COLLEGIUM OF ECONOMIC ANALYSIS
WORKING PAPER SERIES

The European energy crisis and the US natural gas market dynamics. A structural VAR investigation

Karol Szafranek and Michał Rubaszek

SGH KAE Working Papers Series Number: 2024/099 March 2024

The European energy crisis and the US natural gas market dynamics. A structural VAR investigation.*

Michał Rubaszek and Karol Szafranek

SGH Warsaw School of Economics, Collegium of Economic Analysis, Warsaw, Poland

Abstract

The Russian invasion of Ukraine triggered severe disruptions in the European energy market, causing also significant shifts in global natural gas flows. We investigate how this European shock has affected the dynamics and altered the estimates of the elasticities on the US natural gas market. We use the Bayesian Structural Vector Autoregression framework proposed by Baumeister and Hamilton (2019, BH) for the crude oil market and applied by Rubaszek, Uddin, and Szafranek (2021, RSU) to analyze the dynamics of the US natural gas market. By extending the RSU model for natural gas trade and deriving model's posterior using most recent data, we approximate the impact of the European energy crisis on the US market. We show that due to our modification the estimates of the elasticities on the US natural gas market change, while simply updating the same prior beliefs with most recent data impacts the posterior estimates to a very limited extent. We also find that a shock even as major as the European energy crisis has only marginally affected the US natural gas market, thus corroborating that the EU and US natural gas markets evolve independently.

Keywords: Natural gas market; structural VAR; Impulse-response function; Bayesian inference.

JEL classification: C11, C32, Q31, Q43.

*This article was realized thanks to the financial support from the National Science Centre (Poland) within grant No. 2020/39/B/HS4/00366.

1 Introduction

Natural gas is a strategic source of energy in the US and Europe. The data provided by IEA indicate that its share in total energy supply amounted to 23.6%, 26.7% and 35.3% for the global, European and the US economy, respectively (IEA, 2023). Natural gas plays a crucial role in residential and commercial heating, and at the same time serves as an important input for industrial production and electricity generation. It is therefore not surprising that the unprecedented increases in its prices observed in Europe in years 2021-2022, i.e., in times of the Russian invasion of Ukraine, constituted a significant disturbance to the functioning of the European and global economy. The European energy crisis was not only reflected in the substantial inflationary pressure and subdued growth in Europe, but also reshaped the structure of the global natural gas market (Szafranek et al., 2023; Emiliozzi et al., 2023).

The global natural gas market is geographically segmented into a number of local markets, of which American, European and Asian are the most important ones (see Kan et al., 2019, for a detailed overview of the global natural gas market structure). Local markets, which are connected by a pipeline grid, are usually highly integrated (e.g., Nakajima and Toyoshima, 2019; Broadstock et al., 2020; Chen et al., 2022; Papiez et al., 2022; Szafranek et al., 2023). On the contrary, natural gas prices in the different regions of the world are very often decoupled from each other, which can be explained by transportation costs and differences in market organization (e.g., Wakamatsu and Aruga, 2013; Geng et al., 2016; Zhang and Ji, 2018). It can be noted, however, that the development of the LNG market for the last decade has reinforced the linkages between distant gas markets, especially across the Atlantic (Mu and Ye, 2018; Emiliozzi et al., 2023). Consequently, a shock to natural gas prices in one region usually leads to a reaction in the remaining markets. For instance, Szafranek and Rubaszek (2023) indicate that shocks to the US natural gas prices are transmitted to natural gas prices in Europe, but the reverse causality is less visible. In this context, the first aim of this study is to evaluate the effects of the European energy crisis of 2021-2022 on the dynamics of the US natural gas market.

The European energy crisis was characterized by a massive increase in the natural gas prices. In mid-2021, when the demand for natural gas begun to recover along the rebound in the economic activity in the EU from Covid-19 recession, Russia started to limit its exports via Yamal and Brotherhood pipelines (McWilliams et al., 2023; Kotek et al., 2023). In addition, domestic production in the Netherlands was low and adverse weather conditions limited wind power generation. Consequently, natural gas prices at the most liquid European hub (Dutch TTF) surged from below 20 EUR/MWh in April 2021 to the local peak of 182 EUR/MWh recorded on 21 December 2021. The price rose even further after the Russian invasion of Ukraine. On 7 March 2022, as Russian tanks approached Kiev, the TTF price jumped to 227 EUR/MWh, whereas the announcement on Nord Stream shutdown pushed the TTF price to the record high of 330 EUR/MWh on 26 August 2022. At the same time, natural gas prices in the most liquid US hub (Henry Hub) increased from around 2.5USD/MMBtu in April 2021 to the maximum level of 9.68USD/MMBtu recorded on 22 August 2022. In this study we investigate if these price increases in the US market can be attributed to the European energy crisis.

To explore the dynamics of the US natural gas market during the European energy crisis we apply the state of the art Bayesian structural VAR methodology proposed by Baumeister and Hamilton (2015), and then applied by Baumeister and Hamilton (2019) to the global oil market, by Rubaszek, Uddin, and Szafranek (2021) to the US natural gas market and Casoli et al. (2022) to the European natural gas market. The big advantage of this methodology is that it can be applied to identify structural shocks and drivers of natural gas dynamics in a correct way. Moreover, it is suitable to properly derive supply and demand elasticities at the natural gas market.

In the above context, our study contributes to the literature that applies structural VAR framework to analyze the dynamics of the US natural gas market, which follows a similar debate for the crude oil market. The latter is predominantly focused on whether oil prices are driven by demand or supply shocks and on how to best measure global demand (e.g., Kilian, 2009; Kilian and Murphy, 2014; Caldara et al., 2019; Baumeister and Hamilton, 2019; Kilian, 2019; Hamilton, 2021). For the natural gas market, the discussion based on structural VAR framework is dominated by studies focusing on the United States (e.g., Arora and Lieskovsky, 2014; Wiggins and Etienne, 2017; Jadidzadeh and Serletis, 2017; Hou and Nguyen, 2018; Nguyen and Okimoto, 2019; Rubaszek and Uddin, 2020; Rubaszek et al., 2021). The reason is that the US market was fully deregulated following the Natural Gas Policy Act of 1978, hence it can be claimed that since mid-1990s natural gas prices have been entirely determined by market forces (Joskow, 2013). This systemic change justifies the application of structural models, such as structural VARs, in which natural gas prices are driven by supply and demand factors. The broad picture that emerges from these studies is that shocks specific to energy prices, which are referred to as "demand shocks", are an essential source of natural gas price volatility. In turn, shocks to aggregate income and supply shocks are less important determinants of natural gas prices. Specifically, this is the main finding of investigations applying the simplest trivariate VAR (for natural gas production, prices and aggregate economic activity) and the recursive identification scheme (Arora and Lieskovsky, 2014; Hou and Nguyen, 2018; Rubaszek and Uddin, 2020). The extension of this trivariate system for crude oil prices shows that the contribution of demand shocks can be further decomposed into shocks specific to natural gas and crude oil markets (Nguyen and Okimoto, 2019). In turn, Jadidzadeh and Serletis (2017), who consider a trivariate structural VAR model for the crude oil market extended for the real price of natural gas, indicate that the contribution of oil market shocks to the variation in natural gas prices is close to 50%. Finally, Wiggins and Etienne (2017) and Rubaszek et al. (2021) explore the dynamics of the US natural gas market with the four-variate specification of the structural VAR model proposed for the crude oil market by Kilian and Murphy (2014) and Baumeister and Hamilton (2019). These investigations, in which the set of endogenous variables is extended for natural gas inventories, point to somewhat larger contribution of supply shocks to natural gas price fluctuations.

In this study we apply the four-variate specification of Rubaszek et al. (2021), but with a modified definition of the forth endogenous variable, which describes the dynamics of underground inventories. We show that the transformation of this variable was questionable in the previous applications, including the studies for the crude oil market. Moreover, we extend the definition of the variable for international trade in natural gas. This change allows us to provide new evidence on the relative importance of structural shocks affecting the dynamics of the US natural gas market. On the basis of the forecast error variance decomposition we confirm that natural gas price variability is predominantly determined by market-specific demand shocks, which contribution amounts to around 70% in the long-term horizon. Our study also indicates that supply and aggregate activity shocks are of lower importance for natural gas prices. Their contribution to natural gas price variance is less than 10%. This could imply that the previous "four-variate system" studies of Wiggins and Etienne (2017) and Rubaszek et al. (2021) might have overestimated the contribution of supply shocks to natural gas price fluctuations.

This article also contributes to the voluminous literature attempting to establish how demand for energy and energy commodities reacts to changes in prices, with roughly 2 thousand studies on this subject available in the Dahl Energy Demand Database. A meta-analysis of these studies presented by Labandeira et al. (2017) points to the average short-term and long-term price elasticity of natural gas demand at -0.18 and -0.68, respectively. On the other hand, the estimates for the supply price elasticity reported across a number of studies are typically low (Dahl and Duggan, 1996; Krichene, 2002; Ponce and Neumann, 2014; Rubaszek et al., 2021). We present new estimates for the short-run elasticities characterizing the US natural gas market. Our posterior median estimate for the price elasticity of supply amounts to 0.004, which indicates that the supply curve is price inelastic. In turn, demand reacts strongly to changes in natural gas prices, as the posterior median for the demand price elasticity amounts to -0.498. As regards the income elasticity of demand, the posterior is somewhat below unity with the median posterior value at 0.615.

Moreover, we quantify that in the short-run changes in natural gas prices exert a negligible effect on the US economic activity. Finally, we also arrive at economically meaningful estimate for the parameter measuring how changes in production affect net exports and inventories dynamics, while in previous works this parameter suggested, counterintuitively, that higher production is accompanied by increased natural gas withdrawals. Importantly, this result is driven by the modification of the demand equation, and not simply by updating the same prior beliefs with most recent data.

