COLLEGIUM OF ECONOMIC ANALYSIS
WORKING PAPER SERIES

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Michał Rubaszek and Karol Szafranek

SGH KAE Working Papers Series Number: 2022/078 June 2022

Have European natural gas prices decoupled from crude oil prices? Evidence from TVP-VAR analysis.*

Michał Rubaszek[a] and Karol Szafranek[a]

[a]*SGH Warsaw School of Economics, Collegium of Economic Analysis*

Abstract

Unprecedented increases in European natural gas prices observed in late 2021 and early 2022 raise a question about the sources of these events. In this article we investigate this topic using a time-varying parameters structural vector autoregressive model for crude oil, US and European natural gas prices. This flexible framework allows us to measure how disturbances specific to the analyzed markets propagate within the system and how this propagation mechanism evolves in time. Our findings are fourfold. First, we show that oil prices are hardly affected by shocks specific to natural gas markets, whether in the US or Europe. Second, we demonstrate that oil shocks have limited impact on US gas prices, which points to the decoupling of both markets. Third, we evidence that over longer horizons natural gas prices in Europe are still mostly determined by oil shocks, with idiosyncratic shocks leading to short-lived decoupling of both commodity prices. Fourth, we illustrate that along the gradual shift from oil price indexation to gas-on-gas competition, the contribution of idiosyncratic shocks to European natural gas prices has increased. Nonetheless, we discuss why the notion that EU natural gas and crude oil prices have decoupled might be premature.

Keywords: Energy market, oil-gas relationship, TVP-VAR model, Bayesian inference.

JEL classification: C11, C32, Q31.

*Correspondence should be directed to karol.szafranek@sgh.waw.pl. Postal address: Al. Niepodległosci 162, 02-554 Warsaw, Poland. This article was realized thanks to the financial support from the National Science Centre (Poland) within grant No. 2020/39/B/HS4/00366. We are grateful to Elena Maria Diaz for comments presented during discussion at the FMND 2022 conference.

1 Introduction

Natural gas is a strategic source of energy in the global economy, including most European countries. It plays a crucial role in residential and commercial heating. It also serves as an important input for industrial production and electricity generation. Moreover, natural gas is considered to be a bridge fuel in energy transition, as gas power plants emit much less carbon dioxide than coal plants and are a far better complement to unstable renewable energy sources due to their dispatchability. In 2022 these features have been recognized by the European Commission, which labelled natural gas as a green energy source that be can exploited by countries in their transition to a low-carbon economy. For the above reasons the unprecedented increase in prices of this commodity observed in the second half of 2021 and early 2022 across European hubs constituted a significant disturbance to the functioning of the European economy. First and foremost, it has generated considerable inflationary pressure, thus posing risk to the economic recovery following the outbreak of the Covid-19 pandemic. Second, it has raised fundamental concerns with respect to Europe's energy security and the costs of the decarbonization policy.

The rising role of natural gas as a source of energy is also reflected by an increase in the number of studies attempting to explain the dynamics of its prices. They usually point to the fact that the global natural gas market is geographically segmented into several local markets due to transportation costs and the presence of heterogeneous institutions (see Kan et al., 2019, for a detailed overview of the global natural gas market structure). Consequently, natural gas prices evolve fairly independently in different parts of the world, especially after the shale gas revolution in the US (Wakamatsu and Aruga, 2013; Geng et al., 2016b; Zhang and Ji, 2018). This distinguishes natural gas from crude oil, which prices are determined by global rather than local factors. This dichotomy in terms of geographical coverage, combined with the fact that both energy commodities are imperfect substitutes, has motivated researchers to investigate the relationship among the dynamics of regional natural gas and global crude oil prices. One of the conclusions is that the natural gas market is strongly influenced by the developments in the crude oil market, with little evidence for reverse causality (Lin and Li, 2015; Jadidzadeh and Serletis, 2017; Tiwari et al., 2019; Gong et al., 2021).[1] Additionally, some authors indicate that the long-term relationship between both commodities in the US market has decoupled since mid 2000s, which did not happen in the European market (Erdos, 2012; Geng et al., 2016a; Zhang and Ji, 2018; Wang et al., 2019).

Another widely discussed issue in the literature concerns the source of natural gas price fluctuations. The authors usually focus on the US market and apply the structural vector autoregression (VAR) framework. One of the reasons is that the natural gas market in

[1]The work by Batten et al. (2017) is an exception as the authors find that before 2006 and for very short horizons natural gas prices were Granger causing crude oil prices.

the US was the first one that was fully deregulated following the Natural Gas Policy Act of 1978. Consequently, since mid-1990s natural gas prices have been entirely determined by market forces (Joskow, 2013). This justifies the application of dynamic models in which prices of this commodity are driven by supply and demand factors. The studies using structural VAR models point to three regularities. First, demand shocks seem more important in explaining the dynamics of natural gas prices rather than supply shocks (Arora and Lieskovsky, 2014; Hou and Nguyen, 2018; Hailemariam and Smyth, 2019; Rubaszek et al., 2021). Second, the dynamics of the US natural gas market is not stable over time (Wiggins and Etienne, 2017; Hou and Nguyen, 2018; Nguyen and Okimoto, 2019; Rubaszek and Uddin, 2020; Rubaszek et al., 2020), which justifies the use of time-varying parameters models as postulated by Granger (2008). Third, natural gas prices are affected by oil prices (Jadidzadeh and Serletis, 2017).

Against this background, the price formation mechanism on the European natural gas market is relatively unexplored. This might be related to the fact that modelling this market is challenging for two reasons.

First, the analysis of supply requires taking into account that it is predominantly based on imports via pipelines from Russia. According to Eurostat the EU's reliance on gas imports from Russia stood at almost 40% in 2020. Other import directions via pipelines include mostly Norway and Algeria. The demand is further balanced by domestic sources and an increasing share of liquefied natural gas (LNG). It should be noted, however, that over time the role of domestic sources has declined, with decreasing supply from the UK and the Netherlands, while the LNG market has experienced a significant development over the last decades and is forecast to grow even stronger, given the EU's pledge to limit Russian imports. This evolution may reinforce the linkages between distant gas markets, leading to the convergence of prices across Atlantic (Mu and Ye, 2018). Nonetheless, the present import-based supply has not only raised energy security questions (Rodriguez-Gomez et al., 2016; Bouwmeester and Oosterhaven, 2017), but also makes it difficult to assess supply response to economic factors.

The second challenge in modelling the European gas market is related to the fact that it has undergone the liberalization process only over the last two decades. This involved several legislative packages, which are described in details by Bastianin et al. (2019). In 1998, the First Gas Directive opened up the market to competition by facilitating the entry into the competitive segments of the industry (transmission, distribution, supply and storage). In 2003, the Second Gas Directive unbundled transmission from supply. In 2009, the Third Gas Directive introduced common rules for the functioning of natural gas market, including incentives for launching trading hubs. These changes have resulted in a gradual but sizeable shift from oil price indexation (OPI) to gas-on-gas (GoG) competition (del Valle et al., 2017; Chyong, 2019). According to IGU (2021), between 2005 and 2020 the share of GoG contracts in total gas consumption increased from 15% to 80%, whereas the share of OPI went down from 78% to 20%.

The above developments urge the question on whether European natural gas prices are still driven by changes in oil prices or rather the role of US natural gas prices and fundamental factors specific to the European natural gas market has increased over time. So far this question has been only partially answered in the literature. A number of studies applied cointegration techniques in search for the long-term relationship between oil and natural gas prices in the US and in Europe (see Ji et al., 2018, for a comprehensive survey). Specifically, Brown and Yucel (2009) conclude that the co-movement between European and US gas prices is driven by crude oil prices rather than gas-to-gas arbitrage across the Atlantic. In turn, Asche et al. (2017) show that European gas prices and Brent oil prices are cointegrated, but the long-term relationship is regime dependent. The authors also claim that in GoG markets the relationship between oil and natural gas prices should be weaker as natural gas should be priced as a unique commodity. This kind of result is presented for the US, but not for Europe (Erdos, 2012). However, it can be expected that a similar decoupling will be observed in Europe, given the ongoing shift towards the GoG pricing model. In this respect, two studies should be mentioned. Nick and Thoenes (2014) propose a structural VAR model to show that natural gas prices in Germany are affected by temperature, storage and supply shortfalls in the short-term, while in the long-term they are tied to crude oil and coal prices. Hulshof et al. (2016) find that daily spot prices at the Dutch Title Transfer Facility (TTF) hub are over short-term horizon only mildly affected by changes in oil prices, but react to European idiosyncratic factors such as the level of natural gas inventories, temperature and the production of wind electricity. Finally, there are also a few very recent studies indicating that the impact of oil prices on the natural gas market should be analyzed using time-varying parameters (TVP) models. For instance, Gong et al. (2021) estimate a TVP-VAR model to investigate dynamic volatility spillovers between four major energy commodities (crude oil, gasoline, heating oil and natural gas) in the US market. Ji et al. (2018) employ a model with varying parameters (estimated in a rolling window) to analyze the oil–gas relationship within the connectedness network framework. In turn, Gao et al. (2021) show that univariate models allowing for gradual changes in coefficients and drastic changes in volatility have the best forecasting performance for European gas prices. These three studies clearly indicate that the changing structure of the natural gas market requires the use of models with time-varying parameters.

In this work, we contribute to the above studies by investigating how changes in oil and natural gas prices in the US affect natural gas prices in Europe. We start by estimating a constant coefficient structural VAR model for the three variables. Based on this framework we analyze the determinants in European natural gas prices using impulse response functions, forecast error variance decomposition and historical decomposition. Next, given the gradually changing structure of the European natural gas market we relax our key model assumption on parameters being constant over the entire sample and move to the time-varying parameters model with stochastic volatility (henceforth TVP-VAR-SV). This approach allows us to study the evolving relationship between oil prices, US natural gas prices and European natural gas prices at each point in time.

Our study allows us to make two general conclusions. The constant coefficient framework indicates that over the entire sample the dynamics of natural gas prices in Europe was driven predominantly by local factors over the short-run, but their importance decreases in the medium and long-term horizon as oil shocks account for up to around 40% of EU natural gas prices variability. On the contrary, natural gas prices in the US evolved independently of the developments in the oil market. Consequently, natural gas prices were also decoupled across the Atlantic. This outcome confirms the prevailing evidence in the literature. Next, the TVP-VAR-SV analysis demonstrates that over the last two decades, with the ongoing shift from OPI to GoG structure, the contribution of local shocks to European natural gas prices fluctuations has gradually increased in time. However, despite this trend, in the long-term European gas prices are still determined mostly by the developments in the crude oil market. The TVP-VAR-SV model also shows that the most recent developments, i.e. drastic natural gas prices increases, can be explained by increased volatility of local shocks rather than by the decoupling from the oil market. We believe that these results provide a new insight into the discussion on the dynamics of the European natural gas market.

The remainder of the article is structured as follows. Section 2 describes the data. In section 3 we present the constant coefficient structural VAR model and discuss the results. In section 4 we move to the time-varying parameters framework and investigate the interplay between the energy commodity prices in time. Section 5 grants conclusions and policy implications.

