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EWI Working Paper, No 08/24

November 2024

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ISSN: 1862-3808

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Abstract

The U.S. natural gas market is crucial for domestic energy and increasingly important in global trade. Structural analyses of this market often adapt oil market models but overlook key features, such as external trade flows, potentially limiting their ability to fully capture its dynamics. This paper extends these analyses by developing a Structural Vector Autoregression model that incorporates external gas flows and distinguishes between domestic and export-driven demand shocks, contributing to policy discussions on price fluctuations, particularly after the surge in U.S. gas exports following the Russia-Ukraine war. The model uses monthly data to reduce information loss and better capture market dynamics compared to models using quarterly data. The results indicate that supply and domestic demand shocks cause price overshoots, followed by a steady decline, with limited effects on economic activity. Export demand shocks cause short- and medium-term price increases and gradually expand supply, while inventory demand shocks trigger brief price spikes with minimal long-term impact. The analysis reveals that failing to control for extreme values in COVID-period data yields counterintuitive results, such as reduced gas supply boosting economic activity. A decomposition of 2022–2023 price fluctuations shows domestic demand and inventory demand shocks were the main drivers, while export demand shocks—though important—played a smaller role, influencing prices through alternating effects from increased LNG exports and maintenance disruptions. Finally, the estimated elasticities suggest that natural gas supply is unresponsive to short-term price changes, while demand exhibits limited responsiveness.

Keywords: Natural gas market; Structural VAR; Bayesian inference; Demand and supply elasticities

JEL classification: C11; C32; F14; L71; Q31; Q43.

[†]I thank Gabriel Arce Alfaro, Christiane Baumeister, Marc Oliver Bettzüge, James D. Hamilton, and Jan Hendrik Kopp for their valuable feedback. I have also benefited from the insightful comments received from participants at the 14th RCEA Bayesian Econometrics Workshop and the 13th International Ruhr Energy Conference. The contents of this paper reflect the opinions of its author.

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1. Introduction

The U.S. natural gas market plays a pivotal role in the nation's energy landscape, influencing sectors ranging from manufacturing to residential services (Gautam and Paudel, 2018). In addition to meeting domestic needs, the market provides significant economic opportunities through natural gas exports (Bernstein et al., 2016). According to the Energy Information Administration's (EIA) *Annual Energy Outlook* 2023, natural gas production is projected to grow steadily through 2050. This growth is expected to be driven by increased domestic consumption, particularly in the industrial sector, as well as by the expansion of natural gas exports due to rising global demand for liquefied natural gas (LNG) (EIA, 2023b). These trends underscore the enduring economic importance of the U.S. natural gas market, both domestically and internationally. Therefore, understanding the joint dynamics of supply, domestic demand, export demand, and prices is essential for informed policy decisions.

The literature on U.S. natural gas market dynamics predominantly relies on structural vector autoregression (SVAR) models, originally developed for the global oil market to analyze the distinct roles of supply and demand shocks in driving oil price fluctuations. One strand of this literature follows the recursive structural VAR specification used in the trivariate oil market model by Kilian (2009) (e.g., Hailemariam and Smyth (2019)). This approach examines the joint dynamics of the percentage change in U.S. natural gas production, the log of real natural gas prices, and an index of cyclical variation in U.S. real economic activity, using monthly data.[1] Variations in these variables are explained by three shocks: a natural gas supply shock, an aggregate demand shock, and a gas-market-specific demand shock. The other strand of this literature utilizes quarterly data and follows the four-variable specification used in oil market models proposed by Kilian and Murphy (2014) and Baumeister and Hamilton (2019) (e.g., Wiggins and Etienne (2017)). This approach extends the trivariate specification by incorporating natural gas inventories and adopting alternative identification strategies, such as sign restrictions[2], that explicitly account for inventory demand shocks. Despite differences in identification approaches, the overarching conclusion from both strands is that natural gas price fluctuations are primarily demand-driven. A detailed review of this literature is provided in Section 2.

While these two strands of literature have enhanced our understanding of U.S. natural gas market dynamics, key features such as imports and exports, which are integral to the market's supply and demand structure, have not been fully considered. As a result, these omissions may lead to an incomplete

[1] Recursive identification orders variables so that shocks to earlier variables in the VAR do not contemporaneously affect later ones. In natural gas market models, this typically means that gas production is ordered first, economic activity second, and gas prices last, allowing prices to react instantly to production and activity changes but not vice versa.

[2] The sign restriction approach is an identification method in which certain effects or responses are restricted in direction (positive or negative), rather than fixed at exactly zero. However, this method alone is insufficient because it can result in multiple equally plausible but conflicting models, necessitating additional economically motivated constraints to achieve reliable identification (see Kilian and Murphy (2012) and Baumeister and Hamilton (2019) for more details).

representation of the market's dynamics, particularly in capturing the role of export demand within the broader demand-side shocks that drive natural gas price fluctuations.

This study extends the literature by proposing an SVAR model that incorporates external gas flows into its structural framework. This extension ensures the proper allocation of the total available supply among domestic consumption, export demand, and inventory changes, preventing any misrepresentation of the supply-demand balance that could occur if external flows were excluded.[3] Within this framework, the model explicitly accounts for shocks to export demand for natural gas, thereby enhancing the understanding of demand-driven dynamics previously established in the literature. Furthermore, the analysis employs the Bayesian approach introduced by Baumeister and Hamilton (2015, 2019), which incorporates uncertainty in identifying assumptions and provides a framework for summarizing beliefs about key structural parameters, such as supply and demand elasticities. In doing so, this study revisits the dynamics and elasticities of natural gas supply and demand, providing new evidence on the relative importance of structural shocks in this market and contributing to the literature on the short-run response of energy commodities' supply and demand to price changes.

The model is estimated using a monthly dataset that extends through 2023, which is particularly relevant for three reasons. First, using monthly data reduces the information loss typically associated with temporal aggregation in models that use quarterly data. Temporal aggregation can affect the structural interpretation and identification of VAR models, as it may obscure within-period relationships that are critical for accurately capturing structural shocks. In particular, exclusion restrictions and elasticity bounds—which are essential for identifying these shocks—are more credible at a monthly frequency than at a quarterly one (Beetsma et al., 2009; Kilian and Lütkepohl, 2017). Second, extending the dataset through 2023 captures recent market shifts, especially those related to the increase in natural gas exports to Europe in the aftermath of the Russian invasion of Ukraine. This is relevant to ongoing policy discussions about the role of export demand shocks in natural gas price variation during this period (see, for example, EIA (2023a) and EVA (2023)). Finally, the analysis accounts for extreme observations during the COVID-19 pandemic, demonstrating that failing to control for these outliers can result in counterintuitive economic responses.

The results can be summarized as follows: First, the estimated short-run price elasticity of gas supply is 0.019, indicating that the supply curve remains price inelastic within the month. This minimal responsiveness aligns with the findings of Ponce and Neumann (2014) and Mason and Roberts (2018), highlighting the dominance of physical and technical constraints over economic incentives in the short term. On the demand side, the short-run price elasticity of domestic gas demand is -0.177, suggesting a modest decrease in demand

[3]See Section 3.2 for a detailed explanation of how this specification, which incorporates external gas flows, corrects potential misrepresentations in the supply-demand balance and improves the estimation of domestic consumption elasticity.

in response to price increases. This estimate is consistent with the findings of Labandeira et al. (2017), who report an average short-run price elasticity of -0.180.

Second, the results show that a negative supply shock leads to an initial sharp decline in gas supply, which partially reverses within the first three months. The supply disruption raises natural gas prices, prompting an immediate drawdown of inventories to mitigate the shortfall, though they recover within four months. A shock to domestic consumption gradually increases supply and raises prices, leading to a small, temporary decline in economic activity. As a result of this shock, inventories drop immediately, reach their lowest point in the fourth month, and recover to their original level within a year. Both supply and domestic consumption shocks reduce exports, with the impact being more significant for supply shocks. Inventory demand shocks trigger an immediate but short-lived spike in prices, while export demand shocks cause both short- and medium-term price increases and a gradual rise in natural gas supply.

The analysis reveals that these effects are distorted if extreme values from the COVID-19 pandemic are not accounted for. For example, without adjusting for these outliers, the findings incorrectly suggest that a reduction in gas supply, which typically raises gas prices, leads to an increase in U.S. economic activity. This underscores the importance of accounting for extreme events, such as the COVID-19 pandemic, in structural analyses to avoid misleading inferences about the true economic impacts of shocks.

Third, the analysis of the overall importance of each shock in determining gas price fluctuations reveals that domestic consumption demand shocks and inventory demand shocks are the primary drivers of short-term price variations, accounting for over 85% of the fluctuations at the one-month horizon. However, as the analysis extends to longer periods, up to 16 months, the influence of these shocks, though still dominant, diminishes slightly. Meanwhile, contributions from supply, economic activity, and export demand shocks become more pronounced, indicating a gradual shift in the dynamics affecting gas prices over time. Moreover, the analysis shows that consumption demand shocks and export demand shocks are the primary drivers of natural gas inventories and exports, respectively, with their effects persisting but decreasing over the 16-month horizon. Compared to Arora and Lieskovsky (2014), who identified a minimal short-run impact of supply shocks and a dominant role for speculative demand shocks, this study finds a more substantial short-run effect from supply shocks and a weaker influence from speculative demand. Furthermore, unlike Wiggins and Etienne (2017), who reported that supply and aggregate income shocks had roughly equal influence, this study concludes that these factors initially play a lesser role, with their significance increasing over time. This study's findings are consistent with those of Rubaszek et al. (2021) in emphasizing the role of consumption demand and inventory demand shocks, though they differ in the relative strength of these effects. Differences across studies may stem from variations in data frequency and model specifications.

Lastly, the decomposition of natural gas price movements from January 2022 to October 2023 reveals that domestic factors, particularly consumption demand and inventory demand shocks, were the primary drivers of price fluctuations, especially during periods of extreme weather and low storage levels. Export demand shocks also played a significant role, especially following the Russian invasion of Ukraine in early 2022, which led to increased U.S. LNG exports to Europe. Additionally, the shutdown and subsequent reactivation of the Freeport LNG terminal in 2022 and 2023 had notable impacts on gas prices, underscoring the influence of export dynamics on the U.S. market. For example, maintenance and operational incidents at the terminal contributed to price reductions in mid-2022 and price increases after its reactivation in early 2023. A decomposition analysis of price fluctuations during the 2005 hurricanes shows that supply shocks led to significant price increases immediately following Hurricanes Katrina and Rita in August, but their effects diminished quickly, with demand factors regaining dominance in the subsequent months. This demonstrates that, while supply shocks can cause sharp initial price increases, their effects are short-lived, with demand factors eventually regaining dominance.

The rest of the paper is organized as follows: Section 2 reviews the relevant literature. Section 3 describes the methodology, detailing the SVAR model adapted and extended for this analysis. Section 4 explains the data utilized and outlines the adjustments made to account for extreme observations stemming from the COVID-19 pandemic. Section 5 presents the estimation results. Section 6 discusses robustness checks to validate the reliability of the findings, and Section 7 concludes.

2. Literature review

The deregulation of the U.S. natural gas market was a gradual process shaped by policy changes, economic forces, and technological advancements. Initially, the natural gas wellhead price was regulated by the Federal Power Commission (FPC), which was later reconstituted as the Federal Energy Regulatory Commission (FERC). This regulation resulted in significant supply shortages. In response, the Natural Gas Policy Act of 1978 facilitated incremental price adjustments toward market levels to address these shortages. Subsequent reforms included the introduction of Special Marketing Programs (SMPs) and FERC mandates requiring the separation of sales and transportation services, enabling direct transactions between customers and suppliers. This evolution towards a competitive market was further reinforced by the Natural Gas Wellhead Decontrol Act of 1989, which fully deregulated wellhead prices (Makholm, 2010; Hou and Nguyen, 2018). From the mid-1990s onward, market forces exclusively determined U.S. natural gas prices (Ebinger et al., 2012; Joskow, 2013).

These significant market changes have prompted a corresponding shift in academic research. Initially, the literature primarily focused on the dynamics between natural gas and crude oil prices. Earlier studies, such as those by Serletis and Herbert (1999), Bachmeier and Griffin (2006), Villar and Joutz (2006), and Brown and Yttcel (2008), established a long-run relationship driven by the substitutability between refined petroleum products and natural gas across various consumption sectors. In contrast, more recent studies by Erdős and Ormos (2012), Geng et al. (2016b), and Zhang and Ji (2018) have observed a decoupling of oil and gas prices in the North American market. They attribute this trend to the switch to gas-on-gas competition pricing, the increased natural gas availability in the U.S., and a diminishing substitution effect with petroleum products. Consequently, contemporary research has shifted toward examining the relative importance of fundamental factors in the natural gas market through structural models. Table 1 summarizes studies employing the Structural VAR model, detailing their variables, specifications, identification strategies, data frequencies, and key findings.

The studies summarized in Table 1 cover a diverse range of variables, frequencies, and periods, with a common focus on fundamental factors influencing the dynamics of the U.S. natural gas market. Most of these studies exclude oil prices from their analysis, except for Hou and Nguyen (2018) and Nguyen and Okimoto (2019). Monthly data are used by Arora (2014), Hailemariam et al. (2019), and Rubaszek and Uddin (2020), who construct a three-variable model comprising the quantity of natural gas produced, industrial production as a measure of real economic activity, and the real price of natural gas. In contrast, quarterly data are used by Wiggins and Etienne (2017) and Rubaszek et al. (2021), who expand their variable sets to include natural gas inventories and use real GDP as a measure of economic activity. All studies apply deseasonalization to their data, except for Arora and Lieskovsky (2014), which employs annual differencing.

Model specifications across these studies show significant variation. Arora and Lieskovsky (2014) employ a standard SVAR model, attributing price fluctuations primarily to gas-specific demand shocks related to speculative or precautionary purposes. Wiggins and Etienne (2017) apply a Time-Varying Parameter Vector Autoregression (TVP-VAR) model with smoothly and continuously evolving parameters, enabling them to assess the dynamic effects of various structural shocks on natural gas prices. Their results show that supply and demand shocks are the primary drivers of U.S. natural gas price fluctuations since deregulation, with speculative activities having only a minor impact during certain periods. However, Hailemariam and Smyth (2019) argue that the continuous changes in parameters may not reflect the actual changes in the underlying dynamics, especially in regimes characterized by constant coefficients. Therefore, they implement a Structural Heterogeneous Autoregressive VAR (SHVAR) model, allowing coefficients and volatilities to change at specific dates and to differ across equations. They find that most variations in natural gas prices are attributable to gas-specific demand shocks related to storage, aligning with Arora and Lieskovsky (2014)'s conclusions. Further exploring nonlinearity, Rubaszek and Uddin (2020) employ a threshold SVAR model and find that the dominant role of these gas-specific demand shocks persists across both high and low inventory regimes. Lastly, Rubaszek et al. (2021) adopt a Bayesian SVAR framework, introduced by Baumeister and Hamilton (2019), which incorporates Bayesian inference to account for uncertainty in both parameter estimates and the structural features of the model. Their analysis shows that consumption demand shocks explain a dominant fraction of natural gas price variation.

Regarding the identification strategy, most studies, such as Arora and Lieskovsky (2014), Hou and Nguyen (2018), Nguyen and Okimoto (2019), and Hailemariam et al. (2019), predominantly adopt the

Table 1: Summary of studies analyzing the dynamics of the U.S. natural gas market using SVAR models

Authors (year)	**Variables**	**Model specification**	**Identification strategy**	**Data freq.**	**Study period**	**Key findings**
Arora and Lieskovsky (2014)	Production, consumption, price	SVAR	Recursive	M	1993M11-2012M12	Prices are mainly driven by specific demand shocks related to inventory.
Wiggins and Etienne (2017)	Production, GDP, price, inventory	TVP-VAR	Sign-restrictions	Q	1976Q1-2015Q2	The effects of supply and demand shocks vary significantly over time, with minimal impact from inventory demand shocks.
Hou and Nguyen (2018)	Production, IP, oil price, price	MS-VAR	Recursive	M	1980M2-2016M11	Prices are mainly driven by specific demand shocks related to inventory.
Nguyen and Okimoto (2019)	Oil price, production, IP, price	TSVAR	Recursive	M	1980M2–2016M11	Price response is asymmetric, varying according to the business cycle.
Hailemariam and Smyth (2019)	Production, IP, price	SHVAR	Recursive	M	1978M1-2018M7	Prices are largely explained by demand-specific shocks related to inventory.
Rubaszek and Uddin (2020)	Production, ADS, price, inventory	TSVAR	Recursive	M	1995M1–2018M8	Price response is asymmetric, varying according to the inventory level.
Rubaszek et al. (2021)	Production, GDP, price, gas inventory	BSVAR	Prior distributions and sign restrictions	Q	1993Q1-2020Q3	Prices are primarily driven by consumption demand shocks, followed by inventory demand shocks.