Lastly, we contribute to the discussion on the effect of Russian invasion of Ukraine on the dynamics of energy markets (e.g., Szafranek et al., 2023; Emiliozzi et al., 2023; Gritz and Wolff, 2024). For that purpose we provide the results of historical decomposition for natural gas prices and production. We find that in the period 2021Q2-2022Q2 shocks to foreign demand, which were related to the European energy crisis, pushed US natural gas price up by around 12.0%. This would imply that the situation in Europe was not the main source of US natural gas price surge of about 90% observed in this period. We also show that natural gas production increase during that time, which amounted to about 3.0%, was only to a small extent driven by higher exports.

The rest of the paper is organized as follows. Section 2 focuses on the Bayesian structural VAR methodology. Section 3 presents the empirical model for the US natural gas market as well as the data. Sections 4 provides the results for the benchmark specification. The last section concludes.

2 The theoretical model

Our investigation is based on the Bayesian structural VAR (SVAR) framework, which was proposed by Baumeister and Hamilton (2015), modified and applied to analyze the dynamics of the crude oil market by Baumeister and Hamilton (2019, henceforth BH), and applied to analyze the US natural gas market by Rubaszek, Uddin, and Szafranek (2021, henceforth RSU).

The specification of the SVAR model is:

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{u}_t,\ \mathbf{u}_t \sim N(\mathbf{0}, \mathbf{D}) \tag{1}$$

where $\mathbf{y}_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ is an $n \times 1$ vector of endogenous variables, $\mathbf{A}$ is an $n \times n$ matrix describing contemporaneous structural relations, $\mathbf{x}_{t-1}$ is a $k \times 1$ vector, with $k = mn + 1$, containing m lags of y_t and a constant, $\mathbf{x}'_{t-1} = (\mathbf{y}'_{t-1}, \dots, \mathbf{y}'_{t-m}, 1)'$, $\mathbf{B}$ is an $n \times k$ matrix of parameters at lagged variables, $\mathbf{u}_t$ is an $n \times 1$ vector of uncorrelated structural shocks and $\mathbf{D} = \mathrm{diag}(d_{11}, \dots, d_{nn})$ is a diagonal matrix of size $n \times n$.

We estimate the parameters of the model using Bayesian inference proposed by BH and applied by RSU. Given that the seminal framework by BH is already well established in the literature, its description, which closely follows also RSU, is provided in A.

3 The empirical model for the US natural gas market

We consider a structural VAR model for the US natural gas market. The choice of endogenous variables entering vector $\mathbf{y_t}$ is based on the setup considered by Kilian and Murphy (2012, 2014) and Baumeister and Hamilton (2019) for the crude oil market as well as Wiggins and Etienne (2017); Rubaszek et al. (2021) for the US natural gas market. We change this setup in two aspects. First, we improve the specification of the demand equation with respect to BH and RSU studies. Second, in our specification we account for net exports of natural gas, which will allow us study the impact of the European energy crisis on the US natural gas market.

Specification of the SVAR model Let us consider the following variables describing the US natural gas market: dry production (Q_t), consumption (C_t), real prices (P_t), net exports (NX_t) and changes in natural gas inventories (ΔI_t). According to the data provided by the US Energy Information Administration (EIA) in the Monthly Energy Review, dry production (Q_t) is equal to the sum of consumption (C_t), net imports, net storage withdrawals, plus less important items (O_t, supplemental gaseous fuels and balancing item). Hence:

$$Q_t = C_t + (NX_t + \Delta I_t + O_t) = C_t + Z_t, \tag{2}$$

where $Z_t = (NX_t + \Delta I_t + O_t)$. This means, that we can approximate the growth in consumption demand as:

$$c_t \approx q_t - \Delta z_t, \tag{3}$$

where $q_t = 100 \ln(Q_t/Q_{t-1})$, $c_t = 100 \ln(C_t/C_{t-1})$, and $\Delta z_t = 100\Delta Z_t/Q_{t-1}$.

Thus, our vector of endogenous variables is:

$$\mathbf{y}_t = \begin{bmatrix} q_t & y_t & p_t & \Delta z_t \end{bmatrix}, \tag{4}$$

where $y_t = 100\ln(Y_t/Y_{t-1})$ describes the dynamics of aggregate demand (proxied by US GDP, Y_t). We use GDP as a measure of broad economic activity to account for the fact that natural gas is used by households as well as the corporate sector.[1] Since the model is estimated using quarterly data, we set the maximum lag at $m = 4$.

The structure of contemporaneous relations among the endogenous variables is:

$$q_t = \alpha_{qp} p_t + \mathbf{b}_1^{'} \mathbf{x}_{t-1} + u_t^S \tag{5}$$

$$y_t = \alpha_{yp} p_t + \mathbf{b}_2^{'} \mathbf{x}_{t-1} + u_t^E \tag{6}$$

$$q_t = \beta_{qy} y_t + \beta_{qp} p_t + \Delta z_t + \mathbf{b}_3^{'} \mathbf{x}_{t-1} + u_t^D \tag{7}$$

$$\Delta z_t = \psi_1 q_t + \psi_3 p_t + \mathbf{b}_4^{'} \mathbf{x}_{t-1} + u_t^Z \tag{8}$$

In the notation of equation (1) for the structural VAR model, the above system implies the following representation for matrix $\mathbf{A}$:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & -\alpha_{qp} & 0 \\ 0 & 1 & -\alpha_{yp} & 0 \\ 1 & -\beta_{qy} & -\beta_{qp} & -1 \\ -\psi_1 & 0 & -\psi_3 & 1 \end{bmatrix}. \tag{9}$$

[1] A discussion on pros and cons of using GDP and industrial production as a proxy for aggregate demand is provided by Rubaszek et al. (2021).

Equation (5) is the natural gas supply curve with α_{qp} measuring the price supply elasticity. Equation (6) describes the dynamics of aggregate economic activity. We allow natural gas prices to exert a contemporaneous impact on GDP, where the strength of this relationship is measured by α_{yp}. Equation (7) is the natural gas demand curve with income and price elasticities, β_{qy} and β_{qp}, respectively. Please note that substituting (3) to (7) yields:

$$c_t = \beta_{qy} y_t + \beta_{qp} p_t + \mathbf{b}_3^{'} \mathbf{x}_{t-1} + u_t^D$$

Finally, equation (8) describes that changes in net exports and inventories respond immediately to the level of natural gas production and prices.

The above system of equations also implies that all analyzed variables are allowed to be affected by their past values, which are included in the vector $\mathbf{x}_{t-1}$. Moreover, it can be seen that their dynamics is driven by four structural shocks. The supply shock u_t^S can be interpreted as an unexpected change in natural gas production, which can be related to technological advances but also adverse weather conditions. The income shock u_t^E reflects shifts in the US economic activity. The demand shock u_t^D captures unexpected shifts in natural gas demand that are not accounted for by changes in natural gas prices nor economic activity. The last shock u_t^Z represents foreign or speculative demand, which also includes the impact of the European energy crisis.

Let us notice that the specification of our model is similar to the influential studies for the oil market (Kilian and Murphy, 2014; Baumeister and Hamilton, 2019) as well as the articles for the US natural gas market (Wiggins and Etienne, 2017; Rubaszek et al., 2021). However, there are two main differences. The first one is related to the fact that approximation explicitly described in BH:

$$c_t \approx q_t - \Delta i_t,$$

where $\Delta i_t = \Delta I_t / Q_{t-1}$, is incorrect as it uses the first and not second difference in inventories. As implied by (3), the above approximation should use Δi_t defined as $\Delta^2 I_t / Q_{t-1}$. This error leads to the misspecification of the prior in the demand equation. Second, we substitute the variable describing changes in inventories, Δi_t, by Δz_t, i.e., the variable which also accounts for changes in net exports. For obvious reasons, this modification is relevant in the model for the US natural gas market (RSU study) and not for the global crude oil market (BH study). It also allows us to evaluate the impact of the European energy crisis on the dynamics of the US natural gas market.

The prior Our choices related to the parameters describing the prior $p(\mathbf{A}, \mathbf{B}, \mathbf{D})$ are exactly the same as in RSU and are presented in the upper part of Table 1. Here, we only briefly present the choices made by RSU, noting that the detailed discussion is available in the source paper.

The demand elasticities β_{qp} and β_{qy} are most widely discussed in the literature (see the surveys by Al-Sahlawi, 1989; Labandeira et al., 2017), which allows us to select a credible prior for β_{qp} and β_{qy}. For the former, we center the prior at -0.3 and assume that the response of demand to price changes after one period is also -0.3, which we incorporate in the prior for matrix $\mathbf{B}$. The scale parameter at 0.3

implies that the one-sided 90% confidence interval is $(-0.86, 0.00)$. The prior for the income elasticity of demand β_{qy} is centered at 0.5, which combined with the scale parameter of 0.3 implies one-sided 90% confidence interval of $(0.00, 1.02)$. This corresponds fairly accurately to the range for the β_{qy} put forward by Burke and Yang (2016). Next, we assume that natural gas production is rather price inelastic, hence we center its prior at 0.1, assume that the response of supply to price changes after one period is 0.1, and set the scale parameter at 0.2. As regards the short-term reaction of economic activity to natural gas price changes α_{yp}, we don't expect sizable reaction of the economic activity to changes in gas prices. We centre the prior at -0.05 and fix the scale parameter to 0.05. Finally, given no specific knowledge for ψ_1 and ψ_3 we establish the prior for these parameters around 0 and assume a relatively high standard deviation. In summary, the priors for the individual parameters of $\mathbf{A}$ are:

$$\begin{aligned} \beta_{qp} &\sim t_3^-(-0.3, 0.3), & \beta_{qy} &\sim t_3^+(0.5, 0.3) \\ \alpha_{qp} &\sim t_3^+(0.1, 0.2), & \alpha_{yp} &\sim t_3^-(-0.05, 0.05), \\ \psi_1 &\sim t_3(0.0, 0.5), & \psi_3 &\sim t_3(0.0, 0.5), \end{aligned} \tag{10}$$

where $t_v(c, \sigma)$ denotes t-Student distribution with mode c, scale parameter σ and v degrees of freedom. Next, in the above notation superscripts "+" and "-" indicate that the distribution is truncated to be either positive or negative, respectively. Our choice of t_3 distributions is the same as in BH and RSU.