2 Data

Our analysis is based on monthly data from January 1993 to May 2022, a sample that covers the period in which the US natural gas market was deregulated. We also use data from January 1983 to December 1992 for technical purposes, i.e. as a pre-sample to calibrate prior information for the TVP-VAR-SV model. It can be noted that this choice is standard for studies focused on the US market surveyed above, e.g. the study using the TVP-VAR model by Wiggins and Etienne (2017).

We take nominal prices of WTI crude oil (P^{OIL}) as well as US and EU natural gas (P^{NGUS} and P^{NGEU}) from the World Bank commodity database. These three variables are usually expressed in different units of measure, namely USD per barrel, USD per MMBTu and EUR per MWh. For the sake of comparability, we express them in the common unit, i.e. USD per barrel of oil equivalent (boe). Next, we deflate them using the US consumer price index, taken from the FRED database, which we rescale so that its value for the last observation (May 2022) is equal to unity. Consequently, all real prices are expressed in units from the end of the sample. Finally, all the series were adjusted for seasonal patters, which – although weak – were present, especially in the case of natural gas.

A quick look at the series presented in Figure 1 warrants few observations. First, oil and natural gas prices are visibly correlated, with the link stronger for the EU than the US market. In general, over almost the entire sample EU natural gas prices follow oil prices, which might reflect their partial indexation within long-term contracts. Second, the volatility of natural gas prices in the US tends to be higher than in Europe, which might reflect different structures of both markets. However, in the second half of 2021 and early 2022 we observe a striking increase in European gas prices, by far outpacing changes in the remaining two variables. Third, all the series experience periods of higher and lower variability, which would suggest that a robust model describing these markets should take into account that the volatility of shocks is time-varying.

The above visual characteristics of the data presented in Figure 1 are complemented by descriptive statistics in Table 1. It shows that log changes in European gas prices are less volatile that the remaining series, rightly skewed, leptokurtic and slightly autocorrelated. We also find that the ADF test fails to reject the null for the log levels of all the series. However, this outcome can be attributed to the low power of the test for persistent variables. In our modeling framework we proceed with log levels of real prices of the analyzed variables as is usually done in structural VAR models for oil and natural gas (e.g. Kilian, 2009; Jadidzadeh and Serletis, 2017).

3 Constant coefficient structural VAR approach

3.1 The model

We start our investigation of the European natural gas market by considering a structural VAR model for the trivariate vector $y_t = (p_t^{\mathrm{OIL}}, p_t^{\mathrm{NGUS}}, p_t^{\mathrm{NGEU}})'$, where $p = \log(P)$. This is the most parsimonious specification to analyze the dynamic interactions among the three markets. The structural VAR process with the lag length l is:

$$y_t = B_0 + \sum_{i=1}^{l} B_i y_{t-i} + D\eta_t, \quad \eta_t \sim \mathcal{N}(0, I) \tag{1}$$

where B_0 is a 3×1 vector of constant terms, B_i for $i = 1, 2, ..., l$ denote 3×3 matrices of autoregressive coefficients, D is a 3×3 identification matrix and η_t is a 3×1 vector of structural shocks. It contains innovations to US oil (η^{OIL}), US natural gas (η^{NGUS}) and EU natural gas (η^{NGEU}) prices. In model identification, we impose the recursive identification scheme, in which D is a lower triangular matrix as:

$$D = \begin{bmatrix} * & 0 & 0 \\ * & * & 0 \\ * & * & * \end{bmatrix} \tag{2}$$

Based on the Schwartz information criterion, we set the maximum lag to $l = 2$ and estimate the reduced-form VAR on the main sample with the least squares method. Next, we use the estimated covariance matrix of residuals to compute the elements $*$ of matrix D. Finally, we calculate impulse response functions to structural shocks, forecast error variance decomposition as well as historical decomposition for the three series.

3.2 The results

Impulse response functions. Figure 2 presents the impulse response functions (IRFs) of endogenous variables to one standard deviation of structural shocks along with the 90% confidence bands. The left top panel illustrates that an oil market innovation immediately leads to an increase in crude oil prices by 9%, which in the subsequent two months reaches a peak of almost 11%. After the initial jump, oil prices slowly return to equilibrium, but even after five years their level is still around 3% above the level observed before the occurrence of the shock. The center top panel demonstrates that oil prices are not significantly affected by shocks to US gas prices, which confirms the earlier results in the surveyed literature (e.g. Jadidzadeh and Serletis, 2017). The right top panel shows that oil prices are sensitive to unexpected changes in EU gas prices. This result, which is at odds with the studies surveyed in the Introduction, is driven by the large variation in oil and natural gas prices observed after 2020. In fact, throughout 2021 the relative price of power generation in Europe from natural gas has increased so much that it prompted a switch to oil, increasing global demand for oil by approximately half a million barrels a day (estimated by IEA, 2021). When we restrict the sample to December 2020, the response of oil prices to EU natural gas shock is insignificant.[2]

The reaction of natural gas prices in the US to the structural shocks is presented in the middle row of Figure 2. It can be seen that an oil price shock initially leads to an increase in natural gas prices by around 3-4%. Next, prices revert to the pre-shock level relatively quickly, so that three years after the occurrence of the shock they are almost back to equilibrium. The center panel indicates that the idiosyncratic shock causes an initial jump in prices by about 13% and its gradual reversion to equilibrium, which lasts 5 years. Finally, the reaction to a shock originating in the European gas market, which is depicted in the right panel, is positive and significant, but short-lived. It can be added that again, this result is driven by observations from the last two years of the sample.

The bottom row of Figure 2 presents the reaction of the main variable of our interest: European gas prices. The left panel indicates that an oil shock does not initially lead to a sizable reaction of European gas prices. However, after two years this reaction is significant and amounts to around 5%, which is comparable to the response of oil prices at this horizon. As a result, following an oil shock, the decoupling of European natural gas prices from oil prices is short-lived and broadly disappears after two years. The center panel shows that European gas prices are not significantly affected by the development in the US gas market in the statistical sense. The reaction is not sizable and visibly weaker from the reaction of P^{NGUS} to this shock. The comparison of both variables reaction illustrates how shocks in the US market lead to the decoupling of natural gas prices across the Atlantic. Finally, the right bottom panel shows that idiosyncratic shocks to the European natural gas market lead to a persistent upward shift in prices, where the initial reaction amounts to about 7%, with peak at around 8% shortly after the occurrence of the shock.

The analysis of all IRFs leads to two main conclusions. First, the comparison of IRFs for crude oil and US gas prices indicates that after the occurrence of η^{OIL} and η^{NGUS} innovations, both variables behave differently. This illustrates the observed decoupling of the US gas and crude oil markets. Second, the comparison of IRFs for crude oil and European gas prices indicates that after η^{OIL} as well as η^{NGEU} shocks there is only a temporary decoupling of both markets. However, after two years from the occurrence of shocks the reactions of both variables are almost the same. Moreover, after the η^{NGUS} shock both variables behave similarly from the initial period onwards. This would indicate that the dynamics of these two markets are closely linked over medium and long-term horizons, but not over the short-term one.

[2]Detailed results for this robustness check are available upon request.

Forecast error variance decomposition. How important are the three shocks for the dynamics of the real energy commodity prices? Figure 3 quantifies their contribution to the forecast error variance for individual variables at different horizons. The left panel shows that fluctuations in oil prices are to a major extent determined by shocks specific to the oil market. This confirms that the situation in the natural gas market has a limited impact on crude oil price developments. We note that the non-negligible contribution of EU natural gas shocks to oil prices variation is driven by most recent observations in the sample. Next, the center panel shows that US natural gas prices are predominantly driven by shocks specific to the US natural gas market. The contribution of oil shocks to the forecast error variance increases along the horizon, but stabilizes at less than 15% after one year. The contribution of the European gas market shocks is hardly discernible. Finally, the right panel demonstrates that in the short run European natural gas prices are almost entirely determined by idiosyncratic shocks. However, for further horizons there is a notable increase in the contribution of oil shocks, which rises to over 40%. The contribution of shocks originating in the US gas market is relatively small.

In general, the FEVD analysis leads to three conclusions. It confirms that developments in the natural gas markets, both in the US and in Europe, affect crude oil prices only to a limited extent. Next, it illustrates that US gas prices are not linked to oil prices neither in the short nor in the long horizon. Finally, European gas prices are linked to oil prices over the medium and long term.

Historical decomposition. We end the SVAR analysis by computing the contribution of the three shocks to real energy commodity price developments. The upper panel of Figure 4 illustrates that, apart from the most recent period, oil prices are hardly affected by natural gas markets shocks. The middle panel shows that major fluctuations in the US natural gas prices before the shale gas revolution as well as their subsequent rapid decline have been driven by shocks specific to the US natural gas sector. However, for this variable there is also a visible and non-negligible contribution of oil market shocks, especially following the outburst of the great financial crisis as well as during the period of abundant oil supply throughout 2015 and 2016. It is also discernible that recent increases in US natural gas prices are partly driven by shocks originating in the EU market. Finally, the bottom panel summarizes well the dependence of European natural gas prices on crude oil market developments, especially up until the end of 2016. It unambiguously shows that till that date most of European gas price fluctuations have closely followed crude oil market dynamics, with only a temporal impact of shocks specific to the US and European natural gas markets. However, the chart also shows that since 2018 European gas prices have been predominantly driven by idiosyncratic shocks, specific to the EU market.

4 Time-varying parameters VAR approach

We have so far indicated that for the last decades the European gas market has undergone a structural change, including a gradual shift from oil price indexation to gas-on-gas pricing. Moreover, the results from the previous section indicate that the developments in the European gas market in the last years were much different compared to the pre-Covid period. This would suggest that there are sound reasons to extend the structural VAR analysis by allowing for time-variation in model parameters.

In this section we employ the TVP-VAR-SV model proposed by Primiceri (2005) and subsequently refined by Del Negro and Primiceri (2015). We have decided to use this framework, rather than a regime-switching or threshold model, as it is considered to be best suited to describe the gradually evolving structure of the analyzed system, in our case the European natural gas market. Another reason for our choice is that this approach allows us to capture various sources of nonlinearities present in the system and pin down the varying magnitude of shocks, as all model coefficients evolve continuously in time (Granger, 2008; Ng and Wright, 2013; Lubik and Matthes, 2015). This feature should be of vital importance given the recent developments on the energy markets. The advantages of the TVP-VAR-SV model come at the cost of heavy parametrization and non-trivial estimation. Nonetheless, time-varying parameters models have become increasingly popular in various investigations, in particular related to the evolution and interplay of key macroeconomic variables (e.g. Primiceri, 2005; Lubik et al., 2016; Anh et al., 2018; Bjørnland et al., 2019; Corsello and Nispi Landi, 2020) or the developments in energy commodity markets (e.g. Baumeister and Peersman, 2013; Wiggins and Etienne, 2017; Liu and Gong, 2020; Anand and Paul, 2021; Ding et al., 2021; Lyu et al., 2021; Shang and Hamori, 2021).

