THE PASS-THROUGH OF GLOBAL NATURAL GAS PRICE SHOCKS TO CONSUMER INFLATION: EVIDENCE FROM UKRAINE

by

Dmytro Shevchuk

A thesis submitted in partial fulfillment of
the requirements for the degree of

MA in Economic Analysis.

Kyiv School of Economics

2026

Thesis Supervisor: _____ Professor Olesia Verchenko

Approved by _____
Head of the KSE Defense Committee, Professor

_____

_____

_____

Date_____

Kyiv School of Economics

Abstract

THE PASS-THROUGH OF GLOBAL NATURAL GAS PRICE SHOCKS TO CONSUMER INFLATION: EVIDENCE FROM UKRAINE

by Dmytro Shevchuk

Thesis Supervisor: Professor Olesia Verchenko

In recent years, global energy markets have experienced unprecedented volatility. The full-scale russian invasion of Ukraine in 2022 further intensified inflationary pressures through disruptions in energy supply chains and heightened uncertainty. This thesis investigates the pass-through of global natural gas price shocks to domestic inflation in Ukraine. The analysis focuses on the transmission to aggregate inflation while also examining the underlying inflation channels.

The empirical framework employs monthly data and combines several BSVAR approaches, including homoscedastic and heteroskedastic specifications identified through sign, zero, narrative, and recursive restrictions.

The results indicate that the estimated pass-through critically depends on the identification strategy and model specification. Models with heteroskedasticity consistently reveal positive and persistent responses of Ukrainian CPI to gas price shocks. The estimated pass-through is gradual and hump-shaped, stabilizing within the range of 0.06 pp two years after the shock. Regarding the channels of propagation, direct household natural gas consumption and heating expenditures account for the largest share of the pass-through, while other indirect effects also remain important. Results from the model incorporating time-varying parameters indicate that inflationary consequences of global natural gas price shocks in Ukraine are state-dependent and have become progressively stronger over time.

TABLE OF CONTENTS

LIST OF FIGURES iv

LIST OF TABLES vi

ACKNOWLEDGMENTS vii

AI USE DECLARATION viii

LIST OF ABBREVIATIONS ix

Chapter 1. INTRODUCTION 1

Chapter 2. LITERATURE REVIEW 7

2.1. Energy price shocks as sources of macroeconomic fluctuations 7

2.2. Role of monetary policy in shaping the effects of energy price shocks 13

Chapter 3. METHODOLOGY 15

3.1. Baseline model specification 15

3.2. Estimation approach 20

3.3. Main shock identification strategy 23

3.4. Alternative structural identification and specifications 30

3.4.1. Narrative restrictions 30

3.4.2. Recursive ordering 32

3.4.3. Model specifications with heteroskedasticity 34

3.5. Limitations and challenges discussion 37

Chapter 4. DATA 39

Chapter 5. ESTIMATION RESULTS 47

TABLE OF CONTENTS - Continued

5.1. Stationarity testing 47

5.2. Lag selection 48

5.3. Granger Causality testing 49

5.4. Estimation results: homoscedastic Bayesian SVAR specifications 50

5.5. Heteroskedastic model specifications and robustness checks 56

5.6. Time-varying parameter BSVAR estimation results 61

Chapter 6. CONCLUSIONS AND POLICY RECOMMENDATIONS 64

WORKS CITED 67

APPENDIX A. VISUALIZATIONS OF NATURAL GAS IMPORTS TO UKRAINE 72

APPENDIX B. DATA EXPLORATION 74

APPENDIX C. CONSTRUCTION OF THE NATURAL GAS IMPORT PRICE SERIES 77

APPENDIX D. MONTHLY ESTIMATES 80

APPENDIX E. OUTCOMES OF THE ROBUSTNESS CHECKS 84

LIST OF FIGURES

Number *Page*

Figure 1. CPI (year-on-year, 100-basis index; right axis) and weights of energy components in the Ukrainian CPI (share, %) 3

Figure 2. Ukrainian trade in major energy sources (imports, exports and net balance), TJ 4

Figure 3. Industrial production index (IPI) time series decomposition 42

Figure 4. World industrial production index (WIP) time series decomposition ... 43

Figure 5. Global oil and gas price series dynamics (real USD, left axis); global industrial production (index, right axis) 45

Figure 6. Resulting IRFs for baseline sign and zero identified BSVAR: month-on-month estimates of posterior responses for identified GGS and GD shocks 51

Figure 7. Global gas supply (GGS) shock: global gas price pass-through to Ukrainian inflation 52

Figure 8. Global aggregate demand (GD) shock: global gas price pass-through to Ukrainian inflation 54

Figure 9. Global natural gas price shock: pass-through to Ukrainian inflation 55

Figure 10. Gas price pass-through to Ukrainian inflation: heteroskedastic model specifications 56

Figure 11. Composition of the pass-through from global natural gas price shock to Ukrainian inflation: breakdown by component, % 59

Figure 12. Historical decomposition for domestic consumer inflation 60

Figure 13. Response of CPI inflation to global gas price shock: monthly estimates from TVP-BSVAR with stochastic volatility 61

Figure 14. Response of domestic industrial production to global gas price shock: monthly estimates from TVP-BSVAR with stochastic volatility 63

Figure 15. Ukraine's natural gas imports by supplying market, 1997–2024 72

Figure 16. Ukraine's natural gas import structure by supplier, 1997–2024 73

LIST OF FIGURES - Continued

Figure 17. The developments in main variables 74

Figure 18. Monthly dynamics of natural gas price series, 2012–2025 79

Figure 19. Resulting IRFs for baseline BSVAR: month-on-month estimates 80

Figure 20. Resulting IRFs for BSVAR with stochastic volatility (SV): month-on-month estimates 81

Figure 21. Resulting IRFs for BSVAR with Markov-switching heteroskedasticity (MSH): month-on-month estimates 82

Figure 22. Gas price pass-through to Ukrainian consumer inflation: results for an extended sample (Jan 2006-Aug 2025) 84

Figure 23. Gas price pass-through to Ukrainian consumer inflation: robustness checks for heteroskedastic models 85

Figure 24. Gas price pass-through to Ukrainian consumer inflation: comparison to models with alternative number of lags 86

LIST OF TABLES

Number *Page*

Table 1. Description of variables (entering the baseline model) 17

Table 2. Definition of structural shocks and identification logic 26

Table 3. Shocks identification scheme 28

Table 4. Descriptive statistics 41

Table 5. Stationarity testing results 47

Table 6. Lag selection for SVAR 49

Table 7. Granger Causality Test (selected results of pairwise Granger tests) 50

Table 8. Results of Savage-Dickey density ratio test for the model with stochastic volatility 57

Table 9. Descriptive statistics for the extended sample 75

Table 10. Correlation matrix of continuous variables 76

Table 11. Performance comparison of selected imputation methods based on RMSE and MAE 79

Table 12. Results of Savage-Dickey density ratio test for Markov-switching heteroskedasticity model 83

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my supervisor, Professor Olesia Verchenko, for the continuous support, expert guidance and feedback as well as for the encouragement throughout the process of writing this thesis. I also wish to express my appreciation to all the professors of Research Workshop courses for their helpful comments and insights.

I am grateful to the faculty and staff of KSE for creating an excellent academic environment and providing a high-quality educational experience throughout my studies. The knowledge, skills and opportunities gained during my time at the university have played an important role in both my academic and personal development.

I would also like to convey my thanks to my groupmates without whom this journey would not be so productive and memorable. My deepest gratitude goes to the Armed Forces of Ukraine for making study and work possible. Finally, I would like to thank my family for their support, understanding and belief in me.

AI USE DECLARATION

In my research ChatGPT-5 has been used for the following tasks:

1) Brainstorming research hypotheses, exploring initial research gaps and concepts regarding the methodological aspects of the study. Affected chapters include Introduction.

2) Coding assistance in R, including debugging to eliminate syntax errors and troubleshooting. All AI-assisted code was manually reviewed and verified for accuracy to ensure that it aligns with the described methodology.

3) Improving grammar in specific text sections.

I have critically reviewed and edited the output suggested by AI, and take full responsibility for the integrity of the results, analysis and overall thesis content. I affirm that all substantive intellectual work is my own.

LIST OF ABBREVIATIONS

BSVAR. Bayesian Structural Vector Autoregression.

CPI. Consumer Price Index.

EU. European Union.

IRFs. Impulse Response Functions.

m-o-m. month-on-month.

NBU. National Bank of Ukraine.

pp. percentage points.

SSSU. State Statistics Service of Ukraine.

SVAR. Structural Vector Autoregression.

TTF. Title Transfer Facility.

TVP-BSVAR. Time-varying Parameter Bayesian Structural Vector Autoregression.

USD. United States Dollar.

y-o-y. year-on-year.

Chapter 1

INTRODUCTION

Since the beginning of the war, Ukraine has faced significant challenges. Acceleration of domestic inflation has been one of the most pressing issues for policymakers. At the same time, energy price shocks remain a central driver of inflation across the globe. After russian invasion and related supply chain disruptions there has been rapid surge in oil and gas global prices which have achieved their respective record highs in 2022. In this respect, it becomes important to determine the extent of global energy shocks propagating into national inflation.

The thesis aims to study the issue of natural gas price shocks pass-through to inflation for the case of Ukraine. Defining feature of the Ukrainian small open economy is that domestic inflation can be highly sensitive to the distortions in global energy markets, while the scope for domestic monetary policy to offset such shocks is limited. Annual inflation in Ukraine peaked at 26.6% y-o-y in December 2022 and cooled down to 5.8% in 2023 (NBU, 2024). A big share of domestic inflation surge was driven by a country-specific war shock. But russian invasion also triggered severe global energy supply shortages which led to the unprecedented increase in energy commodity prices and inflation rate spikes worldwide (OECD, 2022). While credible monetary policy was a key to supporting the resilience of Ukraine (Burban, Diev, Grieco and Iberrakene, 2024), disentangling the impact of energy price shocks on domestic inflation during wartime is highly relevant.

Changes in energy prices propagate into inflation through the direct and indirect channels. The direct channel operates through the costs of refined petroleum products (such as gasoline, diesel), which are tightly linked to crude oil prices. These products are directly consumed by the households. When it comes to gas, households use it for heating, and gas prices fluctuations almost directly affect

electricity prices, since natural gas plays a considerable role as a source of fuel for power plants. For example, in major global economies such as the US natural gas is the largest source of power, having accounted for 43% of the country's total electricity generation in 2024 (C2ES, 2025). As for Ukraine, natural gas had the biggest share and was responsible for 21.43% of total electricity generation during the first 10 months of 2024, while nuclear power came second with a share of 21.32% (EXPRO Consulting, 2024).

In Ukraine total weight of direct energy expenditures represented record 10.8% of household spending in 2022 (see Figure 1 below) compared to the levels recorded in the past 10 years. Same patterns have been observed across the globe, especially in the EU which was heavily reliant on russian gas and oil imports. Natural gas and electricity prices increased by 32% and 12.5% in the EU at the end of 2022, which meant a sudden shift in the structure of household expenditures because demand for energy is inelastic (Chowdhury and Dixon, 2025).

In Europe energy components have strongly driven the CPI dynamics (Lopez et al., 2024). In Ukraine the government control over prices for utilities for the population (regulated natural gas tariff, price rates for electricity, and other fuels) can mean a muted direct effect of energy price increases on inflation compared to the EU. This makes Ukrainian consumers less sensitive to the increases in energy prices since big share of the budget is spent on other daily necessities. But the matter is double-sided as there are also substantial indirect effects emerging from energy price increases.

Indirect channel arises from the fact that energy is an important production input. Increased energy prices elevate production costs which may lead the producers to raise the prices for their goods and services. Hence, cost of energy indirectly feeds into the prices of wide range of end use products that consumers buy. However, the degree to which prices rise for consumers depends on the producers' ability to

pass on increased costs. For instance, estimations for the U.S. show that 70% of additional costs incurred by manufacturers because of higher energy costs are reflected in the prices paid by consumers (Ganapati, Shapiro, and Walker, 2020).

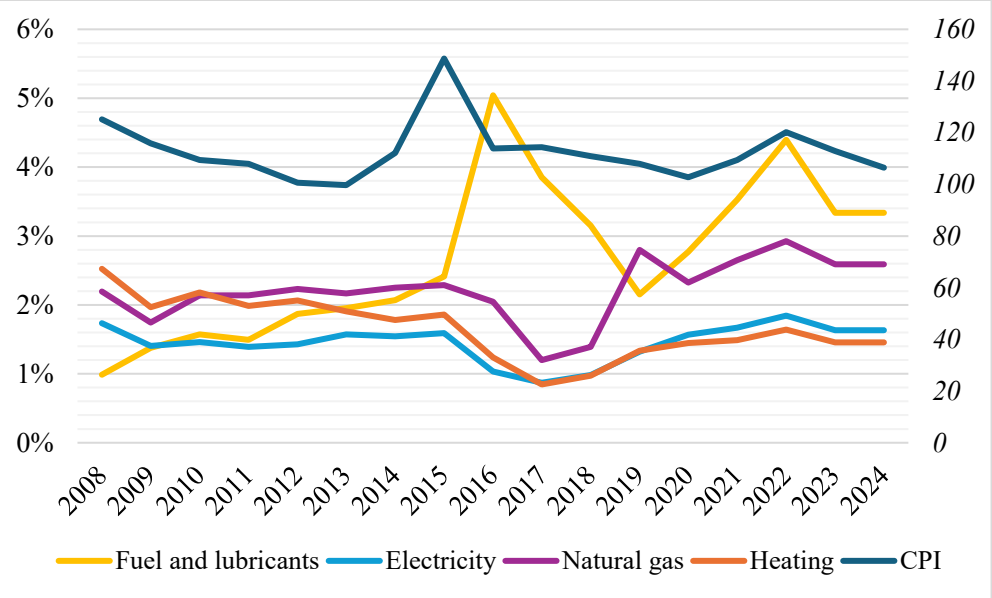


Figure 1. CPI (year-on-year, 100-basis index; right axis) and weights of energy components in the Ukrainian CPI (share, %)

Source: State Statistics Service of Ukraine

In the case of Ukraine indirect channel effect can be even more important because the economy is highly dependent on fossil fuel imports and is therefore particularly vulnerable to fluctuations in energy prices. Figure 2 illustrates that Ukraine is a net energy importer when it comes to major energy sources (natural gas, oil, coal).

The issue is twofold, however, since a big share of energy supply in Ukraine comes from nuclear power. Moreover, absolute amounts of gas consumption by the population and industry have been decreasing consistently during the last 20 years

and fell sharply after the full scale-invasion began, as millions of Ukrainians became refugees, and some industrial facilities were destroyed.

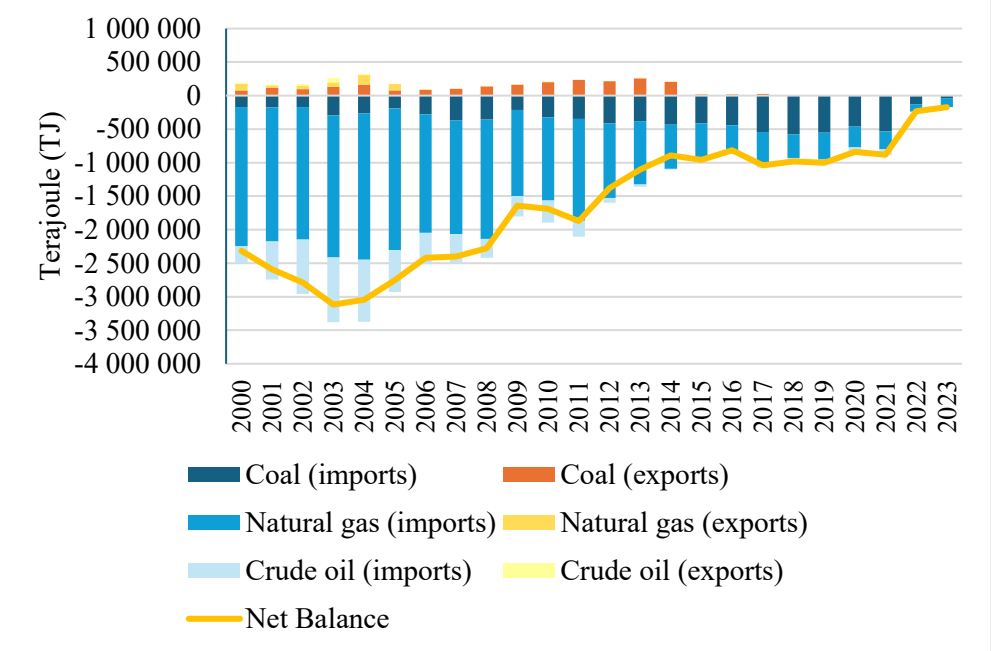


Figure 2. Ukrainian trade in major energy sources (imports, exports and net balance), TJ

Source: International Energy Agency (IEA)

Nonetheless the wartime environment likely amplifies the feedback between energy markets and domestic inflation due to number of factors. First, direct enemy strikes on energy facilities, which have only intensified in 2025, further increase Ukrainian dependence on imports. In October alone Ukraine has imported record volumes of electricity (354 GWh) since the beginning of the year (CES, 2025). In the first half of 2025 Ukraine has increased natural gas imports by a factor of 19.3 compared to the corresponding period in previous year (DiXi Group, 2025).