Apart from the prior distribution for individual parameters of matrix $\mathbf{A}$, we also use prior information for their interactions, for which one can give sound economic interpretation. Specifically, we introduce the prior belief on parameter $h_1 = \det(\mathbf{A})$, which governs how strongly endogenous variables react to structural shocks. Second, we use a priori information on parameter h_2, which describes the reaction of GDP to the economic activity shock and is equal to $h_2 = (\alpha_{qp}(1-\psi_1)-\beta_{qp}-\psi_3)/\det(\mathbf{A})$. We do it to eliminate the combination of structural parameters in which the dynamics of natural gas prices leads to abnormally high or low reaction of aggregate output to the aggregate demand shock. Following BH and RSU, who discuss these two parameters in detail, for h_1 and h_2 we assume that:

$$h_1 \sim At_3(0.75, 1.05, 2), \quad h_2 \sim t_3(0.8, 0.2), \tag{11}$$

where $At_v(\mu, \sigma, \lambda)$ denotes the asymmetric t-Student distribution with v degrees of freedom, location μ, scale σ and skewness λ (see Baumeister and Hamilton, 2018, for details). In the case of the prior for h_1, we set the values for the location and scale parameters at 0.75 and 1.05, using the averages from 50 000 draws for $\theta_A = (\alpha_{qp}, \alpha_{yp}, \beta_{qy}, \beta_{qp}, \psi_1, \psi_3)'$, the skewness parameter is set to 2 and the degrees of freedom to 3 as in the BH paper. This choice implies a 94.3 percent prior probability of h_1 being positive. In the case of the prior for h_2, the values from equation (11) are identical to the ones in BH and imply a 98.6 percent prior probability that h_2 is positive.

In he next step, we choose the prior for $p(\mathbf{D}|\mathbf{A})$. The values of hyperparameters τ_i and κ_i from equation (13) are set in line with the standard Bayesian VAR literature (Doan et al., 1984; Kadiyala and Karlsson, 1997; Sims and Zha, 1998). Following BH and RSU, we choose $\kappa_i = 2$, which means that the weight of the prior for the posterior is equivalent to two full observations from the sample. Next, we set

$\tau_i(\mathbf{A}) = \kappa_i \mathbf{a}_i' \widehat{\mathbf{S}} \mathbf{a}_i$, where $\widehat{\mathbf{S}} = \frac{1}{T_1}\sum_{t=1}^{T_1} \widehat{\mathbf{e}}_t \widehat{\mathbf{e}}_t'$ and $\widehat{\mathbf{e}}_t = (e_{it}, \ldots, e_{nt})'$ is a vector of residuals from autoregression AR(m) models fitted to the series of i-th endogenous variable y_{it} using pre-sample set of observations, i.e. $t = 1, 2, \ldots, T_1$.

Finally, we define the prior $p(\mathbf{B}|\mathbf{A}, \mathbf{D})$. For most parameters from vectors $\mathbf{m}_i$ introduced in equation (14) the prior is centered at zero. This implies that we assume low persistence of endogenous variables, which are expressed either as changes or growth rates. The only exceptions are one-period lag responses of supply and demand to natural gas price changes, for which we center the prior at values equal to the modes of prior distributions for α_{qp} and β_{qp}, respectively. This choice allows us to take into account that the reaction of natural gas producers and consumers to price changes is distributed in time. As regards $\mathbf{M}_i$ matrices from equation (14), their values are set in a standard way and depend on three hyperparameters usually applied in the Bayesian VAR analyses: overall tightness ($\lambda_0 = 0.5$), lag decay ($\lambda_1 = 1$) and tightness around the constant ($\lambda_3 = 100$). The parameters of the model are estimated using Bayesian algorithms with M draws from the posterior distribution after initial M^* burn-in draws ($M = M^* = 1e6$).

4 Data

Our dataset consists of quarterly data spanning the period 1993Q1-2023Q3, which cover the period in which natural gas prices were determined by market forces, following the deregulation triggered by the Natural Gas Policy Act (Joskow, 2013). This sample is split into two subperiods, where the division is set at the early stage of the shale gas revolution. The initial $T_1 = 47$ quarters (1993Q1-2004Q4) are treated as pre-sample observations, for which we downweight information by a factor of 2 ($\mu = 0.5$). The subsequent $T_2 = 75$ quarters (2005Q1-2023Q3) are treated as the main sample.

The US natural gas prices (P_t) are drawn from the World Bank Commodity Price Data. Specifically, we take monthly data and deflate them by the US Consumer Price Index retrieved from the FRED database. Regarding the US natural gas market fundamentals, we take monthly data for natural gas dry production (Q_t), consumption (C_t), net exports (NX_t) and change in inventory (ΔI_t) from the EIA Monthly Energy Review database. We seasonally adjust all these series, to account for their high variation within the year, and take average values of quarterly frequency. Next, we calculate $Z_t = Q_t - C_t$, which represents the sum of net exports (NX_t) and net inventory injections (ΔI_t). Finally, we proxy the economic activity in the US (Y_t) by relying on the most popular measure of economic activity – the real GDP – which we retrieve from the FRED database.

Figure 1 illustrates time series for the dependent variables. Its upper left panel demonstrates that natural gas production in the US oscillated within a corridor until the shale gas revolution and started to increase swiftly after mid-2000s. At the same time natural gas consumption was exhibiting a gradual upward trend. The difference between production and consumption is decomposed in the upper right panel. It shows that in the first part of the sample the US economy was importing natural gas. Thereafter, since the beginning of the shale gas revolution the trade balance in natural gas has started to improve, so that at the end of the sample net exports amounted to around 1000 billion cubic feet a quarter. The panel also shows that changes in inventories fluctuate in the range of ±500bcf a quarter. Finally, the lower right panel depicts that natural gas prices displayed high variability during the entire sample, with sharp swings throughout specific market events, such as hurricane season, the global financial crisis or the European energy crisis of 2021-22.

5 Results

We begin the discussion of the estimation results by looking at the posterior distribution for the contemporaneous relations matrix **A**. Figure 2 illustrates the prior (red line) and posterior distributions (grey histograms), whereas their descriptive statistics are reported in the lower part of Table 1. In the table we also provide the estimates reported by RSU, which are derived using the sample ending in 2020Q3. Given that our estimates differ from RSU for two reasons – we substituted Δi_t for Δz_t in the set of endogenous variables and extended the sample till 2023Q3 – we also reports the posterior of RSU model derived using the sample ending in 2023Q3. The main findings are as follows.

The posterior median for the short-run supply price elasticity at $\alpha_{qp} = 0.004$ confirms the result of RSU that the supply curve for the US natural gas market is price inelastic. Our estimate is very low, twice lower than the one reported by RSU and 30 times lower compared to the value found by BH for the global crude oil market. As regards demand elasticities, the posterior median for price elasticity β_{qp} amounts to -0.498, well above (in absolute terms) the value reported by RSU

(-0.354) or BH (-0.356). This implies that changes in natural gas prices exert strong impact on demand, even in the short-run horizon. In turn, the median posterior for income elasticity β_{qy} at 0.615 is well below the one found by RSU (0.727) or BH (0.725). A quick look at the RSU posterior based on the original and extended sample (RSU20 vs RSU23 in the table) illustrates that the above differences in demand elasticities estimates are predominantly related to the fact that we use a model with the correct specification of equation (7), rather than to extending the sample for the European energy crisis episode. Substituting Δi_t in RSU for Δz_t in our investigation also exerts a sizeable impact on the posterior distribution of parameter ψ_1, which measures how changes in production affect net exports plus changes in inventories. Its median at 0.594 implies that, in the short run, almost 60% of production increase is exported or stored underground. On the contrary, the value reported by RSU (-0.285) would suggest that higher production is (counterintuitively) accompanied by natural gas withdrawals. The above differences illustrate that our modification of model specification delivers more intuitive posterior estimates for ψ_1. As regards the posterior median for the second parameter in equation (8), its value at 0.132 implies that higher natural gas prices are leading to a deterioration in the trade balance, a standard result in the trade literature. Finally, we notice that both our and RSU estimates provide evidence that in the short-run the effect of natural gas prices on economic activity is almost negligible (posterior of α_{yp} centered at -0.007.

We now turn our attention to the posterior impulse response functions. Figure 3 contains a panel of graphs, each one illustrating the dynamic response of an endogenous variable to one standard deviation of a structural shock. The median estimates are indicated by red solid lines, whereas 68% and 95% confidence regions are denotes by grey shaded areas. The left column of the panel shows that a positive supply shock (u^S) immediately raises natural gas production by over 1.8%, and lowers real prices by 1.1%. Over longer horizons, production rises by 2.3%, which is accompanied by a permanent increase in net exports amounting to about half of this production increase, and a decline in real prices by 7.5%. The effect of the supply shock on the economic activity is negative, but insignificant. As regards a shock to the aggregate economic activity (u^E), the second column shows that it leads to higher production and a temporal decline in net exports (or underground storage withdrawal). However, these effects are insignificant. This disturbance also leads to higher natural gas prices, with the peak reaction of 7.1% occurring three quarters after the shock. This result would suggest that natural gas production is almost inelastic with respect to aggregate economic activity and that the entire adjustment of the natural gas sector materializes via prices. Next, the third column of the panel illustrates how the demand shock (u^D) causes an immediate and considerable jump in natural gas prices, amounting to as much as 16.6%, and an instantaneous decrease in net exports (or inventories withdrawal). Over time, it leads to a persistent increase in the level of production, amounting to 0.9%, which partly attenuates the reaction of prices. The response of GDP is slightly negative, but insignificant. Finally, the right column illustrates that the foreign demand shock (u^Z), which initially augments exports by 2.7% value of production, leads to 5.5% increases natural gas prices over the short-term horizon, but leaves a limited trace on economic activity or natural gas production. In the long run, this shock raises exports by 1.9% value of production and raises natural gas prices by 2.4%. This estimate can be related to the US EIA data, showing that in 2022 exports to three European countries (Spain, France and UK) increased by 680 billion cubic feet, which constitutes roughly 2% of US natural gas production.