Note: In the "Variables" column, variables are listed according to the sequence adopted by each study for identifying causal relationships within their respective SVAR models. The terms "production", "consumption", "price", and "inventory" refer to natural gas production, natural gas consumption, real natural gas price, and natural gas inventory, respectively. Additionally, "IP" and "ADS" refer to industrial production and the Aruoba-Diebold-Scotti business conditions index, respectively. In the "Model specification" column, abbreviations are defined as follows: VAR: Vector Autoregression, TVP-VAR: Time-Varying Parameter VAR, MS-VAR: Markov-Switching VAR, TSVAR: Threshold SVAR, SHVAR: Structural Heterogeneous VAR, BSVAR: Bayesian SVAR. The "Data freq." column provides the data frequency in which the analysis is conducted, with "M" and "Q" referring to monthly and quarterly data frequencies, respectively.

recursive identification approach used by Kilian (2009) in the oil market. This approach is applied to analyze the joint dynamics of the percentage change in U.S. natural gas production, the logarithm of real natural gas prices, and an index representing cyclical fluctuations in U.S. real economic activity, based on monthly data. However, this identification strategy imposes exclusion restrictions that assume zero short-run supply elasticity, which may oversimplify real market dynamics, particularly given the non-zero elasticity of supply.[4] To address these limitations, Wiggins and Etienne (2017) follow a sign-restriction-based identification approach, building on the works of Kilian and Murphy (2012), Baumeister and Peersman

[4]The traditional Cholesky identification can be interpreted as a special case of Bayesian inference where exact prior knowledge is assumed about some elements of the structure, leading to identical inferences between the Cholesky and Bayesian posterior medians for those parameters (see Baumeister and Hamilton (2019) for more details).

(2013), and Kilian and Murphy (2014). Unlike the recursive method, which produces unique parameter estimates, sign-identified models generate a range of possible solutions as long as the responses of endogenous variables adhere to a predetermined sign pattern. Wiggins and Etienne (2017) extend the three-variable model of natural gas by incorporating natural gas inventories as a fourth variable, allowing them to capture the effects of speculative behavior and storage dynamics on price fluctuations. Furthermore, Rubaszek et al. (2021) adopt a four-variable model and the identification approach of Baumeister and Hamilton (2015, 2019), which involves a fully Bayesian setup that relaxes the dogmatic priors of the recursive identification and combines sign restrictions with weakly informative prior distributions on structural parameters to disentangle supply and demand shocks.

In summary, the variations in findings across studies analyzing factors affecting U.S. gas price fluctuations can largely be attributed to differences in model specification, identification assumptions, and variable selection. This divergence reflects the evolving understanding of interactions within the U.S. natural gas market. While earlier studies primarily relied on recursive identification and often overlooked the impact of inventories, recent research has adopted alternative approaches that enable them to account for inventories and has utilized quarterly data. However, the roles of natural gas imports and exports have not been fully considered, which can lead to misrepresentations in the supply-demand balance. Therefore, this study extends the literature by proposing an SVAR model that incorporates imports into the supply flow and explicitly allows for shocks to export demand, as well as those shocks examined in Rubaszek et al. (2021)'s analysis. This enables a clear distinction between domestic and export-driven demand shocks and contributes to the ongoing discussion about the role of export demand shocks in natural gas price variation. Additionally, this study uses monthly data to minimize the information loss typically associated with temporal aggregation. Finally, the analysis accounts for extreme values from the COVID-19 pandemic to avoid misleading inferences about the true economic impacts of shocks.

3. Methodology

This section outlines the approach for specifying and estimating an SVAR model of the U.S. natural gas market. Subsection 3.1 describes the specification of the SVAR model and the estimation procedures employed. Building on this foundation, Subsection 3.2 develops a specific model for the U.S. natural gas market. Finally, Subsection 3.3 details the prior assumptions applied to the model's contemporaneous structural parameters.

3.1. Structural VAR specification and estimation

Consider the following SVAR specification for a n-dimensional time series vector y_t:

$$\mathbf{A}y_t = \mathbf{B}x_{t-1} + u_t \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous variables, $\mathbf{A}$ is an $(n \times n)$ matrix summarizing their contemporaneous structural relations, x_{t-1} is a $(k \times 1)$ vector (with $k = mn + 1$) containing a constant and m lags of y ($x_{t-1} = (y'_{t-1}, y'_{t-2}, \ldots, y'_{t-m}, 1)'$), and u_t is an $(n \times 1)$ vector of structural disturbances assumed to be independent and identically distributed (i.i.d.) $\mathcal{N}(0, \mathbf{D})$ and mutually uncorrelated ($\mathbf{D}$ is diagonal).

This study follows the identification and estimation strategy introduced by Baumeister and Hamilton (2015) and further developed by Baumeister and Hamilton (2019) to construct a specific four-variable oil market model, which was later applied to the U.S. natural gas market by Rubaszek et al. (2021). This strategy yields a set-identified SVAR model through two primary steps. The first step involves specifying informative prior beliefs about the values of the structural parameters represented by a density $p(\mathbf{A}, \mathbf{D}, \mathbf{B})$. The second step generates draws from the posterior distribution of the structural coefficients to assess how the data influences the prior beliefs. Further details regarding the two steps are provided in the Appendix.

3.2. A structural VAR model of the U.S. natural gas market

To investigate the dynamics of the U.S. natural gas market, this study follows the model specification of Baumeister and Hamilton (2019). The original model comprises four structural equations that articulate the behavior of buyers and sellers in the global oil market, along with the determinants of global economic growth. However, due to the distinct characteristics of the U.S. gas market, particularly regarding natural gas imports and exports, modifications are necessary. This study adapts Baumeister and Hamilton (2019)'s framework by incorporating natural gas imports and exports into the specification. This extension is essential for precisely estimating the price elasticity of domestic natural gas demand, as it ensures the total available supply is accurately allocated among domestic consumption, exports, and inventory changes. Furthermore, unlike Baumeister and Hamilton (2019), which assumes the presence of additive measurement error in inventory levels, this study assumes no such measurement error. This is because the data for underground natural gas storage in the U.S. are highly accurate.[5]

To explain how the elasticity of domestic consumption can be approximated using the proposed SVAR model, let Q_t denote the total available natural gas supply in the U.S. market for period t. This supply includes dry natural gas production, net imports of pipeline natural gas from Canada, and imports of LNG.[6] Additionally, let EX_t represent the U.S. natural gas exports, which include pipeline natural gas exports

[5] Data on underground natural gas storage in the U.S. are collected through the EIA-191 survey, which achieves nearly 100% final monthly and annual response rates from operators of underground facilities in the U.S. The data are based on metered quantities, and respondents are required to report whether the data are actual or estimated, with revisions incorporated as needed. This ensures high accuracy in the reported storage volumes. See EIA (2024) for more details.

[6] Aggregating domestic production and imports into a single total supply measure is done for two reasons: first, the interest in this analysis lies in the total available supply shocks and in estimating U.S. total gas supply elasticity, which reflects both domestic and import responses and allows for a clearer focus on analyzing the effect of export demand shocks. Second, imports have minimal impact on total supply variability, justifying their combined treatment in the SVAR model. Another specification could isolate gas production in the supply equation, while the final equation would account for net exports. This specification was tested, and the main conclusions regarding market dynamics remained unchanged. Detailed results are available upon request

to Mexico and LNG exports.[7] Let I_t denote the U.S. natural gas inventories in month t, representing the working gas in underground storage. Lastly, let C_t be the domestic consumption in month t. These variables are linked through the following accounting identity:

$$C_t = Q_t - EX_t - i_t^*. \tag{2}$$

where $i_t^* = I_t - I_{t-1}$ represents the inventory change from period $t-1$ to t. This equation posits that the natural gas supply, which is neither exported nor allocated to inventory changes, is consumed domestically. By dividing both sides by Q_{t-1}, the previous period's natural gas supply $t-1$, the following equation is obtained:

$$\frac{C_t}{Q_{t-1}} = \frac{Q_t}{Q_{t-1}} - \frac{EX_t}{Q_{t-1}} - \frac{i_t^*}{Q_{t-1}}. \tag{3}$$

To further analyze changes from one period to the next, both sides of the equation are adjusted by adding $(EX_{t-1}/Q_{t-1}) - (Q_{t-1}/Q_{t-1})$ to reflect these changes and standardize the comparison by setting the baseline at the previous period's supply:

$$\frac{C_t - (Q_{t-1} - EX_{t-1})}{Q_{t-1}} = \frac{Q_t - Q_{t-1}}{Q_{t-1}} - \frac{(EX_t - EX_{t-1})}{Q_{t-1}} - \frac{i_t^*}{Q_{t-1}}. \tag{4}$$

Here, the left-hand side approximates the growth rate of domestic consumption, denoted by c_t. Similarly, $q_t = \frac{(Q_t - Q_{t-1})}{Q_{t-1}}$ represents the growth rate of natural gas supply. Therefore, the relationship can be approximately expressed as:

$$c_t \approx q_t - \frac{\Delta EX_t}{Q_{t-1}} - \frac{i_t^*}{Q_{t-1}}. \tag{5}$$

Considering the domestic demand for natural gas, this study hypothesizes a demand equation of the form:

$$c_t = \beta_{c\mathbf{y}} \mathbf{y}_t + \beta_{cp} p_t + \mathbf{b}' x_{t-1} + u_t^{cd} \tag{6}$$

where $\mathbf{y}_t$ denotes economic activity that may influence demand within the same month, p_t is the price of natural gas, $\mathbf{b}$ is a vector of coefficients associated with lagged variables x_{t-1}, and u_t^{cd} represents unanticipated shocks to domestic demand. The coefficient $\beta_{c\mathbf{y}}$ is the elasticity of domestic consumption demand with respect to economic activity, indicating how consumption changes in response to income variations, and β_{cp} is the elasticity of domestic demand with respect to price, reflecting consumption sensitivity to price changes. Combining Equation 5 with 6, the relationship can be expressed as:

$$q_t - \frac{\Delta EX_t}{Q_{t-1}} - \frac{i_t^*}{Q_{t-1}} \approx \beta_{c\mathbf{y}} \mathbf{y}_t + \beta_{cp} p_t + \mathbf{b}' x_{t-1} + u_t^{cd} \tag{7}$$

Rearranging for q_t and defining $ex_t = \frac{\Delta EX_t}{Q_{t-1}}$ and $i_t = \frac{i_t^*}{Q_{t-1}}$:

$$q_t = \beta_{q\mathbf{y}} \mathbf{y}_t + \beta_{qp} p_t + i_t + ex_t + \mathbf{b}' x_{t-1} + u_t^{cd} \tag{8}$$

[7] This approach to constructing the total supply and export variables closely follows the industry-standard methods employed by the Energy Information Administration (EIA), as detailed in their 'Weekly Natural Gas Storage Report' and 'Natural Gas Annual' reports, which describe the dynamics of supply and demand in the U.S. natural gas market.

Accordingly, the structural model for the U.S. natural gas market is represented by the following simultaneous equations:

$$\text{Total supply:} \qquad q_t = \alpha_{qp} p_t + \mathbf{b}_1' x_{t-1} + u_t^s \tag{9}$$

$$\text{Economic activity:} \qquad \mathbf{y}_t = \alpha_{\mathbf{y}p} p_t + \mathbf{b}_2' x_{t-1} + u_t^{ea} \tag{10}$$

$$\text{Domestic consumption demand:} \qquad q_t = \beta_{q\mathbf{y}} \mathbf{y}_t + \beta_{qp} p_t + i_t + ex_t + \mathbf{b}_3' x_{t-1} + u_t^{cd} \tag{11}$$

$$\text{Inventory demand:} \qquad i_t = \psi_1 q_t + \psi_2 \mathbf{y}_t + \psi_3 p_t + \mathbf{b}_4' x_{t-1} + u_t^{id} \tag{12}$$

$$\text{Exports demand:} \qquad ex_t = \lambda_1 q_t + \lambda_2 \mathbf{y}_t + \lambda_3 p_t + \lambda_4 i_t + \mathbf{b}_5' x_{t-1} + u_t^{exd} \tag{13}$$

where $u_t = \left[u_t^s, u_t^{ea}, u_t^{cd}, u_t^{id}, u_t^{exd}\right]' \sim \mathcal{N}(0, \mathbf{D})$ are uncorrelated structural shocks.

Equation 9 states that U.S. natural gas supply is influenced by natural gas prices through the contemporaneous structural coefficient α_{qp}. Assuming that both gas supply and real gas prices are expressed in log deviations, the coefficient α_{qp} can be interpreted as the short-run price elasticity of natural gas supply. The structural shock u_t^s is identified as a 'U.S. natural gas supply shock,' which can be triggered by geopolitical events, strikes, natural disasters (such as hurricanes), or production decisions.

Equation 10 characterizes real economic activity, which is instantaneously affected by natural gas prices via α_{yp}. The second structural shock, u_t^{ea}, corresponds to an 'economic activity shock' that reflects unexpected changes in the demand for natural gas driven by overall economic conditions, such as recessions or booms in the U.S. Equation 11 models domestic consumption demand. The coefficient β_{qp} represents the short-run price elasticity of natural gas demand, indicating how demand varies in response to price changes. Similarly, $\beta_{q\mathbf{y}}$ characterizes the response of demand to increased economic activity, reflecting how consumption adjusts to changes in the economic environment. The third structural shock, u_t^{cd}, is interpreted as a 'U.S. natural gas domestic consumption demand shock'.

Lastly, Equations 12 and 13 capture the demand for gas inventories and exports, respectively. Inventory demand is allowed to respond contemporaneously to natural gas supply, real economic activity, and real gas prices through coefficients ψ_1, ψ_2, and ψ_3, respectively. The term u_t^{id} represents a separate shock to natural gas inventory demand, often described in the literature as a 'speculative demand shock.' Similarly, Equation 13 allows exports to be affected contemporaneously by those variables as well as by inventories via coefficients λ_1, λ_2, λ_3, and λ_4. The term u_t^{exd} represents a shock to natural gas export demand, driven by unanticipated fluctuations in global demand for U.S. natural gas exports, international market dynamics, shifts in international gas prices, or changes in trade policies.

3.3. Prior information for the contemporaneous parameters in $\mathbf{A}$

This study specifies a set of prior beliefs regarding the elements of the contemporaneous matrix $\mathbf{A}$, based on economic theory and empirical evidence from previous studies. These priors represent initial assumptions about the parameters before observing the data. The detailed specifications of these priors, along with the sign restrictions for each contemporaneous coefficient, are summarized in Table 2.

Table 2: Summary of prior distributions for the contemporaneous coefficients in $\mathbf{A}$

		Student-t distribution			
Parameter	Meaning	Location	Scale	dof	Sign restriction
α_{qp}	Natural gas supply elasticity	0.1	0.2	3	$\alpha_{qp} > 0$
$\alpha_{\mathbf{y}p}$	Effect of p on activity	-0.05	0.05	3	$\alpha_{yp} < 0$
$\beta_{q\mathbf{y}}$	Income elasticity of natural gas demand	0.7	0.2	3	$\beta_{qy} > 0$
β_{qp}	Natural gas demand elasticity	-0.3	0.2	3	$\beta_{qp} < 0$
ψ_1	Effect of q on inventories	0	0.5	3	none
ψ_2	Effect of $\mathbf{y}$ on inventories	0	0.5	3	none
ψ_3	Effect of p on inventories	0	0.5	3	none
λ_1	Effect of q on exports	0	0.5	3	none
λ_2	Effect of $\mathbf{y}$ on exports	0	0.5	3	none
λ_3	Effect of p on exports	0	0.5	3	none
λ_4	Effect of inventories on exports	0	0.5	3	none

Note: "Location" refers to the mode of the t-distribution, "Scale" represents its standard deviation, and "dof" denotes degrees of freedom. "Sign restriction" indicates whether a sign restriction has been enforced. p refers to the real natural gas price, q denotes total natural gas supply, and $\mathbf{y}$ represents real U.S. GDP.

Priors for parameters of the gas supply equation. Barret (1992) provided an early estimate of natural gas supply elasticity at 0.014, based on an analysis of annual data from 1960 to 1990, highlighting the historically perceived inelastic nature of natural gas supply. Using monthly data from August 1987 to October 2012, Ponce and Neumann (2014) also noted a lack of short-run responsiveness from producers to price changes, a phenomenon attributed to the significant infrastructure investments required to scale production. However, they report a substantial long-run price elasticity of supply at 0.76, suggesting a delayed but significant supply response to price adjustments. Furthermore, Arora (2014) explored monthly data spanning from 1993 to May 2013 and estimated short-run and long-run elasticity at 0.07 and 0.42, respectively. Lastly, Mason and Roberts (2018) examined natural gas production in Wyoming from 1994 to 2012 and found that the price elasticity of intra-well production from previously drilled wells is highly inelastic at 0.03, while the elasticity of initial or peak-production rates is negative at -0.12.[8]

Based on these findings, this study assumes a truncated Student-t prior for α_{qp}, denoted as $\alpha_{qp} \sim t_{0,\infty}(0.1, 0.2, 3)$, centered at 0.1, with a scale of 0.2 and 3 degrees of freedom. The mode of the distribution

[8]The authors explain this negative coefficient by the endogenous selection of wells: higher prices make less productive wells viable, thereby lowering average productivity.

is set at 0.1, indicating a prior belief that the most probable value of the short-run supply elasticity is around 0.1, suggesting inelastic but positive responsiveness of supply to price changes. The scale parameter of 0.2 represents moderate uncertainty around this mode, acknowledging variability in empirical estimates and the possibility that the true elasticity may differ due to factors such as infrastructure constraints or market conditions. The degrees of freedom, set at 3, impart heavier tails to the distribution compared to a normal distribution. This accommodates the possibility of more extreme elasticity values observed in the literature. The heavy tails ensure that while the prior centers on 0.1, there remains a non-negligible probability for higher elasticity values, reflecting long-run adjustments and the dynamic nature of natural gas markets.