Second, a switch to alternative sources of uninterrupted energy supply, such as generators, leads to an increase in production costs.

Natural gas is used more heavily in industrial production (metallurgy, chemicals, fertilizers). It means that changes in the cost of gas spill over to many sectors (e.g. manufacturing, transportation, agriculture) through the increase in production and operating costs. As a result, the second-round effects of gas price fluctuations often dominate the direct pass-through (while for oil the opposite is true). In my study I focus on natural gas prices rather than considering full inflationary effect coming from energy markets (including oil, coal and other important energy sources).

Most of the existing research concerning the energy-inflation relationship investigates oil as main energy source and focuses either on the United States or Eurozone, leaving other economies, especially developing ones relatively under-analyzed. This highlights a gap which current thesis aims to fill by providing a detailed analysis of gas price shocks and inflation dynamics for Ukraine.

As of now, there are no studies aimed at assessing the listed perspectives of the relationship between global natural gas price shocks and inflation dynamics in Ukraine. In this respect Ukraine-specific conditions such as energy dependency, regulated gas tariff for households, war-related supply disruptions make its case unique for studying the links that have not been investigated before. This thesis seeks to contribute to the ongoing academic discussion by examining potential nonlinearities, asymmetries and channels linked to the transmission of global natural gas shocks to inflation in Ukraine, as well as to provide policy recommendations about anchoring inflation and inflation expectations under the conditions of war and uncertainty.

The main objective of the thesis is to study and assess the transmission of global natural gas price shocks into domestic inflation in Ukraine across periods of relative macroeconomic stability and wartime disruption.

There are four main hypotheses to be tested empirically. The first hypothesis is that compared to advanced European economies (Germany and France), Ukraine exhibits weaker on-impact inflation responses but stronger persistence of gas-price pass-through. Second, the pass-through of gas price shocks is state-dependent, with heteroskedastic model specifications revealing stronger and more significant inflation responses. Third, indirect channels dominate in the transmission of gas price shocks to inflation in Ukraine, reflecting the structural importance of second-round effects. Fourth, the transmission of global gas price shocks to Ukrainian inflation is time-varying, with stronger inflation responses observed during periods of heightened macroeconomic instability.

Using monthly data for the period of 2013-2025, I apply Bayesian Structural Vector Auto Regression (SVAR) to disentangle the natural gas price shocks contribution to inflation dynamics. This is a standard approach used in the literature to study the transmission of shocks into the macroeconomy, including those emerging on the energy market (Szafranek et al., 2024; Lütkepohl and Kilian, 2017). By incorporating time-varying parameter, I aim to assess whether the current inflationary pressures differ from past episodes, potentially attributing these changes to structural features of the Ukrainian economy and policy choices.

The rest of the thesis is structured as follows. Chapter 2 presents an overview of the main literature describing the theoretical concepts about inflation causes as well as empirical findings on effects of energy price shocks on both inflation and inflation expectations. Chapter 3 focuses on the development of methodology and model specifications. In Chapter 4, the information on the dataset is provided along with key variables, their transformations and sources used. The empirical results are presented in Chapter 5, including impulse response functions, historical decompositions and discussion on the model robustness. Chapter 6 concludes with a summary of key insights and following policy implications.

Chapter 2

LITERATURE REVIEW

Recent surge in global inflation has led to an increased amount of research exploring the connection between energy prices and consumer inflation. In 2022 the euro area and US annual inflation rates climbed to their highest levels since 1980s (10.6% and 9.1% respectively). The Covid-19 pandemic and the outbreak of russia's full-scale invasion generated unprecedented volatility in energy markets.

There are two main perspectives on the study of energy price pass-through that dominate literature. A large part of the research is focused on investigating the empirical link between energy prices and macroeconomy (production, inflation, unemployment etc.), including the magnitude and persistence of the pass-through, its channels, as well as possible time-varying effects. Another part tries to answer the question of optimal monetary policy response. In this section, I analyze theoretical and empirical papers presenting both views to build a complete picture of links between energy prices and both realized and expected inflation.

2.1. Energy price shocks as sources of macroeconomic fluctuations

The issue of commodity price shocks transmission to inflation is extensively studied, especially for developed economies. Global literature finds that energy shocks significantly shape both actual inflation and inflation expectations.

A link between energy prices and macroeconomy dates back to 1860s with the emergence of first commercial oil wells. Yet in the nineteenth century oil played a minor role and was primarily used in manufacturing illuminants (lamp oil). This changed in the twentieth century when oil gained increasing economic importance and became a global industry (Hamilton, 2011). Early studies document adverse

effect of crude oil price changes on economic growth and inflation (Burbidge and Harrison, 1984).

Economic theory distinguishes between two main types of headline inflation depending on the factors that influence it: either supply-side inflation (cost-push) or inflation emerging due to demand-side shocks (excess aggregate demand).

Positive demand shocks stimulate economic growth, leading to higher prices and temporary fall in unemployment. Demand shocks can be thought of as abrupt changes to policy mix (for example, monetary expansion or fiscal stimulus) and sudden shifts in consumer confidence. In accordance with Keynesian framework demand shocks have large, persistent real effects in the short run.

Supply-side shocks are characterized by rising production costs which lead to a simultaneous decrease in output and increase in the general price level in the economy. This combination of rising prices and negative economic growth is known as stagflation which complicates optimal policy response requiring a trade-off between economic growth and stable prices.

Energy price shocks are fundamentally negative supply shocks (Clarida, Gali, and Gertler, 1999). Historically, there has been a strong correlation between oil price increases and economic downturns, suggesting that oil shocks likely played a role in reducing real output. Hamilton (1983) shows the existence of a systematic link between oil price shocks and economic recessions. For the period since World War II to 1972 a substantial majority of the U.S. recessions (7 out of 8) have been preceded by a sharp rise in crude oil prices, stemming from events external to the U.S. economy. It means that generally there has been observed an inverse relationship between oil prices and macroeconomy.

However, these conclusions have been challenged with mixed insights from papers that include a broader timeline (2000s and 2010s), arriving at differing conclusions and magnitudes. The assumption of oil price exogeneity with respect to inflation

and economic activity has been shown to be incorrect and economically implausible by rising number of studies because oil prices themselves respond to global macroeconomic conditions and thus cannot be considered totally exogenous.

Bjørnland (2000) departs from the assumption of energy prices being predetermined within period relative to domestic macroeconomic variables and represents one of the earliest attempts to allow oil prices interact contemporaneously with output and inflation. The study establishes an identification strategy which determines three types of shocks: demand, supply and oil-specific shocks. Accordingly, all the economic fluctuations are interpreted through the lens of these shocks (including oil price changes themselves).

Kilian (2008) argues that diminishing effects of oil shocks over time are primarily due to changing nature rather than structural transformations in the economy. He isolates the impact of different kinds of oil shocks and shows that after 2003 rapid increase in the oil prices is largely due to positive aggregate demand shocks. On the contrary, supply disruptions play a surprisingly minor role. Even episodes typically attributed to Middle Eastern supply shocks are argued to be driven mainly by increase in precautionary (speculative) demand (due to uncertain expectations about future oil supply rather than supply collapse itself). Speculative demand shocks can lead to rapid price increase even when physical oil production remains unchanged (Kilian, 2009).

Study by Hamilton (2009) supports this evidence and shows that surge in oil prices in 2003-2008 was driven by demand and therefore did not cause recessionary effects. Essentially, all disturbances other than supply shocks can be grouped into the category of "oil demand shocks" which contribution has become particularly pronounced since the early 1990s (Baumeister and Peersman, 2013).

Blanchard and Gali (2007) document that macroeconomic effects of oil price change during oil shock episodes in the 1970s-1990s (such as OPEC embargo 1973-1974, Iranian revolution 1978-1979) differ substantially from the more recent ones. The empirical estimates indicate that the magnitude of the shocks has not changed much but the pass-through has reduced over time. This shift is attributed primarily to several structural factors: 1) decreased wage rigidity; 2) more effective monetary stance; 3) lower oil share in total energy supply.

The growing number of empirical studies show that inflation tends to be associated primarily with high energy prices directly hitting consumer prices. All the studies use either time series on the data for a specific country (economic region, like the euro area), or panel data for groups of related countries. According to Koester et al. (2023), increase in energy prices accounted for 38% of the annual increase of consumer prices in the Eurozone in 2022.

Extensive number of recent studies focuses on oil price impact on inflation as oil continues to be the most significant energy commodity. The panel study of 72 economies by Choi et al. (2018) provides an important cross-country perspective on the energy-inflation nexus and finds robust relationship between countries' CPI and world oil inflation. The results imply that domestic inflation rises, on average, by 0.4 percentage points in response to 10 percent global oil price increase. The effect is found to last two years and, importantly, the effect is also estimated to be largely asymmetric, whereby positive oil shocks exert significantly greater inflationary effects than negative ones. In addition to this, Conflitti and Luciani (2019) document long lasting effect (up to 4 years) of oil price shocks on inflation in the U.S. and euro area. The study indicates that even though the magnitude of the pass-through is low, its persistency means a consistent impact over a long time.

Most recent empirical research relies on structural identification of energy shocks which means the utilization of structural vector autoregression modeling (SVAR).

For example, the periods of strong global economic activity can simultaneously push up energy prices and inflation, making it difficult to attribute inflation increases to oil and gas shocks alone without structural identification. Therefore, the usage of SVARs and Bayesian SVARs has become a standard in the literature that aims to investigate the pass-through (Lütkepohl and Kilian, 2017).

Compared to oil, the literature on the effects of natural gas price shocks transmission is relatively recent and more limited, largely because global gas markets have historically been less integrated with gas prices being tied to the price of oil, a practice referred to as "oil indexation" (Lopez et al., 2024). However, post-Covid disruptions and russia's weaponization of energy flows triggered a new wave of empirical studies focused on the propagation of natural gas price increases.

Lopez et al. (2024) extend the analysis of global energy price shocks by investigating the growing role of gas prices in the four major countries of the euro area. Baseline structural BVAR results indicate that the peak effect of 10 percent gas price increase is about 0.1 percentage points higher headline inflation which fully materializes after two years. Although oil shocks have a larger direct pass-through, gas price shocks are estimated to have much greater effect on recent inflation spikes through the indirect channel due to its significance as a production input. Thus, economies with high industrial energy intensity such as Germany exhibit stronger gas shock pass-through. Günter, Reif and Wolters (2024) support this evidence. By employing SVAR approach, they find persistent propagation of supply and demand shocks due to the country's heavy reliance on natural gas consumption (both residential and commercial).

Substantial heterogeneity in the inflationary effects between countries is also found to be due to a larger share of transport-related expenditures in the CPI composition and energy consumption structure (Choi et al., 2018). For example, Kilian and Zhou (2023) show that, in contrast to the Euro area, the U.S. and Canada exhibit

a less persistent response of headline inflation to gasoline price shocks in 2021-2022, while Japan shows extremely low pass-through. At the same time, the response of core inflation is found to be relatively resilient to these shocks across the economies. Only 10% of core inflation rate is explained by gasoline price fluctuations in Euro area, with even lower percentages for the U.S. and Japan – 6% and 2% respectively.

Casoli, Manera and Valenti (2022) explicitly model the contemporaneous relationship of inflation and inflation expectations within a Bayesian setup. Expectations are incorporated as endogenous variable jointly determined with realized inflation which allows authors to capture the role of expectations in amplifying or muting the transmission through the uncertainty channel. The findings suggest that gas supply shocks increased headline inflation in the post Covid-19 period by an average of 0.7 percentage points. This evidence reinforces the emerging consensus that gas shocks have become very important, particularly after the breakdown of russian gas supply chains in 2022.

Some of recent work has also linked energy shocks to firm expectations. For example, Mello and Ponce (2025) show that domestic energy pricing policy as well as firm specific characteristics impact the intensity of oil price pass-through to firms' inflation expectations.

When it comes to Central European (CE) economies, the research is still limited. Szafranek et al. (2024) provide recent analysis of inflation dynamics in Poland. Using Bayesian Structural VAR with a set of zero restrictions combined with sign and block exogeneity restrictions, they demonstrate that external shocks explain around two-thirds of the inflation surge in Poland in post-pandemic period. At the peak in August 2022, energy price shock alone added approximately 3.2 percentage points to headline inflation, implying that big share of inflation spike was imported.

2.2. Role of monetary policy in shaping the effects of energy price shocks

One of the central challenges for policymakers is determining the appropriate level of interest rates when inflation is driven predominantly by energy shocks. The literature on this topic is more obscure and remains an emerging field.

General view is that monetary policy can effectively cool down demand-driven inflation while cost-push inflation is often seen to present a bigger challenge. Supply-side shocks increase inflation by raising production costs, and monetary policy is not designed to deal with supply chain disruptions or to reduce war-related production constraints. So, raising interest rates can neither prevent supply shocks from happening, nor fully offset their inflationary impact. It generates important trade-offs and presents a dilemma for central banks. If central bank responds too aggressively, the risk is the economy falling into mild or deep recession. On the other hand, lack of reaction may lead to de-anchoring of expectations through wage-price spirals. That is why managing inflation expectations by signaling credible path towards price stability is often seen as the main way to lower the persistence of shocks propagation.

Bobasu, Dobrew and Repele (2025) use the Euro area data and conclude that in an energy-importing country fighting supply-driven inflation with interest rates is extremely costly. Regardless of what central bank does, there are negative implications for the domestic economy such as real income loss. However, the degree of loss critically depends on monetary policy response. An active response (active tightening) results in a four times larger fall in consumption than passive policy. This suggests that excessive tightening should be avoided, and some inflation rise should be tolerated. Additionally, there are important distributional implications for energy-driven inflation. Lower-income households are disproportionally affected, meaning that energy price shocks are regressive and

worsen inequality. The authors therefore argue that the primary channel through which monetary policy can respond is by managing inflation expectations.

During large supply shocks, headline inflation rises sharply because it includes volatile components (energy, food). This raises the question of whether headline or core inflation should be targeted. Gorajski et al. (2023) use DSGE model for Poland and show that targeting core inflation provides better trade-off between inflation control and real economic activity. However, the optimal choice is highly country-specific mainly due to the openness of the economy, nature of shocks, and proportions of energy and food spending. Bjørnland, Larsen and Maih (2018) model the U.S. economy with alternate regimes: low and high oil price volatility. Their findings suggest that the effectiveness of monetary policy is state-dependent, as the cost of inflation stabilization rises during shocks of higher volatility. For my study this suggests that the transmission of energy price shocks is regime-specific, becoming stronger during the periods of elevated volatility.

To summarize, there is broad consensus in literature that increases in energy prices cause higher inflation, though the magnitude and persistence of the pass-through vary across empirical studies. Importantly, the effect of energy price shocks depends on the underlying sources of shocks. An increase in the real price of oil or gas due to favorable economic conditions (demand-side) has different influence on macroeconomy compared to an increase caused by supply disruptions, such as those resulting from war. Empirical research shows two main insights: 1) there is substantial heterogeneity in the pass-through between countries; and 2) time variation of the inflationary effects of energy shocks is significant. In the context of Ukraine, the scope of existing research remains extremely limited, and mainly descriptive, which leaves a significant gap in understanding of the propagation mechanism of real energy price shocks into inflation.

Chapter 3

METHODOLOGY

The objective of the study is to examine the transmission of global natural gas price shocks to a small open economy of Ukraine. This chapter discusses the methodology and variables employed to estimate the pass-through of gas price shocks into the Ukrainian inflation. Application of a constant-parameter structural vector autoregression (SVAR) framework estimated with Bayesian inference is motivated as the baseline approach. Next, I establish the strategy for how the shocks are identified. The justified identification relies on a mixture of short-run exclusion (zero) restrictions and sign restrictions. Robustness is assessed along two dimensions: alternative model specifications and alternative identification approaches. The section ends with the discussion of the possible limitations, estimation challenges and steps to resolve them.

3.1. Baseline model specification

The core methodological approach of the study is constant parameter Bayesian Structural Vector Autoregression (SVAR) applied to analyze inflation dynamics in Ukraine. Bayesian SVAR is a general approach used in many studies focusing on pass-through modelling which sets a good benchmark to follow and extend on (for recent works see, for example, Casoli, Manera and Valenti, 2022; Szafranek et al., 2024).