We continue our investigation by performing the forecast variance error decomposition (FEVD), which allows us to assess the contribution of structural shocks to US natural gas market variability. The results reported in the upper panel of Table 2 show that natural gas production is primarily driven by supply shocks, whereas the contribution of market-specific demand and foreign demand shocks is considerably lower. Moreover, the impact of economic activity shocks on the level of production is almost negligible, which reflects the fact that natural gas production is inelastic with respect to aggregate activity. The second panel outlines that market-specific demand shocks are the most important source of natural gas price variability, both in the short-term as well as in the long-term. Specifically, the contribution of demand shocks varies from 71.7% to 83.9% depending on the horizon. What is important, foreign demand shocks account for about 14% of natural gas prices variance. As regards the variability of the last endogenous variable, the bottom panel shows that it can be explained in 40% by both demand and foreign shocks. This estimate is visibly higher than the one reported by RSU.

In the last stage of our investigation, we calculate the historical contribution of each structural shock to the annual dynamics in the real natural gas prices and production. The upper panel of Figure 4 illustrates that in most periods demand shocks (grey bars) are the dominant force shaping the dynamics of real natural gas prices.

The influence of supply shocks (red bars) is of considerably smaller importance. However, it can be seen that since the shale gas revolution supply innovations have visibly contributed to lower dynamics of natural gas prices. The figure also indicates that a severe decline in the economic activity during the great financial crisis and following the COVID-19 outbreak contributed to drop in natural gas prices. The importance of foreign demand shocks (green bars) turned out to be relatively low. The bottom panel of this figure show that production is predominantly driven by supply shocks (red bars), apart from the end of the sample when it was driven rather by innovations to demand (grey bars). The role of the two remaining shocks is hardly visible on the graph.

At the end of our analysis, we focus on the episode of the European energy crisis by presenting the detailed results of historical decomposition for natural gas price and production changes in the period 2021Q2-2023Q3. Figure 5 presents the contribution of the four structural shocks (in pp.) to the cumulated change of both variables in this period, whereas Table 3 reports these contributions for the quarterly growth rates. The upper panel of the figure and the left column of the table show that the total increase of natural gas prices between 2021Q2 and the peak of 2022Q2, which amounted to 89.7% (log growth rate), was due to demand (64.1%), aggregate activity (15.4%) and foreign (11.8%) shocks, whereas the role of US supply shocks was slightly negative (-1.6%). As regards the dynamics of natural gas production, the bottom panel of the figure and the right column of the table illustrate that demand and foreign shocks were the main reason of natural gas production increase in the US, which in the period 2021Q2-2022Q2 amounted to 3.1%. These estimates imply that intensified physical exports of US natural gas to Europe in this period was not the main reason of natural gas prices increase on the US market. Regarding this outcome, one observation is warranted. It cannot be entirely discarded that the European energy crisis affected natural gas prices in the US through other channels, and – in the optics of our model – they are interpreted by the model as market-specific demand shocks.

6 Conclusions

In this study we have revisited the question of the drivers of US natural gas market during the European energy crisis. To this end, we have employed the state-of-the art Bayesian structural VAR framework proposed by Baumeister and Hamilton (2015, 2019) and recently used to describe the US and the European natural gas markets (Rubaszek et al., 2021; Casoli et al., 2022).

In relation to previous works describing the dynamics of the global oil and US natural gas market (Baumeister and Hamilton, 2019; Rubaszek et al., 2021), in this paper we introduce a modification of one endogenous variable, which describes the evolution of underground storage. Apart from using the correct transformation for the value of inventories, we extend the definition of this variable to account for the international trade in natural gas. This change allows us to provide new evidence on the relative importance of US natural gas market drivers. We show that due to this change in model specification, both the estimates of elasticities on the US natural gas market as well as the relative importance of structural shocks driving natural prices change markedly. Our detailed quantitative results are as follows.

First, we find that the posterior median for the price elasticity of natural gas supply is very low at 0.004, indicating that the supply curve is price inelastic in the short run. In turn, our estimates indicate that natural gas demand reacts more strongly to changes in natural gas prices than previously reported, with the posterior median for the demand price elasticity at -0.498. Next, we report that the income elasticity of demand amounts is 0.615, and we quantify that in the short-run changes in natural gas prices exert a negligible effect on the US economic activity. Moreover, on account of the change in model specification and variable definition, we arrive at economically meaningful estimate for the parameter measuring how changes in production affect net exports and changes in inventories.

Second, we confirm that natural gas price variability is predominantly determined by market-specific demand shocks, which contribution amounts to around 70% in the long-term horizon. Our study also indicates that supply and aggregate activity shocks are of lower importance for the U.S. natural gas prices. Their contribution to natural gas price variance is less than 10%, which implies that previous studies might have overestimated the contribution of supply shocks to natural gas price fluctuations.

Lastly, we provide quantitative evidence that during the European energy crisis shocks to foreign demand pushed U.S. natural gas prices up only by around 12.0%, with the demand-specific shocks being the dominant driver of price developments in this period. This implies that the spiking natural gas prices in Europe did not affect significantly the observed surge in U.S. prices during this episode. We also find that natural gas production increase during that time, which amounted to about 3.0%, was only to a small extent driven by higher exports.

Our findings offer two important policy implications. The first one is that European and U.S. policymakers should develop robust risk management strategies and cooperation plans to mitigate the potential impact of future disruptions to the natural gas markets. This is especially important taking into consideration the history of natural gas trade between EU and Russia (Rodriguez-Gomez et al., 2016; Bouwmeester and Oosterhaven, 2017; Gritz and Wolff, 2024). For Europe, the events from years 2021-2022 have resulted in the diversification of natural gas supplies, i.e. the shift of imports away from Russia towards reliable LNG from the U.S., as well as the introduction of measures aimed at mitigating risks associated with over-reliance on natural gas, i.e. accelerated transition towards clean energy. For the U.S., according to our results, the impact of the European energy crisis on the dynamics of natural gas market through the exports channel has been rather limited. However, the crisis has accelerated the development of LNG infrastructure, both in Europe and the U.S. Our simulations presented in this article allow us to state that this greater exports capacity from the U.S. to Europe should increase the dependence of U.S. natural gas prices on the situation in Europe. This justifies the need for enhanced coordination policy.

Second, our results are highly relevant in the context of the ongoing debate on expanding or limiting the U.S. exports of LNG. Pierce et al. (2018) provides a comprehensive discussion on pros and cons of LNG exports from the U.S., at the same explaining why in the late 2010s industry representatives and the U.S. administration were advocating increased natural gas exports. On the contrary, in early 2024 the U.S. administration announced to pause approvals of new LNG exports projects. This pause will last until the U.S. Department of Energy presents the effects of exports on the U.S. economy. This decision is affecting projects with total exports capacity representing approximately a tenth of U.S. natural gas production. Our estimates are hence very useful, as they indicate that if these projects were launched, higher exports would lead to a permanent natural gas price increase by about 10%.

References

Al-Sahlawi, M. A., 1989. The demand for natural gas: A survey of price and income elasticities. Energy Journal 10 (1), 77–90.

Arora, V., Lieskovsky, J., 2014. Natural gas and U.S. economic activity. The Energy Journal 35 (3), 167–182.

Baumeister, C., Hamilton, J. D., 2015. Sign restrictions, structural vector autoregressions, and useful prior information. Econometrica 83 (5), 1963–1999.

Baumeister, C., Hamilton, J. D., 2018. Inference in structural vector autoregressions when the identifying assumptions are not fully believed: Re-evaluating the role of monetary policy in economic fluctuations. Journal of Monetary Economics 100, 48–65.

Baumeister, C., Hamilton, J. D., 2019. Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. American Economic Review 109 (5), 1873–1910.

Bouwmeester, M. C., Oosterhaven, J., 2017. Economic impacts of natural gas flow disruptions between Russia and the EU. Energy Policy 106 (C), 288–297.

Broadstock, D. C., Li, R., Wang, L., 2020. Integration reforms in the European natural gas market: A rolling-window spillover analysis. Energy Economics 92, 104939.

Burke, P. J., Yang, H., 2016. The price and income elasticities of natural gas demand: International evidence. Energy Economics 59 (C), 466–474.

Caldara, D., Cavallo, M., Iacoviello, M., 2019. Oil price elasticities and oil price fluctuations. Journal of Monetary Economics 103, 1 – 20.

Casoli, C., Manera, M., Valenti, D., 2022. Energy shocks in the Euro area: disentangling the pass-through from oil and gas prices to inflation. Working Papers 2022.45, Fondazione Eni Enrico Mattei.

Chen, Y., Wang, C., Zhu, Z., 2022. Toward the integration of European gas futures market under COVID-19 shock: A quantile connectedness approach. Energy Economics 114, 106288.

Dahl, C., Duggan, T. E., 1996. U.S. energy product supply elasticities: A survey and application to the U.S. oil market. Resource and Energy Economics 18 (3), 243–263.

Doan, T., Litterman, R., Sims, C., 1984. Forecasting and conditional projection using realistic prior distributions. Econometric Reviews 3 (1), 1–100.

Emiliozzi, S., Ferriani, F., Gazzani, A., 2023. The European energy crisis and the consequences for the global natural gas market. Occasional Papers 827, Bank of Italy.