4.1 The model

In the time-varying framework the dynamics of the dependent variable y_t is given by a VAR process of order $l = 2$ according to the following rule of motion:

$$y_t = B_{0,t} + \sum_{i=1}^{l} B_{i,t} y_{t-i} + D_t \eta_t, \quad \eta_t \sim \mathcal{N}(0, I) \tag{3}$$

Note that now we allow all parameters, i.e. the vector of constant terms $B_{0,t}$, the coefficients of the autoregressive matrices $\{B_{i,t}\}_{i=1}^{l}$ and the identification matrix D_t to change over time. The drift in the lagged coefficients is designed to capture possible nonlinearities and time variation in the lag structure of the model, which affects the propagation mechanism of shocks. In turn, the variability in the identification matrix reflects heteroscedastic structure of innovations in the system. By allowing for the variation in both parts of the model, we leave it up to data to determine whether it results from changes in the magnitude of economic shocks (i.e. the impulse) or the changes in the propagation mechanism (i.e. the response).

To estimate the model efficiently we assume that $D_t = A_t^{-1}\Sigma_t$, where A_t is a lower triangular matrix that models the contemporaneous relations between endogenous variables, while Σ_t is the diagonal matrix of standard deviations. In our case, i.e. for the recursive identification scheme and trivariate system, they are as follows:

$$A_t = \begin{bmatrix} 1 & 0 & 0 \\ a_{21,t} & 1 & 0 \\ a_{31,t} & a_{32,t} & 1 \end{bmatrix}, \quad \Sigma_t = \begin{bmatrix} \sigma_{1t} & 0 & 0 \\ 0 & \sigma_{2t} & 0 \\ 0 & 0 & \sigma_{3t} \end{bmatrix} \tag{4}$$

Given the above decomposition, we perform common VAR analysis in the time-varying framework by drawing from the posterior distribution. For that purpose we write down model (3) as:

$$y_t = X_t'\beta_t + A_t^{-1}\Sigma_t\eta_t, \tag{5}$$

where β_t is a vector that collects all parameters from $\{B_{i,t}\}_{i=0}^{l}$ and $X_t' = I_3 \otimes [1, y_{t-1}', ..., y_{t-l}']$, with $\otimes$ being the Kronecker product.

Following Primiceri (2005), the time-varying parameters from vector β_t and the free elements of matrix A_t, which are stacked into $\alpha_t = [a_{21,t}, a_{31,t}, a_{32,t}]'$, are governed by the standard random walk. In turn, the vector of standard deviations $\sigma_t = [\sigma_{1t}, \sigma_{2t}, \sigma_{3t}]'$ follows the geometric random walk. Consequently, they are specified as follows:

$$\beta_t = \beta_{t-1} + \nu_t \tag{6}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{7}$$

$$\log\sigma_t = \log\sigma_{t-1} + \epsilon_t \tag{8}$$

All innovations in the system are assumed to be mutually independent and normally distributed with the variance-covariance matrix:

$$Var\left(\begin{bmatrix} \eta_t \\ \nu_t \\ \zeta_t \\ \epsilon_t \end{bmatrix}\right) = \begin{bmatrix} I_3 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{9}$$

where Q, S and W are positive definite, time-invariant matrices.

To estimate the model we rely on Bayesian methods, in particular the Markov Chain Monte Carlo (MCMC) approach and the Gibbs sampler proposed by Del Negro and Primiceri (2015). As regards the prior, we follow the procedure as well as choices described by Primiceri (2005), which is a standard approach in the literature (e.g. Lubik et al., 2016;

Bjørnland et al., 2019; Czudaj, 2019; Anand and Paul, 2021; Chatziantoniou et al., 2021; Lyu et al., 2021). In the first step, we need to set the prior for the initial value of model parameters, i.e. β_0, α_0 and $\log\sigma_0$. We do it by estimating the time-invariant VAR model of the form (1) using pre-sample observations. The point estimates ($\hat{\beta}$, $\hat{\alpha}$ and $\hat{\sigma}$) as well as the respective variance matrices ($\hat{V}_{\hat{\beta}}$ and $\hat{V}_{\hat{\alpha}}$) are taken as parameters of the prior distribution, namely:

$$\beta_0 \sim \mathcal{N}(\hat{\beta}, k_\beta \cdot \hat{V}_{\hat{\beta}}) \tag{10}$$

$$\alpha_0 \sim \mathcal{N}(\hat{\alpha}, k_\alpha \cdot \hat{V}_{\hat{\alpha}}) \tag{11}$$

$$\log\sigma_0 \sim \mathcal{N}(\log\hat{\sigma}, k_\sigma \cdot I_3) \tag{12}$$

As regards the hyperparameters specifying the tightness of the prior, we set them to the standard values from the literature, i.e. $k_\beta = 4$, $k_\alpha = 4$, $k_\sigma = 1$.

In the second step, we impose a prior on matrices Q, S and W by assuming that:

$$Q \sim \mathcal{IW}(k_Q^2 \cdot p_Q \cdot \hat{V}_{\hat{\beta}}, p_Q) \tag{13}$$

$$W \sim \mathcal{IW}(k_W^2 \cdot p_W \cdot I_3, p_W) \tag{14}$$

$$S_j \sim \mathcal{IW}(k_S^2 \cdot p_{S_j} \cdot \hat{V}_{\hat{\alpha}_j}, p_{S_j}) \text{ for } j \in \{1, 2\} \tag{15}$$

where $\mathcal{IW}$ denotes the inverse Wishart distribution. In equation (15) S_1 and S_2 denote two blocks of matrix S, sized 1×1 and 2×2, and corresponding to parameters belonging to separate equations of the TVP-VAR-SV model (see Primiceri, 2005, for details). As regards the hyperparameters, we use the standard values of $k_Q = 0.01$, $k_W = 0.01$ and $k_S = 0.10$, which are also chosen in most studies enumerated at the beginning of this section. However, as robustness, we have also checked how multiplying parameters k_Q and k_S and dividing k_W by a factor of 2 and 4 affects the results. Next, we choose $p_Q = 120$ to accounts for the number of observations in the pre-sample and set $p_W = n + 1$ and $p_{S_j} = j + 1$, as is usually done in the empirical literature. Finally, we set the number of MCMC draws to initialize the sampler to 5×10^3 and the number of MCMC draws to 5×10^4. Since we employ a thinning factor of 10, in the end we retain 5×10^3 draws. In presenting our results we report the median estimates along with 90% credible sets. For the detailed and critical description of the TVP-VAR-SV model, including estimation issues, we refer the reader to Lubik and Matthes (2015).

4.2 The results

The evolution of model parameters. We start our investigation of the TVP-VAR-SV model by inspecting the evolution of model parameters over time. The top and middle rows of Figure 5 present the posterior median for autoregressive coefficients along with the 90% credible sets. The overwhelming impression is that there is virtually no time variation for these parameters. On the contrary, the bottom row of the figure points to high variation in stochastic volatility parameters. It should be noted that this kind of outcome is typical for studies applying the TVP-VAR-SV framework (e.g. Primiceri, 2005; Cogley and Sargent, 2005; Koop and Korobilis, 2013; Lubik et al., 2016; Amir-Ahmadi et al., 2016; Wiggins and Etienne, 2017; Corsello and Nispi Landi, 2020; Anand and Paul, 2021).

The figure also presents the posterior median in models with rescaled hyperparameters k_Q, k_S and k_W by a factor of either 2 or 4. As can be seen, this modification, which introduces more freedom in the evolution of autoregressive parameters and at the same time constrains changes in stochastic volatility components, does not lead to a marked change in parameters estimates. Thus, we conclude that our results are robust to reasonable changes in prior assumptions.[3]

The time-stability of the lag coefficients combined with large movements in stochastic volatility means that the propagation of shocks remains rather constant, whereas the strength of the impulse varies over time. In our case, there are several, occasional and short-lived increases in the time-varying standard deviation of shocks. The most pronounced spike in stochastic volatility occurred in the period following the outbreak of the Covid-19 pandemic, while smaller variation is also discernible during the global financial crisis. In the former case, this is especially visible for the European gas prices. Our reading of this result is that depending on the event, the initial reaction of energy commodity prices should differ, but their further development in time remains similar.

Impulse response functions. Given the evidence provided in Figure 5, we inspect market reaction during several specific time periods. These pertain to the:

Mar. 1996: cold winter in the US,

Dec. 2000: high US natural gas prices during the California crisis,

Sep. 2005: record high US natural gas prices due to the Katrina hurricane,

Jun. 2008: record high oil prices,

Feb. 2009: collapse in energy commodity prices during the global financial crisis (GFC),

Feb. 2014: cold winter in the US coupled with massive natural gas withdrawals,

Mar. 2018: the cold snap in Europe due to the impact of the 'Beast from the East',

Apr. 2020: most severe economic restrictions across the globe due to Covid-19,

Mar. 2022: record high European natural gas prices.

[3]More results for the rescaled values of these parameters are presented in the Appendix.

For all the above periods, in Figure 6 we inspect the posterior median impulse response. It illustrates that the propagation mechanism has indeed remained stable across the sample, while changes in IRFs originate mostly from the movements in stochastic volatility, i.e. the strength of the impulse. It can be seen that in seven episodes that occurred before 2020 the initial response of energy commodity prices is quite similar, despite different economic triggers. For instance, the top left panel illustrates that oil market shocks increase crude oil prices, with the standard magnitude of the response from around 7% in winter 2014 to around 10% throughout the deep recession during the GFC. However, most recently, following the outbreak of the Covid-19 pandemic, the reaction of oil prices to the oil shock almost doubled, amounting to about 18%. The panel also shows that the pace of the return of oil prices to the pre-shock level remained broadly the same, with half-life amounting to about 5 years, in line with the literature on real commodity price persistence (e.g. Ghoshray et al., 2014; Rubaszek, 2021). The remaining two top panels of the figure show that the sensitivity of oil prices to natural gas market shocks in the US and in Europe is limited. Again, we observe two grouped sets of IRFs, before and during Covid-19. Interestingly, the peak of the impact of the US gas market shock on oil prices realizes far later after the occurrence of the shock than in the case of the EU shock.

The middle row of Figure 6 describes the reaction of US natural gas prices to the three structural shocks. In the first year after the oil price shock the reaction of US gas prices varies from around 4% to around 8%. It can be noticed that the pace of reversion is considerably slower than in the constant coefficient VAR. The center panel shows that during most recent events US natural gas prices reaction to market-specific shock amounted to around 21%, visibly more than during the cold winter of 1996, the California crisis, the Hurricane Katrina episode or the record withdrawals in 2014.

The bottom row of Figure 6 illustrates how the reaction of European natural gas prices to the structural shocks evolves over time. Following oil shocks there is a sizable, although lagged, response of EU natural gas prices. The peak response takes place around two years after the shock and is estimated to amount between 6% and 15%, depending on the episode. The central panel shows that the situation on the US natural gas market does not influence EU prices in a significant way, leading to the decoupling of gas prices across the Atlantic. Instead, EU market specific shocks tend to significantly impact European gas prices, with the response amounting even to around 20% for selected episodes and horizons. It should be emphasized that in this case the pace of reversion to pre-shock level is relatively quick, with half-life of about one year.