Priors for parameters of the real economic activity equation. The structural parameter $\alpha_{\mathbf{y}p}$ measures the effect of natural gas price fluctuations on real economic activity. As noted by Kilian (2008), energy price shocks can impact the economy by reducing discretionary income, increasing price uncertainty, promoting heightened precautionary savings, and shifting consumption patterns, particularly for energy-intensive goods. These dynamics suggest that the elasticity of economic activity with respect to natural gas prices is expected to be negative. Consistent with Baumeister and Hamilton (2019), this study adopts a truncated Student-t prior for $\alpha_{\mathbf{y}p}$, denoted as $\alpha_{\mathbf{y}p} \sim t_{-\infty,0}(-0.05, 0.05, 3)$, centered at -0.05 with a scale of 0.05 and 3 degrees of freedom.

Priors for parameters of the consumption demand equation. The consumption demand equation includes two structural parameters: the short-run price elasticity of natural gas demand (β_{qp}) and the effect of real economic activity on U.S. natural gas consumption demand (β_{qy}). The literature on natural gas demand elasticity offers a range of estimates. For example, Al-Sahlawi (1989) consolidated research from 1966 to 1984, noting short-term price elasticity of demand ranging from -0.05 to -0.95, predominantly around -0.30, and a wider long-run elasticity between -0.12 and -4.60. Joutz et al. (2009) analyzed data from 1980 to 2001, revealing short- and long-run elasticities of -0.09 and -0.18, respectively. Furthermore, Bernstein and Madlener (2011) found that the long-run U.S. price elasticity of residential natural gas demand is -0.16, and the short-run equivalent is -0.04. More recently, Joshi (2021) extended this timeline to 2015, observing a broader range of elasticities between -0.062 and -0.547, reflecting evolving market dynamics, particularly the effect of liberalization. Arora (2014) reported short-run elasticities between -0.10 and -0.16 and long-run values from -0.24 to -0.29. Therefore, this study assumes a truncated Student-t prior $\beta_{qp} \sim t_{-\infty,0}(-0.30, 0.2, 3)$ centered at -0.30, with a scale of 0.20 and 3 degrees of freedom. Regarding the $\beta_{q\mathbf{y}}$, the research conducted by Al-Sahlawi (1989) reviewed studies from the mid-1960s to 1984, indicating that the short-term income elasticity of natural gas demand ranges between 0.0 and 1.5, with minimal divergence observed between short- and long-term elasticities. This range was further contextualized by Burke and Yang (2016), who analyzed 44 countries over 1978–2011, predominantly OECD, finding an average income elasticity of 0.70 in a fixed-effects model. Accordingly, this study assumes a truncated Student-t prior for the parameter representing the relationship between income and natural gas demand ($\beta_{q\mathbf{y}}$). This prior is defined as $\beta_{q\mathbf{y}} \sim t_{0,\infty}(0.7, 0.2, 3)$, centered at 0.7 with a scale of 0.2 and 3 degrees of freedom.

Priors for parameters of the inventory and exports equations. Due to the absence of reliable empirical information to construct precise priors for the parameters in these equations, this study follows the approach proposed by Baumeister and Hamilton (2018). Specifically, it adopts non-informative priors, assuming these coefficients follow unrestricted Student-t distributions centered at zero, with a scale parameter of 0.5 and 3 degrees of freedom. This choice of a prior centered at zero reflects a neutral starting point, avoiding any inherent bias toward positive or negative effects. The chosen scale parameter and degrees of freedom allow for a modest degree of uncertainty, thereby giving the data a more significant role in shaping the posterior distributions.

4. Data

The dataset comprises monthly data spanning from January 1992 to October 2023. This period captures the influence of market forces on the dynamics of the natural gas market, as elaborated in Section 2. The selected variables include total natural gas supply (Q_t), real monthly Gross Domestic Product (GDP) ($\mathbf{Y}_t$), real natural gas prices (P_t), natural gas inventories (I_t), and natural gas exports (EX_t). Accordingly, the vector of endogenous variables used in the analysis is presented as follows:

$$y_t = [q_t, \mathbf{y}_t, p_t, i_t, ex_t] \tag{14}$$

where $q_t = 100 \times \ln(Q_t/Q_{t-1})$, $\mathbf{y}_t = 100 \times \ln(\mathbf{Y}_t/\mathbf{Y}_{t-1})$, $p_t = 100 \times \ln(P_t/P_{t-1})$, $i_t = 100 \times [I_t - I_{t-1}/Q_{t-1}]$, and $ex_t = 100 \times [EX_t - EX_{t-1}/Q_{t-1}]$.

Data on real monthly U.S. GDP are obtained from IHS Markit, part of S&P Global, following Neukirchen et al. (2023).[9] U.S. natural gas prices are sourced from the World Bank Commodity Price Database and converted into a real price index using the U.S. Consumer Price Index (CPI) from the U.S. Bureau of Labor Statistics. Data on natural gas market fundamentals, such as supply, working natural gas underground storage[10], imports, and exports, are sourced from the EIA Monthly Energy Review database. Following Rubaszek and Uddin (2020) and Rubaszek et al. (2021), all variables are seasonally adjusted.

[9]This choice is necessitated by the fact that official U.S. GDP data are released only on a quarterly basis. According to IHS Markit, their index "is an indicator of real aggregate output that is conceptually consistent with real GDP in the National Income and Product Accounts (NIPA)," employing "calculation and aggregation methods comparable to those of the official GDP from the U.S. Bureau of Economic Analysis" to produce "a monthly index whose variation at the quarterly frequency mirrors that of official GDP, offering a meaningful and comprehensive measure of monthly changes in output" (IHS Markit, 2022).

[10]Working natural gas underground storage refers to the total volume of natural gas in underground storage that is available for withdrawal, as defined by the U.S. Energy Information Administration (EIA).

Data during the COVID-19 pandemic The disruptive impact of the 2020 pandemic significantly affected U.S. natural gas supply and demand, as well as a broad range of economic indicators. For detailed descriptions and analyses of these disruptions, see Nyga-Łukaszewska and Aruga (2020) and Baumeister (2023). This divergence suggests that structural and reduced-form parameters during the most acute phase of the pandemic, particularly in 2020 and early 2021, should be estimated separately due to the distinct nature of shocks and relationships. However, the limited number of observations available during this period makes estimating a full set of parameters impractical.

Several approaches have been proposed for handling extreme observations in such contexts. Ng (2021) argues that the principal components of economic data now capture both typical economic fluctuations and pandemic-related variations. To address this, Ng proposes adjusting each economic variable by incorporating COVID-19 indicators—such as positivity rates, hospitalizations, and deaths—to create a "de-covid" dataset, which allows for a more accurate estimation of underlying economic factors. Lenza and Primiceri (2022) propose explicitly modeling the increase in shock volatility. Specifically, they introduce a scaling factor in a VAR model, which adjusts the residual covariance matrix during the pandemic period, allowing for different levels of volatility in March, April, and May 2020, with a decay parameter for subsequent months. This approach aims to provide more accurate parameter estimates and predictions by accounting for the elevated uncertainty during the pandemic. Similarly, Carriero et al. (2022) introduce a BVAR model with outlier-augmented stochastic volatility, which combines transitory and persistent changes in volatility to handle extreme observations during COVID-19. This approach models large, infrequent volatility outliers as a separate state, allowing the model to account for sudden spikes in volatility without treating them as permanent. In contrast to these more complex methodologies, Schorfheide and Song (2024) opt for a simpler solution by recommending the exclusion of data points associated with the COVID-19 pandemic in the estimation of their Mixed-Frequency VAR model. This straightforward approach avoids the intricacies and potential complications of modifying the underlying model structure, focusing instead on maintaining the model's performance by selectively omitting extreme observations. Baumeister and Hamilton (2024) also follow this straightforward approach by excluding extreme values.

Following Schorfheide and Song (2024) and Baumeister and Hamilton (2024), this paper excludes data from March 2020 through February 2021—the period most affected by the pandemic—from the analysis. This decision is based on the premise that including this data could introduce significant volatility and anomalies into the model, potentially distorting the relationships under study.

5. Results

This section presents the findings from the estimated SVAR model for the U.S. natural gas market. Subsection 5.1 examines the posterior distributions of the structural parameters, highlighting the impact of the observed data on these estimates. Subsection 5.2 discusses the Impulse Response Functions (IRFs), which illustrate the dynamic effects of structural shocks on the model's variables. Subsection 5.3 quantifies the contributions of different shocks to the forecast error variance of each variable in the model. Finally, Subsection 5.4 provides a historical decomposition, tracing the cumulative impact of various shocks on U.S. natural gas prices during key periods.

5.1. Posterior distributions for structural parameters

Figure 1 compares the prior and posterior distributions for the structural parameters in the **A** matrix, with red lines representing the priors and grey histograms representing the posteriors. This comparison evaluates the impact of the observed data on updating the initial beliefs discussed in Subsection 3.3 and assesses the extent to which these priors influence the outcomes of the subsequent analysis.

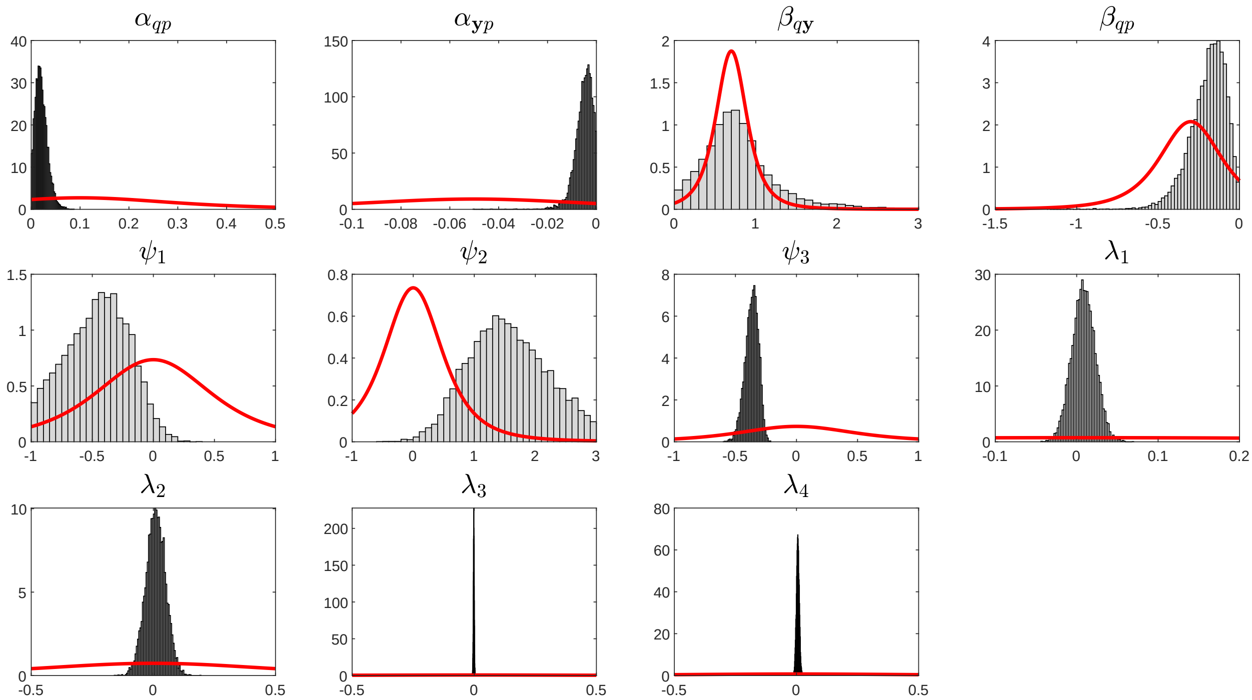

Figure 1: Prior and posterior distributions of the contemporaneous coefficients in **A**.
Note: The solid red curves represent the prior knowledge, and the gray histograms represent the posterior densities.

The results reveal that the posterior distribution for the short-run price elasticity of natural gas supply is tightly concentrated around a value close to zero, suggesting the data are quite informative and lead to a substantial revision of the prior belief. The posterior median of this parameter is 0.019, indicating that a 1% increase in price is associated with only a 0.019% increase in the total supply of natural gas in the U.S., reflecting minimal supply adjustments to price changes within the month. This minimal responsiveness is consistent with the findings of Ponce and Neumann (2014), Hou and Nguyen (2018), and Rubaszek et al. (2021), who report that natural gas supply in the U.S. is inelastic. Such inelasticity can be attributed to infrastructure costs, regulatory constraints, and the technical and logistical complexities of rapidly adjusting production levels in response to market fluctuations (Mason and Roberts, 2018; Egging and Holz, 2016). These factors underscore the dominance of physical and technical considerations over economic incentives in short-term supply responsiveness.

For the effect of natural gas prices on U.S. real economic activity, the posterior distribution of $\alpha_{\mathbf{y}p}$ is centered near zero, with a median value of -0.004. This implies that increases in the real price of natural gas are associated with only a negligible reduction in real economic activity within a monthly period. This result aligns with the findings of Cavalcanti and Jalles (2013) and Alexeev and Chih (2021), who observe that gas and oil price shocks have minor effects on U.S. economic growth.

Regarding the domestic consumption equation, the first structural parameter, $\beta_{q\mathbf{y}}$, represents the impact of economic activity on domestic natural gas demand. While the median value of this coefficient, 0.788, is similar to its prior, the posterior distribution shows a notable shift toward higher values, indicating that the data provide moderate support for the prior belief. This value is consistent with the findings of Burke and Yang (2016), who report that natural gas demand elasticity with respect to GDP ranges between 0.40 and 1.12. The second structural parameter, β_{qp}, measures the price elasticity of natural gas demand. The posterior median of this parameter is -0.177, which is lower than its prior value, indicating that the data provided significant insights into this relationship. This result implies that a 1% increase in natural gas prices leads to a 0.177% decrease in demand, highlighting short-run inelasticity. This estimate aligns with the findings of Labandeira et al. (2017), who report an average short-run price elasticity of -0.180, and is less inelastic than the -0.130 estimated by Arora (2014).

Summary statistics for the posterior estimates of these parameters, along with other relevant magnitudes, are reported in column 1 of Table A.1 in the Appendix.

5.2. Impulse response functions

Figure 2 presents the posterior medians (pointwise) along with 68% and 90% credible intervals for the impulse response functions (IRFs) up to 16 months, each standardized to reflect a 1% increase in natural gas prices on impact. Specifically, u_t^s represents an unanticipated disruption in the natural gas supply. The IRFs illustrate the dynamic responses of the five endogenous variables to structural innovations.

First, consider the effect of a negative flow supply shock, as shown in the first row. This shock causes a sharp initial decline in gas supply, which partially reverses within the first three months. This pattern aligns with the principle that supply constraints in one U.S. location, or in imports from a single source, often prompt compensatory increases in production or enhanced import flows from other locations. The results further indicate that a natural gas supply shock lowers real economic activity after a significant lag; however, this effect is insignificant when considering the 90% credible sets. At the same time, this supply disruption leads to an immediate increase in the real price of natural gas, peaking after three months and

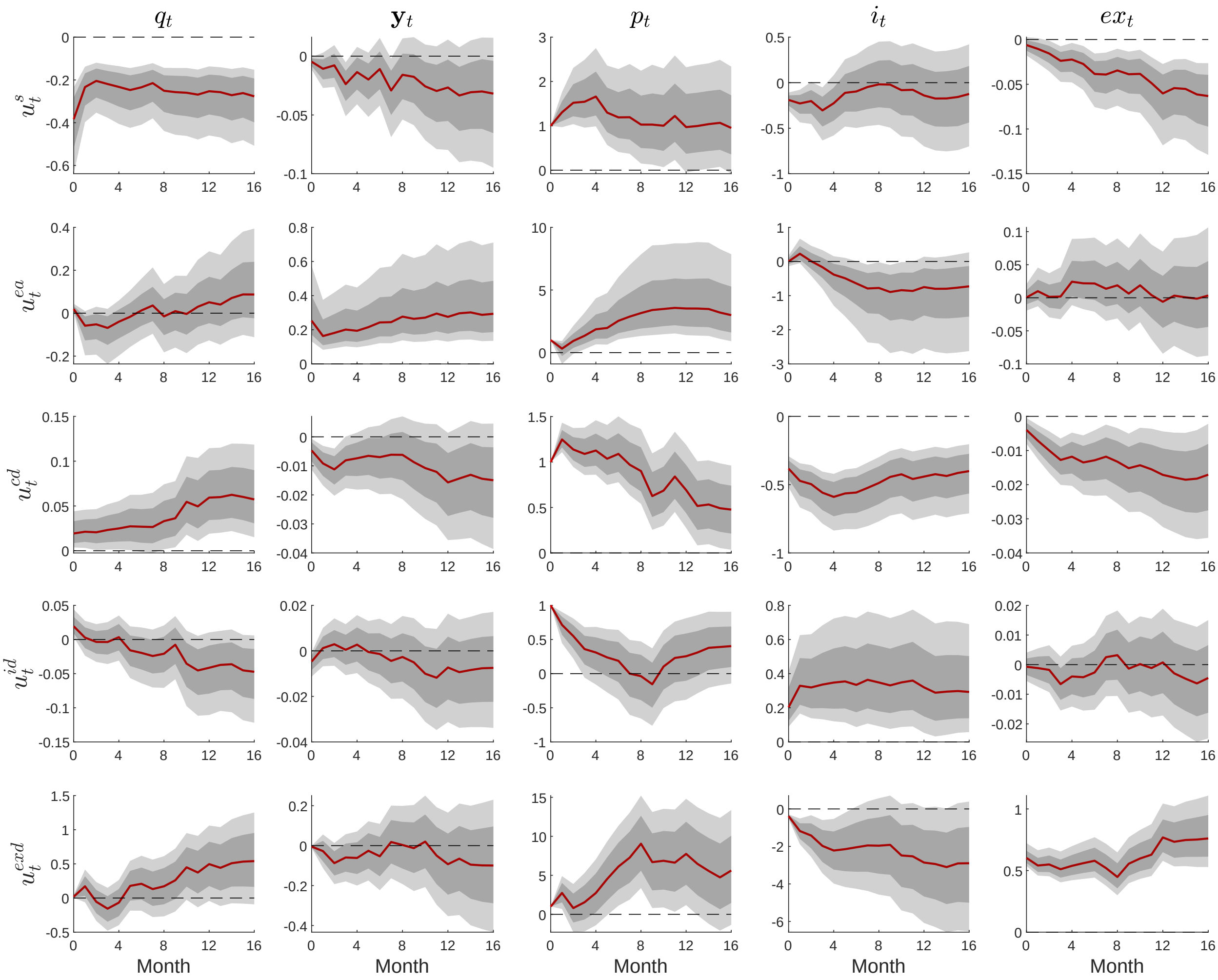

Figure 2: Structural impulse responses

Note: The rows represent the responses to different shocks, denoted as u_t^s (supply shock), u_t^{ea} (economic activity shock), u_t^{cd} (consumption demand shock), u_t^{id} (inventory demand shock), and u_t^{exd} (export demand shock). The columns represent the variables: q_t (total U.S. natural gas supply), $\mathbf{y}_t$ (real U.S. GDP), p_t (real gas price), i_t (U.S. gas inventories), and ex_t (U.S. gas exports). The red solid lines represent the Bayesian posterior median, while the dark- and light-shaded grey areas denote the 68% and 90% posterior credible regions, respectively.

then reverting to its initial value after one year. Natural gas inventories are immediately drawn down to mitigate the supply shortfall, though this effect dissipates within four months, as the credible sets return to include zero. Additionally, there is a reduction in natural gas exports, reflecting the decreased availability for foreign markets. These dynamics are consistent with findings from analyses of the U.S. natural gas and oil markets by Hailemariam and Smyth (2019) and Valenti et al. (2023), respectively, and with findings from analyses of the global crude oil market by Kilian and Murphy (2014) and Baumeister and Hamilton (2019).