Geng, J.-B., Ji, Q., Fan, Y., 2016. The impact of the North American shale gas revolution on regional natural gas markets: Evidence from the regime-switching model. Energy Policy 96, 167 – 178.

Gritz, A., Wolff, G., 2024. Gas and energy security in Germany and central and Eastern Europe. Energy Policy 184, 113885.

Hamilton, J. D., 2021. Measuring global economic activity. Journal of Applied Econometrics 36 (3), 293–303.

Hou, C., Nguyen, B. H., 2018. Understanding the US natural gas market: A Markov switching VAR approach. Energy Economics 75, 42 – 53.

IEA, 2023. World energy balances. International Energy Agency.

Jadidzadeh, A., Serletis, A., 2017. How does the U.S. natural gas market react to demand and supply shocks in the crude oil market? Energy Economics 63 (C), 66–74.

Joskow, P. L., 2013. Natural gas: From shortages to abundance in the United States. American Economic Review 103 (3), 338–343.

Kadiyala, K. R., Karlsson, S., 1997. Numerical methods for estimation and inference in Bayesian VAR models. Journal of Applied Econometrics 12 (2), 99–132.

Kan, S., Chen, B., Wu, X., Chen, Z., Chen, G., 2019. Natural gas overview for world economy: From primary supply to final demand via global supply chains. Energy Policy 124 (C), 215–225.

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crudeoil market. American Economic Review 99 (3), 1053–1069.

Kilian, L., 2019. Measuring global real economic activity: Do recent critiques hold up to scrutiny? Economics Letters 178 (C), 106–110.

Kilian, L., Murphy, D. P., 2012. Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market VAR models. Journal of the European Economic Association 10 (5), 1166–1188.

Kilian, L., Murphy, D. P., 2014. The role of inventories and speculative trading in the global market for crude oil. Journal of Applied Econometrics 29 (3), 454–478.

Kotek, P., Selei, A., Takacsne Toth, B., Felsmann, B., 2023. What can the EU do to address the high natural gas prices? Energy Policy 173, 113312.

Krichene, N., 2002. World crude oil and natural gas: A demand and supply model. Energy Economics 24 (6), 557 – 576.

Labandeira, X., Labeaga, J. M., Lopez-Otero, X., 2017. A meta-analysis on the price elasticity of energy demand. Energy Policy 102 (C), 549–568.

McWilliams, B., Sgaravatti, G., Tagliapietra, S., Zachmann, G., 2023. How would the European Union fare without Russian energy? Energy Policy 174, 113413.

Mu, X., Ye, H., 2018. Towards an integrated spot LNG market: An interim assessment. Energy Journal 39 (1), 211–234.

Nakajima, T., Toyoshima, Y., 2019. Measurement of connectedness and frequency dynamics in global natural gas markets. Energies 12 (20), 3927.

Nguyen, B. H., Okimoto, T., 2019. Asymmetric reactions of the US natural gas market and economic activity. Energy Economics 80, 86 – 99.

Papiez, M., Rubaszek, M., Szafranek, K., Smiech, S., 2022. Are European natural gas markets connected? A time-varying spillovers analysis. Resources Policy 79, 103029.

Pierce, J. J., Boudet, H., Zanocco, C., Hillyard, M., 2018. Analyzing the factors that influence U.S. public support for exporting natural gas. Energy Policy 120, 666–674.

Ponce, M., Neumann, A., 2014. Elasticities of Supply for the US Natural Gas Market. Discussion Papers of DIW Berlin 1372, DIW Berlin, German Institute for Economic Research.

Rodriguez-Gomez, N., Zaccarelli, N., Bolado-Lavín, R., 2016. European ability to cope with a gas crisis. Comparison between 2009 and 2014. Energy Policy 97, 461–474.

Rubaszek, M., Uddin, G. S., 2020. The role of underground storage in the dynamics of the US natural gas market: A threshold model analysis. Energy Economics 87, Article 104713.

Rubaszek, M., Uddin, G. S., Szafranek, K., 2021. The dynamics and elasticities on the U.S. natural gas market. A Bayesian Structural VAR analysis. Energy Economics 103, 105526.

Sims, C. A., Zha, T., 1998. Bayesian methods for dynamic multivariate models. International Economic Review 39 (4), 949–968.

Szafranek, K., Papiez, M., Rubaszek, M., Smiech, S., 2023. How immune is the connectedness of European natural gas markets to exceptional shocks? Resources Policy 85, 103917.

Szafranek, K., Rubaszek, M., 2023. Have European natural gas prices decoupled from crude oil prices? Evidence from TVP-VAR analysis. Studies in Nonlinear Dynamics & Econometrics, In Press.
URL `https://doi.org/10.1515/snde-2022-0051`

Wakamatsu, H., Aruga, K., 2013. The impact of the shale gas revolution on the u.s. and japanese natural gas markets. Energy Policy 62, 1002 – 1009.

Wiggins, S., Etienne, X. L., 2017. Turbulent times: Uncovering the origins of US natural gas price fluctuations since deregulation. Energy Economics 64 (C), 196–205.

Zhang, D., Ji, Q., 2018. Further evidence on the debate of oil-gas price decoupling: A long memory approach. Energy Policy 113 (C), 68–75.

Tables and Figures

Table 1: Priors and posteriors for contemporaneous relations matrix **A**.

	Reported statistic	α_{qp}	α_{yp}	β_{qy}	β_{qp}	ψ_1	ψ_3	h_1	h_2
Prior	Type	t^+	t^-	t^+	t^-	t	t	At	t
	Location	0.10	-0.05	0.50	-0.30	0.00	0.00	0.75	0.80
	Scale	0.20	0.05	0.30	0.30	0.50	0.50	1.05	0.20
	D.o.f.	3	3	3	3	3	3	3	3
	Skew	—	—	—	—	—	—	2	—
	90% LB	0.000	-0.143	0.000	-0.856	-1.177	-1.177	-0.043	0.329
	90% UB	0.507	0.000	1.021	0.000	1.177	1.177	3.612	1.271
Posterior	5%	0.000	-0.019	0.159	-1.106	0.077	-0.268	0.407	0.965
	50%	**0.004**	**-0.007**	**0.615**	**-0.498**	**0.594**	**-0.132**	**0.639**	**0.994**
	95%	0.015	-0.001	1.427	-0.129	0.963	-0.082	1.209	1.000
	mean	0.005	-0.008	0.683	-0.544	0.564	-0.148	0.701	0.990
RSU20	5%	0.001	-0.030	0.250	-0.729	-0.707	-0.256	0.424	0.926
	50%	**0.009**	**-0.009**	**0.727**	**-0.354**	**-0.285**	**-0.195**	**0.578**	**0.990**
	95%	0.034	-0.001	1.774	-0.142	0.043	-0.150	0.923	0.999
	mean	0.013	-0.011	0.837	-0.385	-0.305	-0.198	0.614	0.979
RSU23	5%	0.001	-0.024	0.245	-0.811	-0.494	-0.216	0.402	0.928
	50%	**0.007**	**-0.008**	**0.744**	**-0.385**	**-0.137**	**-0.163**	**0.570**	**0.991**
	95%	0.027	-0.001	1.911	-0.166	0.151	-0.123	0.963	0.999
	mean	0.009	-0.010	0.870	-0.424	-0.151	-0.165	0.612	0.981

Notes: In the table t denotes a Student t distribution and At denotes an asymmetric Student t distribution proposed by Baumeister and Hamilton (2018). Signs + and − indicate that the distribution is truncated to be either positive or negative, respectively. D.o.f stands for degrees of freedom for each distribution. 90% LB and UB denote the lower and upper bounds for the confidence intervals (for truncated distributions one-sided confidence sets are reported). For the posterior distributions of the subsequent coefficients the 5th percentile, the median, the 95th percentile as well as the mean are reported. The posterior is based on quarterly data spanning the period 1993Q1-2023Q3. The RSU20 describes the posterior distribution reported by Rubaszek et al. (2021, Table 1), which is based on the sample 1993Q1-2020Q3. In turn, RSU23 refers to the posterior of the RSU model derived using data from the period 1993Q1-2023Q3.

Table 2: Forecast error variance decomposition.

	FEVD				**FEVD in RSU**			
	Natural gas production							
	u^S	u^E	u^D	u^Z	u^S	u^E	u^D	u^Z
h=1	99.5	0.0	0.3	0.1	98.2	0.1	1.4	0.4
h=4	86.1	3.1	8.0	2.8	79.8	5.0	11.7	3.4
h=8	83.4	3.8	9.6	3.2	75.3	6.3	13.8	4.6
h=12	83.2	3.9	9.7	3.2	74.9	6.5	14.0	4.6
h=16	83.2	3.9	9.7	3.2	74.8	6.6	14.0	4.6
	Real natural gas prices							
	u^S	u^E	u^D	u^Z	u^S	u^E	u^D	u^Z
h=1	1.1	0.9	83.9	14.1	8.3	2.6	77.5	11.7
h=4	5.7	7.8	72.9	13.6	10.6	7.9	63.6	17.9
h=8	6.4	8.4	71.8	13.5	11.4	8.9	62.1	17.5
h=12	6.4	8.5	71.7	13.5	11.5	9.1	61.9	17.5
h=16	6.4	8.5	71.7	13.4	11.5	9.2	61.9	17.5
	Natural gas net exports and changes in inventories							
	u^S	u^E	u^D	u^Z	u^S	u^E	u^D	u^Z
h=1	12.3	0.5	35.8	51.4	1.7	2.2	64.5	31.6
h=4	12.2	3.0	42.6	42.2	5.2	7.2	59.2	28.3
h=8	12.6	3.8	42.2	41.4	6.6	8.3	57.6	27.5
h=12	12.6	3.9	42.2	41.3	6.7	8.5	57.4	27.4
h=16	12.6	3.9	42.2	41.3	6.7	8.6	57.3	27.4