Formal specification of the basic homoscedastic model in the structural form is as follows:

$$A_0 y_t = b_0 + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + cX_t + v_t \qquad (1)$$

Or in the compact form:

$$A_0 y_t = b_0 + \sum_{j=1}^{p} A_j y_{t-j} + cX_t + \upsilon_t \quad (2)$$

where $y_t = \begin{bmatrix} y_{1t} \\ \vdots \\ y_{nt} \end{bmatrix}$ is $n \times 1$ vector of endogenous variables; $t = 1, \dots, T$; A_0 and A_j are $n \times n$ matrices of contemporaneous parameters and structural parameters at lag j respectively; b_0 represents the vector of constant terms (intercept); $p = 12$ is the lag order; X_t is the vector of exogenous variables m; $\upsilon_t \sim N(0, I_n)$ corresponds to the $n \times 1$ vector of structural shocks.

In my study I employ $n = 5$ endogenous variables and $m = 3$ exogenous variables. Therefore, vectors y_t and X_t take the following form:

$$y_t \equiv [CPI_t, IPI_t, NEER_t, TTF_t, WIP_t,] \quad (3)$$

$$X_t \equiv \begin{bmatrix} BRENT_t \\ COVID\ dummy_t \\ WAR\ dummy_t \end{bmatrix} \quad (4)$$

The variables used in the model, their definitions and transformations applied are summarized in Table 1 below. Most variables are included in the model following the approach of Szafranek et al. (2024) and Lopez et al. (2024). At the same time, I modify the framework for the context of Ukraine by incorporating the variables that reflect the dynamics of domestic economy (production, inflation etc.).

Table 1. Description of variables (entering the baseline model)

Variable	Name	Definition	Transformation applied
Endogenous variables			
Domestic inflation rate	CPI	the Ukrainian consumer price index (2010 = 100)	1) seasonal adjustment 2) natural logarithm first difference
Domestic economic activity	IPI	the Ukrainian industrial production index (2016 = 100)	1) seasonal adjustment 2) natural logarithm first difference
Exchange rate	NEER	index of nominal effective exchange rate (NEER)	natural logarithm first difference
Global natural gas price	TTF	real TTF price (in USD deflated by US CPI)	natural logarithm first difference
Global economic activity	WIP	the world industrial production index, 100-basis	natural logarithm first difference
Exogenous variables			
Global crude oil price	BRENT	real BRENT price (in USD deflated by US CPI)	natural logarithm first difference
Pandemic period	COVID	exogenous dummy controlling for COVID-19 pandemic	_
War period	WAR	exogenous dummy controlling for the full-scale invasion period	_

Note: seasonal adjustment was done using X-13ARIMA-SEATS.

It is important to note that A_0 is necessarily a non-singular matrix meaning that it is fully invertible. In other words, there exist an inverse matrix A_0^{-1} such that

$A_0 A_0^{-1} = I$. Regarding structural economic shocks v_t a standard assumption is made about them having a mean of zero and being serially uncorrelated. This simply implies that each shock is treated as unexpected and isolated cause. That is, on average, shocks do not push economy in one direction and are not predictable from the past shocks. According to the ordinary approach in the literature the variance-covariance matrix of v_t is normalized to obtain the following form (Lütkepohl and Kilian, 2017):

$$E(v_t v_t') \equiv \Sigma_v = I_n \tag{5}$$

This implies the following: 1) shocks' variances do not change over time; 2) shocks are unconditionally homoscedastic; 3) since the scale of the shocks is arbitrary, the variance of each shock is normalized to 1. Therefore, impulse responses can be interpreted as responses to one standard deviation in the structural shocks.

I utilize $p = 12$ lags for all endogenous variables as in Baumeister and Hamilton (2019). This is considered to be the baseline in the literature which captures seasonal and annual dynamics. Still, I perform formal lag-selection and consider the Akaike information criteria (AIC) as well as Bayesian information criterion (BIC).

Since the structural model contains unknown contemporaneous relations stored as A_0, the model needs to be transformed into a reduced form representation to be estimated. For this both sides of the equation (1) are multiplied by A_0^{-1}:

$$A_0^{-1} A_0 y_t = A_0^{-1} b_0 + A_0^{-1} A_1 y_{t-1} + A_0^{-1} A_2 y_{t-2} + \ldots + A_0^{-1} A_p y_{t-p} \tag{6}$$
$$+ A_0^{-1} c X_t + A_0^{-1} v_t$$

Then the reduced form is formulated as:

$$y_t = d + B_1 y_{t-1} + B_2 y_{t-2} + \ldots + B_p A_p y_{t-p} + \eta X_t + u_t \qquad (7)$$

Or rewriting in the compact way:

$$y_t = d + \sum_{j=1}^{p} B_j y_{t-j} + \eta X_t + u_t \qquad (8)$$

where $d = A_0^{-1} b_0$ is a reduced-form constant vector; $B_j = A_0^{-1} A_j$ are $n \times n$ reduced-form autoregressive coefficient matrices, $j = 1, \ldots, p$; $\eta = A_0^{-1} c$ is the reduced-form exogenous coefficient matrix; and $u_t = A_0^{-1} v_t$ are the reduced-form innovations which are simply linear combinations of structural shocks v_t; $u_t \sim N(0, \Sigma_u)$.

Reduced-form innovations u_t capture the portion of each variable not explained by its own lags and the lags of the other variables. The covariance matrix of the reduced-form residuals is: $E(u_t u_t') \equiv \Sigma_u$. It contains information about which variables move together and the strength of the co-movements:

$$\Sigma_u = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & \sigma_{nn} \end{bmatrix} \qquad (9)$$

where diagonal entries $\sigma_{11}, \ldots, \sigma_{nn}$ present volatilities of each equation's shock; off-diagonal entries represent contemporaneous correlations between errors.

Hence, the covariance matrix Σ_u can be thought of as a mixture of shocks. In order to decompose the observed co-movements into economically interpretable shocks, Σ_u should be factorized. Since by construction $u_t = A_0^{-1} v_t$ and taking into consideration that Σ_v is diagonal $(\Sigma_v = I_n)$, we can see that:

$$\Sigma_u = E(u_t u_t') = A_0^{-1} E(v_t v_t')(A_0^{-1})' = A_0^{-1} \Sigma_v (A_0^{-1})' = A_0^{-1}(A_0^{-1})' \quad (10)$$

Equation (10) draws a relationship between structural and reduced forms. It implies that by estimating the reduced-form parameters $(B_1, \dots, B_p, \Sigma_u)$ it is possible to recover A_0 and construct structural shocks. Therefore, the central task is to recover the elements of A_0^{-1} from consistent estimates of the reduced form parameters $(B_1, \dots, B_p, \Sigma_u)$ to reconstruct structural shocks and obtain the values of regressive parameters. However, since the covariance matrix Σ_u has $\frac{n(n+1)}{2} = 15$ unique elements while structural impact matrix A_0 has $n^2 = 25$ unknowns, this reflects the need for structural identification by applying the restrictions.

3.2. Estimation approach

Bayesian SVAR is particularly suitable in my study because it handles the problem of small samples. Classical VARs with 5 variables included and 12 lags easily exceed 300 parameters which would lead to overparameterization of the model and unstable coefficients. Usage of structural specification of VAR mitigates this issue allowing to estimate reliable inference.

The model is Bayesian in a sense that it is estimated using Bayesian inference rather than frequentist methods. While classical SVARs are estimated by OLS, I employ Bayesian approach meaning that I treat model parameters as random variables and

obtain the results (posterior distribution) by combining prior information with the likelihood implied by the data (Lütkepohl and Kilian, 2017). Bayesian inference is based on Bayes' rule which is formally written as:

$$p(\theta|Y) = \frac{p(Y|\theta)p(\theta)}{p(Y)} \tag{11}$$

where $Y = \{y_t\}_{t-1}^{T}$ denotes the observed data; $\theta = \{B_1, \dots, B_p, d, \eta, \Sigma_u\}$ denotes the vector of model reduced-form parameters; $p(\theta|Y)$ equals posterior distribution; $p(Y|\theta)$ represents likelihood; $p(\theta)$ denotes specified prior distribution; $p(Y)$ is marginal likelihood.

First step involves the specification of the assumptions about the prior distribution of the coefficients and innovations' covariance matrix. I let the reduced-form parameters be defined as: $B = [d, B_1, \dots, B_p, \eta]$. I specify a Minnesota-type prior distribution on reduced-form coefficients B which is formally written as:

$$\beta_{ij,l} \sim N(0, \sigma_{ij,l}^2), \sigma_{ij,l}^2 = \frac{\lambda_1^2}{l^{2\lambda_3}} \frac{\sigma_i^2}{\sigma_j^2} \tag{12}$$

where λ_1 is overall tightness; λ_3 is lag decay; σ_i^2 is residual variance scaling.

The covariance matrix Σ_u follows a Gaussian inverse-Wishart prior of the form:

$$\Sigma_u \sim IW(S_0, \vartheta_0) \tag{13}$$

where S_0 is a scale matrix; ϑ_0 represents degrees of freedom.

Then using the prespecified prior distributions for model parameters (B, Σ_u) and data, it is possible to estimate the characteristics of the posterior distribution. The posterior is given by:

$$\beta|\Sigma_u, Y \sim N(\beta_1, V_1) \tag{14}$$
$$\Sigma_u|Y \sim IW(S_1, \vartheta_1)$$

So, the posterior is basically prior beliefs conditional on the data. Since the posterior is not fully tractable, the next step is to simulate from the posterior distribution. The posterior distribution is approximated by using Markov Chain Monte Carlo (MCMC) method. MCMC builds a chain of random draws where each sample depends only on the previous one. Hence, the chain converges to the true posterior because it gradually moves away from the starting values. Gibbs sampling is the most common algorithm used to implement MCMC in empirical papers. As in Szafranek et al. (2024), I specify the total number of iterations equaling 20 000 to ensure that the posterior is stable.

The logic of the algorithm is the following:

Step 1. Take a random draw of the reduced-form parameters (B, Σ_u) from the posterior. For the taken draw compute the lower-triangular Cholesky decomposition $P = chol(\Sigma_u)$ (such that $PP' = \Sigma_u$).

Step 2. Generate random draws of the orthonormal rotation matrix Q. For each combination (B, P, Q) calculate structural impulse responses. Candidate impact matrices are $A_0^{-1} = PQ$.

Step 3. Accept a draw if implied structural impulse responses satisfy the restrictions.

Step 4. Repeat first three steps for a predefined number of iterations.

Main empirical results include estimation of the impulse response functions (IRFs) of the endogenous variables to the specified shocks which enables one to report the magnitude and timing characteristics of the pass-through. Forecast error variance decomposition (FEVD) can be used to determine how much fluctuation in inflation can be attributed to identified global energy price shocks and domestic shocks. Along with these, historical decompositions are estimated which break observed historical movements in CPI and other variables of interest into contributions of each shock over time.

3.3. Main shock identification strategy

Shock identification is the central part of the model. A simple VAR model is the most basic way to perform multivariate time series analysis. While it is a useful approach to explore data interconnections, this method is widely criticized for having a vague relationship with economic theory due to its purely empirical nature and is subject to Lucas Critique (Canova, 1995). Therefore, this study employs structural VAR which by establishing structural foundation allows for defining economically meaningful relationships between the variables and clear interpretation of the results.

In a SVAR structure is built by imposing restrictions on the contemporaneous relations between the endogenous variables which are stored in the structural matrix A_0 (or alternatively the restrictions can be imposed on A_0^{-1} which is done in my study) (Lütkepohl and Kilian, 2017). Several common strategies can be used to identify the shock structure. I utilize the identification of shocks via a combination of zero and sign restrictions which presents a set identification. Application of sign restrictions was pioneered by Uhlig (2005) and has become a popular tool allowing to impose economically meaningful restrictions on the

responses of the selected variables while the responses of other endogenous variables in the model are kept unrestricted.

Identification problem is that it is necessary to distinguish economically meaningful shocks v_t from reduced-form innovations u_t. Without restrictions it is impossible because there exist infinitely many different matrices A_0^{-1} which generate the same Σ_u, since any orthonormal rotation Q satisfies $\Sigma_u = (A_0^{-1}Q)(A_0^{-1}Q)'$.

As was shown earlier, for each draw of reduced-form parameters (B, Σ_u) the algorithm searches for admissible structural decompositions and produces only those IRFs that are consistent with the imposed restrictions. In my case of mixed identification, set of admissible draws include only those which satisfy all the imposed sign and zero restrictions.

I denote the structural impulse response matrix at horizons zero and h respectively as:

$$\Psi_0 = A_0^{-1}, \Psi_h = \left(\sum_{j=1}^{p} B_j \Psi_{h-j}\right), h \geq 1 \tag{15}$$

Then for each identified shock k, the set of possible restrictions for the selected variables i and horizons h is:

$$sign\big(\Psi_h(i,k)\big) \in \{+, -, 0\} \tag{16}$$

As in Uhlig (2005), my identification scheme is agnostic in the sense that I only employ minimal horizon $(h = 0)$ short-run restrictions. I single out as many shocks as variables $(n = 5)$ which implies full identification because the number

of identified shocks $k = 5$ is equal to the number of endogenous variables. Let the vector of structural shocks be:

$$\upsilon_t = (\upsilon_t^{DD}, \upsilon_t^{DS}, \upsilon_t^{EXC}, \upsilon_t^{GGS}, \upsilon_t^{GD}) \tag{17}$$

While all the shocks are economically identified, the responses of many variables to the shock υ_t^{EXC} are kept unrestricted, meaning that this shock mostly captures residual innovations.

As shown by Kilian (2009), energy shocks are not homogeneous. Thus, identifying the source of the shock is essential for understanding its inflationary consequences. Since energy shocks emerge either on supply or demand side, it is necessary to distinguish supply-side shocks from those driven by changes in demand in the model. Spike in gas prices driven by supply shortages affect the economy differently than the one induced by surge in global demand.

To correctly identify the shocks, I set sign restrictions on endogenous variables responses. In such a way I specify the direction of the impact of a shock on a particular variable and ensure that each shock can be plausibly described from the economic theory view. For instance, a negative gas supply shock is expected to raise gas prices together with inflation but decrease output. In contrast, a positive demand shock leads to an increase in both gas prices and global output. Economic interpretation of the identified structural shocks and logic behind the signs of impact is explained in Table 2 below.

Table 2. Definition of structural shocks and identification logic

Structural shock	Definition and impact description
Domestic demand (DD) shock	Defined as an expansion in the aggregate domestic demand. Reflects expansionary fiscal policy or increase in private consumption leading to an increase in output and rising inflationary pressures inside of the country. Impact sign restrictions: • IPI: positive • CPI: positive
Domestic supply (DS) shock	Defined as a negative domestic supply shock, capturing negative changes in domestic production capacity (e.g. decline in productivity; disruption in production chains; input costs increase unrelated to global energy prices). As a result, production costs rise which leads to increasing consumer prices. Output declines. Therefore, shock generates a trade-off between output and inflation. Impact sign restrictions: • IPI: negative • CPI: positive
Exchange rate (EXC) shock	Denotes national currency depreciation and captures exogenous movements in the domestic currency (Hryvnia) not explained by other structural shocks (for example, risk sentiment; financial or speculative pressures and flows). Currency depreciation leads to higher import prices and generates inflationary pressure for the domestic economy. Output can also be affected but since evidence suggests the presence of mixed

Table 2 – Continued

Structural shock	Definition and impact description
	(ambiguous) effects, the response of the domestic output is unconstrained. Impact sign restrictions: • NEER: negative
Global natural gas supply (GGS) shock	Defined as a decrease in the global supply of natural gas, indicating exogenous changes. Reduction in the gas supply raises global gas prices and results in production costs increase (especially for energy-intensive industries). As a result, global output falls. Impact sign restrictions: • TTF: positive • WIP: negative
Global aggregate demand (GD) shock	Defined as an increase in global aggregate demand, primarily reflecting synchronized expansions in global economic conditions. Leads to an increase in global economic activity and production. Raises demand for energy, pushing up its price. In theory, domestic economic conditions also change in response to global demand shock, with both output and inflation increasing. Impact sign restrictions: • TTF: positive • WIP: positive

Sources: Kilian (2009); Szafranek et al. (2024); Lopez et al. (2024); Mumtaz and Surico, (2009).

The complete summarized identification scheme for the baseline SVAR model is presented in Table 3. Sources of the restrictions come from the economic theory and the literature (see *Chapter 2*), so that each of the identified structural shocks is economically plausible. A central identifying assumption is that Ukraine is a small open economy (SOE) relative to global energy markets and global activity. This implies that domestic shocks do not affect global variables contemporaneously. In the model this mechanism is implemented through the imposition of zero restrictions. Table 3 reveals that domestic demand and supply shocks, by construction, do not exert any impact on global natural gas prices as well as global production. Therefore, by using zero restrictions I separate the model into two blocks: global and domestic. In such a way I build a clear division between external and internal sources of macroeconomic fluctuations.