The second row shows that an unexpected increase in economic activity does not influence natural gas supply. However, this economic shock leads to an increase in the real price of gas, peaking after almost one year. Changes in natural gas inventories are negligible in the short run; however, a drawdown occurs as time progresses. Natural gas exports remain unaffected. These responses to the economic activity shock are generally consistent with the results observed in Rubaszek and Uddin (2020) and Valenti et al. (2023).

The third row shows that a domestic consumption demand shock leads to a slight increase in supply on impact to meet rising demand. This increase continues gradually, peaking at twelve months before stabilizing, suggesting a lagged supply adjustment process in response to the shock. Real gas prices respond positively on impact but start to decrease after the second month, reaching a minimum after one year before stabilizing, likely reflecting market adjustments in response to the increased supply. Economic activity responds to the increase in gas prices with a small, temporary decrease. This finding aligns with Hailemariam and Smyth (2019), who also observed similar economic impacts from gas demand shocks. Inventory levels show a negative response on impact, reaching their lowest level in the fourth month before gradually recovering to their original level after one year. Meanwhile, natural gas exports exhibit a relatively small negative response to the positive demand shock, highlighting a shift in gas flows to meet domestic demand.

The fourth row examines responses to a positive shock to inventory demand, often characterized in the literature as a speculative demand shock. Such a shock could arise from increased precautionary demand for natural gas, driven by heightened uncertainty about future demand or supply conditions (see Kilian and Murphy (2014)). The results reveal that this shock is associated with an immediate jump in the real price of natural gas, which quickly diminishes and becomes statistically insignificant by the fourth month, indicating a short-lived market reaction. This shock also leads to a persistent increase in gas inventories. These findings are consistent with those of Kilian and Murphy (2014), who observe that oil prices initially overshoot in response to such shocks before gradually declining, with minimal effects on supply and global economic activity.

The last row presents the IRFs to an export demand shock. Natural gas supply shows no immediate reaction to this shock but begins to increase gradually thereafter. On impact, the real price of natural gas responds positively and continues to exhibit a substantial and statistically significant response in the following months, though this significance diminishes after one year. These trends suggest that market adjustments, primarily driven by changes in supply-demand dynamics from export activities, take several months to fully stabilize. In contrast, gas inventories initially decrease to meet the heightened export demands, but this decrease becomes statistically insignificant by the fourth month, as indicated by the 90% credible sets.

5.3. Forecast error variance decomposition

This section quantifies the impact of each shock on the variables in the estimated SVAR model by calculating the variance of the model's forecast error and determining the share of that variance attributable to each shock at different time horizons. The results, presented in Table 3, show the average contributions of each shock to the overall variation in natural gas supply, real economic activity, real price of natural gas, natural gas inventories, and natural gas exports, expressed in percentage terms.

Table 3: Percent contribution of shocks to the overall variability of each variable

	Natural gas supply					Economic activity					Real natural gas price				
Horizon	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}
1	94.29	1.24	1.77	1.76	0.34	0.45	95.97	1.62	1.30	0.16	8.48	3.61	54.06	31.54	0.73
2	92.33	1.52	2.04	2.13	1.18	0.75	94.21	2.03	1.65	0.80	8.82	4.67	52.45	31.09	1.65
3	90.96	1.86	2.33	2.40	1.67	2.06	91.53	2.55	1.99	1.12	8.86	5.23	51.19	31.41	2.00
6	85.88	3.04	3.12	3.96	3.28	3.69	87.17	3.26	2.88	2.14	10.04	6.87	48.27	29.92	3.75
12	76.30	4.99	5.80	6.70	5.37	6.88	77.74	4.99	4.80	4.70	10.54	7.63	46.16	28.56	6.15
16	74.57	5.54	6.13	7.11	5.81	7.38	76.01	5.40	5.10	5.16	10.71	7.95	45.60	27.92	6.81

	Natural gas inventories					Natural gas exports				
Horizon	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}
1	3.16	1.22	76.90	16.62	1.36	1.01	0.67	2.16	0.47	94.94
2	3.47	2.51	75.20	16.47	1.70	1.59	1.18	2.99	0.78	92.67
3	4.27	3.29	73.27	15.98	2.38	2.54	1.47	3.75	1.83	89.59
6	6.07	5.44	68.79	15.60	3.16	4.62	3.62	4.59	2.83	83.50
12	7.44	7.22	63.57	15.71	5.04	7.19	5.96	5.74	5.12	75.14
16	7.82	7.48	62.34	15.91	5.43	7.92	6.44	6.11	5.89	73.73

Note: This table provides posterior median estimates of the contribution of each shock to the forecast error variance of each variable. Credibility sets are available in Table A.2 in the Appendix. Horizons are expressed in months. The terms u_t^s, u_t^{ea}, u_t^{cd}, u_t^{id}, and u_t^{exd} refer to supply, economic activity, consumption demand, inventory demand, and exports demand shocks, respectively.

For the real gas price at the 1-month horizon, consumption demand shocks account for 53.85% of the variation, followed by inventory demand shocks, which contribute an additional 32.07%. By the 16-month horizon, these contributions adjust slightly to 45.35% for consumption demand and 28.17% for inventory demand, reflecting a sustained but diminishing influence on gas price movements. Moreover, the impact of supply shocks, economic activity shocks, and export demand shocks on price variations is minimal initially but increases gradually, suggesting a prolonged adjustment process. Specifically, their combined impact accounts for less than 13% of the price variation initially but becomes more significant by the 16-month horizon, with economic activity shocks increasing from 3.57% to 7.96% and export demand shocks from 0.70% to 6.84%.

These results can be compared with those discussed in Section 2. According to Arora and Lieskovsky (2014), supply shocks initially have a minimal impact (3.2%) that increases significantly in the long run (16%), and the 'other' shock, which includes the demand and supply of natural gas for speculative or precautionary purposes, dominate the short term (76%). In contrast, this study finds a relatively higher effect from supply shocks in the short run and a much lower effect from speculative demand shocks. The findings from Rubaszek et al. (2021) align more closely with this study regarding the significant role of consumption demand shocks and inventory demand shocks. However, Rubaszek et al. (2021) reports a stronger effect in both the short run (79%) and the long run (65%) for consumption demand shocks, with lesser impacts from inventory demand shocks (12% in the short run and 19% in the long run). Compared to Wiggins and Etienne (2017), who report a balanced contribution from supply and aggregate income shocks (20%–30%), this study initially finds these factors to play a lesser role, with their significance increasing over time. The discrepancies between this study's results and those reported by Rubaszek et al. (2021) and Wiggins and Etienne (2017) may be attributed to differences in data frequency or model specifications.

Regarding the other endogenous variables, Table 3 indicates that the variation in natural gas supply is predominantly driven by supply shocks (u_t^s), accounting for 94% on impact and 75% in the long run. This underscores the significant role of supply conditions in the short term, which marginally decreases as other factors come into play over time. In the case of natural gas inventories, consumption demand shocks (u_t^{cd}) are initially the most influential, explaining 76.34% of the variation, but this influence diminishes to 61.87% by the 16th month, indicating a sustained and significant impact over time. Finally, natural gas exports are primarily influenced by export demand shocks (u_t^{exd}), which account for 95.09% of the variation initially, decreasing to 73.18% by the 16th month, underscoring the critical role of external market demands in shaping U.S. natural gas export volumes.

5.4. Historical decomposition

The estimates obtained from structural IRFs and structural FEVDs describe the average movements in the U.S. gas market over the analyzed period, representing unconditional expectations. The main objective of this section is to decompose the movements in real gas prices and trace the cumulative effects of each shock from January 2022 to October 2023. This period was marked by escalating geopolitical tensions triggered by the Russian invasion of Ukraine in early 2022, which significantly increased U.S. natural gas exports to Europe and sparked policy discussions concerning the impact of these exports on U.S. gas price fluctuations in 2022 (see EIA (2023a) and EVA (2023)). Figure 3 presents the historical decomposition of natural gas price movements from January 2022 to October 2023.

The results reveal that natural gas dynamics during this period were predominantly influenced by consumption demand shocks (dark gray bars) and inventory demand shocks (light gray bars). For example, early 2022 experienced notably positive cumulative effects from consumption demand shocks due to weather-induced spikes in natural gas usage in the Northeast and Midwest. Speculative demand shocks also contributed positively, particularly in March and April 2022, likely due to low storage levels at the onset of the injection season. Similarly, throughout the first half of 2023, fluctuations in gas prices were primarily driven by domestic consumption shocks and inventory dynamics. The marked decline in gas prices, especially in January and February—typically peak months for heating—was largely due to

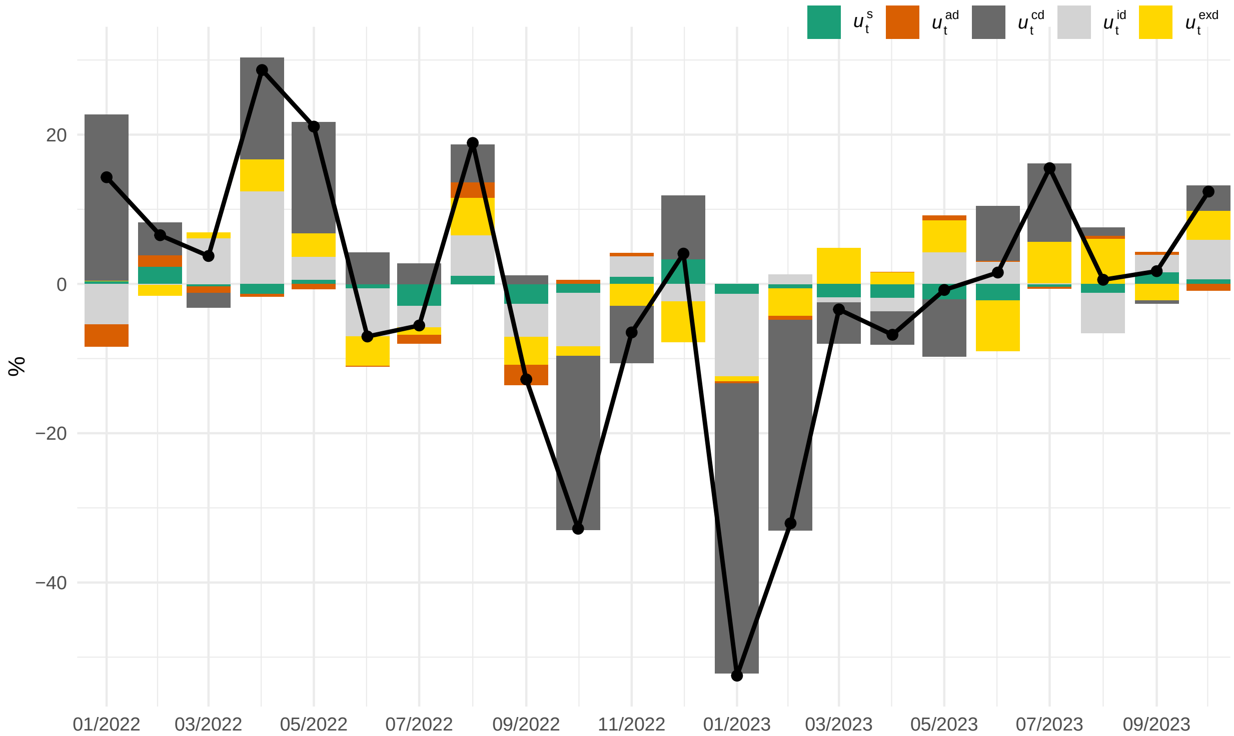

Figure 3: Historical decomposition of the U.S. natural gas real price changes, Jan 2022 – Oct 2023
Note: Each bar in the graph represents the median estimate of historical contribution of separate shocks—supply (u_t^s), aggregate demand (u_t^{ad}), consumption demand (u_t^{cd}), inventory demand (u_t^{id}), and export demand (u_t^{exd})—for each month during the specified period. The colors correspond to these specific shocks, as labeled directly on the figure. The solid black line represents the logarithmic changes in the real prices of U.S. natural gas.

milder-than-average temperatures, which reduced consumption in the residential and commercial sectors (Fleury, 2024).

The findings also show that accumulated export demand shocks (yellow bars) consistently influenced gas price dynamics throughout the period, with impacts alternating between positive and negative across different months. For example, these shocks contributed to price spikes in April, May, and August 2022, which were associated with increased LNG exports to Europe during these months.[11] Conversely, they also contributed to the price declines in June, July, and other months of 2022, which can be attributed to the explosion and subsequent shutdown of the Freeport LNG export terminal.[12] This incident led to a significant reduction in U.S. LNG exports, contributing to a domestic surplus of natural gas. In contrast, the results

[11]For example, according to the EIA monthly statistics, U.S. LNG exports to the Netherlands in August 2022 (50,020 MMcf) surged to the highest level of the year, marking a 53% increase compared to July (32,637 MMcf) and 62% higher than September (30,924 MMcf), illustrating a significant spike in U.S. LNG exports to Europe during this month.

[12]Freeport LNG is a U.S. liquefaction and export facility for Liquefied Natural Gas (LNG) located in Freeport, Texas. It ranks as the seventh-largest LNG export facility globally and the second-largest in the United States. Additional details about this terminal and the incident that occurred in June 2022 can be found on its official website.

indicate that accumulated export demand shocks have driven much of the gas price increases since March 2023. This rise could be attributed to the reactivation of the Freeport terminal in early 2023, alongside increased pipeline exports to Mexico during the summer, marking a return to positive contributions from exports to natural gas price fluctuations. However, the decline in export demand shocks in June 2023 can be explained by extensive maintenance activities at key LNG export facilities. For example, the Sabine Pass LNG terminal underwent major maintenance, reducing its feed gas deliveries from an average of 4.6 Bcf/d in May to nearly 3 Bcf/d in June. Additionally, the Freeport LNG plant in Texas faced operational issues in mid-June, further lowering overall feed gas deliveries (S&P Global Commodity Insights, 2023). This underscores how maintenance events at export infrastructure can affect price fluctuations.

Overall, the historical decomposition of U.S. natural gas prices from 2022 to 2023 highlights the consistent and substantial impact of accumulated demand-side shocks as the primary drivers of gas price dynamics. The analysis further shows that within these demand-side shocks, domestic consumption demand and inventory demand shocks were the dominant influences. Additionally, while less dominant, export demand shocks also played a crucial role in shaping price dynamics. Significant export shocks often correlated with movements in gas prices, with increases in export shocks generally aligning with upward price movements.

In addition to the 2022–2023 analysis, further investigations are conducted into the historical decomposition of natural gas price fluctuations during two other significant periods. The first examination focuses on 2005, specifically analyzing the impact of Hurricanes Katrina and Rita in August of that year on U.S. natural gas price dynamics. The results, presented in Figure A1, show that the price increases in August, September, and October 2005 were primarily driven by natural gas supply shocks. This can be attributed to the loss of offshore gas production following the hurricanes, which caused a more than 20 percent drop in domestic U.S. gas production. In the remaining months of 2005, consumption demand and speculative demand shocks were the primary drivers of gas price dynamics. These findings demonstrate that supply shocks, such as those caused by hurricanes, lead to significant price increases in the immediate aftermath, but their effects diminish quickly, with demand factors regaining dominance in the subsequent months.