A careful look at Figure 6 leads to the observation that at longer horizons the responses of oil and European gas prices to all shocks are almost the same, which is not the case for shorter horizons. In the case of the oil shock, this is illustrated in details in Figure 7. Specifically, it presents the ratio of oil to European gas price response, at various horizons and for different moments in time, so that a value of 1 means that the reactions of both variables are the same. The figure delivers strong evidence that the decoupling of European natural gas prices from oil prices is short-lived. At horizons above 2 years, the reaction of both variables is almost exactly the same (without any restrictions imposed on VAR model parameters). Moreover, this result is valid across the sample, which covers almost three last decades.

We continue our investigation by checking how the use of the TVP-VAR-SV framework influences our perception about the dynamics of the analyzed trivariate system for energy commodity prices compared to the broadly used constant coefficient structural VAR model. In Figure 8 we compare posterior median IRF obtained from the TVP-VAR-SV approach for the last period of the sample to the IRF obtained from the structural VAR. This allows us to compare both models with information available at the end of our sample. In general, we observe that in the TVP-VAR-SV model the response of energy commodity prices to shocks is more pronounced and sometimes more persistent than in the structural VAR model. However, both models are unanimously pointing to the segmentation of gas markets and to the link between European gas and crude oil prices in the longer horizons. This would suggest that, despite the changes in the structure of the European natural gas market, including a shift from the oil price indexation towards gas-on gas competition, European prices are still linked to oil prices over the long-term horizon.

Forecast error variance decomposition. We conclude the TVP-VAR-SV analysis by quantifying time-varying contribution of the three shocks to the forecast error variance of endogenous variables at four selected horizons, i.e. on impact, after one year, three years and five years ahead. The top row of Figure 9 shows that in the very short-term energy commodities prices are almost exclusively driven by market-specific shocks. The left column of the figure indicates that for oil prices the contribution of idiosyncratic shock to variance remains dominant also at longer horizons. Specifically, in the long run around 90% of their variability stems from the shock specific to the oil market, while the contribution of US and EU gas market shocks are negligible. As regards natural gas prices, we observe sizable discrepancies between the US and EU markets. For the former, the role of idiosyncratic shocks is dominant for all horizons and periods. The contribution of oil and European gas market shocks is usually below 30% and 5%, respectively. In the case of European gas prices the situation is different. The contribution of oil market shocks to forecast error variance at the five-year horizon is well above 60%, which points to the strong link between both energy commodity prices over the long-run. However, the figure also shows that there has been a gradual increase in the contribution of idiosyncratic shocks to the forecast error variance, which might reflect the changing structure of the European gas market. Finally, it can be seen that the developments in the US natural gas market play a minor role in the evolution of EU natural gas prices.

5 Conclusion and discussion

In this article we have investigated the joint dynamics of crude oil and natural gas prices in the US and Europe over the years 1993-2022. Our aim was to establish the relationship among the three analyzed variables and how this relationship evolved over time. The main research question was if prices of these energy commodities are determined together or rather evolve independently. For that purpose we have developed and simulated constant and time-varying parameters structural VAR models.

Our results confirm and extend two previous findings from the literature. Specifically, we have not found much evidence that oil prices are affected by shocks specific to natural gas markets, whether American or European. Second, we have shown that the dynamics of the US natural gas market is predominantly driven by idiosyncratic innovations and is only partially affected by crude oil shocks. In other words, we confirm that after deregulation and shale gas revolution, US natural gas prices and crude oil prices have separated from each other.

What is most important, we have presented new insights about the functioning of the European gas market. For the last three decades it has undergone a profound transformation, including the deregulation process and a shift from oil price indexation towards gas-on-gas competition. It can be therefore expected that, similarly to what has been observed in the US, natural gas prices should decouple from oil prices and be fully determined by market forces specific to the market. This kind of expectations could have been recently reinforced by unprecedented spikes in European gas prices, which strongly exceeded increases in crude oil prices. Indeed, since October 2021 the price of natural gas in Europe was more than twice higher than the price of crude oil, if both expressed in the same energy unit. Our results are not supporting this decoupling story. They indicate that over longer horizons European gas prices remain strongly linked to oil prices. The structural VAR analysis shows that decoupling of both variables is short-lived, whereas simulations with the TVP-VAR-SV model demonstrate that this kind of dependence among both variables is stable over the investigated period. It can be added that the TVP-VAR-SV model interprets the most recent unprecedented spikes in European gas prices as the realization of highly volatile idiosyncratic shocks, rather than decoupling of both markets.

One might therefore ask why the deregulation process has not broken the link between gas and crude oil prices in Europe, as it happened in the US. One of the reasons might be that Europe has not experienced shale gas revolution. In the US, it has led to oversupply of natural gas that, due to the lack of infrastructure, could not be easily exported. The second reason is that unlike in the US, the supply of natural gas in Europe is based on imports through pipelines from conventional sources. Even within gas-on-gas competition, natural gas exporters might decide to limit supply if prices are too low compared to oil prices as they implicitly apply oil indexation. In this respect, the price elasticity of natural gas supply from Russia, Algeria and Norway to the European market is worthy of a detailed investigation.

Our second important new result is that the impact of the shale gas revolution, originating in the US, on the European gas market has been so far hardly visible. Again, one can expect that the development of LNG infrastructure, hence increased linkages of US and European gas markets, should enable the arbitrage across the Atlantic and the elimination of the substantial price gap observed after the shale gas revolution in the US. So far this arbitrage has not worked due to the lack of liquefying capacities in the US and natural gas prices in both markets evolved almost independently. However, with the further development of the infrastructure, European countries might have a better bargaining position in negotiating new contracts for imports through pipelines from traditional sources. Indeed, in the past there were episodes when the Russian Gazprom granted price concessions under pressure from cheaper LNG imports. This factor can help in the shift of the European natural gas market from crude oil pricing into pricing based on market forces determined by current supply and demand. At the same time, higher exports capacities of LNG in the US might also weaken the divergence of the US gas market from the crude oil market.

We believe that our findings help in better understanding the evolving joint dynamics of the three energy commodity prices. The results of our analysis contain new insights important in designing and developing the common European gas market. Overall, we show that expecting the decoupling of EU natural gas prices from crude oil prices along the deregulation process of the European gas market might be premature.

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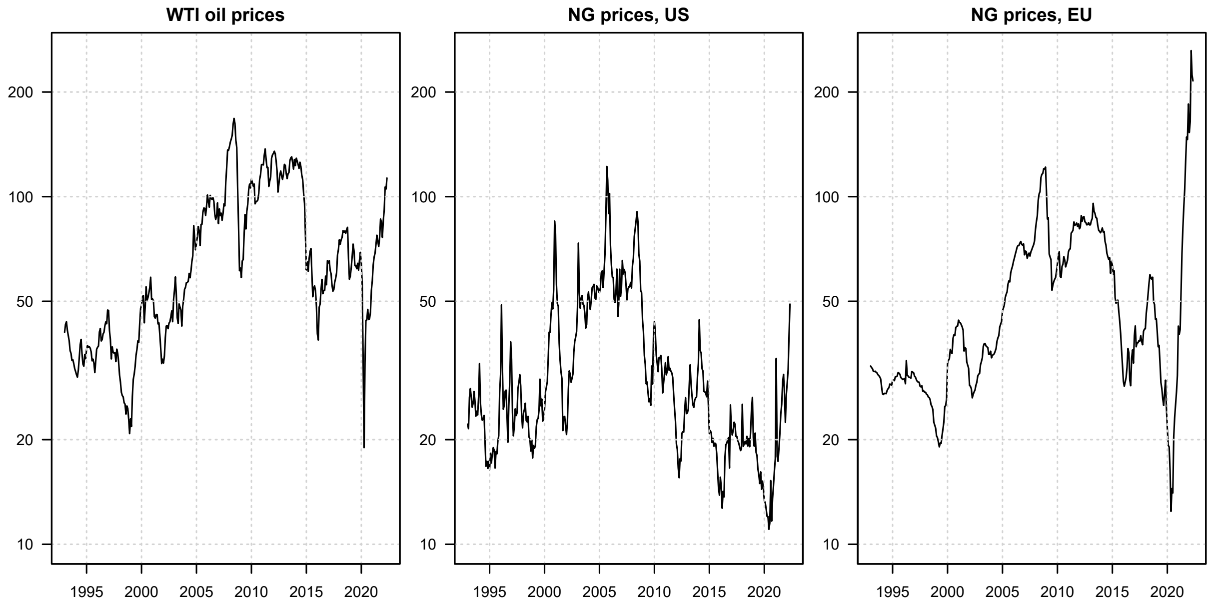
Tables and figures

Table 1: Descriptive statistics for the real prices of oil and natural gas in the US and in Europe

	ADF		Moments						ACF		
	Level	Diff	Min	Mean	SD	Max	Skew.	Kurt.	Lag 1	Lag 2	LB
OIL	-1.91	-10.92	-56.74	3.48	31.82	56.07	-0.73	13.07	0.21	-0.03	0.000
NGUS	-2.48	-11.28	-64.84	2.71	47.71	66.55	0.18	6.34	-0.02	-0.05	0.576
NGEU	-0.89	-6.15	-27.07	6.44	26.37	47.11	1.01	10.34	0.19	0.16	0.000

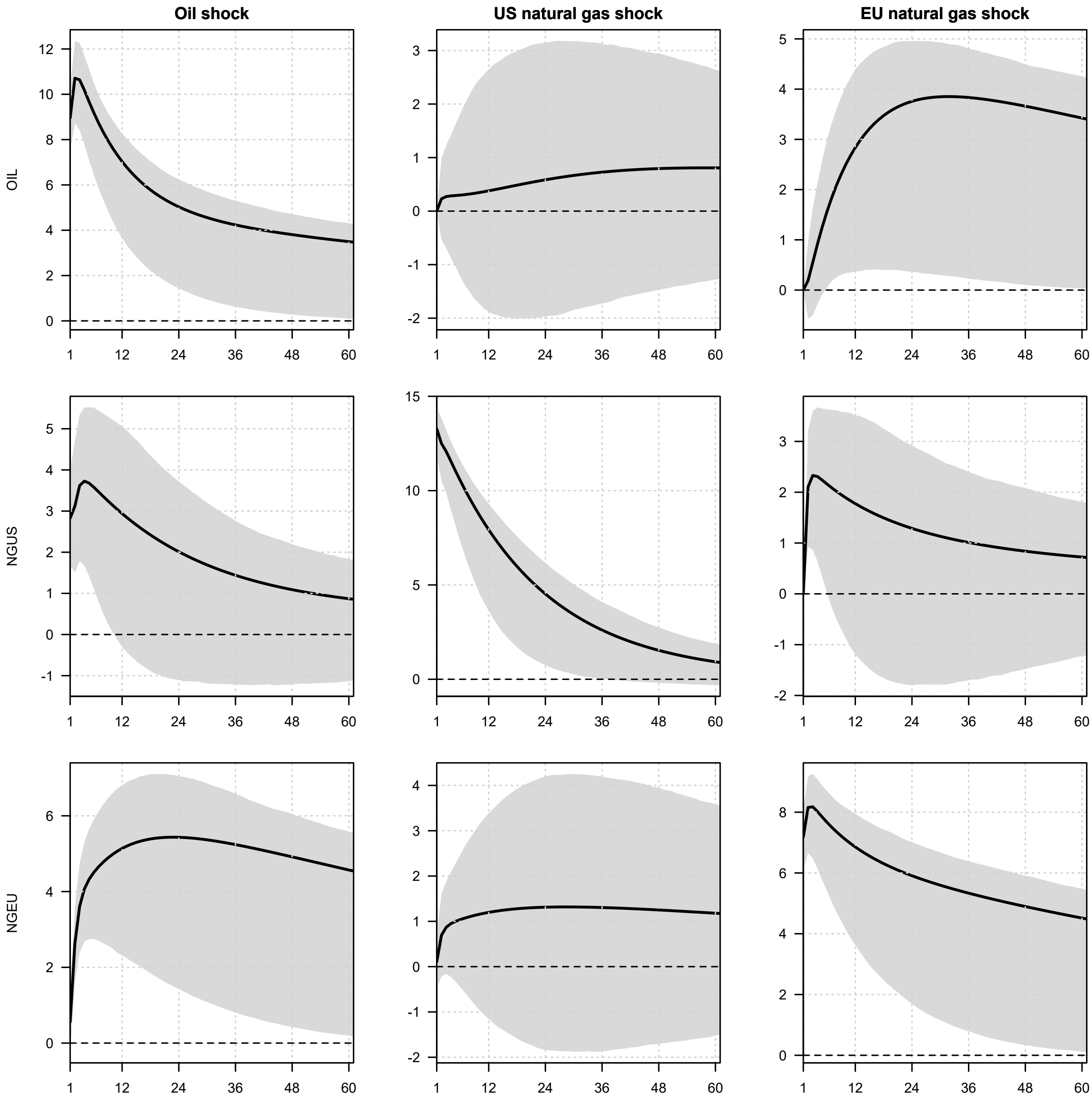
Notes: The table presents the descriptive statistics for monthly log changes (in per cent) in real oil and natural gas prices calculated on the main sample. The specification of the Augmented Dickey-Fuller (ADF) test includes a constant and two lags. The 1% and 5% critical values are -3.44 and -2.87, respectively. The mean and standard deviation is presented in annualized terms. ACF stands for autocorrelation coefficients and LB for the p-value of the Ljung-Box test with the null of no autocorrelation for the first two lags.