Table 3. Shocks identification scheme

Variable	Domestic shocks		Global (external) shocks		
	DD	DS	EXC	GGS	GD
CPI	+	+	.	.	.
IPI	+	–	.	.	.
NEER	.	.	–	.	.
TTF	0	0	0	+	+
WIP	0	0	0	–	+

Note: in the table regarding the responses of variables to particular shock, I follow the approach of Szafranek et al. (2024) and use "·" (a dot) to denote an unrestricted response of a given variable to a specified shock; notation "+" indicates an increase in the variable value; notation "–" indicates a decrease in the variable value; "0" implies a zero restriction.

Global natural gas supply and aggregate demand shocks are identified primarily through their immediate impact on natural gas price and global activity, while the domestic inflation rate and industrial production responses are left unrestricted and therefore constitute an empirical result rather than an identifying assumption. In this sense I let the data speak on how domestic variables react to identified global shocks. This allows to measure dynamic causal effects that come directly from the underlying data which is a benchmark approach in the literature (De, Compton and Giedeman, 2020; Peersman and Van Robays, 2012). Additionally, I do not impose assumptions on natural gas supply/demand elasticities or structural relationships beyond minimal restrictions.

Proxy for global oil price as well as dummies for COVID-19 and war in Ukraine period (full-scale Russian invasion in 2022) are used as exogenous controls and do not enter the identification matrix. But their addition ensures that gas supply shock does not capture shocks in oil-market developments or war disruptions in the Ukrainian economy.

In terms of the structural impact matrix A_0, this is incorporated by placing zeros on the rows corresponding to the global variables and columns corresponding to the domestic ones (see Equation 18).

$$\Psi_0 = \begin{bmatrix} + & + & * & * & * \\ + & - & * & * & * \\ * & * & - & * & * \\ 0 & 0 & 0 & + & + \\ 0 & 0 & 0 & - & + \end{bmatrix} \tag{18}$$

Following the procedure by Rubio-Ramírez, Waggoner and Zha (2010) it is also made sure that the number of zero restrictions imposed on shock j does not exceed $n - j$. This constraint is a technical algorithmic condition rather than an economic

restriction. For the algorithm to be computationally feasible, shocks should be ordered starting with those subject to the largest number of zero restrictions.

3.4. Alternative structural identification and specifications

Since the empirical results significantly depend on the underlying economic rationale that is used for the structural identification, it is important to avoid conditioning on one specification.

Main advantage of sign restrictions strategy is that it allows to disentangle the underlying source of the increase in natural gas prices. The literature broadly demonstrates that energy price shocks propagate heterogeneously to the euro area and US prices depending on whether the shock emerges on the supply or demand side (see *Chapter 2*). On the one hand, sign restrictions may not be enough to uniquely pin down the shocks. On the other hand, under the system of sign plus zero restrictions the admissible set of structural decompositions can become extremely small (overidentification) because the data cannot support many jointly imposed contemporaneous exclusions while also separating all desired shocks. That is why in the baseline specification the domestic block is limited to inflation rate, industrial production and exchange rate but I can expand the number of domestic variables (e.g. including interest rate IR) by employing a different identification. Therefore, I employ several alternative identification schemes to check the robustness of the results and whether conclusions from the baseline model hold across the various identification strategies.

3.4.1. Narrative restrictions

Following the novel approach pioneered by Antolín-Díaz and Rubio-Ramírez (2018), I complement the baseline model with narrative restrictions to strengthen

identification. Imposition of narrative restrictions means incorporation of external historical information into the identification procedure. In such a way these restrictions constrain admissible structural draws to those consistent with the chosen narrative events.

The rationale to augment the sign and zero structure with narrative is dictated by the limitations of sign-restricted SVARs. By employing a minimal combination of uncontroversial sign and zero restrictions I produce a set-identified posterior with a large number of admissible structural models. This is seen to be the main downside of such strategy since set-identification comes at cost of lower precision and bears the risk of including economically implausible rotations (Kilian and Murphy, 2012).

With narrative restrictions only models that both agree with signs and zero restrictions as well as established narrative are accepted. Therefore, inclusion of narrative restrictions effectively shrinks the admissible set and allows for a more credible and precise identification of selected shocks. The ability of narrative restrictions to narrow the set of posterior draws has been widely shown in literature (Antolín-Díaz and Rubio-Ramírez, 2018). This is especially the case regarding energy markets because historically their dynamics have been heavily influenced by geopolitical events (russia-Ukraine contractual disputes regarding natural gas supply in 2006 and 2009; russian full-scale invasion of Ukraine in 2022; recent blockade of energy flows through the Strait of Hormuz).

As in Lopez et al. (2024), I separate informative narrative episodes for identifying exogenous gas supply shocks relevant for the Ukrainian context. In practice, it is only necessary to identify one or two historical events. I link the model to the following historical episode of energy disruptions:

1. Russian invasion of Ukraine. Important narrative episode is the full-scale invasion of Ukraine in February 2022 which triggered a sharp reduction in russian

gas exports to Europe (Lopez et al., 2024). Accordingly, imports from Europe to Ukraine plummeted as well while TTF hub gas price increased by more than 100% (m-o-m) on peak in March 2022. This episode is a historically unprecedented one and represents large exogenous negative disruption to natural gas supply.

Arguably, post-2014 geopolitical shift can be considered as another event constituting a negative gas supply shock. Due to the failure to negotiate on debt repayment and gas prices, russia's Gazprom cut off the supply of natural gas to Ukraine in June 2014. This was done amid russia's occupation of Crimea and eastern Ukraine regions (Kardaś and Konończuk, 2014). While this event presents exogenous disruption to gas supply to Ukraine, it did not halt the supply to Europe as russia continued to pump gas through Ukraine for transit to the European Union.

Therefore, I use narrative sign restrictions based on the 2022 episode to represent the negative gas supply shock: $TTF \uparrow in\ GGS\ shock$.

3.4.2. Recursive ordering

Recursive ordering is a special case of exclusion restrictions which imposes full casual ordering for the model's variables where earlier variables are made exogenous with respect to later. This fact implies that all contemporaneous relations are determined mechanically by variable order.

Recursive identification is imposed through Cholesky decomposition:

$$\Sigma_u = PP' \tag{19}$$

$$A_0^{-1} = P = chol(\Sigma_u)$$

where P is a lower triangular matrix with positive diagonal:

$$P = \begin{bmatrix} p_{11} & 0 & 0 & 0 & 0 \\ p_{21} & p_{22} & 0 & 0 & 0 \\ p_{11} & p_{32} & p_{33} & 0 & 0 \\ p_{41} & p_{42} & p_{43} & p_{44} & 0 \\ p_{51} & p_{52} & p_{53} & p_{54} & p_{55} \end{bmatrix} \quad (20)$$

Regarding Equation 20, zeros above the diagonal indicate recursive restrictions; each row of the matrix corresponds to the variable i; each column of the matrix corresponds to the structural shock in that variable.

Therefore, for 5 endogenous variables, there are 5! possible orderings. It gives a different unique matrix P for each ordering meaning that the model is point-identified (only one unique decomposition exists) rather than set-identified as in the case with sign restrictions (where there are multiple structural matrices A_0^{-1} that satisfy the restrictions). For the purposes of my study, I set the following ordering:
1) For 5-variable model: $TTF \rightarrow WIP \rightarrow IPI \rightarrow NEER \rightarrow CPI$.

2) For 6-variable model: $TTF \rightarrow WIP \rightarrow IPI \rightarrow NEER \rightarrow CPI \rightarrow IR$.

So, global block variables go first and are followed by the domestic block variables. It means that global gas price does not react contemporaneously to any other variable while inflation rate is enabled to react to everything simultaneously.

However, the credibility of the recursively identified models depends entirely on plausibility of ordering. Economically convincing ordering may be difficult to find and often requires strong assumptions. In this respect, it is more restrictive than my baseline identification approach. Sign restrictions provide a more agnostic way of identification by imposing only qualitative, theory-consistent responses. At the same time, it comes with a trade-off. While the sign-restricted identification is less

restrictive on timing, it is more restrictive on economic behavior (signs are applied to identify the direction of responses for the variables that are unrestricted in the recursive identification).

Additionally, recursive ordering (including Cholesky factorization) does not impose economic structure on the source of the shock. I capture the innovations in variables that can reflect a combination of underlying factors (demand, supply or both). In this sense, I cannot explicitly impose the differentiation of gas supply shock from those gas price movements emerging on the demand side. So, the reported shock is total natural gas price shock.

3.4.3. Model specifications with heteroskedasticity

Heteroskedastic models use time variation in shock variances for identification and therefore allow for more flexible error covariance structures. I employ two specifications: stochastic volatility (SV) and Markov-switching heteroskedasticity (MSH).

Key difference of SV model with the baseline specification is that the reduced-form covariance matrix evolves over time with stochastic volatility dynamics (e.g. log-volatilities following AR(1) processes). In the literature, stochastic volatility VAR extension has been shown to dominate other VAR specifications. Main findings across empirical studies demonstrate that it gives largest forecasting and model fit gains (see Carriero, Clark, and Marcellino, 2019). Since energy markets can be extremely volatile, it means that variance of energy shocks changes over time. Implementation of stochastic volatility incorporates this fact by allowing shock transmission to differ in periods of different volatility (for example, high-volatility versus low-volatility periods).

In MSH, volatility switches between two discrete regimes capturing crisis versus normal periods and structural breaks. The identification for both heteroskedastic

specifications is set to lower triangular factorization (Cholesky decomposition) which is an exact identification strategy. To compare each of the heteroscedastic models to the homoscedastic model, I run Savage-Dickey density ratio (SDDR) test which shows how much the models with variable volatility are better than the simple model with constant volatility. It compares the predictive power of two models (null vs. alternative) and reports the logarithm of Bayes factors (BF) (a ratio of evidence in favor of one model over the other for each structural shock).

As an extension, I estimate time-varying parameter (TVP) Bayesian SVAR with stochastic volatility as in Del Negro and Primiceri (2015). It is employed in order to estimate how the inflationary effects of global energy shocks have varied over different periods, and whether they became more or less pronounced in recent times.

Formal specification of the TVP-BSVAR takes the following reduced form:

$$y_t = C_t + \sum_{j=1}^{p} B_{(t,j)} y_{t-j} + A_t^{-1} \sum_t u_t \qquad (21)$$

where C_t is the intercept that allows the baseline level of variables to shift; $B_{t,j}$ are the time-varying matrices of parameters; u_t are the innovations (error terms); $u_t \sim N\left(0, \Sigma_{u,t}\right), \Sigma_{u,t} = S_t S_t'$.

Since TVP-BSVAR includes SV as a component, this presents a possibility to separate whether inflation increased because the shock was large (time-varying volatility) or because the economy became more vulnerable to energy prices (time-varying parameters). Therefore, this model specification allows me to account for time-varying uncertainty and the changes in the transmission during wartime.

However, the estimation of time-varying parameter model comes with a trade-off. While it allows us to incorporate time-varying uncertainty and analyze the state-dependent pass-through, this also means an increase in the dimensionality of the model and more parameters being estimated, implying much heavier computation process. In the settings of a small sample the model with extensive number of variables is not viable. Thus, I include only 3 lags instead of 12. Second, I decrease the number of variables to three: global natural gas price, Ukrainian inflation and industrial production. Additionally, unlike in the homoscedastic models, I utilize the full sample for which the data is available (from January 2006 to August 2025). This helps to increase the number of datapoints relative to the number of estimated parameters.

It is important to understand that neither of the alternative specifications considered above can validate or invalidate the results of the main approach since they answer different structural questions. Hence, these are only useful as a robustness check.

Apart from this, it is also necessary to identify whether the pass-through is driven primarily by direct household energy expenditure or by broader indirect production channels. For this I further investigate the transmission channels of gas price shock propagation to inflation. Following the approach of Lopez et al. (2024), I decompose the pass-through into several CPI subcomponents. However, the decomposition is adapted to the Classification of Individual Consumption According to Purpose reported by State Statistics Service of Ukraine (SSSU). I consider four components, namely heating, direct residential natural gas consumption, electricity, and other, where the first two capture the direct inflationary effects with the latter two capturing indirect ones. This decomposition procedure is primarily motivated by the fact that wartime distortions, supply chain disruptions, and lower market competition all can create more persistent second-round effects in Ukraine, increasing the pass-through.

3.5. Limitations and challenges discussion

A key advantage of sign-restricted structural VAR model is that sign restrictions can be derived from economic theory more easily than a complete set of exclusion restrictions. By employing sign-restrictions, I explicitly incorporate the direction of response but not the exact causal contemporaneous timing.

This comes with a trade-off. First, while conventional recursive SVAR is point-identified, sign-restricted SVAR is set identified by definition because many structural matrices A_0^{-1} rather than one unique matrix satisfy sign restrictions. Therefore, there are potentially a big number of models that are all consistent with the imposed sign restrictions. In practice, it means that main estimation outputs such as structural IRFs represent distributions over admissible models rather than one structural model.

In the context of Bayesian inference posterior distribution of IRFs of sign-identified model depends not only the likelihood, rotation algorithm, prior but also on how prior specifies the weights of the admissible structural models. This increases the sensitivity of the model to the choice of the prior which is a primary reason for the usage of alternative identification schemes for credible results.

Second, the logic of small open economy creates a need to separate the set of endogenous variables into two blocks: international and domestic ones. This ensures that global variables do not get immediate feedback from the domestic shocks. Following a common approach in literature (see, for example, Mumtaz and Surico, 2009; Szafranek et al., 2024) I impose additional zero restrictions which effectively transform the model into one with mixed (sign plus zero) restrictions. It makes it more computationally difficult. Model estimation in R can take up from couple of minutes to a few hours.

In principle, nothing restricts me from estimating the baseline model with frequentist methods. Yet there are several important caveats which prompt me to

focus solely on the Bayesian approach. Main concern is that to date there exists few frequentist approaches which are tailored to solve the models with mixed restrictions. Standard methods that are used to summarize the results (such as bootstrapping) for conventional recursive SVARs cannot be utilized for the models employing sign identification. Additionally, the resulting confidence bands are too wide and therefore uninformative (Lütkepohl and Kilian, 2017).

Chapter 4

DATA

The study employs monthly time series data. The full sample includes observations from 2006m1 to 2025m8 ($T = 236$). The dataset consists of 13 variables (8 continuous and 2 dummy variables). The main constraint for the beginning of the sample is due to availability of selected domestic data on the inflation rate and industrial production, which only became consistently available on a monthly basis from the year 2006 onwards.

In the baseline model specification, the sample period is restricted to 2013m1-2025m8 ($T_1 = 152$) due to the structural changes in Ukraine's natural gas import system. Starting from 2013 Ukraine began a rapid diversification of its natural gas imports sources. This transition led to a substantial increase in imports from European partners through reverse flow mechanism. Most notably, Slovakia, Hungary and Poland have become key entry points for gas supplied from the European market (see Appendix A). For the robustness checks I utilize the full sample ($T = 236$).

The data on consumer prices inflation in Ukraine (CPI to previous month) and its components, as well as industrial production index, which is used as a proxy for domestic economic activity, is obtained from State Statistics Service of Ukraine (SSSU). Brent crude oil and TTF (Title Transfer Facility) natural gas prices (both are in USD) are collected from the World Bank commodity database and are used as benchmarks for global oil and gas prices respectively. The choice of TTF price index over alternative benchmarks (US Henry Hub or Asian JKM) is based on TTF being the most liquid natural gas trading hub in the world and structurally the most relevant for the Ukrainian context. Important note is that I use real energy prices

(deflated by US CPI) to remove the influence of general inflation. This presents the consensus in empirical literature (see Lopez et al., 2024).

As shown in Kilian and Zhou (2022b) and Szafranek et al. (2024), the choice of inadequate proxy for energy prices can significantly alter the estimates of pass-through. Hence, I also employ alternative proxy for gas price in the form of reconstructed series of Ukraine's average import price of natural gas (IMPORT) and utilize it to check the robustness of the results (see Appendix C for details).

Exchange rate is a crucial variable serving to establish the relationship between prices within the domestic economy and those in external energy markets. The Nominal Effective Exchange Rate (NEER) is used as a proxy, which measures Ukrainian hryvnia value relative to a basket of foreign currencies. In alternative model specifications I use key policy rate to control for the monetary stance. Data on exchange rate and key interest rate is sourced from statistics of the National Bank of Ukraine (NBU).

I utilize the world industrial production index (WIP) to measure global economic activity and collect it from Baumeister and Hamilton (2019). WIP covers both developed (OECD) and major emerging economies. Additionally, two control variables in the form of exogenous monthly dummy variables are included to account for unique economic disruptions. COVID lockdown dummy is developed to control for months of strict restrictions (March 2020 – June 2021) and war dummy accounts for the period of full-scale russian invasion of Ukraine (from February 2022 onward).