The second analysis, covering January 2015 to December 2017, evaluates the relative importance of various shocks, with a particular focus on export demand shocks. This period is significant due to the rapid expansion in export capacity, which led to the U.S. becoming a major gas exporter by 2017. The findings, presented in Figure A2, underscore the evolving impact of export dynamics on gas price fluctuations. Overall, the results indicate that during this period, price dynamics were primarily driven by shocks from consumption demand, speculative demand, and natural gas supply. In terms of export demand shocks, the results reveal that in 2015, accumulated export shocks had a minimal impact on gas price dynamics. However, from the second half of 2016 onwards, there is a notable increase in the influence of export shocks on gas prices. Additionally, the analysis identifies a negative export demand shock in August 2017, likely due to the impact of Hurricane Harvey. The hurricane caused widespread disruptions, including the closure of several regional ports by the U.S. Coast Guard on August 28, which halted LNG exports, particularly from Cheniere Energy's Sabine Pass facility, where no LNG tankers departed for several days. Moreover, pipeline flows from Texas to Mexico decreased due to the shutdown of compressor stations (NGI, 2017). These findings suggest that the influence of export demand shocks has grown over time, corresponding with the expansion of U.S. natural gas export infrastructure.

6. Sensitivity Analysis

This section presents a series of sensitivity analyses to evaluate the robustness of the SVAR model's findings for the U.S. natural gas market. Subsection 6.1 assesses the impact of excluding observations from the COVID-19 pandemic period on the model's results. Subsection 6.2 investigates how the findings are influenced by the shale gas revolution, focusing on data from 2009 onwards. Finally, Subsection 6.3 examines the effects of using weaker priors for short-run supply and demand elasticities, evaluating how these adjustments influence the posterior distributions and impulse response functions.

6.1. Sensitivity to the effects of excluding pandemic-related observations

This subsection evaluates the impact of excluding observations from March 2020 to February 2021, a period significantly affected by the COVID-19 pandemic. To investigate whether this exclusion alters the results, two exercises are conducted:

The first exercise involves a pre-pandemic analysis, where the model is estimated using data only up to December 2019. The posterior medians for the contemporaneous coefficients in $\mathbf{A}$ are reported in the column labeled "S1" in Table A.1. Posterior IRFs are presented in Figure A3 in the Appendix. The results reveal that the magnitudes of the structural parameters and the IRFs are very similar to those obtained in the baseline analysis, except for the IRFs related to export shocks, which show significance only in the short run. This difference in the response of prices to export shocks may suggest an increased sensitivity of U.S. gas prices to export shocks in recent years, particularly in 2022 and 2023.

The second exercise estimates the model using the entire sample period from January 1992 to October 2023, without excluding any observations. The posterior medians for the contemporaneous coefficients in $\mathbf{A}$ are reported in the column labeled "S2" in A.1, and the posterior IRFs are plotted in Figure A4 in the Appendix. The results show that while the structural parameters are largely similar to those in the baseline model, the IRFs reveal some counterintuitive outcomes, particularly in the response of economic activity to various shocks. For instance, the findings suggest that a reduction in gas supply, which typically increases gas prices, appears to boost U.S. economic activity (as shown in the (1,2) panel of Figure A4). Given these results, caution is advised when interpreting the findings from this full-sample analysis. These anomalies imply that external disruptions, such as pandemics, can significantly alter traditional economic responses, highlighting the need for adjustments in economic modeling and policy considerations during such periods.

Overall, these results underscore the importance of adapting models to account for the unique effects of such disruptions in order to avoid counterintuitive economic responses. For subsequent sensitivity analyses, the model will continue to exclude observations from March 2020 to February 2021, following the approach used in the baseline analysis, to ensure consistency in evaluating the model's robustness.

6.2. Sensitivity to the effects of the shale gas revolution

The baseline analysis of this study spans the period from 1992 to 2023, a timeframe selected to comprehensively examine the factors influencing U.S. gas prices following the deregulation of the U.S. natural gas market. To assess the sensitivity of the baseline results, this exercise uses data from January 2009 onward. This approach aligns with literature focusing on this period to examine the effects of the shale gas revolution, as seen in studies by Arora and Lieskovsky (2014), Geng et al. (2016a), Hailemariam and Smyth (2019), and Hu et al. (2020).

Corresponding summary statistics of the coefficients from the contemporaneous matrix are labeled as "S3" in Table A.1. Under this shorter sample, the posterior median of demand elasticity is relatively smaller at -0.130. This finding aligns with Arora (2014), who observe that demand elasticity becomes slightly more inelastic after the shale revolution, which could be explained by less adjustment in consumption behavior when prices are low compared to when they are high. This result could also be attributed to the reduced impact of both the income and substitution effects. When prices are low, the expenditure on natural gas constitutes a smaller portion of consumers' budgets, leading to a lesser impact on their overall purchasing power, thus minimizing the income effect. Additionally, the incentive to switch to substitutes is reduced because alternatives like coal have become less competitive, leading to a greater reliance on natural gas and thereby weakening the substitution effect (Mason et al., 2015). The results also show that the posterior median of supply elasticity remains low at 0.024. This low supply elasticity is consistent with survey evidence for oil shale producers, as summarized by Golding (2019), who explains that U.S. shale producers are unlikely to respond quickly to price increases due to a sector-wide focus on achieving returns and positive cash flow, along with extensive hedging to secure revenue targets. Golding also notes that large public companies face investor pressure to maintain spending discipline, while smaller firms, though more likely to increase production, have limited impact due to capital constraints and less prolific acreage. The IRFs, presented in Figure A5 in the Appendix, show the same qualitative pattern as the baseline. However, the response of real gas prices to supply and demand shocks becomes less persistent. This change could reflect a more adaptable U.S. gas market, primarily influenced by technological and infrastructural advances during the shale gas revolution. These advances have facilitated quicker adjustments to supply shocks and demand changes.

6.3. Sensitivity to alternative prior assumptions and model identification

This subsection evaluates the robustness of the baseline model to alternative assumptions regarding prior distributions and model identification strategies. Specifically, it investigates whether the key findings are sensitive to changes in these assumptions. Two exercises are conducted: first, by employing significantly weaker priors for the short-run supply and demand elasticities; and second, by incorporating non-Gaussianity as an additional source of identification.

The first exercise assesses the influence of prior assumptions on the posterior distributions of key structural parameters, specifically the short-run supply elasticity α_{qp} and the demand elasticity β_{qp}. In contrast to the baseline analysis, which employs scale parameters $\sigma^{\alpha_{qp}} = 0.2$ and $\sigma^{\beta_{qp}} = 0.2$ for the supply and demand price elasticity coefficients, respectively, this analysis tests the effect of significantly weaker priors by setting both $\sigma^{\alpha_{qp}}$ and $\sigma^{\beta_{qp}}$ to 1.0. This adjustment increases the variance of the priors for these two coefficients by a factor of 25 compared to the baseline specification, thereby reducing the influence of prior information on the estimation outcomes. The posterior medians of the supply and demand elasticities are presented in column "S4" of Table A.1, and the IRFs are shown in Figure **??** in the Appendix. Overall, both the structural parameters and the IRFs remain relatively unchanged compared to the results obtained from the baseline specification. This observation aligns with the findings of Baumeister and Hamilton (2019), who note that many key conclusions of their Bayesian model change very little when substantially less weight is placed on different components of the prior information.

The second exercise incorporates non-Gaussianity as an additional source of identification, following the identification strategy proposed by Braun (2023). This approach leverages the statistical properties of the error terms by assuming that the structural shocks are mutually independent and display some degree of non-Gaussianity. It integrates economically motivated prior distributions, as introduced by Baumeister and Hamilton (2019), with identification by non-Gaussianity. Accordingly, this approach ensures that economic interpretations remain relevant throughout the analysis. The structural shocks are modeled using Dirichlet Process Mixture Models, where each shock's marginal distribution is estimated nonparametrically. This allows the analysis to reduce the reliance on strong economic priors, making the model more data-driven. Summary statistics for this exercise are presented in column "S5" of Table A.1, and the corresponding IRFs are shown in Figure A9 in the Appendix. The results closely align with those from the baseline analysis, indicating that the key findings are robust even when non-Gaussianity in the error terms is utilized as an additional source of identification.

The outcomes of these exercises demonstrate that the baseline results are not highly sensitive to the specific identifying assumptions employed. Whether the priors on the short-run elasticities are weak or strong, or whether non-Gaussianity is incorporated as an additional identification strategy, the key structural parameters and the dynamic responses of the system remain largely consistent.

7. Conclusion

This paper proposes a Structural Vector Autoregression (SVAR) model that incorporates natural gas imports and exports to provide a more comprehensive understanding of U.S. natural gas market dynamics. The model extends previous studies by allowing for a clearer distinction between domestic and export-driven demand shocks. The findings contribute to the ongoing discourse by providing new insights into the relative importance of various structural shocks and revisiting the estimates of natural gas supply and demand elasticities.

The findings of this study reveal the significant inelasticity of natural gas supply in the short run, as reflected by a near-zero elasticity estimate—a pattern consistent with previous research (e.g., Ponce and Neumann, 2014; Labandeira et al., 2017). This limited responsiveness to price changes reveals the infrastructural, regulatory, and technical constraints that impede short-run adjustments in supply. Similarly, the small price elasticity of demand indicates limited consumer responsiveness to price fluctuations within the month. These results suggest that short-term economic and policy interventions may have limited effectiveness in altering natural gas supply and demand. The impulse response analysis reveals that a negative supply shock leads to an immediate but short-lived spike in prices, with inventories being drawn down and exports temporarily reduced, while an unexpected rise in economic activity gradually increases prices without affecting supply. In response to a domestic consumption demand shock, prices initially rise but decline after two months, reaching a low point around one year as supply adjusts. Speculative inventory demand shocks cause a temporary increase in prices, followed by stabilization. Export demand shocks result in a price increase in the short and medium term.

The FEVD analysis indicates that short-term fluctuations in natural gas prices are predominantly driven by consumption and inventory demand shocks, which together account for over 85% of the price variation at the one-month horizon. Over time, the influence of export demand shocks, supply, and economic activity becomes more pronounced, reflecting a gradual adjustment process in the market. Historical decomposition results for the period from 2022 to 2023 suggest that natural gas price dynamics were largely shaped by demand-side factors, particularly domestic consumption and inventory demand shocks. Additionally, export demand shocks, though less dominant, consistently influenced natural gas prices throughout this period. These shocks alternated between positive effects, driven by increased exports, and negative effects, resulting from maintenance disruptions at key LNG facilities that caused temporary declines in exports. The analysis of past events, such as the hurricanes in 2005, highlights how supply shocks from natural disasters or other large-scale disruptions can lead to significant immediate price increases, though their impact tends to diminish quickly as demand factors regain influence in the following months. This underscores the dominant role of demand-side factors in shaping natural gas price dynamics.

The main implication of this study is that adapting structural models developed for the global oil market to regional energy markets, such as the U.S. and European natural gas markets, requires specific adjustments to model specifications. These adjustments are necessary to ensure that the unique domestic and external dynamics of regional markets are accurately captured, leading to more informed economic and policy decisions.

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Online Appendix

A. Identification approach

Consider the following SVAR specification for a n-dimensional time series vector y_t:

$$\mathbf{A}y_t = \mathbf{B}x_{t-1} + u_t \tag{A1}$$

where y_t is an $n \times 1$ vector of endogenous variables, $\mathbf{A}$ is an $(n \times n)$ matrix summarizing their contemporaneous structural relations, x_{t-1} is a $(k \times 1)$ vector (with $k = mn + 1$) containing a constant and m lags of y $(x'_{t-1} = (y'_{t-1}, y'_{t-2}, \ldots, y'_{t-m}, 1)')$, and u_t is an $(n \times 1)$ vector of structural disturbances assumed to be independent and identically distributed (i.i.d.) $\mathcal{N}(0, \mathbf{D})$ and mutually uncorrelated ($\mathbf{D}$ is diagonal). Following Baumeister and Hamilton (2019) and Braun (2023), the model includes $m = 12$ lags.

The reduced-form VAR associated with this structural model is represented as follows:

$$y_t = \Phi x_{t-1} + \varepsilon_t, \tag{A2}$$

$$\Phi = \mathbf{A}^{-1}\mathbf{B}, \tag{A3}$$

$$\varepsilon_t = \mathbf{A}^{-1}u_t, \tag{A4}$$

$$E(\varepsilon_t \varepsilon'_t) = \boldsymbol{\Omega} = \mathbf{A}^{-1}\mathbf{D}(\mathbf{A}^{-1})', \tag{A5}$$

This study follows the identification and estimation strategy introduced by Baumeister and Hamilton (2015) and further developed by Baumeister and Hamilton (2019) to construct a specific four-variable oil market model, which was later applied to the U.S. natural gas market by Rubaszek et al. (2021). This strategy yields a set-identified SVAR model through two primary steps. The first step involves specifying informative prior beliefs about the values of the structural parameters represented by a density $p(\mathbf{A}, \mathbf{D}, \mathbf{B})$. The second step generates draws from the posterior distribution of the structural coefficients to assess how the data influences the prior beliefs.

Prior information about $\mathbf{A}$ is expressed in the form of an arbitrary prior distribution $p(\mathbf{A})$. Higher values of $p(\mathbf{A})$ correspond to more plausible values of $\mathbf{A}$, while $p(\mathbf{A}) = 0$ is associated with any values of $\mathbf{A}$ that are entirely excluded. This prior can incorporate a mix of exclusion restrictions, sign restrictions, and informative assumptions about the elements of $\mathbf{A}$. To represent prior information about the other parameters, this identification approach employs natural conjugate distributions that facilitate the analytical characterization of results and allow for straightforward analytical solutions.

The prior for the inverse of the structural variances is assumed to follow a gamma distribution, $\Gamma(\kappa_i, \tau_i)$:

$$p(\mathbf{D} \mid \mathbf{A}) = \prod_{i=1}^{n} p(d_{ii} \mid \mathbf{A}), \tag{A6}$$

$$p(d_{ii}^{-1}|\mathbf{A}) = \begin{cases} \frac{\tau_i^{\kappa_i}}{\Gamma(\kappa_i)}(d_{ii}^{-1})^{\kappa_i-1}\exp(-\tau_i d_{ii}^{-1}) & \text{for } d_{ii}^{-1} \geq 0, \\ 0 & \text{otherwise,} \end{cases} \tag{A7}$$

where d_{ii} denotes the row i, column i element of $\mathbf{D}$. The ratio κ_i/τ_i represents the expected value of d_{ii}^{-1} before learning from the data, whereas κ_i/τ_i^2 is the variance of this prior distribution. A stronger belief in these prior values is indicated by large κ_i and τ_i, leading to a more concentrated prior distribution around κ_i/τ_i. Following Baumeister and Hamilton (2019), this study sets $\kappa_i = 2$, which gives the priors a weight equivalent to four observations of data, and allows τ_i to depend on $\mathbf{A}$.

Prior information about the lagged structural parameters $\mathbf{B}$ is represented with a conditional normal distribution, $\mathbf{b}_i|\mathbf{A}, \mathbf{D} \sim \mathcal{N}(\mathbf{m}_i, d_{ii}\mathbf{M}_i)$:

$$p(\mathbf{B}|\mathbf{D}, \mathbf{A}) = \prod_{i=1}^{n} p(\mathbf{b}_i|\mathbf{D}, \mathbf{A}), \tag{A8}$$

$$p(\mathbf{b}_i|\mathbf{D}, \mathbf{A}) = \frac{1}{(2\pi)^{k/2}|d_{ii}\mathbf{M}_i|^{1/2}} \exp\left(-\frac{1}{2}(b_i - \mathbf{m}_i)'(d_{ii}\mathbf{M}_i)^{-1}(\mathbf{b}_i - \mathbf{m}_i)\right), \tag{A9}$$

where $\mathbf{b}_i'$ denotes the ith row of $\mathbf{B}$, $\mathbf{m}_i$ represents the prior mean for $\mathbf{b}_i$, and $d_{ii}\mathbf{M}_i$ is the variance associated with this prior. Thus, the matrix $\mathbf{M}_i$ reflects the confidence level in this prior information, with greater variances signifying higher uncertainty. Conversely, a scenario with minimal valuable prior knowledge is akin to the scenario where $\mathbf{M}_i^{-1}$ approaches zero. This study assumes that the prior expected value for these coefficients, $\mathbf{m}_i$, is zero, implying that changes in the underlying variables are difficult to forecast, and that the prior variance is $100 \times \mathbf{I}$.