Figure 1: Time series for the prices of oil and natural gas in the US and Europe.



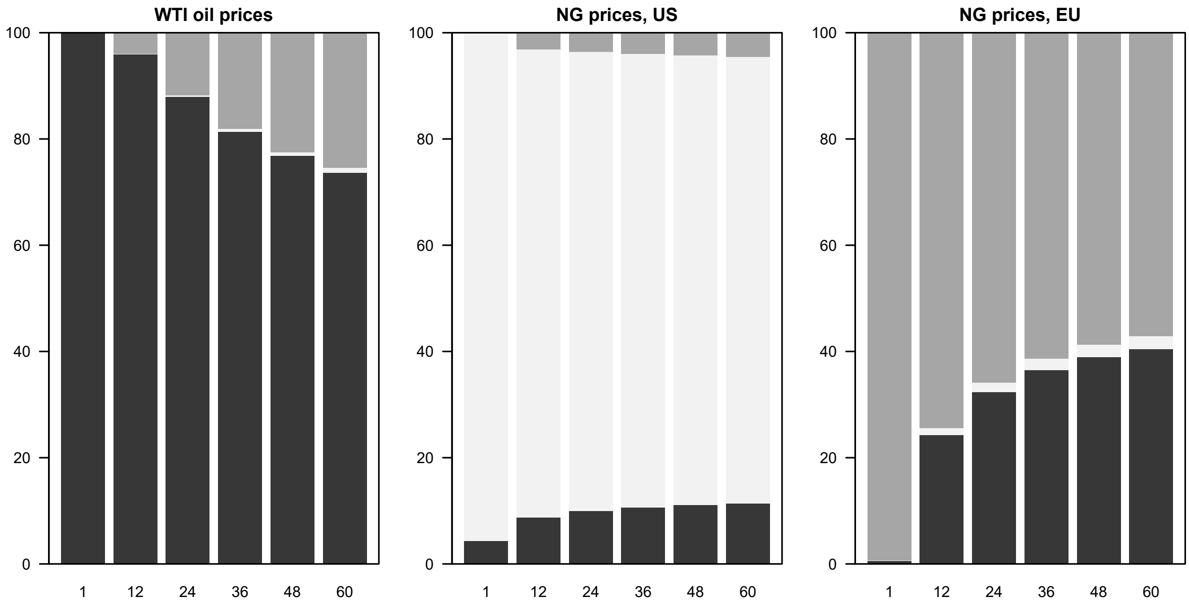
Notes: The figure presents the development in real oil and natural gas prices over the main sample. For the sake of comparability, all series are expressed in USD per barrel of oil equivalent. The y-axis is put in logarithmic scale.

Figure 2: Impulse response functions in the constant coefficient SVAR model.



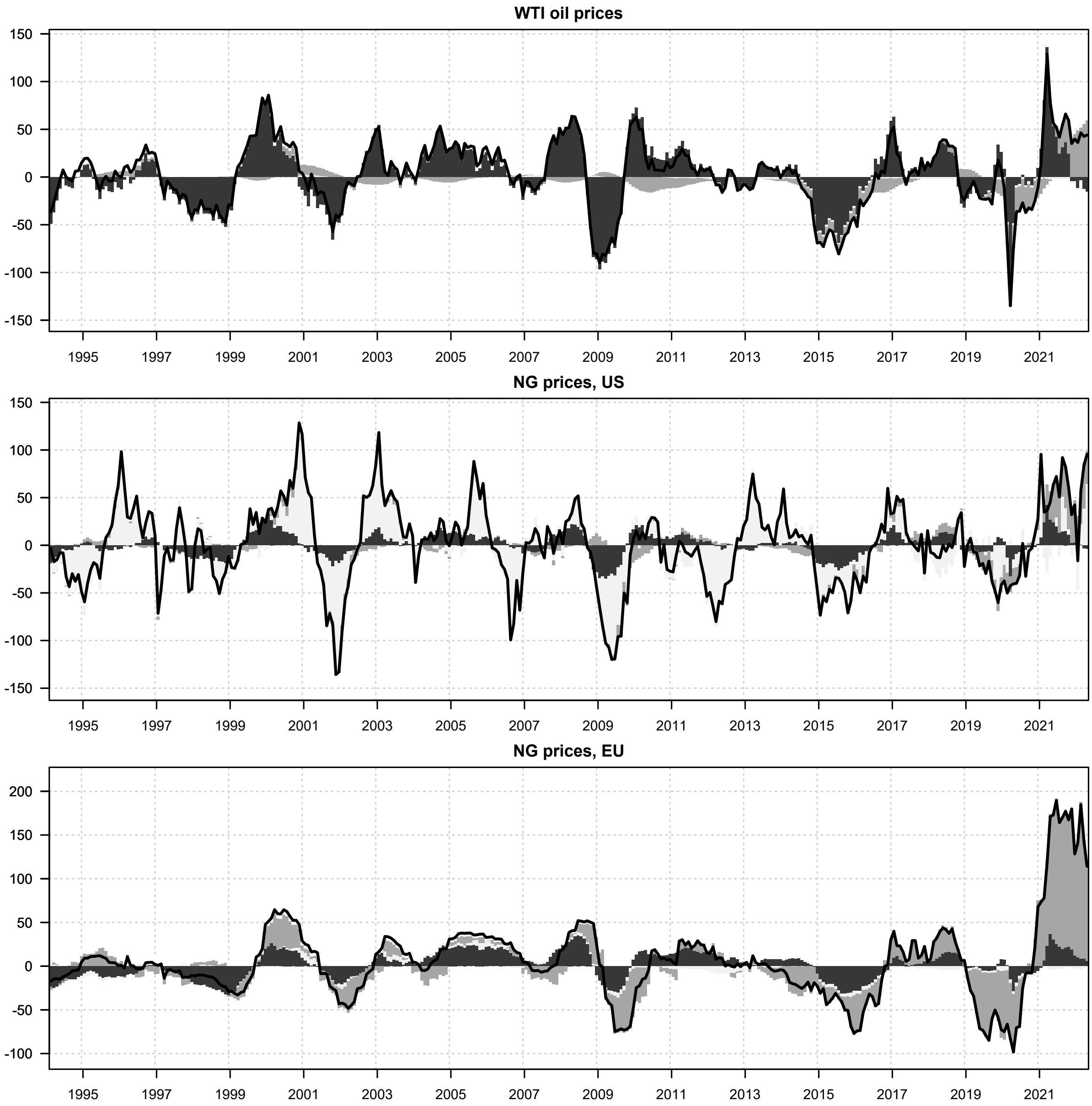
Note: The figure presents the impulse response functions to structural shocks in the constant coefficient SVAR model estimated on the main sample. The black solid lines represent the mean value, whereas the shaded area denote the upper and lower 90% bootstrapped confidence bounds. All values are multiplied by 100 so that they are expressed as per cents.

Figure 3: Forecast error variance decomposition in the constant coefficient SVAR model.



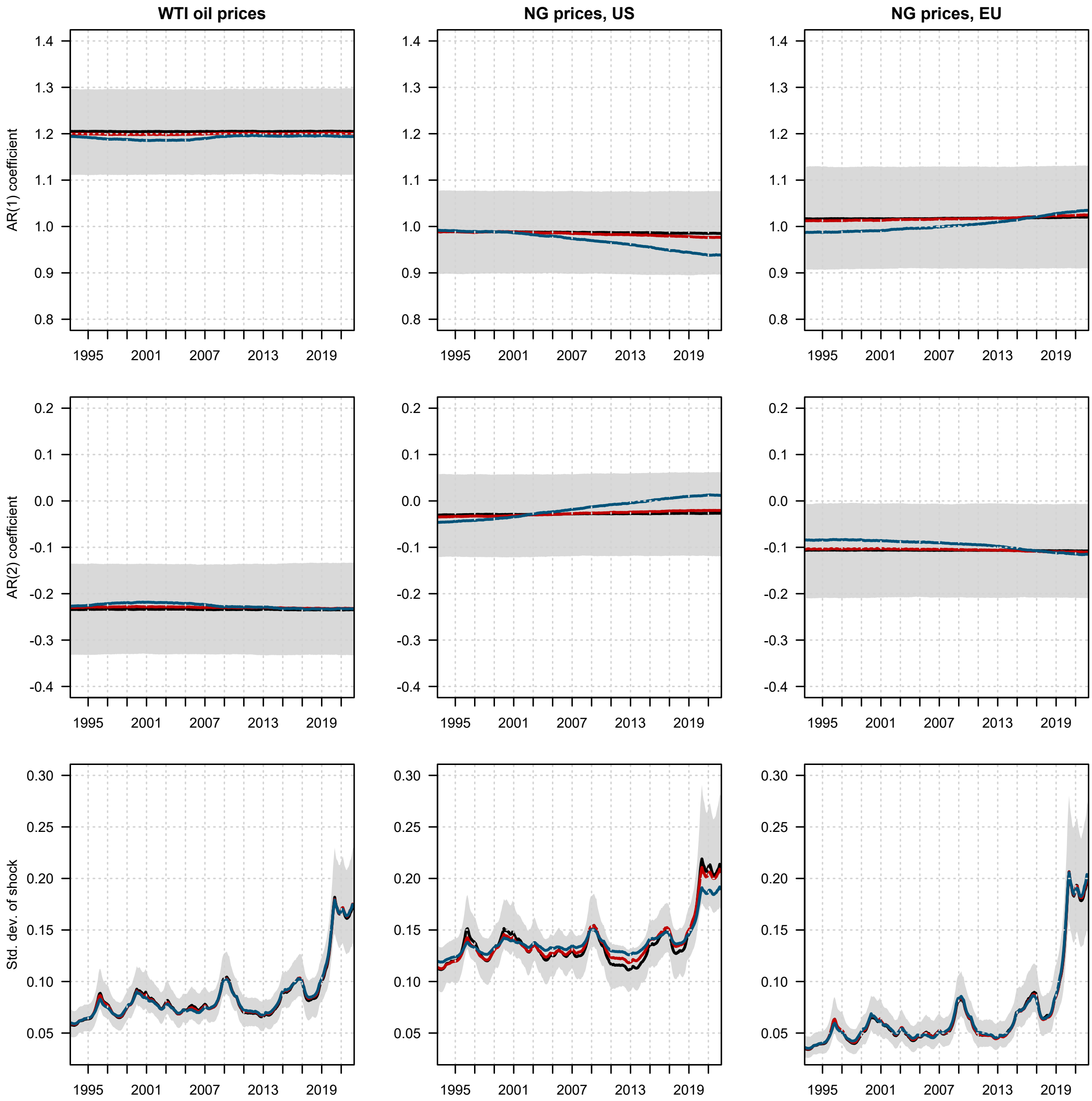
Note: The figure presents FEVD for selected horizons for the log level in real oil and natural gas prices. The dark gray, light gray and medium gray colors represent the contribution of oil, US natural gas and EU natural gas market shocks (in per cents), respectively.