The descriptive statistics of the dataset are presented in Table 4 below. Global oil price reaches the maximum of 0.5 dollars measured in real USD with global gas price being much more relatively volatile (mean and standard deviation are close to each other) which likely reflects extreme price spikes in the period of 2021-2022. Meanwhile, the statistics of domestic CPI show strong cumulative inflation since

2013 (mean value of the index for the considered period is 274 relative to the base of 100). Apart from the possibility of being driven by global energy price spikes, actual inflation can be strongly amplified by the fluctuations in other commodity prices (e.g. agricultural products, industrial metals), and inflation expectations. Maximum and minimum CPI values of 104 and 500 indicate a highly volatile historical range, reflecting the presence of massive inflationary surges and overall inflation persistence. Due to the presence of high inflationary pressure, monetary policy has been strongly reactive. Mean key policy rate of 15% for the period of 2013-2025 likely shows that NBU often had to raise the rate to fight inflation, stabilize exchange rate and expectations.

Table 4. Descriptive statistics

Variable	Obs.	Mean	Std. Dev	Min	Max
Domestic inflation rate (CPI)	152	274	113	104	502
Heating CPI subindex (Heating)	152	518	229	113	711
Electricity CPI subindex (Electricity)	152	499	286	123	1004
Natural gas CPI subindex (NGAS)	152	905	445	100	1394
Domestic economic activity (IPI)	152	94	18	47	126
Exchange rate (NEER)	152	0.38	0.12	0.26	0.72
Interest rate (IR)	152	15	6.2	6	30
Global oil price (BRENT)	152	0.28	0.091	0.091	0.5
Global gas price (TTF)	152	0.042	0.035	0.0062	0.24
Global economic activity (WIP)	152	133	8.8	117	150
Import price (IMPORT)	152	1.4	0.81	0.11	4.8
COVID dummy	152	0.11	0.31	0	1
WAR dummy	152	0.28	0.45	0	1

Note: untransformed (raw) data. Summary statistics for raw data for the full sample are presented in Table 9 in Appendix B.

Regarding the state of the domestic real economy, the data reveals that industrial output is still below long-term baseline level. Mean and minimum values of 94 and 47 respectively suggest the presence of episodes of large negative shocks which led to significant contractions in the real economic sector (e.g. Covid pandemic, russian invasions in 2014 and 2022). Compared to Ukraine, global production is much smoother, demonstrates steady growth path and strong recoveries. Domestic business cycle is far more volatile than global one because Ukraine's production fluctuations are not only driven by global demand and external shocks but also by domestic shocks, the war and structural breaks (see Figure 3 and Figure 4).

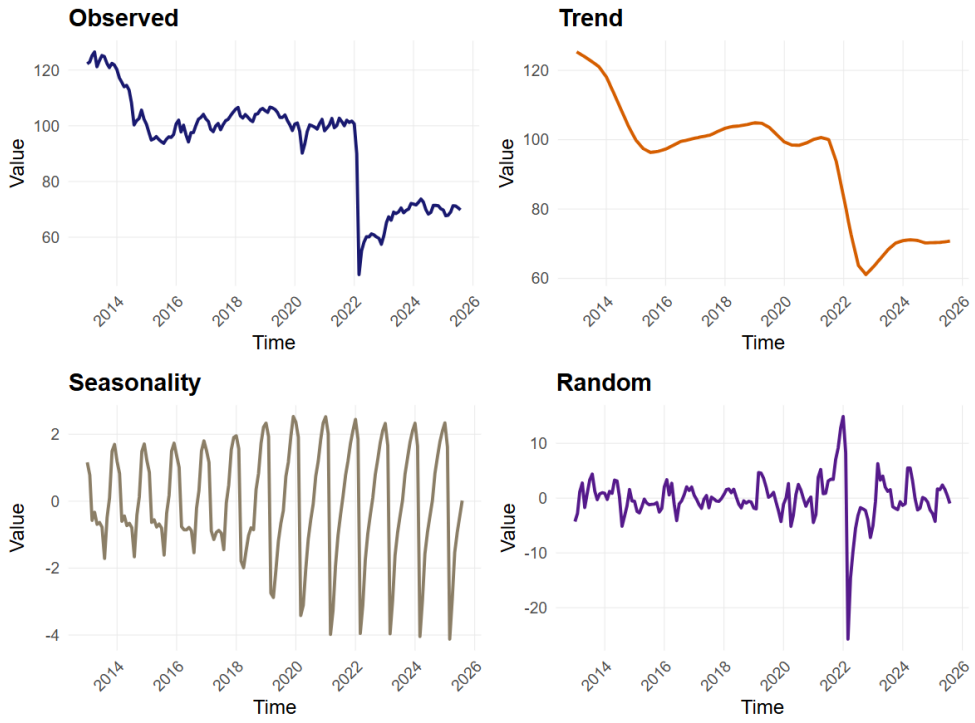


Figure 3. Industrial production index (IPI) time series decomposition

Note: decomposition is done using STL (Seasonal-Trend decomposition using LOESS) method.

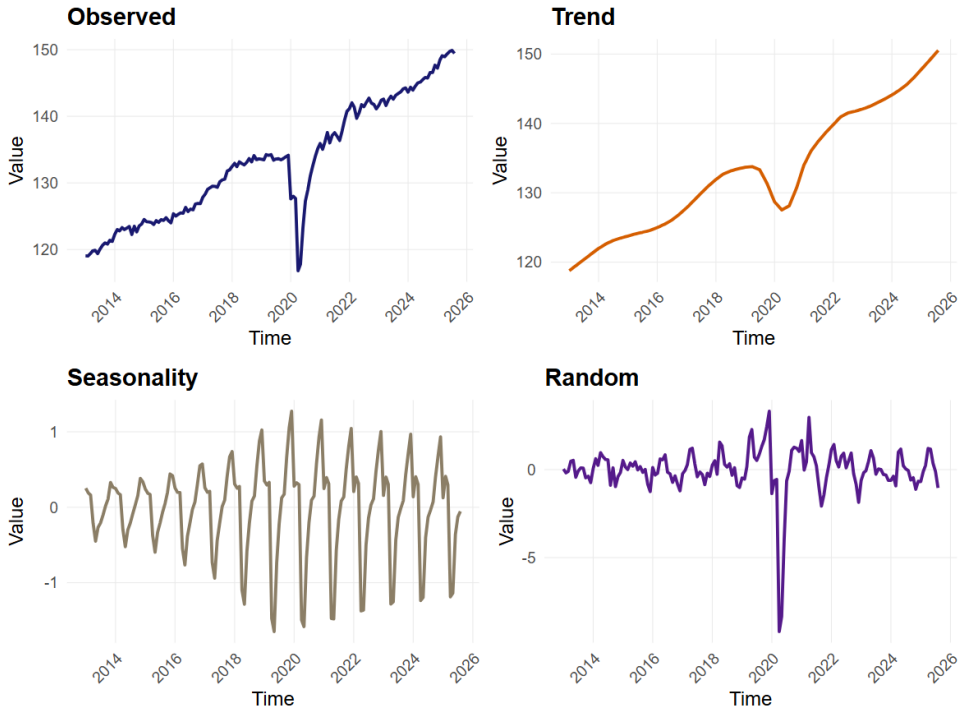


Figure 4. World industrial production index (WIP) time series decomposition

Note: decomposition is done using STL (Seasonal-Trend decomposition using LOESS) method.

The trend line appears to explain the largest part of changes in domestic production. Although the seasonal component is present as well, its magnitude is comparatively small validating that most of the dynamics in the industrial activity is primarily explained by negative external disruptions to the Ukrainian economy. In the dataset 11% of observations represent the period of Covid-19 (lockdown shock and global demand collapse) and about one-third of the sample belongs to wartime economy.

The correlation matrix for the continuous variables (see Table 10 in Appendix B) reveals that global oil and gas real prices are positively correlated. However, the magnitude is not very big (0.41) which may reveal the fact that natural gas and oil

prices have decoupled in recent years, particularly due to liberalization of gas markets.

Both oil and natural gas real prices have statistically significant correlation with global industrial production. But the direction differs. While natural gas prices are positively correlated with global industrial output, the price of oil appears to be negative correlated, though the magnitude is small (-0.22). This divergence in correlation may reflect differences in oil and gas use cases. Natural gas is a primary input in many industries (manufacturing, fertilizers etc.) and therefore tends to move together with industrial production. In turn this means that global gas price spikes are primarily driven by the increases in global demand during the last 10 years because high demand for manufacturing goods drives up the demand for natural gas. This strongly supports the evidence of the recent literature (see *Chapter 2*). Figure 5 exhibits that real gas prices and production tend to move closely during the past ten years. It also shows that dynamics of real oil prices diverge with the developments in global output at the beginning of the sample, tighten in the middle and then again, the relationship loosens at the end of the sample. So, negative correlation may not be truly informative but rather a result of a chosen sample period.

Crucially, positive correlation is observed between domestic consumer inflation and global natural gas prices which is in line with economic theory and main modelling assumptions (see *Chapter 3*). Additionally, there is significant negative correlation between inflation rate and exchange rate (-0.74). This suggests that there is strong exchange-rate pass-through to prices in Ukraine. The link between CPI and interest rate appears to be positive. This is surprising and seems to be counterfactual to economic logic. One explanation can be the volatile sample structure (2014 invasion, Covid, full scale war). Consequently, the data consists of high inflation periods combined with aggressive stabilization policy (rate hikes).

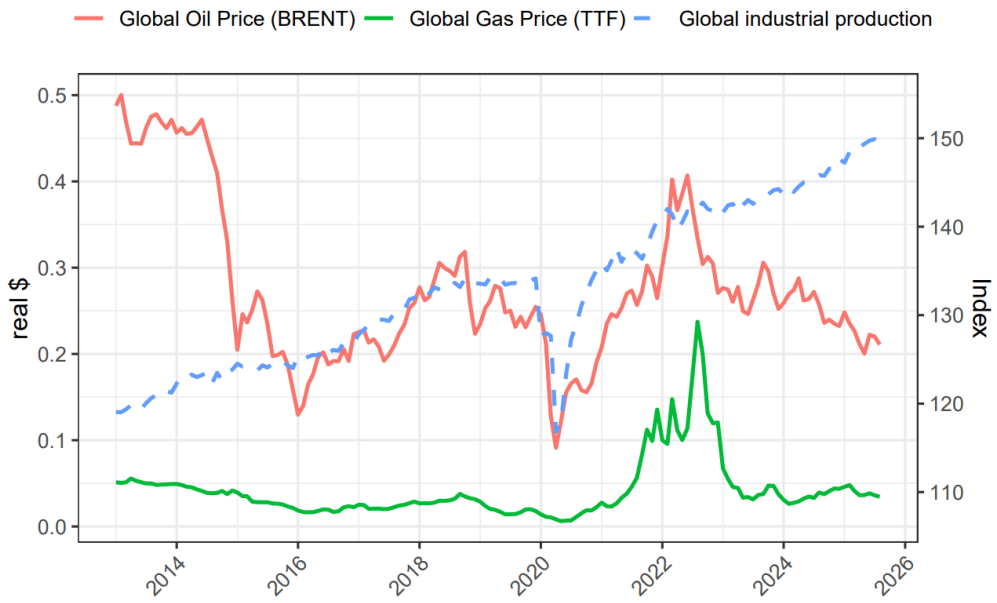


Figure 5. Global oil and gas price series dynamics (real USD, left axis); global industrial production (index, right axis)

The highest correlation (0.95) is observed between Ukrainian CPI and global industrial production indicating that significant share of domestic inflation can be imported. Periods of elevated global demand are characterized by global expansion: increase in production, increasing commodity prices and higher import prices which can lead to higher prices domestically. Simultaneously high negative correlation (-0.85) between domestic industrial output and consumer prices supports the idea that inflation in Ukraine is largely supply-driven.

Indeed, global and domestic real production do not comove and are negatively correlated (-0.8). This observation is mostly attributed to Ukrainian-specific factors and wartime reality. When global economy was rapidly recovering after Covid, Ukrainian economy has plunged into a deeper recession due to the full-scale russian invasion which caused substantial human, infrastructural and economic losses. Since the usage of the war dummy is not enough to fully capture the divergence

between Ukrainian and global production trends, as a supplement, I utilize Markov-switching specification that allows to explicitly model the switch between 2 regimes (peace and war).

For stationarity, logarithm differences transformation is used for most of the endogenous variables. Since the interest rate is measured in percentage, it is kept in levels. This is in line with number of other empirical studies that incorporate similar indicators (Casoli, Manera and Valenti, 2022; Arias, Rubio-Ramírez, and Waggoner, 2018). Such approach allows for a clear and more intuitive interpretation. Time series visualization for main transformed variables is presented in Figure 17 (see Appendix B).

One of the major concerns is that there has been couple of events during the investigated period which represent major structural shifts in the economy of Ukraine. This brings potential limitations to the analysis such as insufficient length of the time period considered. In this context, the dataset can be considered short and volatile which can complicate obtaining comprehensive results.

To summarize, preliminary analysis of the data supports some insights drawn from the literature and in many aspects reinforces the initial hypotheses of the research.

Chapter 5

ESTIMATION RESULTS

5.1. Stationarity testing

Results of stationarity testing imply that the variables are either stationary in levels or in first difference (see Table 5 below). Both the ADF and KPSS tests suggest that most variables in levels contain unit root and therefore, are integrated of order 1. So, they are non-stationary in levels but become stationary after differencing procedure.

Table 5. Stationarity testing results

Variable	ADF		KPSS		Conclusion on stationarity
	Level	1st Diff	Level	1st Diff	
Domestic inflation rate	-1.41	-4.89***	3.01**	0.34	I(1)
Domestic economic activity	-2.67	-8.84***	2.18***	0.05	I(1)
Exchange rate	-7.27***	-8.83***	1.71***	0.30	I(1)
Interest rate	-2.57	-7.25***	0.16	0.07	I(0)
Global oil price	-3.09	-7.91***	0.644**	0.14	I(1)
Global natural gas price	-3.21*	-5.40***	0.445*	0.05	I(1)
Import gas price	-2.99	-10.41***	0.427*	0.05	I(1)
Global economic activity	-3.55**	-6.04***	2.82***	0.03	I(1)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Chosen ADF test type includes both an intercept and a linear time trend. Lag length selection set to automatic via AIC. The reported numbers are t-values. The critical values for test statistics in the ADF test are -3.99, -3.43 and -3.13 for 1%, 5%, and 10% significance levels respectively.

While the Bayesian framework allows to effectively handle non-stationarity through appropriate prior setting, I utilize stationary data due to several reasons. First, my study focuses on short-run energy price pass-through rather than long-run convergence. Second, stationarity ensures that the resulting posterior distribution is stable in TVP and structural heteroskedastic models where the risk of explosive roots is high.

For some of the variables, unit root testing yields conflicting results. For the interest rate the ADF test fails to reject the null hypothesis of a unit root, while the KPSS test fails to reject the null of stationarity. Since economically the interest rate does not contain a permanent stochastic trend, I retain it in levels which also matches standard convention in the literature (Lopez et al., 2024).

Considering the variable of the exchange rate, both tests reject their respective null hypotheses. This conflicting evidence signals the presence of structural breaks or regime shifts within the sample period. This is highly characteristic of Ukrainian exchange rate where policy shifts between fixed and floating regimes combined with war-induced shocks have created significant disruptions for the hryvnia. I transform the exchange rate into first differences, so it represents the monthly rate of currency depreciation or appreciation. In this way it matches the transformations made to the energy price series and consumer price index.

5.2. Lag selection

Table 6 presents the results of the test for choosing SVAR lag length. The Akaike information criterion (AIC) has minimum value for lag order of 12 while Hannan-Quinn (HQ) Criterion suggests the lag length of 3. The Bayes information criterion (BIC) is more conservative and suggests optimal lag order of 1. Following the framework laid in the literature I choose 12 lags for my modelling, so that the lag length aligns with the frequency of the data (see Lopez et al., 2024; Baumeister

and Hamilton, 2019). At the same time, I use lag order of 3 to conduct robustness checks and verify that the empirical conclusions are not a byproduct of lag selection.

Table 6. Lag selection for SVAR

Criteria	Suggested lag order	Value
AIC	12	11.899
HQ	3	13.350
BIC (SC)	1	14.974
FPE	4	195454.280

5.3. Granger Causality testing

Prior to the BSVAR setup, I conduct bivariate Granger Causality testing across selected lag horizons to assess whether global gas price helps predict the developments in domestic variables. Table 7 demonstrates that testing yields distinct results for the nominal and real block of the domestic economy. While natural gas price contains predictive information with respect to domestic output, it does not Granger-cause inflation considering investigated lag orders.

However, the results for reverse relationship indicate that industrial output Granger-causes gas price. So, these variables mutually influence each other, suggesting the presence of a feedback loop. Importantly, inflation does not Granger-cause energy prices. Although the conclusions about structural (contemporaneous) causality cannot be made, the results provide limited supporting evidence for the hypotheses of the study.