The overall prior distribution is

$$p(\mathbf{A}, \mathbf{D}, \mathbf{B}) = p(\mathbf{A}) \prod_{i=1}^{n} [p(d_{ii}|\mathbf{A})p(\mathbf{b_i}|\mathbf{D}, \mathbf{A})] \tag{A10}$$

The second step includes describing how the data $Y_T = (y_1', y_2', \ldots, y_T')'$ affects the prior beliefs about the unknown parameters $\mathbf{B}$, $\mathbf{A}$, and $\mathbf{D}$. The posterior distribution is decomposed as follows:

$$p(\mathbf{A}, \mathbf{D}, \mathbf{B}|Y_T) = p(\mathbf{A}|Y_T)p(\mathbf{D}|\mathbf{A}, Y_T)p(\mathbf{B}|\mathbf{A}, \mathbf{D}, Y_T) \tag{A11}$$

The posterior distribution for the covariance matrix is represented as $p(\mathbf{D}|\mathbf{A}, \mathbf{Y}_T) = \prod_{i=1}^{n} \gamma\left(d_{ii}^{-1}; \kappa_i^*, \tau_i^*(\mathbf{A})\right)$, where:

$$\kappa_i^* = \kappa_i + T/2 \tag{A12}$$

$$\tau_i^*(\mathbf{A}) = \tau_i(\mathbf{A}) + (1/2)\zeta_i^*(\mathbf{A}) \tag{A13}$$

The value of $\zeta_i^*(\mathbf{A})$ is the sum of squared residuals obtained from regressing $\widetilde{Y}_i(\mathbf{A})$ on $\widetilde{\mathbf{X}}_i$:

$$\zeta_i^*(\boldsymbol{A}) = (\widetilde{Y}_i'(\boldsymbol{A})\widetilde{Y}_i(\boldsymbol{A})) - (\widetilde{Y}_i'(\boldsymbol{A})\widetilde{\boldsymbol{X}}_i)(\widetilde{\boldsymbol{X}}_i'\widetilde{\boldsymbol{X}}_i)^{-1}(\widetilde{\boldsymbol{X}}_i'\widetilde{Y}_i(\boldsymbol{A})), \tag{A14}$$

$$\widetilde{Y}_i(\boldsymbol{A}) = [\mathbf{a}_i' y_1 \ldots \mathbf{a}_i' y_T \boldsymbol{m_i}(\boldsymbol{A})' \boldsymbol{P}_i]', \tag{A15}$$

$$\widetilde{\boldsymbol{X}}_i = [\boldsymbol{x}_0' \ldots \boldsymbol{x}_{T-1}' \boldsymbol{P}_i]'. \tag{A16}$$

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

The posterior distribution for the lagged structural coefficients $\mathbf{B}$ can be written as $p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T) = \prod_{i=1}^{n} \phi\left(\mathbf{b}_i; m_i^*, d_{ii} M_i^*\right)$, where

$$\mathbf{m}_i^*(\mathbf{A}) = (\widetilde{\boldsymbol{X}}_i' \widetilde{\boldsymbol{X}}_i)^{-1} (\widetilde{\boldsymbol{X}}_i' \widetilde{\boldsymbol{Y}}_i(\mathbf{A})), \tag{A17}$$

$$\mathbf{M}_i^* = (\widetilde{\boldsymbol{X}}_i' \widetilde{\boldsymbol{X}}_i)^{-1}. \tag{A18}$$

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

$$p(\mathbf{A}|Y_T) = \frac{k_T p(\mathbf{A}) \left[\det(\mathbf{A}\hat{\Omega}_T \mathbf{A}')\right]^{T/2}}{\prod_{i=1}^{n} [(2/T)\tau_i^*(\mathbf{A})]^{\kappa_i^*}} \prod_{i=1}^{n} \tau_i(\mathbf{A})^{\kappa_i}. \tag{A19}$$

where $p(\mathbf{A})$ refers to the original prior density for $\mathbf{A}$, and $\hat{\boldsymbol{\Omega}}_T$ is the sample variance matrix that is calculated with the reduced-form VAR model.

B. Posteriors of the contemporaneous coefficients in A

Table A.1: Summary statistics of the contemporaneous coefficients in **A**

Parameter	Baseline	S1	S2	S3	S4	S5
α_{qp}	**0.019**	**0.021**	**0.022**	**0.024**	**0.020**	**0.007**
	(0.009, 0.033)	(0.009, 0.037)	(0.010, 0.037)	(0.010, 0.042)	(0.009, 0.034)	(0.002, 0.015)
$\alpha_{\mathbf{y}p}$	**-0.005**	**-0.004**	**-0.008**	**-0.010**	**-0.005**	**-0.004**
	(-0.008, -0.002)	(-0.008, -0.001)	(-0.015, -0.003)	(-0.016, -0.005)	(-0.009, -0.002)	(-0.009, -0.002)
$\beta_{q\mathbf{y}}$	**0.741**	**0.788**	**0.807**	**0.786**	**0.730**	**0.908**
	(0.398, 1.187)	(0.461, 1.322)	(0.517, 1.262)	(0.430, 1.379)	(0.496, 1.183)	(0.526, 1.80)
β_{qp}	**-0.177**	**-0.184**	**-0.145**	**-0.130**	**-0.166**	**-0.219**
	(-0.300, -0.088)	(-0.323, -0.088)	(-0.256, -0.065)	(-0.265, -0.046)	(-0.299, -0.079)	(-0.365, -0.126)
ψ_1	**-0.482**	**-0.484**	**-0.575**	**-0.563**	**-0.510**	**-0.305**
	(-0.881, -0.209)	(-0.914, -0.181)	(-1.013, -0.269)	(-1.017, -0.204)	(-0.929, -0.220)	(-0.537, -0.111)
ψ_2	**1.550**	**1.465**	**0.646**	**1.599**	**1.581**	**1.487**
	(0.908, 2.344)	(0.781, 2.325)	(0.252, 1.146)	(0.545, 3.034)	(0.924, 2.404)	(0.866, 2.311)
ψ_3	**-0.362**	**-0.393**	**-0.374**	**-0.348**	**-0.368**	**-0.343**
	(-0.422, -0.311)	(-0.466, -0.333)	(-0.438, -0.320)	(-0.410, -0.297)	(-0.430, -0.312)	(-0.398, -0.291)
λ_1	**0.008**	**0.022**	**0.045**	**-0.001**	**0.008**	**0.018**
	(-0.006, 0.023)	(0.011, 0.022)	(0.032, 0.060)	(-0.039, 0.042)	(-0.006, 0.023)	(0.008, 0.028)
λ_2	**0.010**	**-0.009**	**0.043**	**0.155**	**0.010**	**0.000**
	(-0.030, 0.049)	(-0.039, 0.022)	(0.020, 0.067)	(0.033, 0.278)	(0.030, 0.050)	(-0.027, 0.028)
λ_3	**-0.002**	**-0.001**	**-0.003**	**-0.005**	**-0.002**	**-0.002**
	(-0.004, 0.000)	(-0.003, 0.000)	(-0.005, -0.001)	(-0.010, 0.003)	(-0.003, 0.000)	(-0.002, 0.001)
λ_4	**0.006**	**0.004**	**0.010**	**0.002**	**0.005**	**0.004**
	(0.000, 0.012)	(0.000, 0.008)	(0.004, 0.016)	(-0.016, 0.020)	(-0.000, 0.011)	(0.001, 0.008)

Notes: This table presents the posterior medians (in bold) and 68 percent credibility regions (in parentheses) for the structural parameters of matrix **A**, used in our SVAR model. The "Baseline" column contains results from the baseline model estimation, while columns "S1" to "S5" correspond to various sensitivity analyses described in Section 6. Specifically, "S1" re-estimates the baseline model using data until December 2019 (2019:M12). "S2" uses the full dataset from January 1992 to October 2023 (1992:M1 to 2023:M10), including pandemic data, without modifications. "S3" tests model robustness starting from January 2009, assessing the effect of the shale gas revolution. "S4" evaluates the impact of employing less informative priors on the short-run supply and demand elasticities. "S5" leverages non-Gaussianity as an additional source of identifying information. For definitions of each parameter, please refer to Table 2.

C. Detailed forecast error variance decompositions with credibility sets

Table A.2: Percent contribution of shocks to the overall variability of each variable (with credibility sets)

	Natural gas supply					Economic activity				
Horizon	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}
1	**94.29**	**1.24**	**1.77**	**1.76**	**0.34**	**0.45**	**95.97**	**1.62**	**1.30**	**0.16**
	(85.01, 98.12)	(0.11, 3.91)	(0.26, 5.40)	(0.18, 7.20)	(0.01, 2.02)	(0.04, 1.88)	(90.27, 98.68)	(0.29, 4.55)	(0.14, 4.56)	(0.01, 1.31)
2	**92.33**	**1.52**	**2.04**	**2.13**	**1.18**	**0.75**	**94.21**	**2.03**	**1.65**	**0.80**
	(83.04, 96.74)	(0.27, 4.41)	(0.42, 5.70)	(0.39, 7.42)	(0.1, 4.31)	(0.11, 2.65)	(88.19, 97.35)	(0.53, 5.05)	(0.31, 4.88)	(0.08, 2.81)
3	**90.96**	**1.86**	**2.33**	**2.40**	**1.67**	**2.06**	**91.53**	**2.55**	**1.99**	**1.12**
	(81.67, 95.61)	(0.45, 4.96)	(0.60, 6.05)	(0.56, 7.67)	(0.29, 4.77)	(0.50, 5.33)	(84.95, 95.52)	(0.76, 5.87)	(0.5, 5.36)	(0.18, 3.55)
6	**85.88**	**3.04**	**3.12**	**3.96**	**3.28**	**3.69**	**87.17**	**3.26**	**2.88**	**2.14**
	(76.85, 91.45)	(1.17, 6.39)	(1.07, 6.95)	(1.45, 9.31)	(1.14, 7.01)	(1.27, 7.89)	(80.13, 92.07)	(1.32, 6.7)	(0.99, 6.64)	(0.65, 5.10)
12	**76.3**	**4.99**	**5.80**	**6.70**	**5.37**	**6.88**	**77.74**	**4.99**	**4.80**	**4.70**
	(67.64, 82.96)	(2.47, 8.89)	(2.84, 10.31)	(3.35, 11.96)	(2.59, 9.84)	(3.31, 12.03)	(70.31, 84.05)	(2.56, 8.93)	(2.27, 8.95)	(2.19, 8.82)
16	**74.57**	**5.54**	**6.13**	**7.11**	**5.81**	**7.38**	**76.01**	**5.40**	**5.10**	**5.16**
	(65.87, 81.51)	(2.88, 9.52)	(3.16, 10.63)	(3.67, 12.37)	(2.92, 10.39)	(3.69, 12.73)	(68.30, 82.65)	(2.87, 9.54)	(2.51, 9.39)	(2.50, 9.50)

	Real natural gas price					Natural gas inventories				
Horizon	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}
1	**8.48**	**3.61**	**54.06**	**31.54**	**0.73**	**3.16**	**1.22**	**76.90**	**16.62**	**1.36**
	(5.00, 14.10)	(1.79, 6.45)	(41.05, 66.45)	(23.33, 39.2)	(0.26, 1.79)	(0.91, 7.04)	(0.11, 4.02)	(61.8, 85.60)	(5.6, 33.43)	(0.31, 3.94)
2	**8.82**	**4.67**	**52.45**	**31.09**	**1.65**	**3.47**	**2.51**	**75.20**	**16.47**	**1.70**
	(5.49, 14.07)	(2.69, 7.43)	(39.88, 64.29)	(22.88, 38.66)	(0.71, 3.10)	(1.13, 7.21)	(0.71, 5.60)	(60.43, 83.90)	(5.85, 32.78)	(0.43, 4.57)
3	**8.86**	**5.23**	**51.19**	**31.41**	**2.00**	**4.27**	**3.29**	**73.27**	**15.98**	**2.38**
	(5.62, 13.96)	(3.17, 8.07)	(39.04, 62.88)	(23.32, 38.84)	(0.98, 3.49)	(1.59, 8.44)	(1.07, 7.05)	(59.07, 81.88)	(5.79, 31.65)	(0.7, 5.67)
6	**10.04**	**6.87**	**48.27**	**29.92**	**3.75**	**6.07**	**5.44**	**68.79**	**15.60**	**3.16**
	(6.67, 14.98)	(4.59, 9.83)	(36.96, 59.26)	(22.37, 36.8)	(2.24, 5.73)	(2.81, 10.61)	(2.29, 10.41)	(55.45, 77.64)	(6.12, 30.26)	(1.19, 6.67)
12	**10.54**	**7.63**	**46.16**	**28.56**	**6.15**	**7.44**	**7.22**	**63.57**	**15.71**	**5.04**
	(7.47, 14.98)	(5.52, 10.40)	(35.93, 55.87)	(21.59, 35)	(4.32, 8.40)	(4.02, 12.24)	(3.69, 12.26)	(51.29, 72.24)	(7.18, 28.90)	(2.55, 8.91)
16	**10.71**	**7.95**	**45.60**	**27.92**	**6.81**	**7.82**	**7.48**	**62.34**	**15.91**	**5.43**
	(7.65, 15.02)	(5.83, 10.71)	(35.81, 55.01)	(21.22, 34.05)	(4.83, 9.22)	(4.33, 12.60)	(3.96, 12.56)	(50.35, 71.12)	(7.46, 28.87)	(2.87, 9.45)

	Natural gas exports				
Horizon	u_t^s	u_t^{ea}	u_t^{cd}	u_t^{id}	u_t^{exd}
1	**1.01**	**0.67**	**2.16**	**0.47**	**94.94**
	(0.09, 0.05)	(0.45, 0.03)	(90.83, 3.34)	(2.76, 5.38)	(2.08, 97.71)
2	**1.59**	**1.18**	**2.99**	**0.78**	**92.67**
	(0.31, 0.18)	(0.91, 0.11)	(88.03, 4.26)	(3.69, 6.50)	(2.60, 96.10)
3	**2.54**	**1.47**	**3.75**	**1.83**	**89.59**
	(0.74, 0.32)	(1.40, 0.42)	(84.45, 5.64)	(4.07, 7.52)	(4.65, 93.68)
6	**4.62**	**3.62**	**4.59**	**2.83**	**83.50**
	(1.96, 1.38)	(2.00, 1.01)	(77.64, 8.49)	(7.19, 8.56)	(6.07, 88.6)
12	**7.19**	**5.96**	**5.74**	**5.12**	**75.14**
	(3.85, 3.04)	(2.99, 2.62)	(68.67, 11.92)	(10.43, 9.78)	(8.85, 81.01)
16	**7.92**	**6.44**	**6.11**	**5.89**	**72.73**
	(4.34, 3.39)	(3.27, 3.15)	(65.88, 12.96)	(11.04, 10.23)	(9.91, 79.08)

Note: This table provides posterior median estimates of the contribution of each shock to the forecast error variance of each variable. Values in brackets indicate corresponding 68% posterior credibility sets. Horizons are expressed in months. The terms u_t^s, u_t^{ea}, u_t^{cd}, u_t^{id}, and u_t^{exd} refer to supply, economic activity, consumption demand, inventory demand, and exports demand shocks, respectively. Estimates are based on the model specified in Section 3.2, using monthly data from 1992 to 2023.

D. Additional historical decomposition results for U.S. natural gas prices during specific episodes

D.1. Historical decomposition of U.S. natural gas prices during Hurricanes Katrina and Rita

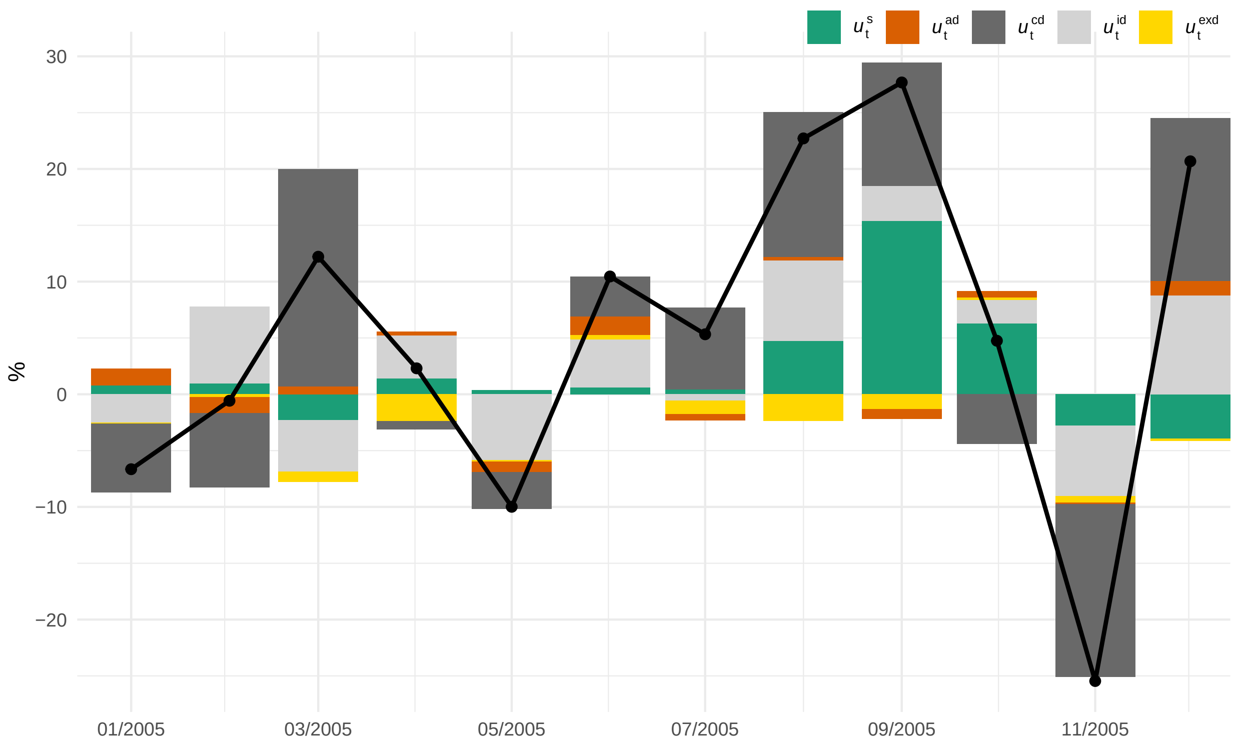

Figure A1: Historical decomposition of the U.S. natural gas real price changes, Jan 2005 – Dec 2005
Note: Each bar in the graph represents the median estimate of historical contribution of separate shocks—supply (u_t^s), aggregate demand (u_t^{ad}), consumption demand (u_t^{cd}), inventory demand (u_t^{id}), and export demand (u_t^{exd})—for each month during the specified period. The colors correspond to these specific shocks, as labeled directly on the figure. The solid black line represents the logarithmic changes in the real prices of U.S. natural gas. Estimates are based on the model specified in Section 3.2, using monthly data from 1992 to 2023.