Figure 4: Historical decomposition for the log annual growth rate in real oil and natural gas prices in the constant coefficient SVAR model.



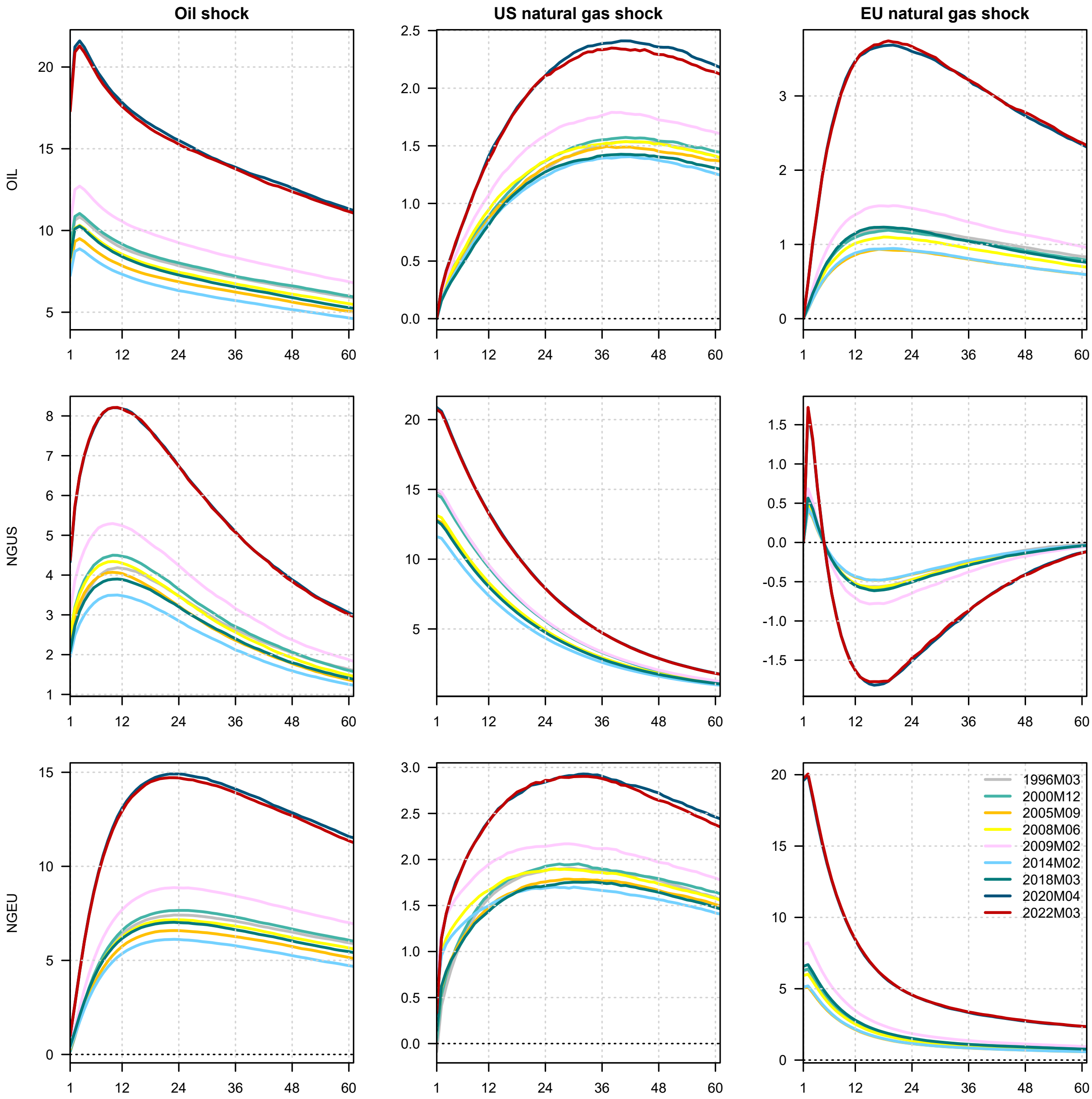
Note: The black solid line represents the logarithmic annual rate of change in the real prices of oil and natural gas (in per cent). The dark gray, light gray and medium gray colors represent the contribution of oil, US natural gas and EU natural gas market shocks (in pp), respectively.

Figure 5: The evolution of selected coefficients in the TVP-VAR-SV model.



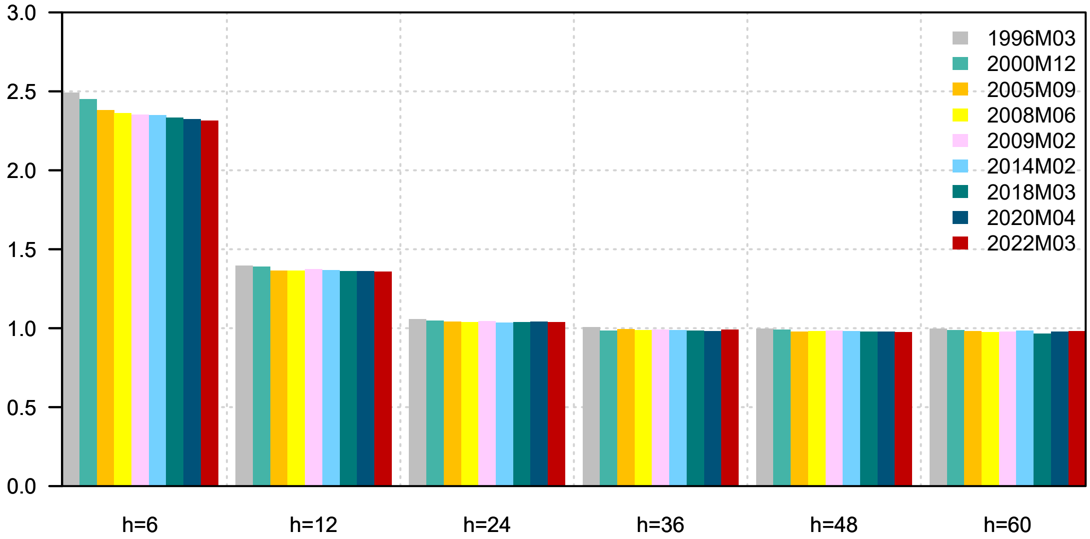
Note: The black solid line represents the posterior median, whereas the shaded area denotes the 90 percent posterior credible sets. The red and blue lines represent the posterior median in models with hyperparameters multiplied (k_Q and k_S) and divided (k_W) by a factor of 2 and 4, respectively.

Figure 6: Impulse response functions in the TVP-VAR-SV model.



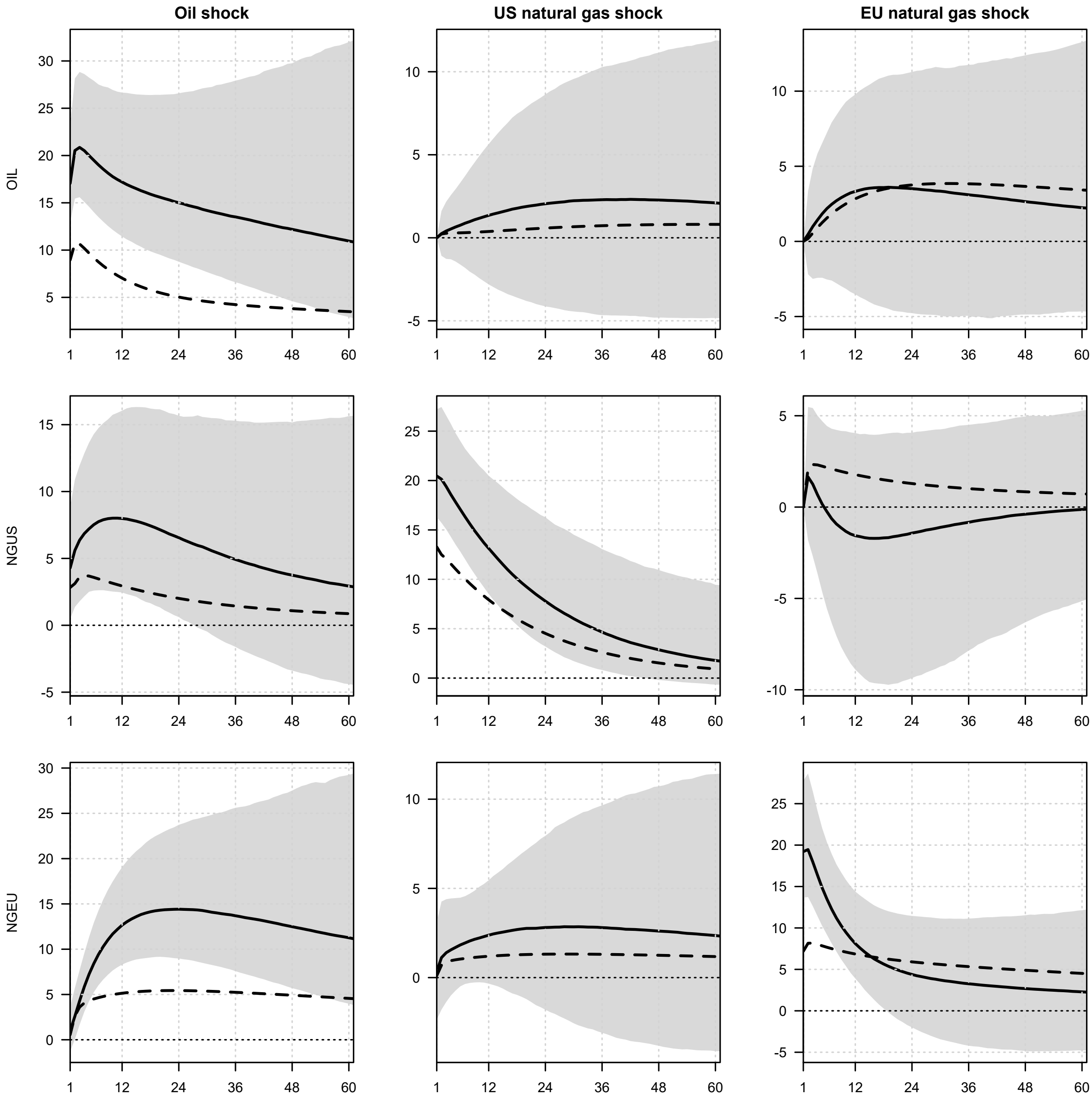
Note: The solid lines represent the posterior median impulse responses at various points in time. Market events are described in section 4.2. All values are multiplied by 100 so that they are expressed as per cents.