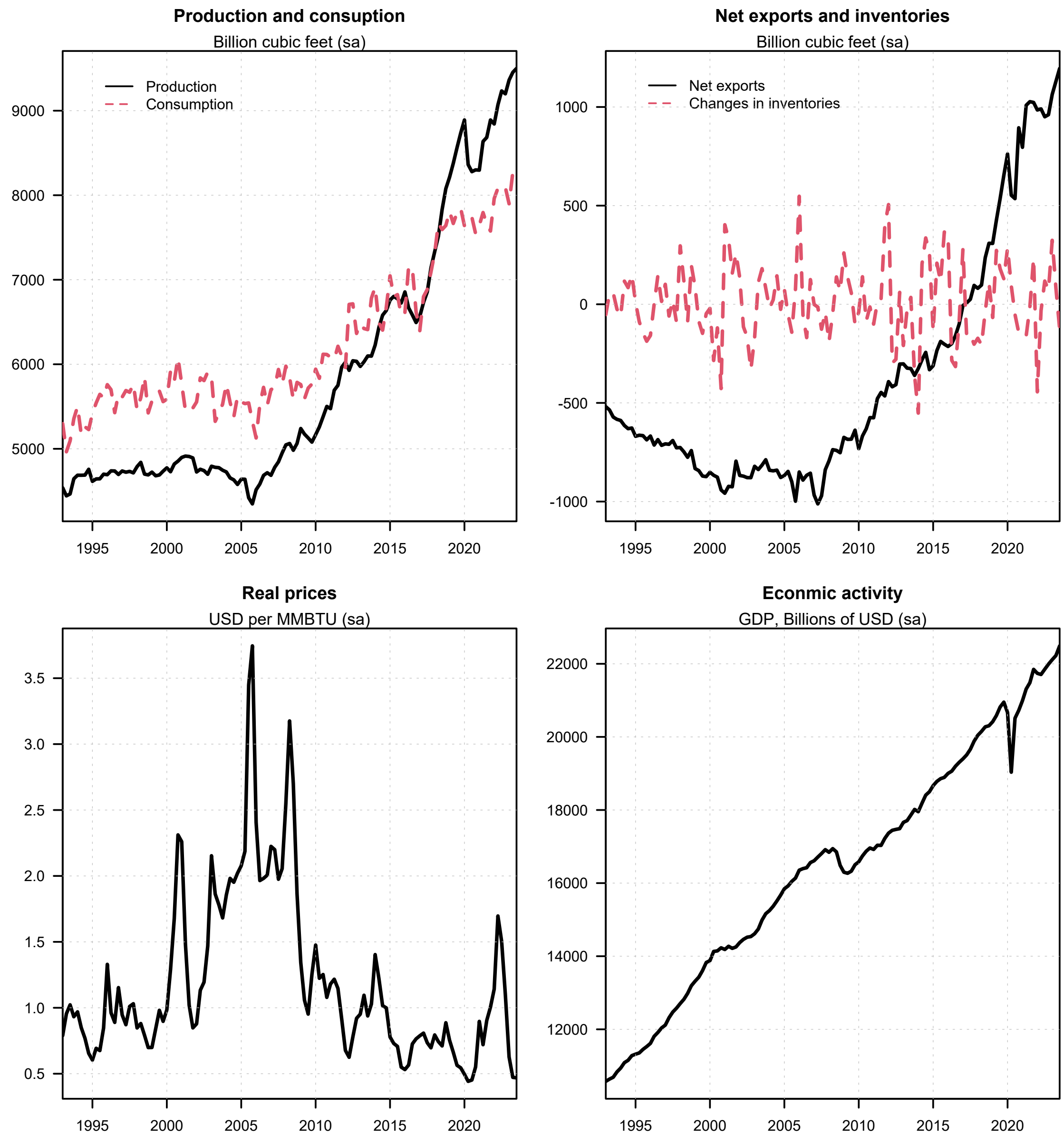
Notes: In the table u^S, u^E, u^D and u^Z denote the contributions of supply, income, demand and foreign shocks (in %) to the overall variability in natural gas market in the US FEVD was computed with the model estimated on quarterly data spanning the period 1993Q1-2023Q3. The RSU FEVD refers to FEVD reported by Rubaszek et al. (2021, Table 2) for the model estimated with data from 1993Q1-2020Q3.

Table 3: Historical decomposition of real natural gas prices and production during the European energy crisis.

	Real natural gas prices					Natural gas production				
	u^S	u^E	u^D	u^Z	Δp_t	u^S	u^E	u^D	u^Z	Δq_t
2021q3	-0.2	9.3	7.7	6.9	23.8	-0.45	-0.30	0.32	0.26	-0.16
2021q4	-0.5	6.3	0.9	5.0	11.6	0.84	0.33	0.54	-0.07	1.64
2022q1	-1.9	0.9	19.8	-5.1	13.7	-1.38	0.19	0.21	-0.28	-1.27
2022q2	0.9	-1.2	35.7	5.1	40.6	0.48	0.23	0.75	0.32	1.78
2022q3	-1.0	-5.1	3.4	-8.4	-11.1	0.07	0.04	1.05	-0.08	1.09
2022q4	2.1	-1.1	-24.3	-7.1	-30.4	-1.41	-0.18	0.51	0.00	-1.08
2023q1	0.7	-0.2	-52.6	-2.8	-55.0	0.82	-0.07	0.05	0.22	1.02
2023q2	-1.3	-2.0	-24.4	0.3	-27.3	1.30	-0.03	-0.88	-0.15	0.24
2023q3	-1.2	1.5	-5.8	5.6	0.2	0.75	-0.07	-0.98	-0.07	-0.37

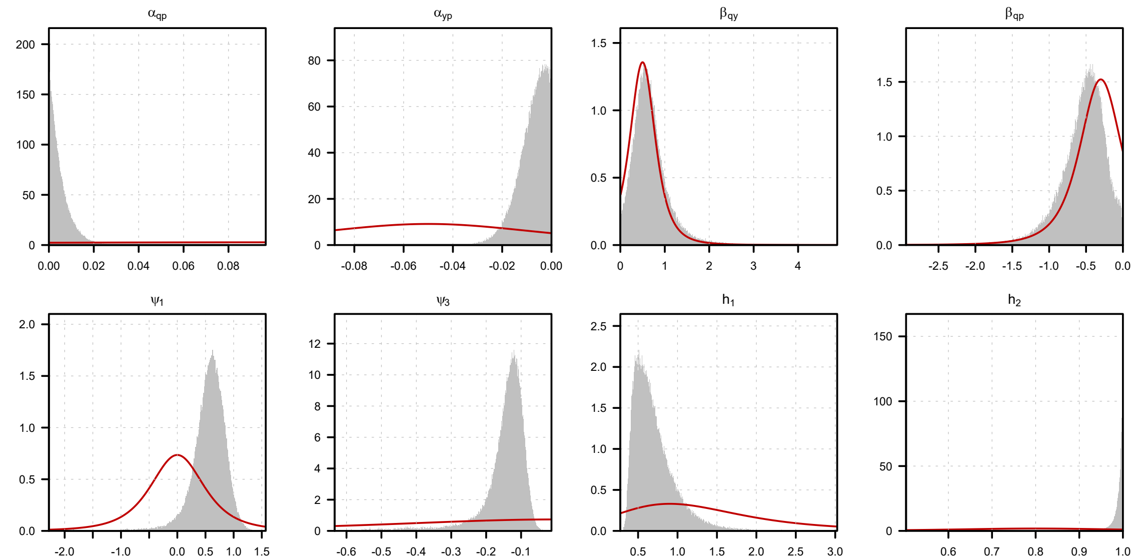
Notes: In the table u^S, u^E, u^D and u^Z denote the contributions (in pp.) of supply, income, demand and foreign shocks, respectively, to the quarterly rate of change in the US real natural gas prices (Δp_t) and production (Δq_t) in the period 2021Q3-2023Q3.

Figure 1: Time series describing the dynamics of the US natural gas market.