D.2. Historical decomposition of U.S. natural gas prices from 2015 to 2017

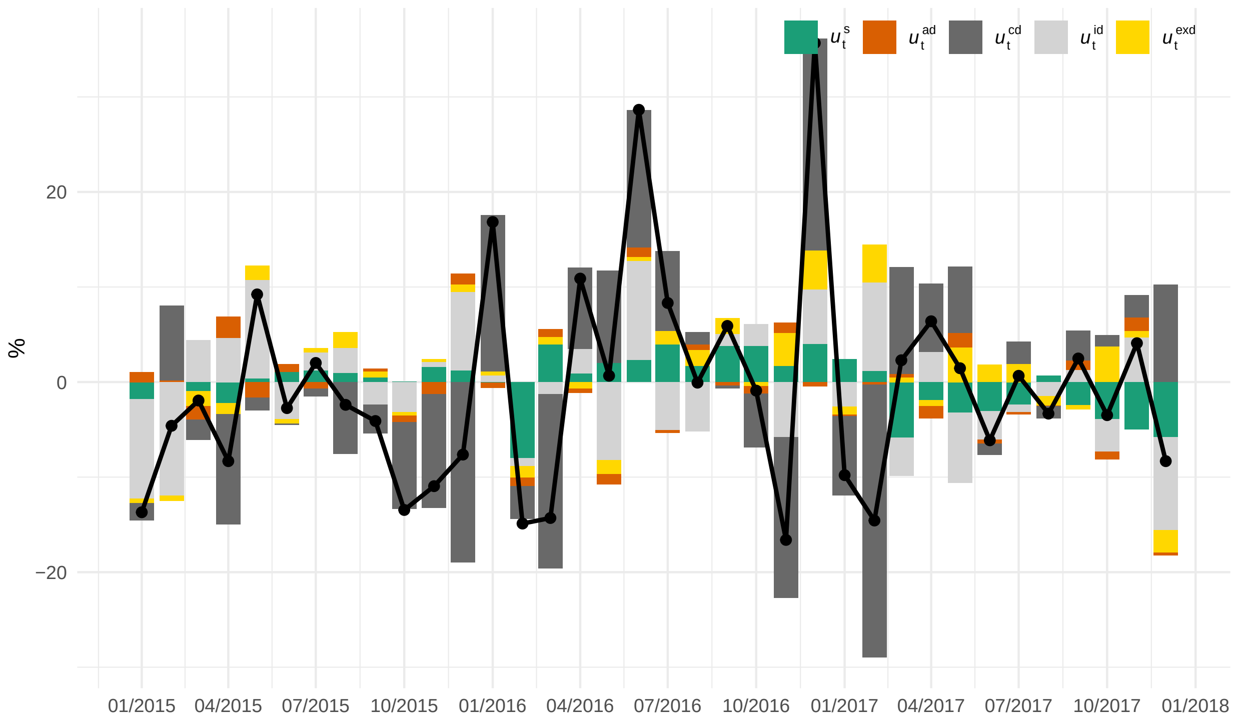

Figure A2: Historical decomposition of the U.S. natural gas real price changes, Jan 2015 – Dec 2017

Note: Each bar in the graph represents the median estimate of historical contribution of separate shocks—supply (u_t^s), aggregate demand (u_t^{ad}), consumption demand (u_t^{cd}), inventory demand (u_t^{id}), and export demand (u_t^{exd})—for each month during the specified period. The colors correspond to these specific shocks, as labeled directly on the figure. The solid black line represents the logarithmic changes in the real prices of U.S. natural gas. Estimates are based on the model specified in Section 3.2, using monthly data from 1992 to 2023.

E. Detailed results of the sensitivity analyses

E.1. Results of the pre-pandemic analysis (through 2019)

This analysis investigates the stability and consistency of the baseline model's IRFs, using data exclusively from the period prior to the COVID-19 pandemic, ending in December 2019. By isolating the pre-pandemic period, this exercise aims to establish a baseline understanding of market dynamics unaffected by the extraordinary economic disruptions caused by the pandemic.

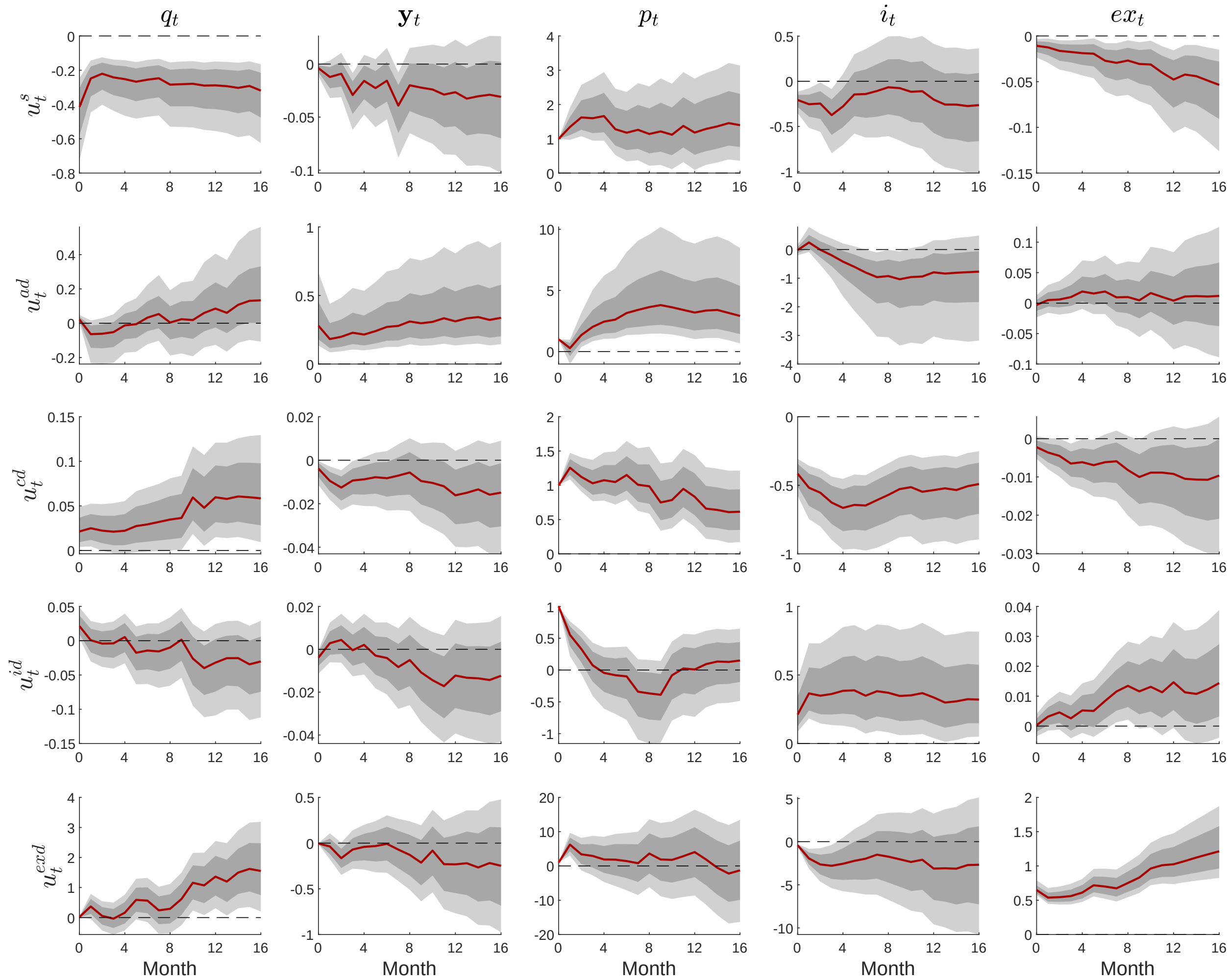

Figure A3: Impulse response functions for the model estimated from January 1992 to December 2019

Note: The rows represent the responses to different shocks, denoted as u_t^s (supply shock), u_t^{ea} (economic activity shock), u_t^{cd} (consumption demand shock), u_t^{id} (inventory demand shock), and u_t^{exd} (export demand shock). The columns represent the variables: q_t (total U.S. natural gas supply), $\mathbf{y}_t$ (real U.S. GDP), p_t (real gas price), i_t (U.S. gas inventories), and ex_t (U.S. gas exports). The red solid lines represent the Bayesian posterior median, while the dark- and light-shaded grey areas denote the 68% and 90% posterior credible regions, respectively.

E.2. Results of the full sample analysis including the COVID-19 pandemic period

This section presents the results of an analysis incorporating the entire dataset spanning January 1992 to October 2023. It examines the extent to which the inclusion of COVID-19-related data affects the estimation of the IRFs.

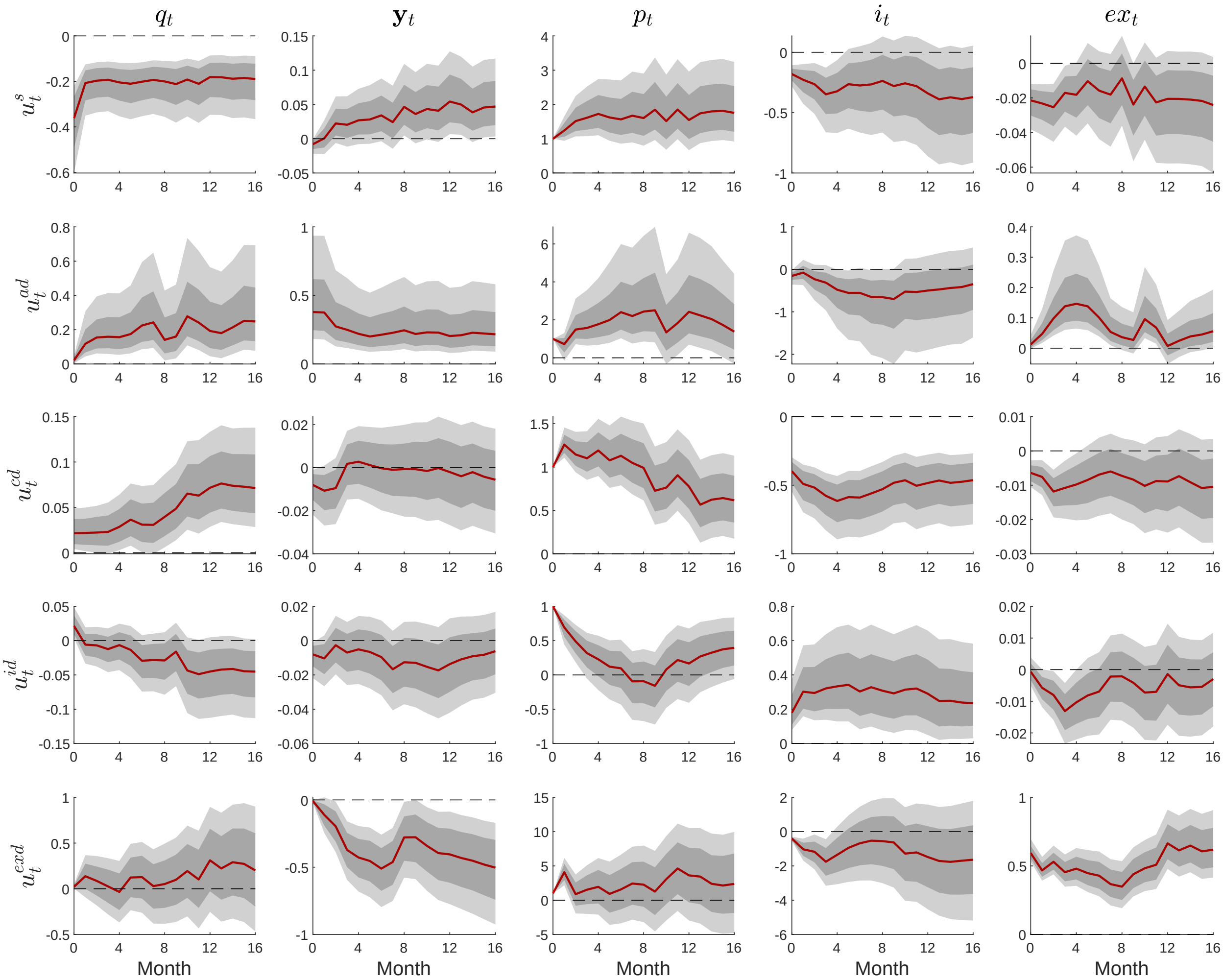

Figure A4: Impulse response functions for the model estimated using the entire sample from January 1992 to October 2023, including observations during the COVID-19 pandemic.

Note: The rows represent the responses to different shocks, denoted as u_t^s (supply shock), u_t^{ea} (economic activity shock), u_t^{cd} (consumption demand shock), u_t^{id} (inventory demand shock), and u_t^{exd} (export demand shock). The columns represent the variables: q_t (total U.S. natural gas supply), $\mathbf{y}_t$ (real U.S. GDP), p_t (real gas price), i_t (U.S. gas inventories), and ex_t (U.S. gas exports). The red solid lines represent the Bayesian posterior median, while the dark- and light-shaded grey areas denote the 68% and 90% posterior credible regions, respectively.

E.3. Results of the sensitivity analysis starting in 2009

This section presents the results of sensitivity analyses focusing on the impact of the shale gas revolution from January 2009 to October 2023, while explicitly excluding data from the COVID-19 pandemic period. The analysis explores how shifts in market dynamics, driven by technological and infrastructural advancements, have influenced the structural dynamics within the U.S. gas market.

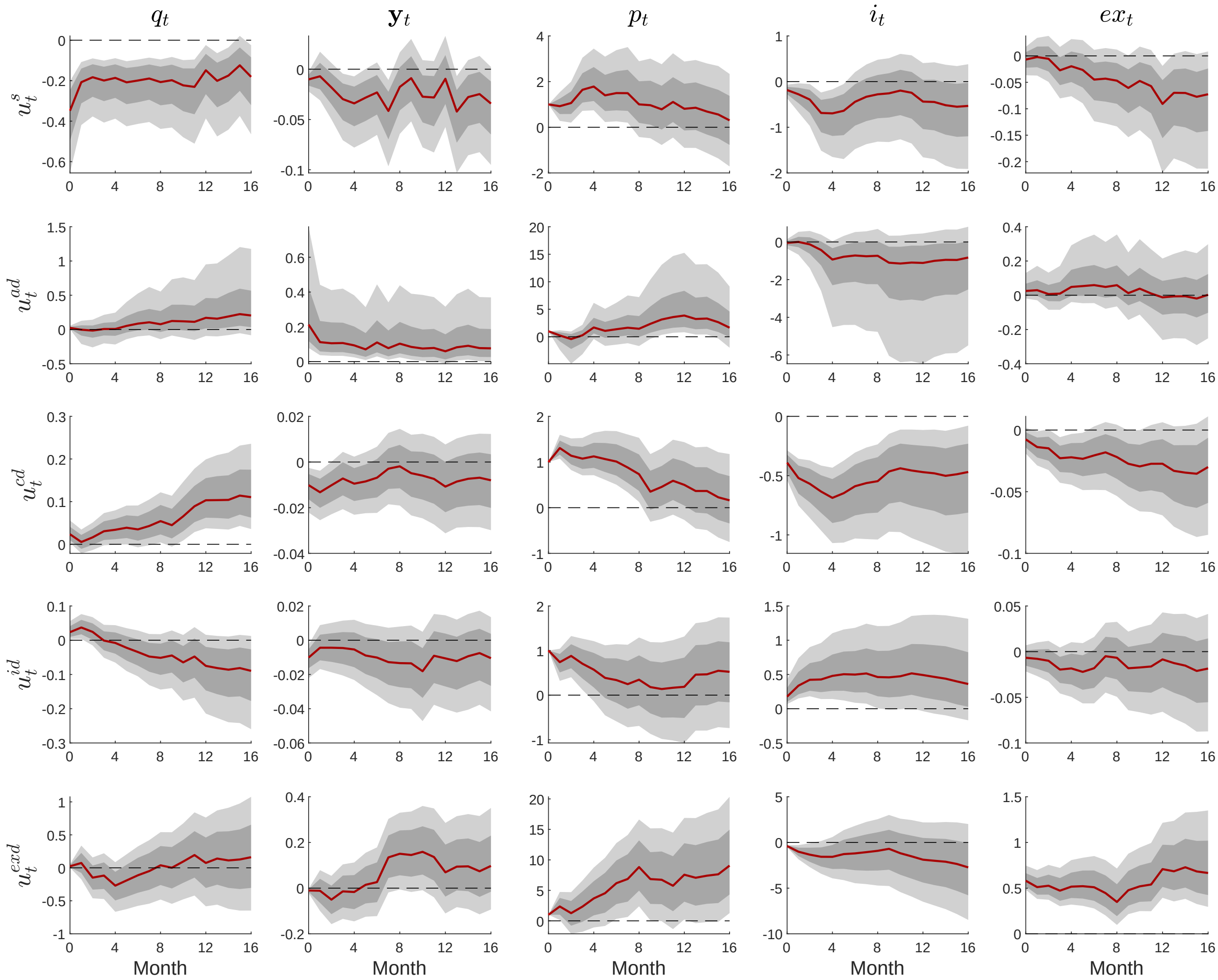

Figure A5: Impulse response functions for the model estimated from January 2009 to October 2023, excluding the COVID-19 pandemic period from March 2020 to February 2021.