Figure 7: The short-term divergence and long-term convergence of oil and EU natural gas prices



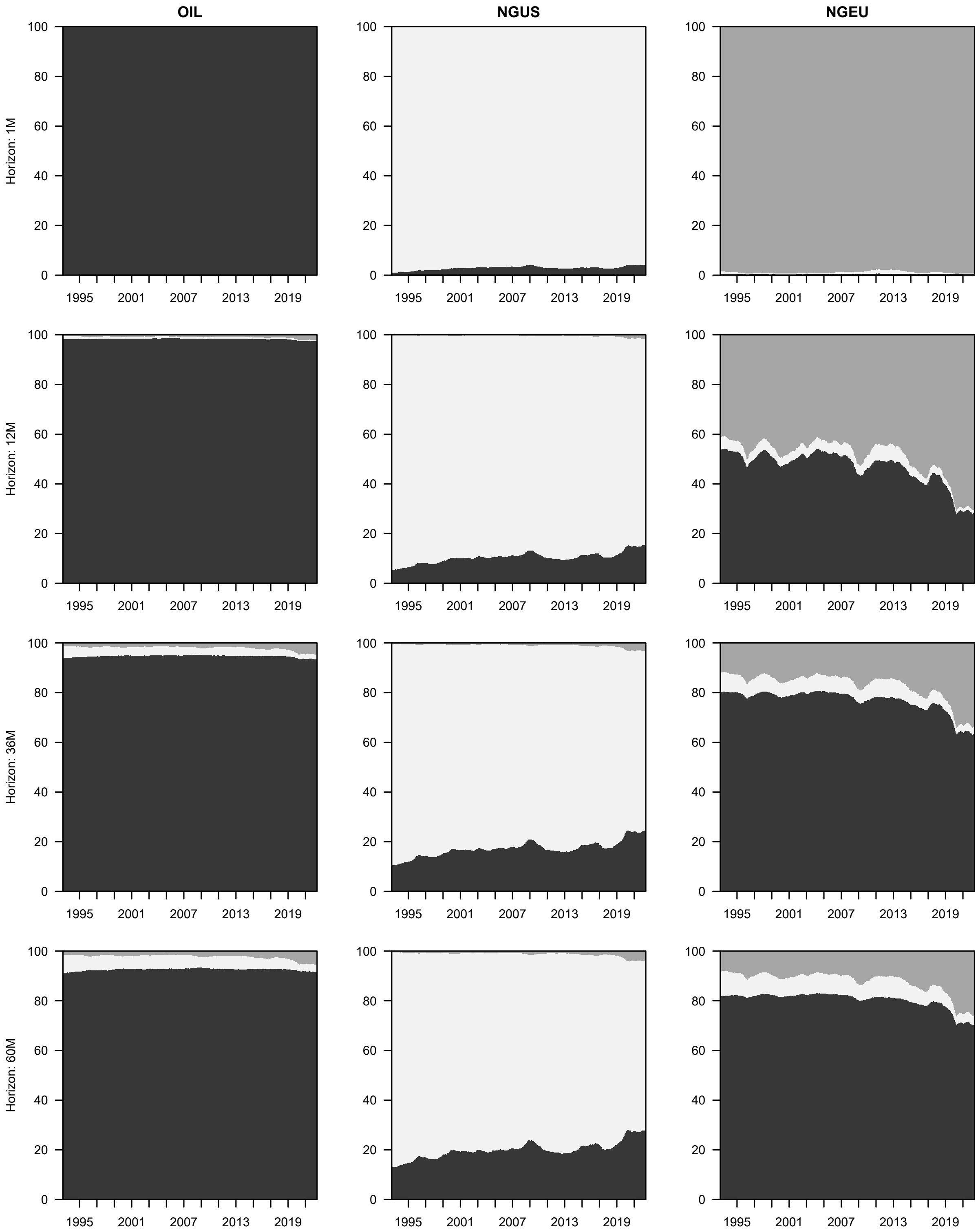
Note: Each bar represents the ratio of the median reaction of oil prices and EU natural gas prices to the oil shock at a specific horizon and for a certain market event. A value of one means that the change in prices of both commodities is the same.

Figure 8: The comparison of impulse response functions in the SVAR and TVP-VAR-SV model.



Note: The black solid line represents the posterior median, whereas the shaded area denotes the 90 percent posterior credible sets for the last period in the sample from the time-varying parameters SVAR model (i.e. May 2022). The dashed line illustrates the impulse response function from the constant coefficient SVAR model. All values are multiplied by 100 so that they are expressed as per cents.

Figure 9: Forecast error variance decomposition in the TVP-VAR-SV model.



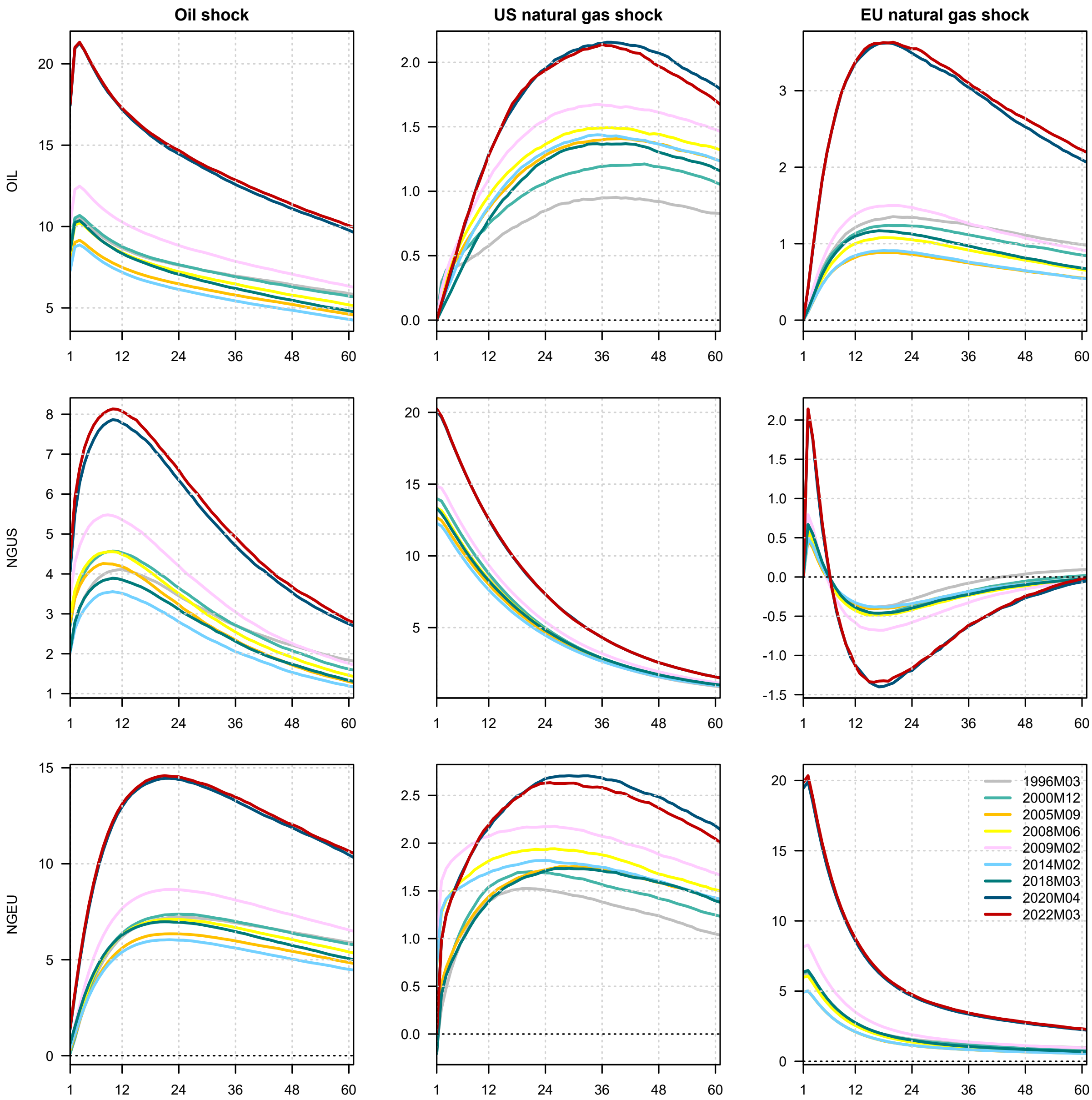
Note: The figure presents the evolution of the forecast error variance decomposition for the log level in real oil and natural gas prices. The dark gray, light gray and medium gray colors represent the contribution of oil, US natural gas and EU natural gas markets shocks (in per cents), respectively. As median contributions are reported, their sum is normalized to add up to 100.