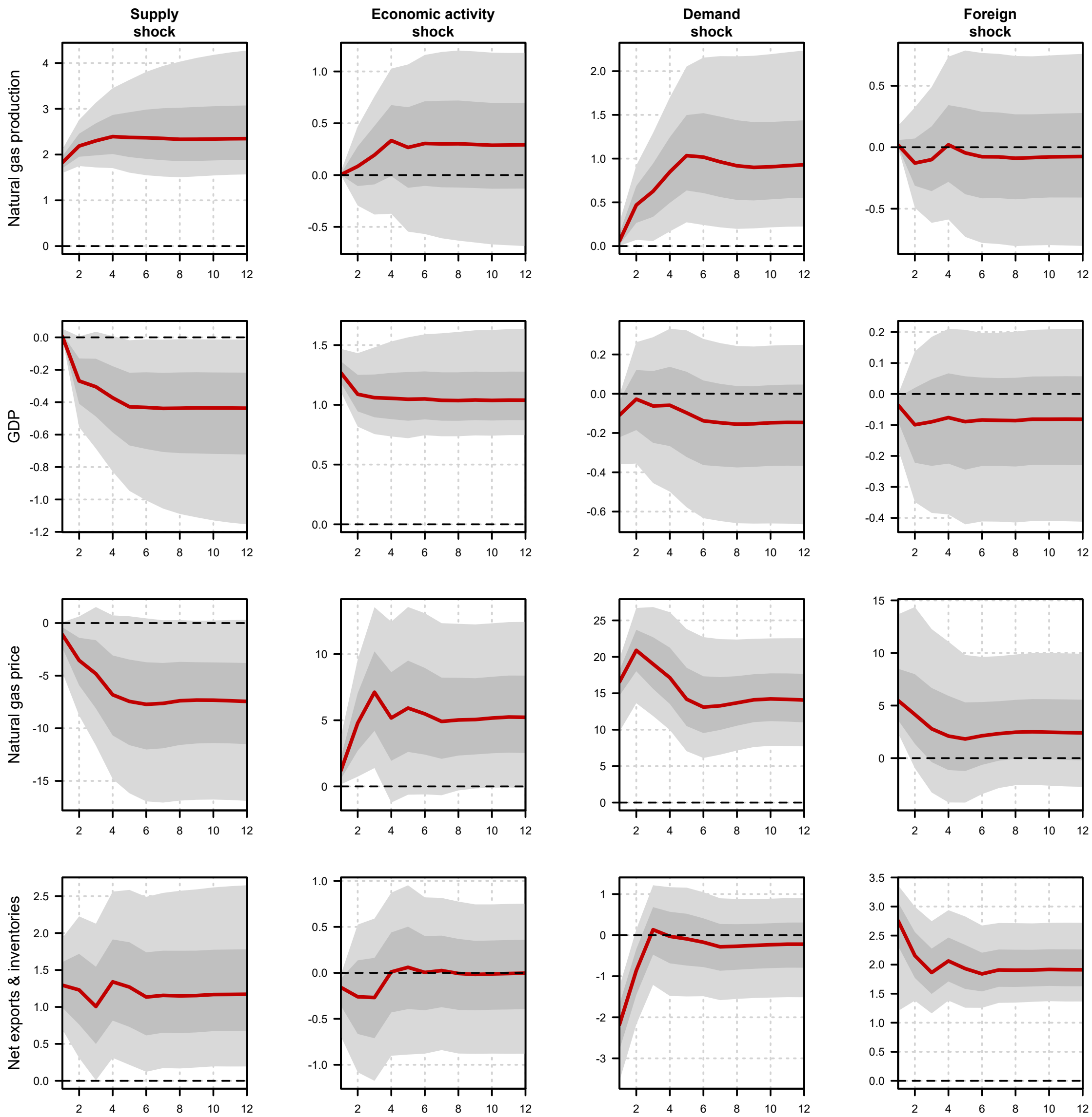
Source: EIA Monthly Energy Review database, World Bank Commodity Price Data and FRED database.

Figure 2: Prior and posterior distribution of model parameters for the baseline model.



Note: The baseline prior is represented using solid red lines, whereas the posterior is depicted using grey histograms. These distributions concern the contemporaneous coefficients in matrix $\mathbf{A}$ in the baseline model.

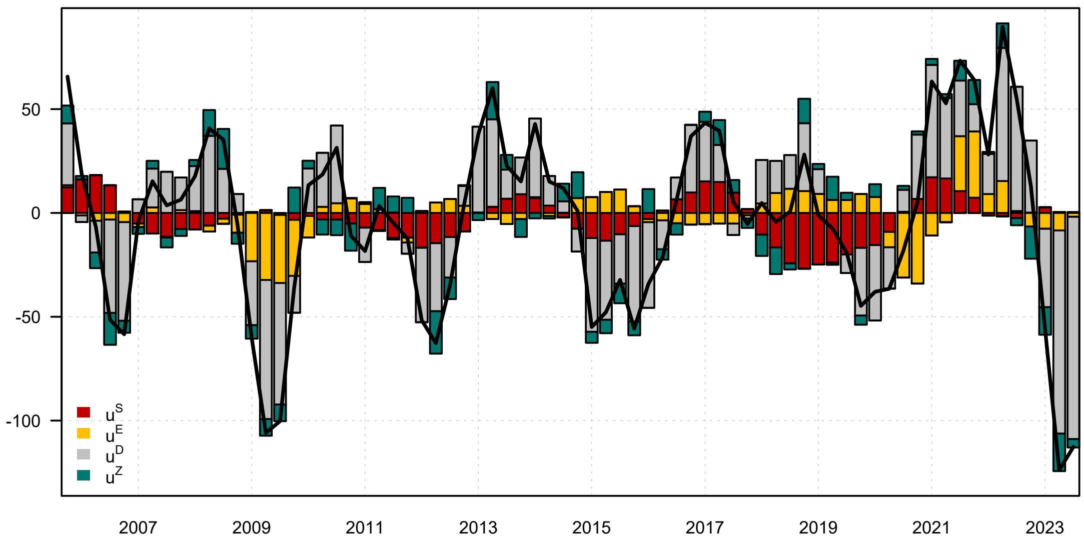
Figure 3: Impulse response functions for the baseline model.



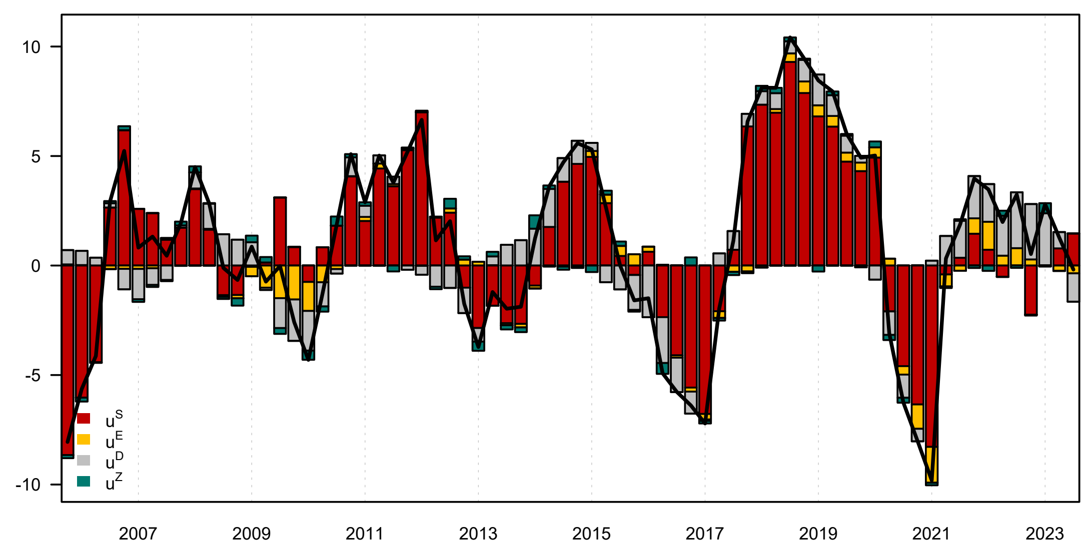
Notes: the red solid lines represent the Bayesian median posterior response. The grey areas denote the 68 and 95 percent posterior credible sets, respectively. The model was estimated on quarterly data spanning the period 1993Q1-2023Q3.

Figure 4: Historical decomposition for the annual growth rate of natural gas market variables.

Panel A: Real natural gas prices



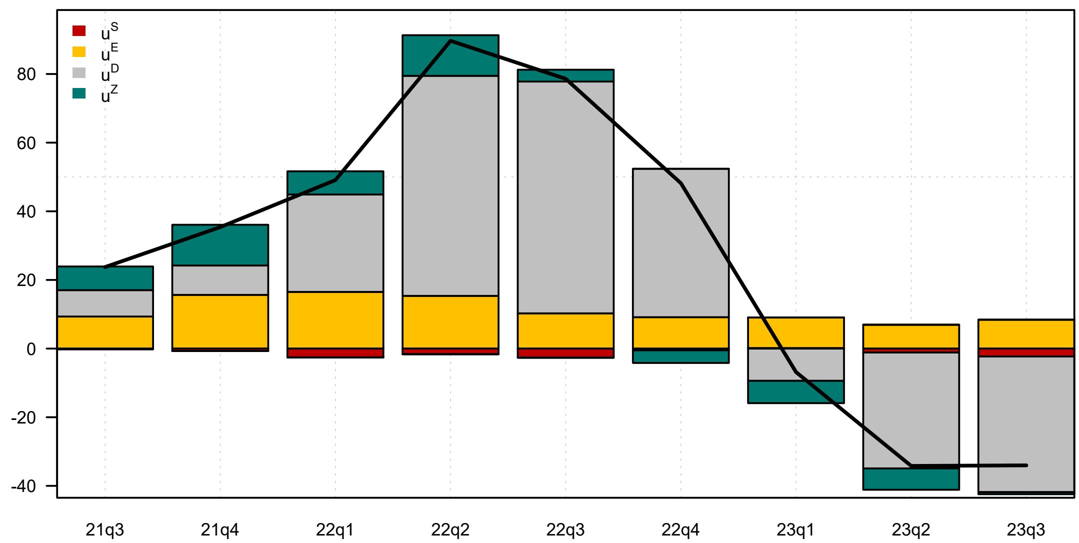
Panel B: Natural gas production



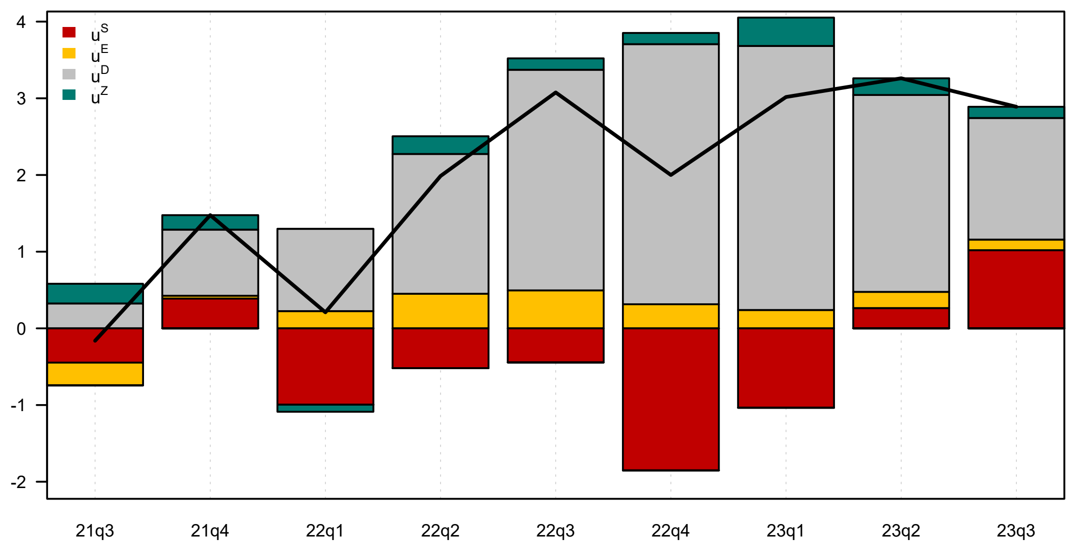
Notes: Black solid line represents the logarithmic annual rate of change in the US real natural gas prices and production obtained by summing the four subsequent quarterly rates of change. In the figure u^S, u^E, u^D and u^Z denote the contribution of the supply, income, demand and foreign shock, respectively.