Table 7. Granger Causality Test (selected results of pairwise Granger tests)

Lag length of VAR	1	3	12
Null hypothesis	F-statistic	F-statistic	F-statistic
TTF does not Granger-cause CPI	0.19	0.98	0.52
	(0.662)	(0.404)	(0.897)
CPI does not Granger-cause TTF	0.24	0.34	0.76
	(0.624)	(0.794)	(0.687)
TTF does not Granger-cause IPI	0.18	4.06	2.93
	(0.674)	**(0.008)**	**(0.001)**
IPI does not Granger-cause TTF	9.72	3.36	4.08
	(0.002)	**(0.021)**	**(0.000)**

Note: the corresponding p-values are presented in parentheses.

5.4. Estimation results: homoscedastic Bayesian SVAR specifications

Figure 6 shows the posterior impulse responses to identified global gas supply and global aggregate demand shocks estimated from the baseline Bayesian SVAR. The original model is estimated on monthly transformed variables. The full matrix of monthly IRFs is presented in Appendix D.

The results reveal that the identified natural gas negative supply shock exhibits the expected characteristics of a cost-push disturbance, leading to a sharp increase in gas price (about 10 percentage points on impact) and contraction in global output. However, the effects of the shock on domestic variables are short-lived, relatively small. Also, the credibility interval, which is a basic criterion for statistical significance in Bayesian econometrics, implies that the effect is not significant. This indicates limited persistence of gas prices pass-through into domestic macroeconomy.

Global aggregate demand shock generates simultaneous increases in gas prices and global economic activity. Posterior medians of domestic inflation rate and industrial output responses indicate that demand-driven gas price increase has more persistent effects. In this sense, results suggest that the inflationary impact of gas price fluctuations in Ukraine depends on the underlying source of the shock. Still, the credibility bands cross the zero line which means that we cannot be certain about the effect because it can go in either direction.

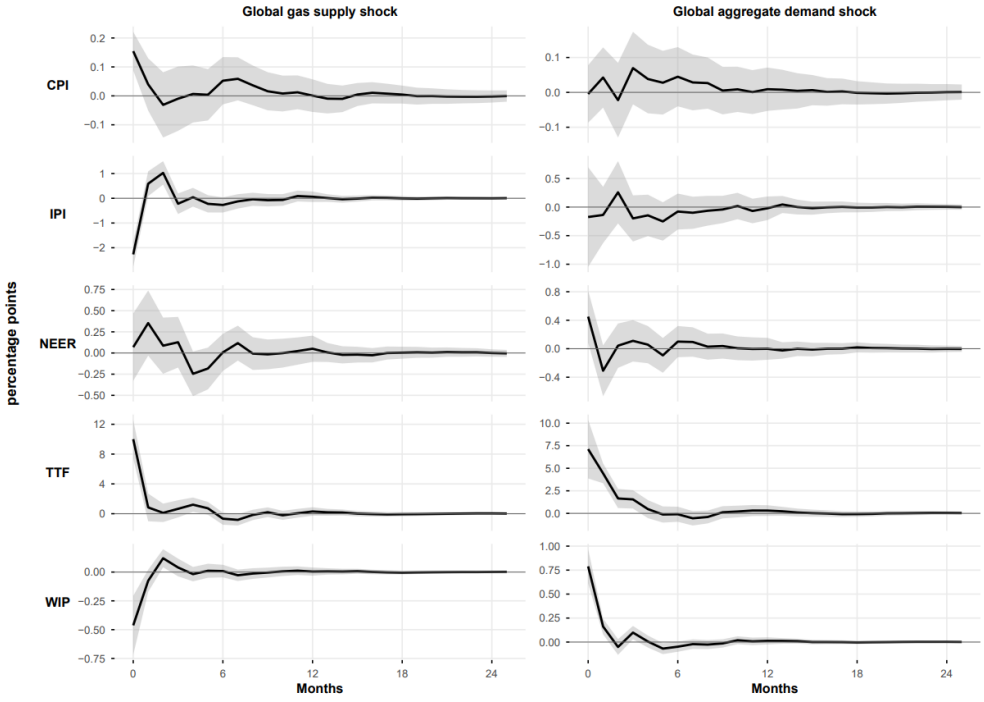


Figure 6. Resulting IRFs for baseline sign and zero identified BSVAR: month-on-month estimates of posterior responses for identified GGS and GD shocks

Note: The figure shows impulse responses from the estimated posterior distribution. Columns represent shocks and rows denote the response variables. All results are measured in percentage points (pp). The shocks are normalized to represent the magnitude of one standard deviation. The black solid lines indicate the median of impulse responses. Grey shaded areas (ribbons) correspond to the 68% probability bands. Sample: January 2013 to August 2025.

For the purposes of clear interpretation, in Figure 7 reported impulse responses are subsequently rescaled, so that identified global negative gas supply shock implies a 10% increase in the gas prices on impact. The monthly variables' responses are then converted into year-on-year responses which eases the interpretation of the resulting estimates. On impact, gas price increase resulting from the negative supply shock in the global natural gas market has certain positive effect on year-on-year inflation, increasing it by 0.15 pp. The peak response of annualized inflation to a natural gas supply shock reaches approximately 0.32 percentage points after 12 months. However, no certain conclusion about the true response is possible as the lower limit of the credibility interval stays below zero.

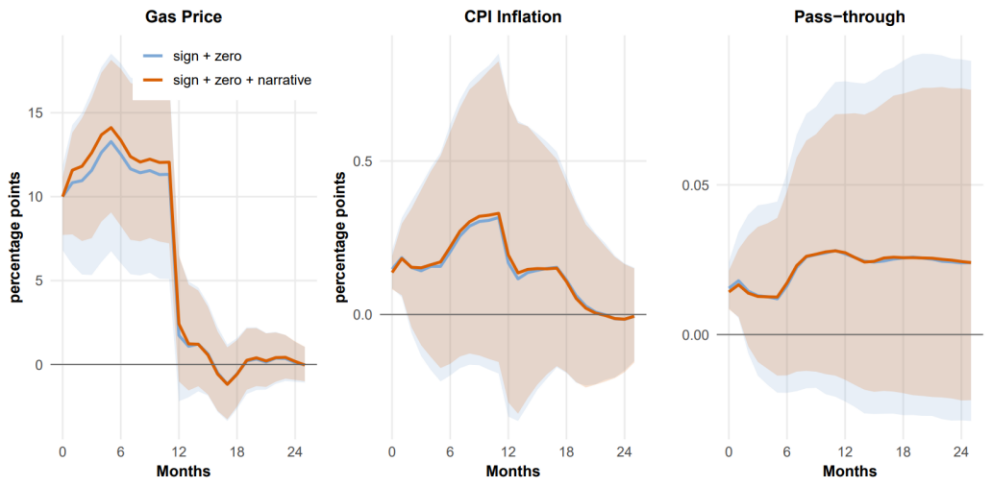


Figure 7. Global gas supply (GGS) shock: global gas price pass-through to Ukrainian inflation

Note: The figure demonstrates structural impulse response functions (IRFs) to a 10% increase in the price of natural gas price (TTF hub). Models are identified with a combination of sign and zero restrictions (blue) and sign, zero and narrative restrictions (orange). The CPI response is a flow (annualized inflation at a given month), while pass-through (right-hand side panel) is a cumulative stock (total price-level effect relative to the size of the shock). Solid lines indicate the closest to median responses from the admissible models. Shaded areas (ribbons) correspond to the 68% probability bands. Sample: January 2013 to August 2025.

Following the approach laid in Lopez et al. (2024), the pass-through is measured as the cumulative CPI inflation response divided by the cumulative gas price response to the same shock. Thus, pass-through is accumulated IRF which grows and stabilizes at a higher level while the credibility bands widen over time. It represents the accumulated effect on the price level over time. I show in Figure 7 that the cumulative pass-through to the price level reaches around 0.028 percentage points (pp) in about 11 months after the shock and stays there, while the wide credibility interval implies that the transmitted effect of the shock is not clearly positive or negative at any horizon.

The response from GD shock does not produce more precise estimates either (Figure 8). Therefore, the baseline Bayesian SVAR does not yield certain responses of domestic inflation to gas price shocks. The transmission of unexpected increase in global gas prices to inflation is limited in magnitude and subject to considerable uncertainty for shocks emerging both on demand and supply sides. While this finding may be in line with the relatively low weight of natural gas in the consumption basket and the presence of mitigating factors such as regulated natural gas tariff for population (see Figure 18 in Appendix C), it also may be due to inherently weak identification strategy.

The inclusion of narrative restrictions does not materially change the estimated dynamics. Considering both GGS and GD shocks, the median responses of CPI inflation and the estimated pass-through very closely follow those obtained under the baseline scheme. Credibility intervals become somewhat narrower, suggesting improved identification precision but only for GGS shock. It is an expected result because additional restrictions tighten the posterior by eliminating some admissible rotations. However, the credibility intervals still cross the zero line at all horizons, so a certain conclusion on the magnitude and direction of the impact is not possible. Therefore, even when historically informed restrictions are imposed the model still does not detect significant inflationary transmission. At the same time,

main insight that I draw is that the weakness of the baseline results cannot be attributed to insufficient historical information within the identification strategy.

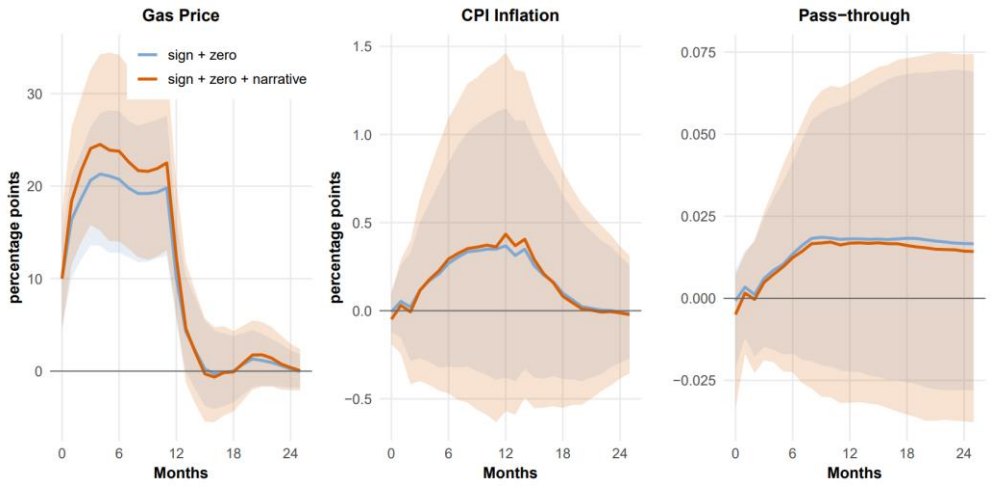


Figure 8. Global aggregate demand (GD) shock: global gas price pass-through to Ukrainian inflation

Note: The figure demonstrates structural impulse response functions (IRFs) to a 10% increase in the price of natural gas price (TTF hub). Models are identified with a combination of sign and zero restrictions (blue) and sign, zero and narrative restrictions (orange). The CPI response is a flow (annualized inflation at a given month), while pass-through (right-hand side panel) is a cumulative stock (total price-level effect relative to the size of the shock). Solid lines indicate the closest to median responses from the admissible models. Shaded areas (ribbons) correspond to the 68% probability bands. Sample: January 2013 to August 2025.

Figure 9 shows the impulse response functions (IRFs) for gas price shock from the homoscedastic model with Cholesky identification. Under this identification IRFs should be interpreted as responses to recursively ordered shocks, not as exactly the same structural shocks as in the sign and zero restricted model. Following a 10% gas price shock, the 68% credible interval for the response of inflation is above zero both on impact and on the horizon of approximately 1 year where the median response reaches a maximum of 1 percentage point. The models produce relatively

moderate and stable pass-through which reaches the magnitude of 0.07-0.1 percentage points 2 years after the shock.

These results imply the presence of a significant positive effect on domestic consumer inflation from the gas price shock. At the same time, in the model with 6 variables (interest rate included) both the response of inflation and pass-through have bigger median magnitudes but are less precisely estimated with wider probability bands.

Overall, these findings suggest that the absence of meaningful pass-through from gas price shocks to inflation in the baseline model identified with sign and zero restriction is likely driven by weak identification rather than the absence of an economic effect.

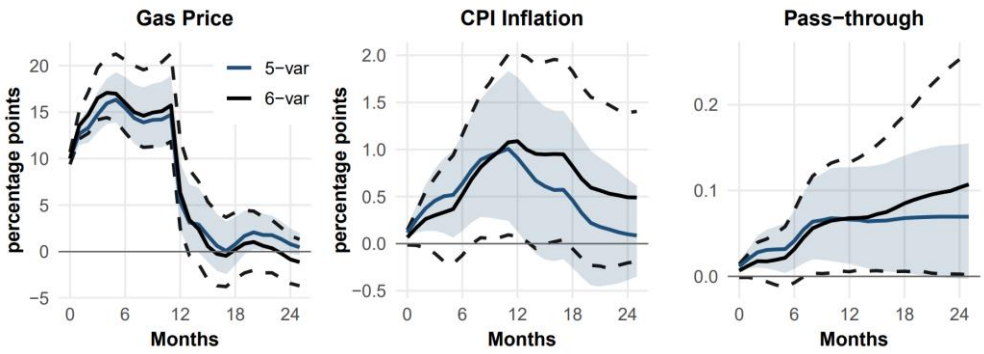


Figure 9. Global natural gas price shock: pass-through to Ukrainian inflation

Note: The figure demonstrates structural impulse response functions (IRFs) to a 10% increase in the price of natural gas price (TTF hub). The models are identified with lower triangular (Cholesky) factorization. The CPI response is a flow (annualized inflation at a given month), while pass-through (right-hand side panel) is a cumulative stock (total price-level effect relative to the size of the shock). Solid blue and black lines indicate median responses. Shaded areas (ribbons) and dashed bands correspond to the 68% probability bands. Sample: January 2013 to August 2025.

5.5. Heteroskedastic model specifications and robustness checks

Figure 10 compares the IRFs from the alternative model specifications which allow for heteroskedasticity. The results reveal a notable difference. Again, the annualized posterior responses normalized to a 10% increase in the gas price are reported. Both SV and MSH models generate similar posterior responses for gas prices, domestic inflation rate and the pass-through measure. Estimates indicate that y-o-y inflation rate response peaks around 0.7 pp in about 12 months after the shock. The pass-through of gas price increase to inflation gradually builds up and reaches approximately 0.06 pp two years after the shock.

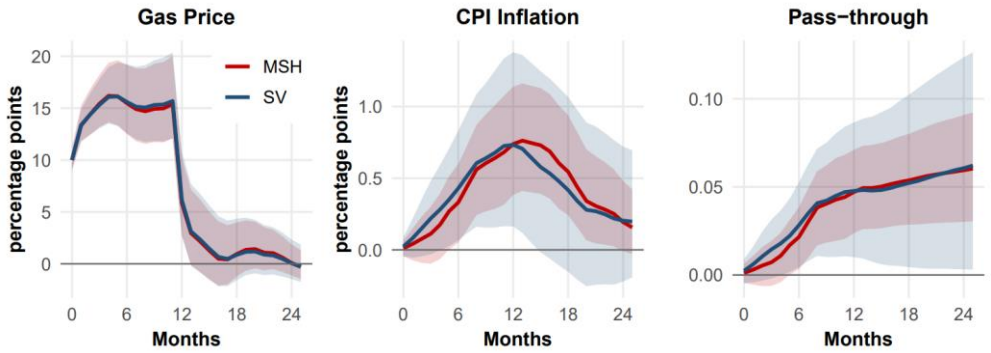


Figure 10. Gas price pass-through to Ukrainian inflation: heteroskedastic model specifications

Note: The figure demonstrates structural impulse response functions (IRFs) to a 10% increase in the price of natural gas price (TTF hub). Both stochastic volatility (SV) and Markov-switching heteroskedasticity (MSH) specifications are identified with lower triangular factorization (6 variables, 12 lags). The CPI response is a flow (annualized inflation at a given month), while pass-through (right-hand side panel) is a cumulative stock (total price-level effect relative to the size of the shock). Solid blue and red lines indicate median responses. Shaded areas (ribbons) correspond to the 68% probability bands. Sample: January 2013 to August 2025.

Probability bands imply that the medium-term impact of the gas shock on inflation is clear and significant, but the long-term cumulative effect is characterized by high

uncertainty. At the same time, MSH specification produces slightly more persistent responses with marginally higher peaks. Importantly, these estimates are in line with the empirical studies which disentangle the pass-through for the Euro area (see Lopez et al., 2024; Alessandri and Gazzani, 2023), although for Ukraine the effect of gas price shock on domestic inflation is relatively much weaker on impact.

Table 8 presents SDDR test for SV specification. It reveals that for most shocks the posterior probability of the null hypothesis of homoskedasticity approaches zero. In the MSH specification the situation is similar where the data confirms the presence of various volatility for 5 out of 6 shocks and the null is rejected (Appendix D). Hence, the results indicate predominant support for heteroscedastic specifications compared to homoscedastic one.