Appendix

A Results for rescaled priors in the TVP-VAR-SV model

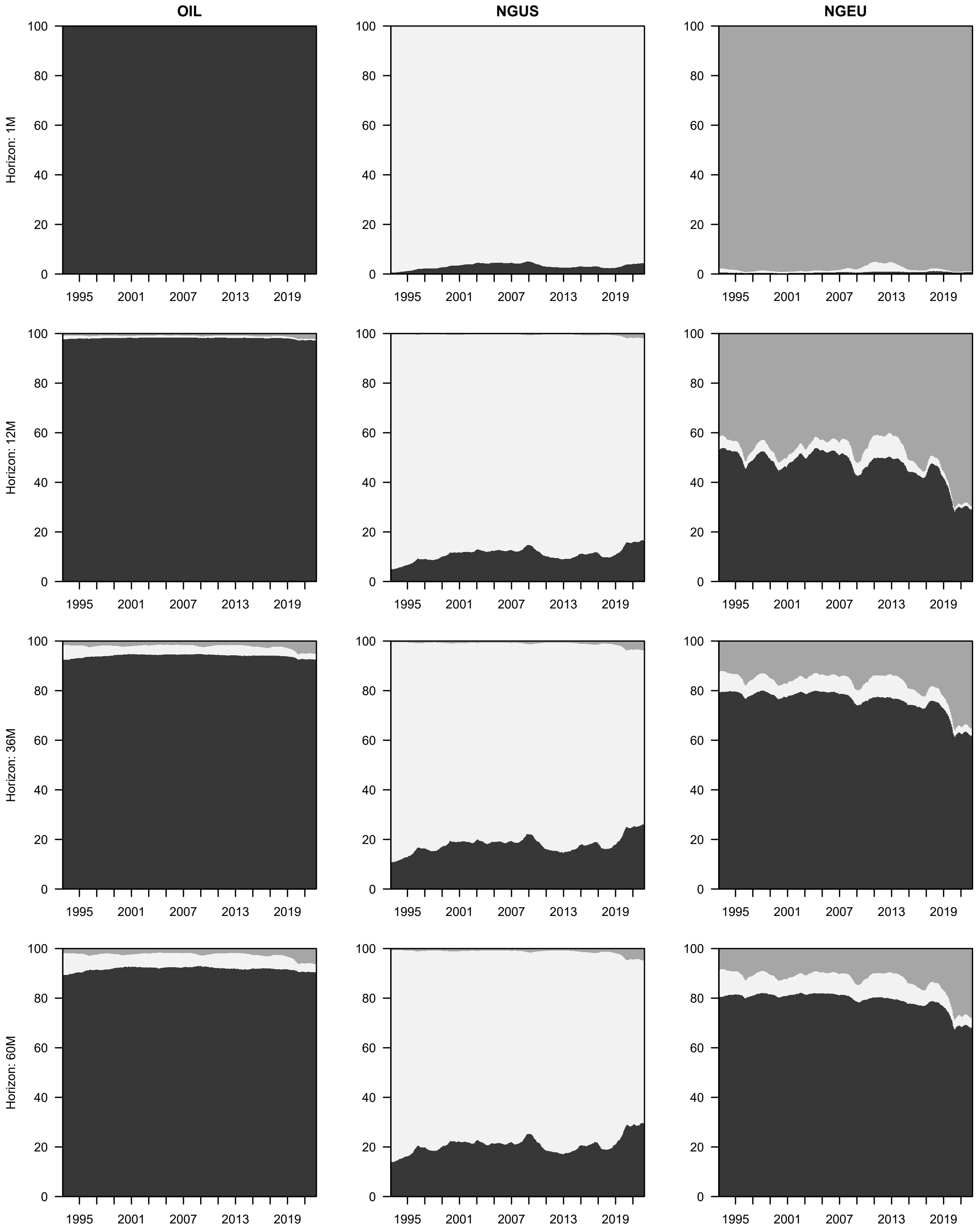
In Figure 5 of the article we present posterior median for TVP-VAR-SV parameters if the hyperparameters k_Q, k_W and k_S are rescaled by 2 ($k_Q = 0.02$, $k_W = 0.005$ and $k_S = 0.20$) and 4 ($k_Q = 0.04$, $k_W = 0.0025$ and $k_S = 0.40$). We recall that this rescaling allows for more variability in autoregressive coefficients and constraints the variability of stochastic volatility parameters. In the Appendix we present how this rescaling affects impulse-response functions and forecast error variance decomposition by presenting corresponding charts to figures 6 and 9.

Figure A1: IRF in the TVP-VAR-SV model rescaled by 2.



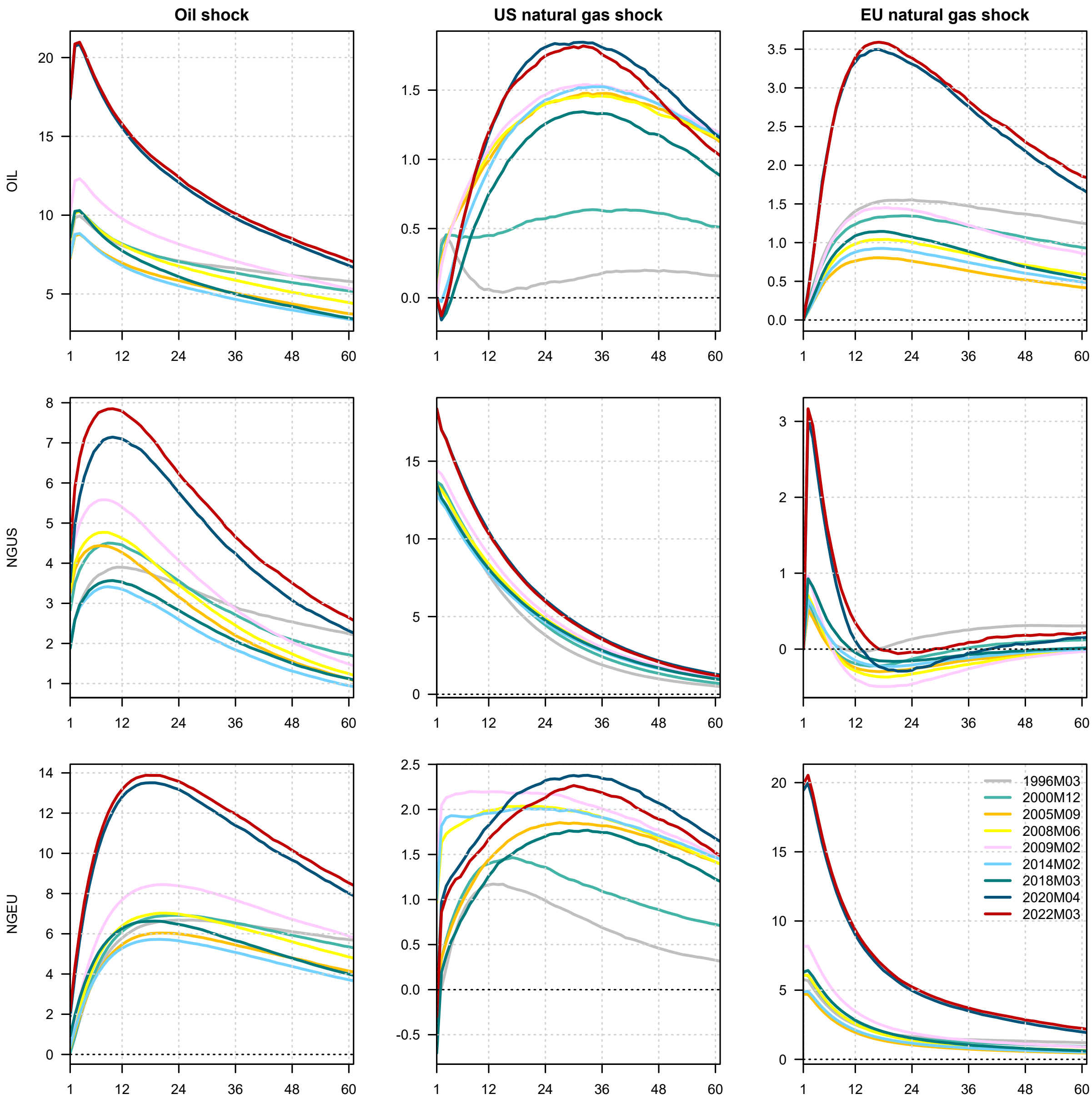
Note: As in Figure 6.

Figure A2: FEVD in the TVP-VAR-SV model rescaled by 2.



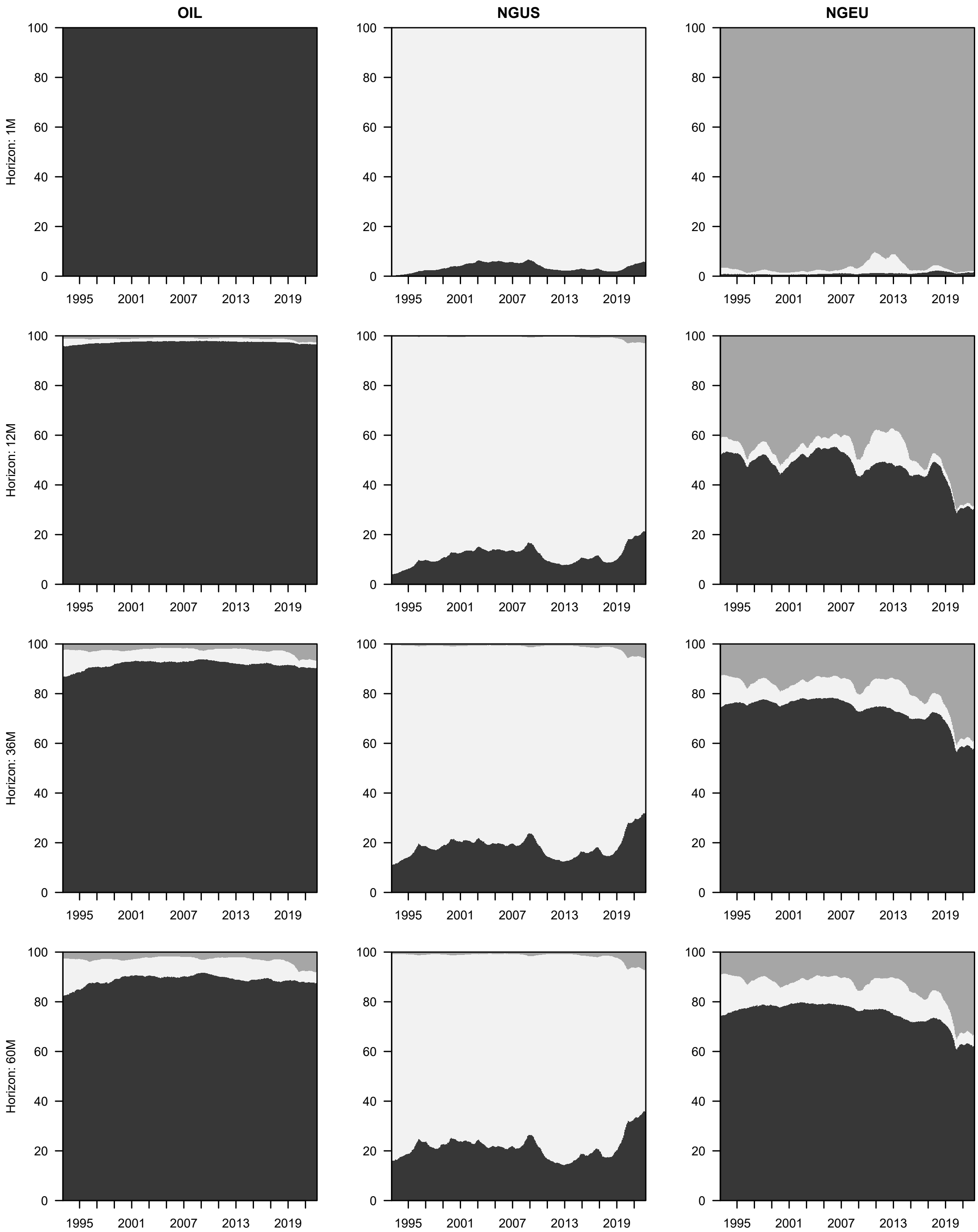
Note: As in Figure 9.

Figure A3: IRF in the TVP-VAR-SV model rescaled by 4.



Note: As in Figure 6.

Figure A4: FEVD in the TVP-VAR-SV model rescaled by 4.



Note: As in Figure 9.