Note: The rows represent the responses to different shocks, denoted as u_t^s (supply shock), u_t^{ea} (economic activity shock), u_t^{cd} (consumption demand shock), u_t^{id} (inventory demand shock), and u_t^{exd} (export demand shock). The columns represent the variables: q_t (total U.S. natural gas supply), $\mathbf{y}_t$ (real U.S. GDP), p_t (real gas price), i_t (U.S. gas inventories), and ex_t (U.S. gas exports). The red solid lines represent the Bayesian posterior median, while the dark- and light-shaded grey areas denote the 68% and 90% posterior credible regions, respectively.

E.4. Results of the sensitivity analysis with weaker priors on supply and demand elasticities

This section presents impulse response functions from sensitivity analyses where weaker priors were applied to supply and demand elasticities. The model covers data from January 1992 to December 2023, excluding the pandemic-related period from March 2020 to February 2021, and explores how weaker priors affect the estimation of these parameters.

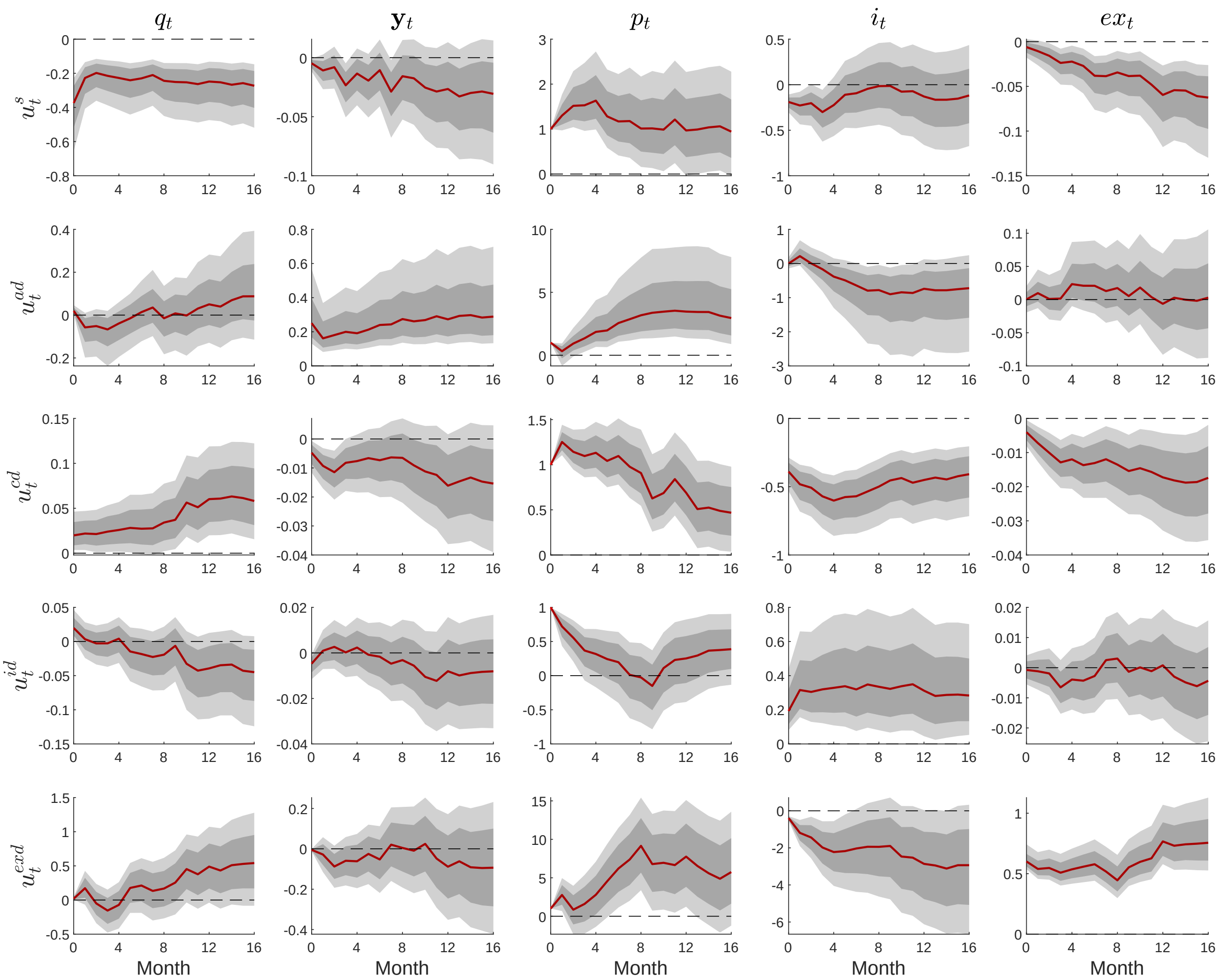

Figure A6: Impulse response functions from the model estimated using the full dataset from January 1992 to December 2023, excluding the period from March 2020 to February 2021, with weaker priors for supply and demand elasticities.

Note: The rows represent the responses to different shocks, denoted as u_t^s (supply shock), u_t^{ea} (economic activity shock), u_t^{cd} (consumption demand shock), u_t^{id} (inventory demand shock), and u_t^{exd} (export demand shock). The columns represent the variables: q_t (total U.S. natural gas supply), $\mathbf{y}_t$ (real U.S. GDP), p_t (real gas price), i_t (U.S. gas inventories), and ex_t (U.S. gas exports). The red solid lines represent the Bayesian posterior median, while the dark- and light-shaded grey areas denote the 68% and 90% posterior credible regions, respectively.

E.5. Results of incorporating non-Gaussianity for structural shock identification

This exercise introduces non-Gaussianity as an additional source of identifying informatio. The analysis employs a novel identification strategy proposed by Braun (2023), which combines economically motivated prior distributions, as introduced by Baumeister and Hamilton (2019), with identification by non-Gaussianity. This approach ensures that economic interpretations remain relevant throughout the analysis.

To model non-Gaussianity, the distribution of each structural error is approximated using a nonparametric Dirichlet process mixture model (DPMM). This nonparametric approach offers two key advantages. First, it allows for flexible modeling of the unknown density functions of structural shocks, enhancing the model's robustness against error-term misspecification and potentially improving estimation efficiency by adapting to the actual distribution of shocks. Second, the DPMM framework enables a straightforward assessment of non-Gaussianity in the data by comparing the posterior predictive density to the kernel of a standard normal distribution, as detailed by Braun (2023). Such comparisons provide insights into the identifying information derivable from the statistical properties of each shock. A detailed description of the SVAR-DPMM model is available in the source article.

Before presenting the results of the non-Gaussian SVAR model, it is essential to assess the empirical validity of the assumptions regarding non-Gaussianity and mutual independence in the U.S. natural gas market. This validation occurs in two steps.

The first step involves examining the deviation of structural shocks from Gaussianity. Figure A7 presents the posterior median estimates of predictive densities for standardized structural shocks, with 68% posterior confidence intervals (shaded areas), compared against the density of a standard normal distribution (gray line). This figure reveals significant degrees of non-Gaussianity in the structural shocks, particularly in supply, economic activity, and export shocks. These distributional characteristics underscore the potential for leveraging non-Gaussian distributions to identify structural shocks in the U.S. gas market.

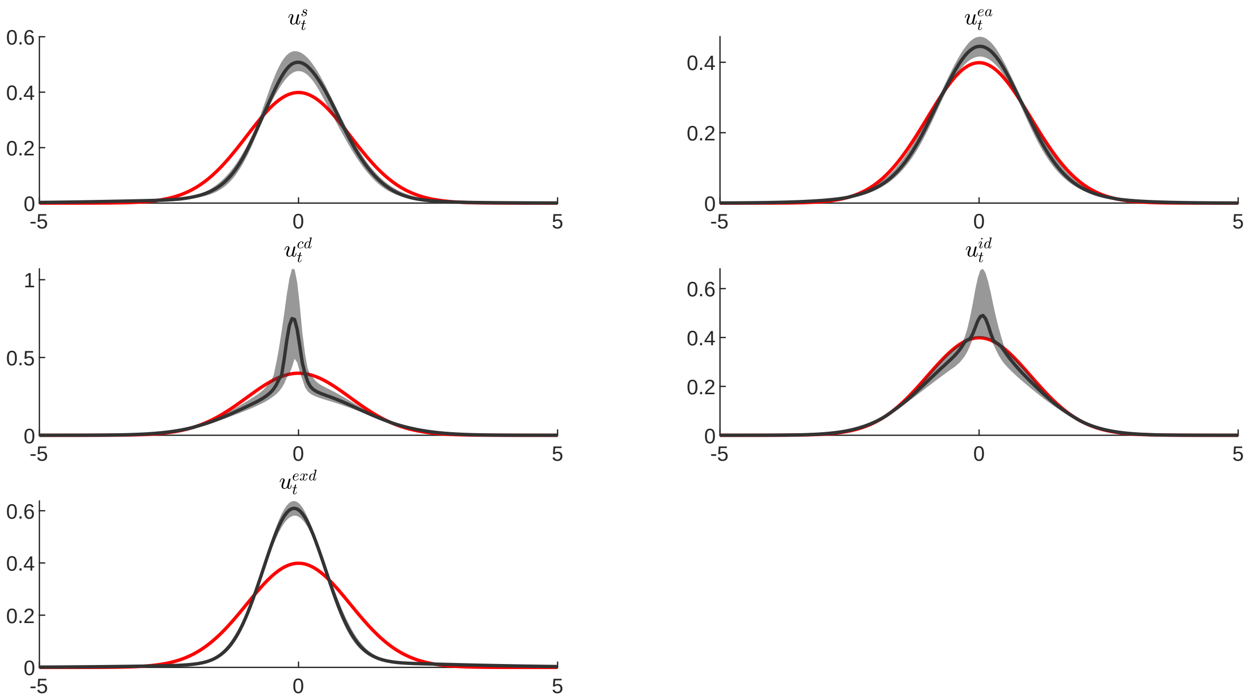

Figure A7: Posterior predictive densities of standardized structural shocks $\hat{u}_{i,T+1} = \sigma_i^{-\frac{1}{2}}(\hat{u}_{i,T+1} - \mu_i)$, showcased with a 68% credible interval. The black line refers to the density of a standard normal distribution.

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The second step assesses the mutual independence of the structural shocks. Figure A8 presents the posterior of the test statistic from the test introduced by Matteson and Tsay (2017). For comparison, the figure also overlays the distribution of this test statistic with that of the same statistic computed for randomly permuted shocks, denoted as $U_0(\mathbf{E})$. In accordance with the principle of mutual independence, each shock $\hat{u}_{j,t}$ is resampled independently from the other shocks, rather than resampling all components in the vector u_{ij} together. This process is repeated at each iteration of the posterior inference algorithm. The comparison, as illustrated in Figure A8, demonstrates a close match between the distributions of $U(\mathbf{E})$ and $U_0(\mathbf{E})$, indicating no significant evidence against the mutual independence of the shocks.

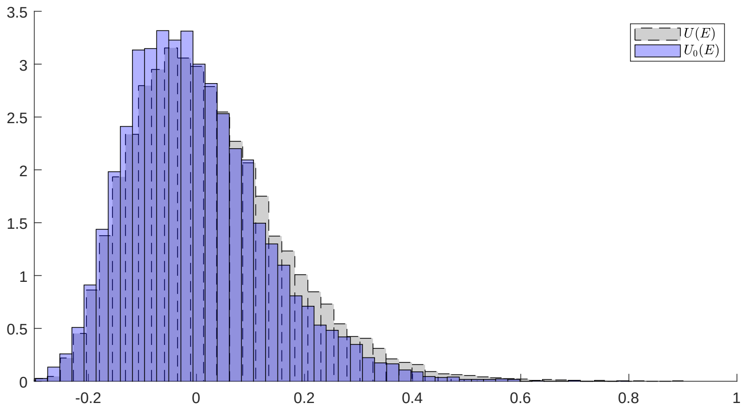

Figure A8: Posterior distributions of the mutual independence test statistics $U(E)$, as per Matteson and Tsay (2017).
Note: The distributions of test statistics based on actual data are compared with those obtained from randomly repermuted shocks, denoted as $U_0(E)$, to assess the empirical plausibility of the mutual independence assumption. A close resemblance between the distributions of U(E) and U0(E) indicates no substantial evidence against the mutual independence of shocks in the non-Gaussian model.

Given the large deviations from Gaussianity characterizing many natural gas market shocks, and their established mutual independence, non-Gaussianity can be exploited as an additional source of identifying information. The results of the IRFs are presented in Figure A9. These results show no significant difference between the IRFs obtained by leveraging non-Gaussianity and those from the baseline model.

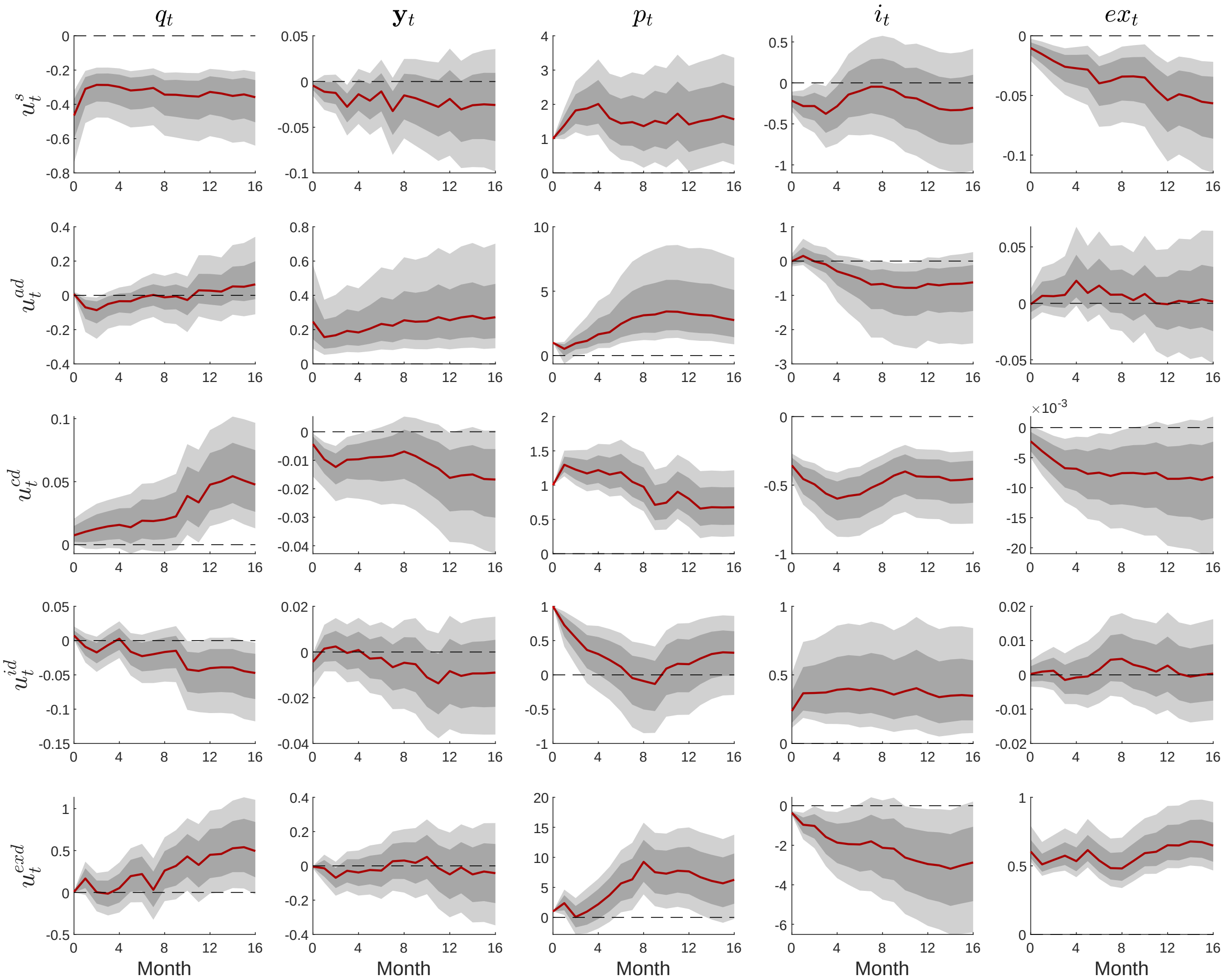

Figure A9: Impulse response functions with Non-Gaussianity as an additional source of identification.

Note: The rows represent the responses to different shocks, denoted as u_t^s (supply shock), u_t^{ea} (economic activity shock), u_t^{cd} (consumption demand shock), u_t^{id} (inventory demand shock), and u_t^{exd} (export demand shock). The columns represent the variables: q_t (total U.S. natural gas supply), $\mathbf{y}_t$ (real U.S. GDP), p_t (real gas price), i_t (U.S. gas inventories), and ex_t (U.S. gas exports). The red solid lines represent the Bayesian posterior median, while the dark- and light-shaded grey areas denote the 68% and 90% posterior credible regions, respectively.