In this respect, it is possible to conclude that a standard BSVAR with constant volatility may bias the results because it ignores significant changes in the amplitude of shocks over time.

Table 8. Results of Savage-Dickey density ratio test for the model with stochastic volatility

Shocks	log(SDDR)	NSE	Pr[H0|data]	Pr[H1|data]
TTF shock	-0.475	0.867	0.383	0.617
WIP shock	-88.777	17.636	0.000	1.000
IPI shock	-120.874	13.717	0.000	1.000
NEER shock	-73.011	15.495	0.000	1.000
CPI shock	-0.026	6.714	0.494	0.506
IR shock	-2.297	39.246	0.091	0.909

Note: log(SDDR) denotes the logarithm of Bayes factor. NSE stands for numerical standard errors. Pr[H0|data] and Pr[H1|data] are the implied posterior probabilities of the homoskedasticity and heteroskedasticity hypotheses respectively.

Other results are omitted for conciseness and are presented in Appendix D. Under the assumptions of heteroskedasticity, global natural gas price shock still exerts no clear effect on domestic economic activity. The policy rate rises gradually and persistently in response to unexpected gas price shock. This suggests a strong monetary policy response to inflationary pressure. Appendix E contains further robustness checks. I verify that the results remain stable under alternative variable ordering and usage of a different proxy for global gas price series. However, the results for the extended sample differ from the baseline implying that the estimated pass-through is sensitive to the sample period choice. For the extended sample both model specifications no longer provide strong evidence regarding the magnitude and the direction of the inflation response to gas price shock. One plausible explanation relates to the structural transformation of the Ukrainian natural gas market. TTF hub prices likely became more economically relevant for Ukraine post-2013 following the gradual diversification of natural gas imports and transition toward reverse-flow imports from European countries.

As an additional robustness check, the models were re-estimated using a shorter lag structure (3 lags). The results suggest that the estimated transmission is sensitive to lag length selection (Appendix E). Although the pass-through of a gas price shock to inflation remains positive, its magnitude becomes substantially lower. At the same time, 68% credibility bands become narrower and reflect lower estimation uncertainty but lie only marginally above the zero line.

To better understand the propagation channel of a gas price shock, the total pass-through to consumer inflation was decomposed into contributions from heating, electricity, direct household natural gas consumption, and other indirect effects. Figure 11 focuses on economically interpretable medium-term pass-through composition. It reveals that the direct natural gas component constitutes the dominant share of the pass-through, accounting for approximately 40-60% of the total inflationary effect. However, contribution of this component reflects

primarily pre-2022 period. As illustrated in Appendix C (Figure 18), residential natural gas tariffs in Ukraine closely followed import and TTF hub price dynamics in 2015-2021, whereas a wartime moratorium subsequently interrupted this relationship. Consequently, the decomposition results should not be interpreted as evidence of uninterrupted direct pass-through during the considered sample.

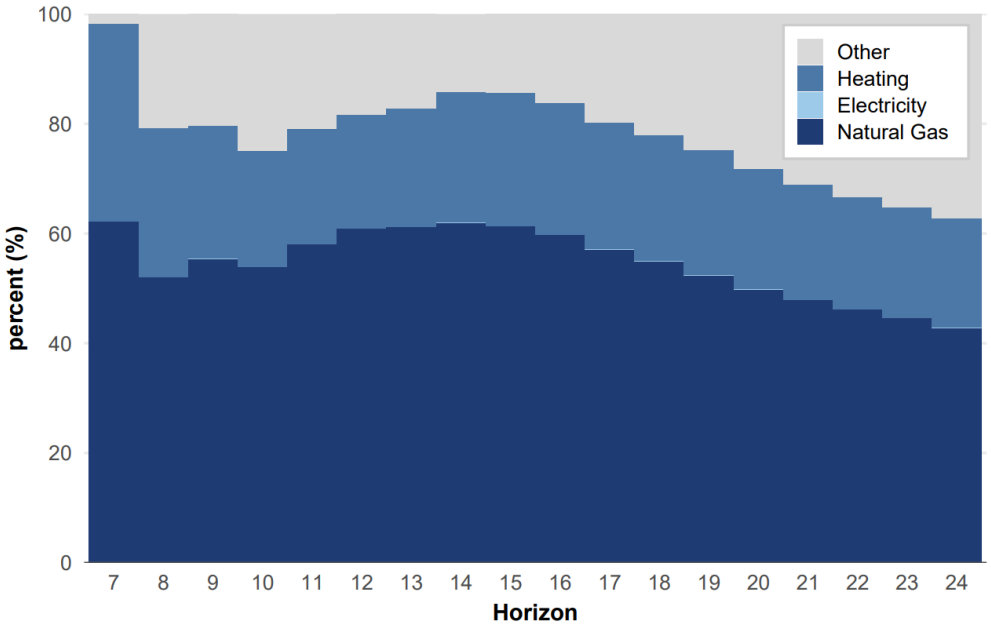


Figure 11. Composition of the pass-through from global natural gas price shock to Ukrainian inflation: breakdown by component, %

Note: estimates are based on SV model specification identified with lower triangular factorization (6 variables, 12 lags). Sample: January 2013 to August 2025. The figure starts from horizon 7, so that unstable early shares are excluded. Component "Other" is calculated as the difference of the separated components ("Natural Gas", "Electricity", "Heating") and the estimates for CPI inflation, and reflects other indirect effects.

Heating-related transmission also contributes positively but to a smaller extent. By contrast, the contribution of electricity prices inflation remains negligible (near 0%) throughout the horizons. This is likely due to the presence of regulated electricity

tariff for households as well as relatively large share of non-gas electricity generation in Ukraine (e.g. nuclear energy). The remaining indirect effects become increasingly important at further horizons, which suggests that global gas price shocks propagate gradually through broader production costs and supply-side channels (second-round effects).

Additionally, I estimate historical decomposition for inflation in Ukraine to understand its drivers in different periods (Figure 12). High inflation during 2014-2016 is driven primarily by domestic macroeconomic instability and exchange rate depreciation. Overall analysis shows that the contribution of domestic shocks dominates inflation dynamics. The share of global shocks remains relatively small throughout the considered period. Probably, the y-o-y estimates can be more informative.

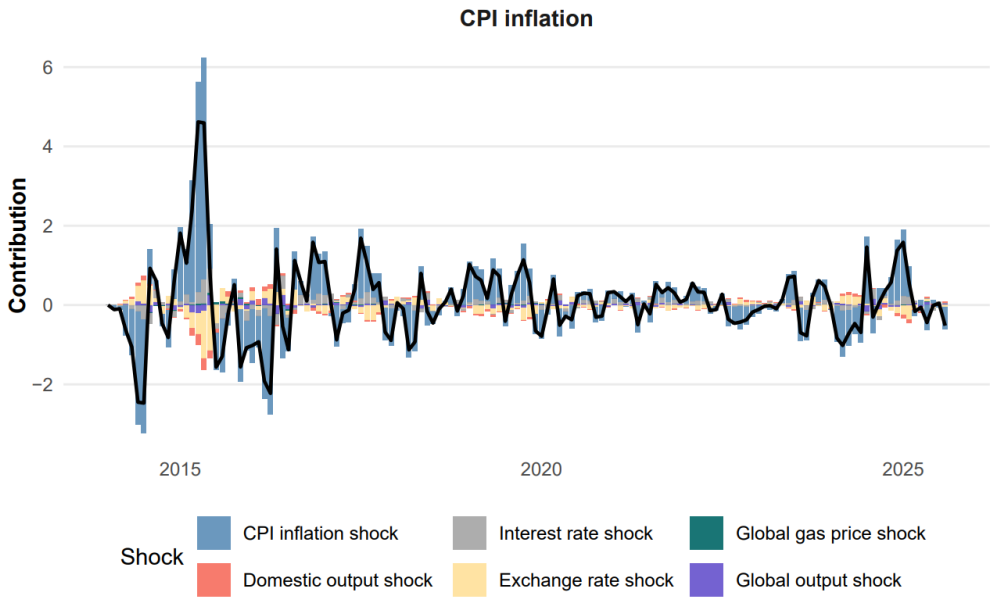


Figure 12. Historical decomposition for domestic consumer inflation

Notes: Estimated based on the results of SV model specification. The black solid line indicates the logarithmic monthly inflation. Contributions from the shocks to inflation dynamics are reported at posterior median.

5.6. Time-varying parameter BSVAR estimation results

Figure 13 shows the impact of unexpected global natural gas price shock on Ukrainian CPI inflation estimated under the assumptions of both time-varying parameters and shock volatility. Main finding is that the inflationary effect of the shock remains positive throughout the sample period, but its magnitude varies considerably.

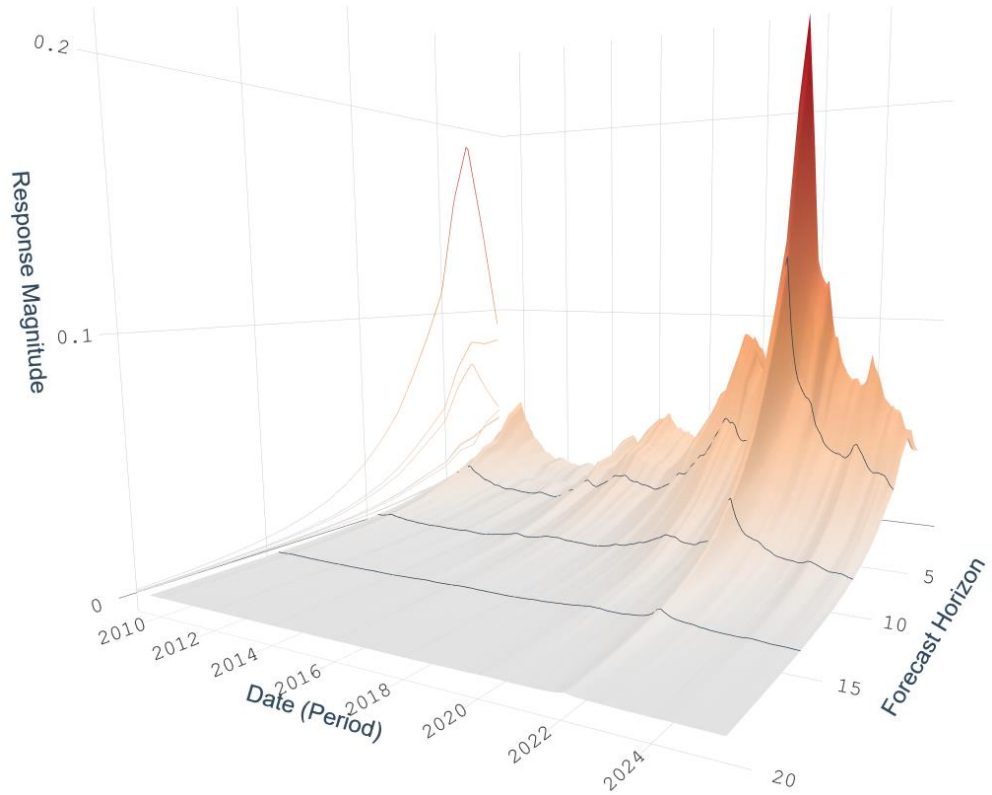


Figure 13. Response of CPI inflation to global gas price shock: monthly estimates from TVP-BSVAR with stochastic volatility

Note: Response is measured in percentage points (pp). The shock is normalized to represent the magnitude of a one standard deviation in global gas price increase. 3D surface plot represents median posterior responses. Sample: February 2006 to August 2025 (where first 40 observations are used as training sample for prior determination).

Specifically, the magnitude of inflation response strengthened from 2015 onward. Moreover, the persistence of the response has increased as well. Estimated IRFs reveal that the responses of CPI decay relatively quickly in earlier years (2009-2013), while in later periods the effects remain positive for substantially longer horizons. The average cumulative inflation responses increased from 0.108 percentage points m-o-m during 2009-2013 to 0.303 pp during 2014-2021 and further to 0.526 pp during 2022-2025. Relative to the pre-2014 period, this corresponds to an increase of approximately 180% for the post-2014 period and nearly 386% during the wartime period. The average half-life of inflation responses rises from approximately 5.4 months before 2014 to 6 months during 2022-2025. Such increased persistence may reflect several factors, e.g. increased energy intensity of production, stronger indirect effects. Taken together, these findings show that in recent years gas price shocks do not result in temporary fluctuations but generate medium-term inflationary pressures.

The strongest responses are observed during the periods of economic stress, particularly around the full-scale russian invasion of Ukraine. In February 2022 the estimated CPI inflation response reaches its maximum value, peaking at approximately 0.24 pp m-o-m after three months. Period of COVID-19 outbreak is also characterized by relatively strong inflation response (almost 0.1 pp about three months after the shock). Therefore, this provides evidence in favor of state-dependent transmission, indicating that inflation responses tend to be amplified in periods of war, crisis or elevated uncertainty.

One more interesting observation is that the location of the peak response of monthly CPI inflation remains relatively stable, generally occurring within the first few months after the gas price shock (around horizons 2 and 4). However, the magnitude of the peak changes substantially over time. This implies that the speed of transmission has remained similar while the intensity of transmission has increased.

On Figure 14 I show that the effect of the gas price shock on industrial production is also highly time-varying. Despite the growing magnitude, the response stays very short lived across the sample period. Hence, the lack of significant response persists even in the time-varying specification with stochastic volatility. This reinforces the conclusion that holds across the specified models: the impact of global gas price shock on domestic industrial production is associated with high uncertainty.

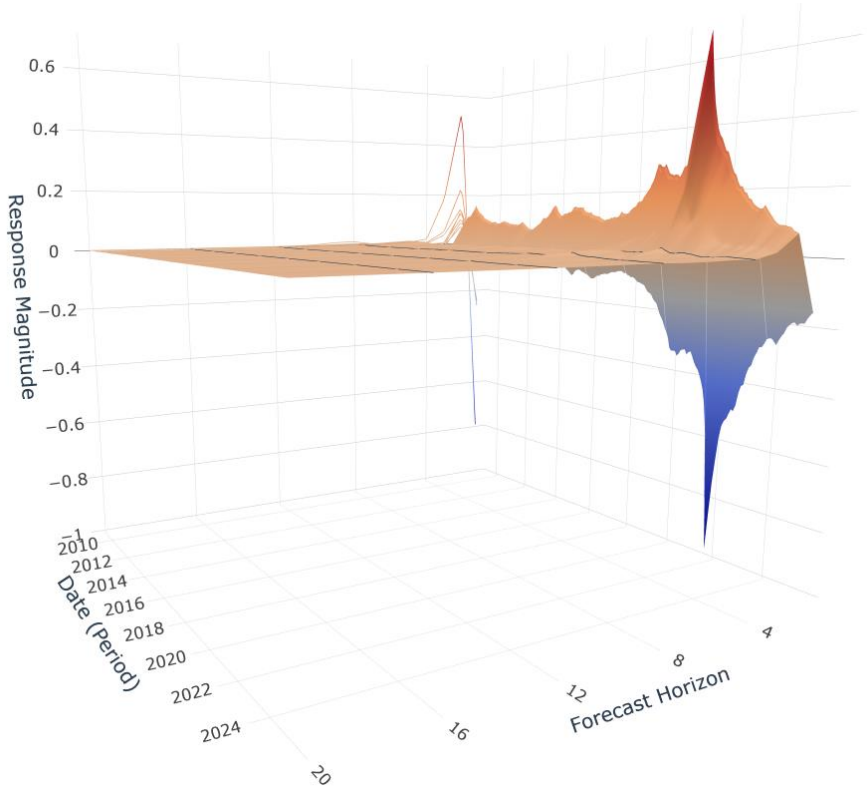


Figure 14. Response of domestic industrial production to global gas price shock: monthly estimates from TVP-BSVAR with stochastic volatility

Note: Response is measured in percentage points (pp). The shock is normalized to represent the magnitude of a one standard deviation in global gas price increase. 3D surface plot represents median posterior responses. Sample: February 2006 to August 2025 (where first 40 observations are used as training sample for prior determination).

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

This study investigates the effect of price shocks in global natural gas market on the dynamics of domestic inflation in Ukraine using monthly time series data and Bayesian SVAR methodological framework. The analysis combines sign, zero, and narrative restrictions with recursive identification schemes and heteroskedastic model specifications. In addition to estimating aggregate pass-through, the thesis also examines the transmission channels of gas price shocks through CPI decomposition and historical decomposition analysis.

In the baseline model I have proposed a Bayesian SVAR identified based on zero and sign restrictions allowing to disentangle the impact of gas shocks based on their source. My findings imply that the effect of gas shocks emerging both on the supply and demand side is associated with high uncertainty about true probability and direction of impact. While the robustness homoscedastic model confirms that external gas-price disturbances are relevant for Ukrainian inflation dynamics, their effects are not permanent and are partly meditated by exchange rate and monetary-policy responses.

