationship between oil prices and electricity prices: Before crisis, with relatively strong elasticity 0.6 – 0.8, after which follows the period of dampening, during which the elasticity falls approximately to 0.2 and stays there until 2015. The recovery starts from 2016 and gradually grows until it reaches current values 0.4 – 0.6. Two basic periods can be derived from results regarding gas prices – the period of almost null impact until the first half of 2015 and the period of growing impact that replaces the first and continues until today. Taking into account that prior to the crisis, gas prices were fully determined by long-term oil indexed contracts, it is only to be expected that the effect of oil prices on gas prices was substantial. Should we include this assumption into the full picture of the relationship between oil prices and gas prices (although data from this period is unavailable), we receive a trend very similar to the one we can see in the case of electricity.

## References

1. Bai, Jushan and Pierre Perron (1998): Estimating and Testing Linear Models with Multiple Structural Changes, *Econometrica*, 66, 47–78.
2. Frühwirth-Schnatter, Sylvia (2006): *Finite Mixture and Markov Switching Models*, New York: Springer Science + Business Media LLC.
3. Hamilton, James D. (1994b): State Space Models, Chapter 50 in Robert F. Engle and Daniel L. McFadden, *Handbook of Econometrics*, Volume 4, Amsterdam: Elsevier Science B.V.
4. Koop, Gary and Dimitris Korobilis (2012): Forecasting Inflation Using Dynamic Model Averaging, *International Economic Review*, 53, 867-886.
5. Primiceri, Giorgio E. (2005): Time Varying Structural Vector Autoregressions and Monetary Policy, *Review of Economic Studies* 72, 821–52.

**Roman Vrbovský ([analytici@nbs.sk](mailto:analytici@nbs.sk))**