Figure 5: Historical decomposition of cumulated natural gas market dynamics during the European energy crisis.

Panel A: Real natural gas prices % change



Panel B: Natural gas production % change



Notes: Black solid line represents the logarithmic change in the US real natural gas prices and production obtained by summing cumulatively all quarterly rates of change starting from 2021Q3. In the figure u^S, u^E, u^D and u^Z denote the contribution of the supply, income, demand and foreign shock, respectively.

A Modelling framework

Below we describe the methodology for estimating our SVAR model.

Prior The starting point for setting the prior relies on its decomposition into three components:

$$p(\mathbf{A}, \mathbf{B}, \mathbf{D}) = p(\mathbf{B}|\mathbf{A}, \mathbf{D}) \times p(\mathbf{D}|\mathbf{A}) \times p(\mathbf{A}). \tag{12}$$

The prior for the covariance matrix, $p(\mathbf{D}|\mathbf{A})$, is represented as a product of priors for individual elements of $\mathbf{D}$:

$$\begin{aligned} p(\mathbf{D}|\mathbf{A}) &= \prod_{i=1}^{n} p(d_{ii}|\mathbf{A}) \\ d_{ii}^{-1}|\mathbf{A} &\sim \Gamma(\kappa_i, \tau_i(\mathbf{A})), \end{aligned} \tag{13}$$

where $\Gamma(\kappa, \tau)$ denotes a Gamma distribution with the first two moments equal to κ/τ and κ/τ^2.

Next, the prior $p(\mathbf{B}|\mathbf{A}, \mathbf{D})$ is represented as a product of priors for its individual rows $\mathbf{b}_i$:

$$\begin{aligned} p(\mathbf{B}|\mathbf{A}, \mathbf{D}) &= \prod_{i=1}^{n} p(\mathbf{b}_i|\mathbf{D}, \mathbf{A}) \\ \mathbf{b}_i|\mathbf{A}, \mathbf{D} &\sim N(\mathbf{m}_i, d_{ii}\mathbf{M}_i), \end{aligned} \tag{14}$$

where $N(\mu, \Sigma)$ denotes the multivariate normal density function with the location and scale parameters μ and Σ, respectively.

Finally, the prior for the contemporaneous relations matrix $p(\mathbf{A})$ is freely chosen by the modeller and should reflect the economic structure of the analyzed system.

Posterior We continue by describing how observations $\mathbf{Y}_T = (\mathbf{y}_1', \mathbf{y}_2', \ldots, \mathbf{y}_T')'$ affect our prior beliefs about unknown parameters $\mathbf{A}, \mathbf{B}$ and $\mathbf{D}$. Following BH and RSU, we divide all observations into T_1 initial ones (pre-sample) and T_2 remaining ones, and assume that the impact of pre-sample observations on the posterior is downweighted by a factor $0 \leq \mu \leq 1$.

To derive the posterior distribution, we decompose it into three elements:

$$p(\mathbf{A}, \mathbf{B}, \mathbf{D}|\mathbf{Y}_T) = p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T) \times p(\mathbf{D}|\mathbf{A}, \mathbf{Y}_T) \times p(\mathbf{A}|\mathbf{Y}_T). \tag{15}$$

The posterior for the covariance matrix, $p(\mathbf{D}|\mathbf{A}, \mathbf{Y}_T)$, is represented as a product of the posterior for its diagonal elements:

$$\begin{aligned} p(\mathbf{D}|\mathbf{A}, \mathbf{Y}_T) &= \prod_{i=1}^{n} p(d_{ii}|\mathbf{A}, \mathbf{Y}_T) \\ d_{ii}^{-1}|\mathbf{A}, \mathbf{Y}_T &\sim \Gamma(\kappa_i^*, \tau_i^*(\mathbf{A})), \end{aligned} \tag{16}$$

where:

$$\begin{aligned} \kappa_i^* &= \kappa_i + (\mu T_1 + T_2)/2 \\ \tau_i^*(\mathbf{A}) &= \tau_i(\mathbf{A}) + \zeta_i^*(\mathbf{A}) \end{aligned} \tag{17}$$

and $\zeta_i^*(\mathbf{A}) = \left(\widetilde{\mathbf{Y}}_i'(\mathbf{A})\widetilde{\mathbf{Y}}_i(\mathbf{A})\right) - \left(\widetilde{\mathbf{Y}}_i'(\mathbf{A})\widetilde{\mathbf{X}}_i\right)\left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{X}}_i\right)^{-1}\left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{Y}}_i(\mathbf{A})\right)$ is the sum of squared residuals from regression of $\widetilde{\mathbf{Y}}_i(\mathbf{A})$ on $\widetilde{\mathbf{X}}_i$ defined as:

$$\begin{aligned}\underset{(T+k)\times 1}{\widetilde{\mathbf{Y}}_i(\mathbf{A})} &= \begin{bmatrix}\sqrt{\mu}\mathbf{y}_1'\mathbf{a}_i & \dots & \sqrt{\mu}\mathbf{y}_{T_1}'\mathbf{a}_i & \mathbf{y}_{T_1+1}'\mathbf{a}_i & \dots & \mathbf{y}_T'\mathbf{a}_i & \mathbf{m}_i'\mathbf{P}_i\end{bmatrix}' \\ \underset{(T+k)\times k}{\widetilde{\mathbf{X}}_i} &= \begin{bmatrix}\sqrt{\mu}\mathbf{x}_0 & \dots & \sqrt{\mu}\mathbf{x}_{T_1-1}' & \mathbf{x}_{T_1}' & \dots & \mathbf{x}_{T-1}' & \mathbf{P}_i\end{bmatrix}'\end{aligned} \tag{18}$$

with $\mathbf{P}_i$ being the Cholesky factor of $\mathbf{M}_i^{-1} = \mathbf{P}_i\mathbf{P}_i'$.

Next, the posterior for the matrix of parameters at lagged variables, $p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T)$, is represented as the product of posterior for its individual rows:

$$\begin{aligned}p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T) &= \prod_{i=1}^{n} p(\mathbf{b}_i|\mathbf{D}, \mathbf{A}, \mathbf{Y}_T) \\ \mathbf{b}_i|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T &\sim N(\mathbf{m}_i^*(\mathbf{A}), d_{ii}\mathbf{M}_i^*),\end{aligned} \tag{19}$$

where:

$$\begin{aligned}m_i^*(\mathbf{A}) &= \left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{X}}_i\right)^{-1}\left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{Y}}_i(\mathbf{A})\right) \\ M_i^* &= \left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{X}}_i\right)^{-1}.\end{aligned} \tag{20}$$

Finally, to present the formula for the contemporaneous relations matrix posterior, $p(\mathbf{A}|\mathbf{Y}_T)$, we need to use the covariance matrices calculated with VAR model residuals estimated on the two subsamples, as well as their weighted average:

$$
\begin{aligned}
\widetilde{\mathbf{\Omega}}_1 &= (T_1)^{-1}\left(\sum_{t=1}^{T_1}\mathbf{y}_t\mathbf{y}_t' - \left(\sum_{t=1}^{T_1}\mathbf{y}_t\mathbf{x}_{t-1}'\right)\left(\sum_{t=1}^{T_1}\mathbf{x}_{t-1}\mathbf{x}_{t-1}'\right)^{-1}\left(\sum_{t=1}^{T_1}\mathbf{x}_{t-1}\mathbf{y}_t'\right)\right)\\
\widetilde{\mathbf{\Omega}}_2 &= (T_2)^{-1}\left(\sum_{t=T_1+1}^{T}\mathbf{y}_t\mathbf{y}_t' - \left(\sum_{t=T_1+1}^{T}\mathbf{y}_t\mathbf{x}_{t-1}'\right)\left(\sum_{t=T_1+1}^{T}\mathbf{x}_{t-1}\mathbf{x}_{t-1}'\right)^{-1}\left(\sum_{t=T_1+1}^{T}\mathbf{x}_{t-1}\mathbf{y}_t'\right)\right)\\
\widetilde{\mathbf{\Omega}}_T &= (\mu T_1 + T_2)^{-1}\left(\mu T_1\widetilde{\mathbf{\Omega}}_1 + T_2\widetilde{\mathbf{\Omega}}_2\right)
\end{aligned}
\tag{21}
$$

The posterior marginal distribution for $\mathbf{A}$ is given by:

$$
p(\mathbf{A}|\mathbf{Y}_T) = k_T p(\mathbf{A})\left[\det(\mathbf{A}\widetilde{\mathbf{\Omega}}_T\mathbf{A}')\right]^{T^*}\prod_{i=1}^{n}\frac{[\tau_i(\mathbf{A})]^{\kappa_i}}{[\tau_i^*(\mathbf{A})/T^*]^{\kappa_i^*}}, \tag{22}
$$

where $T^* = (\mu T_1 + T_2)/2$ and k_T is a constant ensuring that $p(\mathbf{A}|\mathbf{Y}_T)$ meets the properties of a density function, namely that it integrates to unity.