In contrast, the consistency of the results across heteroskedastic specifications provides strong evidence that gas price shocks have a meaningful and robust impact on inflation dynamics in Ukraine. I find that a 10% increase in the price of natural gas leads to a pass-through of approximately 0.06 pp two years after the shock. Importantly, the results stay robust across the specifications.

Comparing to the Euro zone, gas price shock effect on impact is estimated to be lower for Ukraine. But the estimates of the total pass-through building up over time are comparable in magnitude and timing. At the same time, the estimated pass-through is sensitive to the sample period. Stronger and more significant

transmission effects are observed in the baseline post-2013 sample which coincides with Ukraine's increasing integration into European gas markets and suggests the growing relevance of Dutch TTF benchmark price for domestic inflation dynamics. Extending the sample back to 2006 weakens the estimated effects. Although the analysis does not establish causality, the results are consistent with the hypothesis that pass-through is not constant and depends on structural integration into global energy markets.

The decomposition of total pass-through across CPI components indicates that direct household natural gas consumption and heating expenditures account for 60-80% of the total depending on the horizon, while the contribution of the electricity component is negligible. This finding differs to a degree from the euro-area evidence documented in Lopez et al. (2024), where electricity and indirect channels are estimated to play a larger role. However, the interpretation of natural gas component for Ukraine should be careful and requires consideration of regulatory factors such as a moratorium on residential gas tariff increases since 2022.

At the same time, in Ukraine indirect effects become increasingly important over longer horizons which indicates that gas price shocks gradually propagate through production costs and second-round effects. Further ways that would improve the understanding of gas price pass-through can include incorporating sectoral or micro-level data to disentangle transmission channels more precisely and explicit modeling of expectations formation mechanisms.

Analysis of historical decomposition of domestic inflation fluctuations reveals that inflation dynamics in Ukraine are primarily driven by domestic shocks rather than external ones, particularly during crisis episodes. External energy shocks play a secondary role, with global aggregate demand shocks contributing more significantly to inflation than gas price shocks.

TVP-BSVAR results indicate that inflationary consequences of global natural gas price shocks in Ukraine are both time-varying and state-dependent. Inflation response becomes noticeably stronger both in terms of magnitude and persistence after 2014 and reaches its highest levels during the period surrounding the full-scale Russian invasion in 2022. As opposed to the inflation results, the response of domestic industrial production to gas price shocks remains insignificant across most specifications, including the TVP-BSVAR with stochastic volatility. This indicates that gas price shocks in Ukraine primarily operate through price channels.

The findings of this study provide several important implications for monetary and energy policy in Ukraine. First, monetary authorities should not treat gas price shocks as purely temporary because second-round effects can substantially influence broader price dynamics. So, maintaining credible inflation targeting and anchoring inflation expectations remains essential. Second, since direct channels account for a substantial share of total pass-through, policies aimed at improving energy efficiency and modernizing residential heating infrastructure can contribute to energy security as well as greater price stability.

Overall, these findings highlight that global gas price shocks represent an important source of inflationary pressure in Ukraine. At the same time, the results are sensitive to identification strategy and model specification and provide the evidence toward heteroskedastic identification being substantially more informative for the Ukrainian data.

WORKS CITED

Alessandri, Piergiorgio, and Andrea Gazzani. 2025. "Natural Gas and the Macroeconomy: Not All Energy Shocks Are Alike." *Journal of Monetary Economics*, 103749. https://doi.org/10.1016/j.jmoneco.2025.103749.

Antolín-Díaz, Juan, and Juan F. Rubio-Ramírez. 2018. "Narrative Sign Restrictions for SVARs." *American Economic Review* 108 (10): 2802–29. https://doi.org/10.1257/aer.20161852.

Arias, Jonas E., Juan F. Rubio-Ramírez, and Daniel F. Waggoner. 2018. "Inference Based on Structural Vector Autoregressions Identified with Sign and Zero Restrictions: Theory and Applications." *Econometrica* 86 (2): 685–720. https://doi.org/10.3982/ecta14468.

Baumeister, Christiane, and James D. Hamilton. 2019. "Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks." *American Economic Review* 109 (5): 1873–1910. https://doi.org/10.1257/aer.20151569.

Baumeister, Christiane, and Gert Peersman. 2013. "Time-Varying Effects of Oil Supply Shocks on the US Economy." *American Economic Journal: Macroeconomics* 5 (4): 1–28. https://doi.org/10.1257/mac.5.4.1.

Bjørnland, Hilde Christiane. 2000. "The Dynamic Effects of Aggregate Demand, Supply and Oil Price Shocks-A Comparative Study." *The Manchester School* 68 (5): 578–607. https://doi.org/10.1111/1467-9957.00220.

Bjørnland, Hilde C., Vegard H. Larsen, and Junior Maih. 2018. "Oil and Macroeconomic (In)Stability." *American Economic Journal: Macroeconomics* 10 (4): 128–51. https://doi.org/10.1257/mac.20150171.

Blanchard, Olivier J., and Jordi Galí. 2007. "The Macroeconomic Effects of Oil Price Shocks: Why Are the 2000s so Different from the 1970s?" *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1008395.

Bobasu, Alina, Michael Dobrew, and Amalia Repele. 2025. "Energy Price Shocks, Monetary Policy and Inequality." *European Economic Review*, 104986–86. https://doi.org/10.1016/j.euroecorev.2025.104986.

Burban, Valentin, Pavel Diev, Fabio Grieco, and Théo Iberrakene. 2024. "Monetary Policy in Times of War: The Case of Ukraine." https://www.banque-france.fr/system/files/2024-10/Blog_372-VE.pdf.

Burbidge, John, and Alan Harrison. 1984. "Testing for the Effects of Oil-Price Rises Using Vector Autoregressions." *International Economic Review* 25 (2): 459–84. https://doi.org/10.2307/2526209.

C2ES. 2020. "Natural Gas." Center for Climate and Energy Solutions. C2ES. July 1, 2020. https://www.c2es.org/content/natural-gas/.

Canova, Fabio. 1995. "The Economics of Var Models." *Springer EBooks* 46 (January): 57–106. https://doi.org/10.1007/978-94-011-0669-6_3.

Carriero, Andrea, Joshua Chan, Todd E Clark, and Massimiliano Marcellino. 2021. "Corrigendum to 'Large Bayesian Vector Autoregressions with Stochastic Volatility and Non-Conjugate Priors' [J. Econometrics 212 (1) (2019) 137–154]." *Journal of Econometrics* 227 (2): 506–12. https://doi.org/10.1016/j.jeconom.2021.11.010.

Casoli, Chiara, Matteo Manera, and Daniele Valenti. 2024. "Energy Shocks in the Euro Area: Disentangling the Pass-through from Oil and Gas Prices to Inflation." *Journal of International Money and Finance* 147 (August): 103154. https://doi.org/10.1016/j.jimonfin.2024.103154.

CES. 2025. "Ukraine War Economy Tracker - Centre for Economic Strategy." Centre for Economic Strategy. July 24, 2023. https://ces.org.ua/en/tracker-economy-during-the-war/.

Choi, Sangyup, Davide Furceri, Prakash Loungani, Saurabh Mishra, and Marcos Poplawski-Ribeiro. 2018. "Oil Prices and Inflation Dynamics: Evidence from Advanced and Developing Economies." *Journal of International Money and Finance* 82 (April): 71–96. https://doi.org/10.1016/j.jimonfin.2017.12.004.

Chowdhury, Aftab, and Huw Dixon. 2025. "Energy Expenditures and CPI Inflation in 2022: Inflation Was Even Higher than We Thought." *Energy Economics* 145 (April): 108482. https://doi.org/10.1016/j.eneco.2025.108482.

Clarida, Richard, Jordi Galí, and Mark Gertler. 1999. "The Science of Monetary Policy: A New Keynesian Perspective." *Journal of Economic Literature* 37 (4): 1661–1707. https://doi.org/10.1257/jel.37.4.1661.

Coibion, Olivier, and Yuriy Gorodnichenko. 2015. "Is the Phillips Curve Alive and Well after All? Inflation Expectations and the Missing Disinflation." *American Economic Journal: Macroeconomics* 7 (1): 197–232. https://doi.org/10.1257/mac.20130306.

Conflitti, Cristina, and Matteo Luciani. 2019. "Oil Price Pass-through into Core Inflation." *The Energy Journal* 40 (01). https://doi.org/10.5547/01956574.40.6.

De, Kuhelika, Ryan A. Compton, and Daniel Giedeman. 2020. "Oil Shocks and the U.S. Economy: Evidence from a FAVAR Model." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3658783.

Del Negro, Marco, and Giorgio E. Primiceri. 2015. "Time Varying Structural Vector Autoregressions and Monetary Policy: A Corrigendum." *The Review of Economic Studies* 82 (4): 1342–45. https://doi.org/10.1093/restud/rdv024.

DiXi Group. 2025. "Gas Imports to Ukraine." https://dixigroup.org/import-gazu-v-ukraïnu-zris-u-ponad-19-raziv-za-piv-roku-lideri-postachannya-shvejczariya-ta-nimechchina/.

EXPRO Consulting. 2024. "Shares of Energy Sources on the RDM, IDM and Balancing Market in Ukraine: 10 Months of 2024." Expro.com.ua. https://expro.com.ua/novini/chastki-djerel-energ-na-rdn-vdr-ta-balansuyuchomu-rinku-v-ukran-10-msyacv-2024-r-

Ganapati, Sharat, Joseph S. Shapiro, and Reed Walker. 2020. "Energy Cost Pass-through in US Manufacturing: Estimates and Implications for Carbon Taxes." *American Economic Journal: Applied Economics* 12 (2): 303–42. https://doi.org/10.1257/app.20180474.

Górajski, Mariusz, Zbigniew Kuchta, and Agnieszka Leszczyńska-Paczesna. 2023. "Price-Setting Heterogeneity and Robust Monetary Policy in a Two-Sector DSGE Model of a Small Open Economy." *Economic Modelling*, February, 106227. https://doi.org/10.1016/j.econmod.2023.106227.

Guntner, Jochen, Magnus Reif, and Maik H. Wolters. 2024. "Sudden Stop: Supply and Demand Shocks in the German Natural Gas Market." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4889239.

Hamilton, James D. 1983. "Oil and the Macroeconomy since World War II." *Journal of Political Economy* 91 (2): 228–48. https://doi.org/10.2307/1832055.

Hamilton, James D. 2009. "Causes and Consequences of the Oil Shock of 2007–08." *Brookings Papers on Economic Activity* 2009 (1): 215–61. https://doi.org/10.1353/eca.0.0047.

Hamilton, James. 2011. "Historical Oil Shocks." *NBER WORKING PAPER SERIES*, no. 16790 (February). https://doi.org/10.3386/w16790.

Kardaś, Szymon, and Wojciech Konończuk. 2014. "Russia and Ukraine's 'Cold Gas War.'" OSW Centre for Eastern Studies. June 25, 2014. https://www.osw.waw.pl/en/publikacje/analyses/2014-06-25/russia-and-ukraines-cold-gas-war.

Kilian, Lutz. 2008. "Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy?" *Review of Economics and Statistics* 90 (2): 216–40. https://doi.org/10.1162/rest.90.2.216.

Kilian, Lutz. 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market." *American Economic Review* 99 (3): 1053–69. https://doi.org/10.1257/aer.99.3.1053.

Kilian, Lutz, and Daniel P. Murphy. 2012. "Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market Var Models." *Journal of the European Economic Association* 10 (5): 1166–88. https://doi.org/10.1111/j.1542-4774.2012.01080.x.

Kilian, Lutz, and Xiaoqing Zhou. 2022. "Oil Prices, Gasoline Prices, and Inflation Expectations." *Journal of Applied Econometrics* 37 (5). https://doi.org/10.1002/jae.2911.

Kilian, Lutz, and Xiaoqing Zhou. 2023. "Oil Price Shocks and Inflation." *Federal Reserve Bank of Dallas, Working Papers* 2023 (2312). https://doi.org/10.24149/wp2312.

López, Lucia, Florens Odendahl, Susana Párraga Rodríguez, and Edgar Silgado-Gómez. 2024. "The Pass-through to Inflation of Gas Price Shocks." *SSRN Electronic Journal*, January. https://doi.org/10.2139/ssrn.4917066.

Lütkepohl, Helmut, and Lutz Kilian. 2017. *Structural Vector Autoregressive Analysis*. Cambridge University Press. https://doi.org/10.1017/9781108164818.

Mello, Miguel, and Jorge Ponce. 2025. "From Global Energy Price Shocks to Firms' Inflation Expectations." *Latin American Journal of Central Banking*, March, 100168. https://doi.org/10.1016/j.latcb.2025.100168.

Mumtaz, Haroon, and Paolo Surico 2009. "The Transmission of International Shocks: A Factor-Augmented VAR Approach." *Journal of Money, Credit and Banking* 41 (February): 71–100. https://doi.org/10.1111/j.1538-4616.2008.00199.x.

NBU. 2024. "NBU 2023 Inflation Update." National Bank of Ukraine. https://bank.gov.ua/en/news/all/komentar-natsionalnogo-banku-schodo-rivnya-inflyatsiyi-u-2023-rotsi.

OECD. 2022. *Impacts of the Russian invasion of Ukraine on financial market conditions and resilience: Assessment of global financial markets*. OECD Publishing, Paris. https://doi.org/10.1787/879c9322-en.

Peersman, Gert, and Ine Van Robays. 2012. "Cross-Country Differences in the Effects of Oil Shocks." *Energy Economics* 34 (5): 1532–47. https://doi.org/10.1016/j.eneco.2011.11.010.

Rubio-Ramírez, Juan F., Daniel F. Waggoner, and Tao Zha. 2010. "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference." *Review of Economic Studies* 77 (2): 665–96. https://doi.org/10.1111/j.1467-937x.2009.00578.x.

Szafranek, Karol, Grzegorz Szafrański, and Agnieszka Leszczyńska-Paczesna. 2024. "Inflation Returns. Revisiting the Role of External and Domestic Shocks with Bayesian Structural VAR." *International Review of Economics & Finance* 93 (March): 789–810. https://doi.org/10.1016/j.iref.2024.03.054.

Uhlig, Harald. 2005. "What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure." *Journal of Monetary Economics* 52 (2): 381–419. https://doi.org/10.1016/j.jmoneco.2004.05.007.

APPENDIX A

VISUALIZATIONS OF NATURAL GAS IMPORTS TO UKRAINE

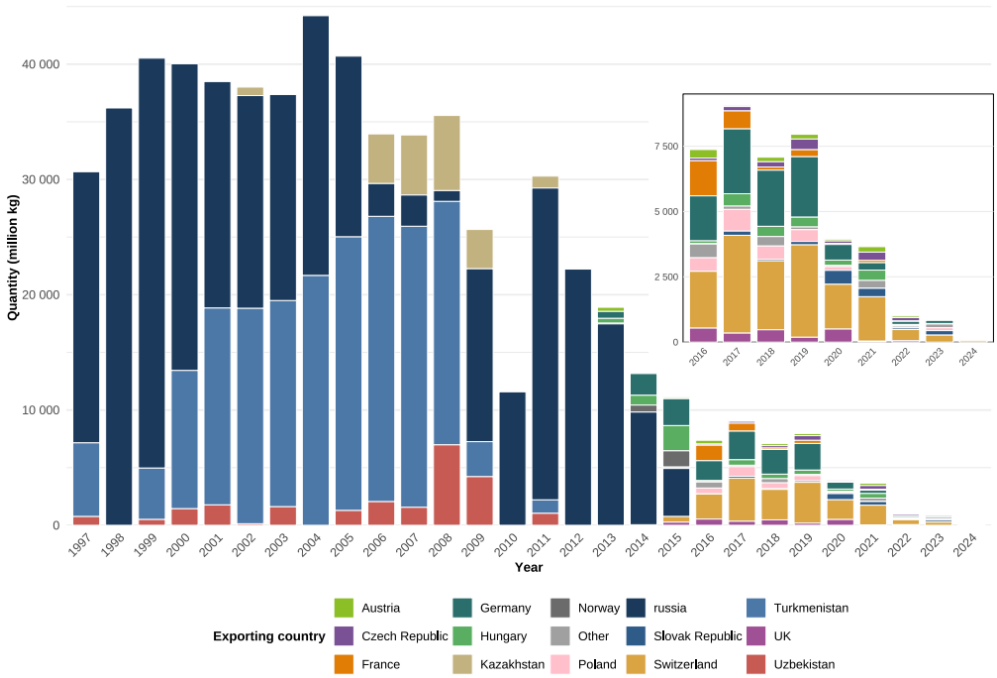


Figure 15. Ukraine's natural gas imports by supplying market, 1997–2024

Note: Natural gas refers to natural gas in gaseous state (HS-6: 271121).

Source: own visualization based on trade data from the World Integrated Trade Solution (WITS)

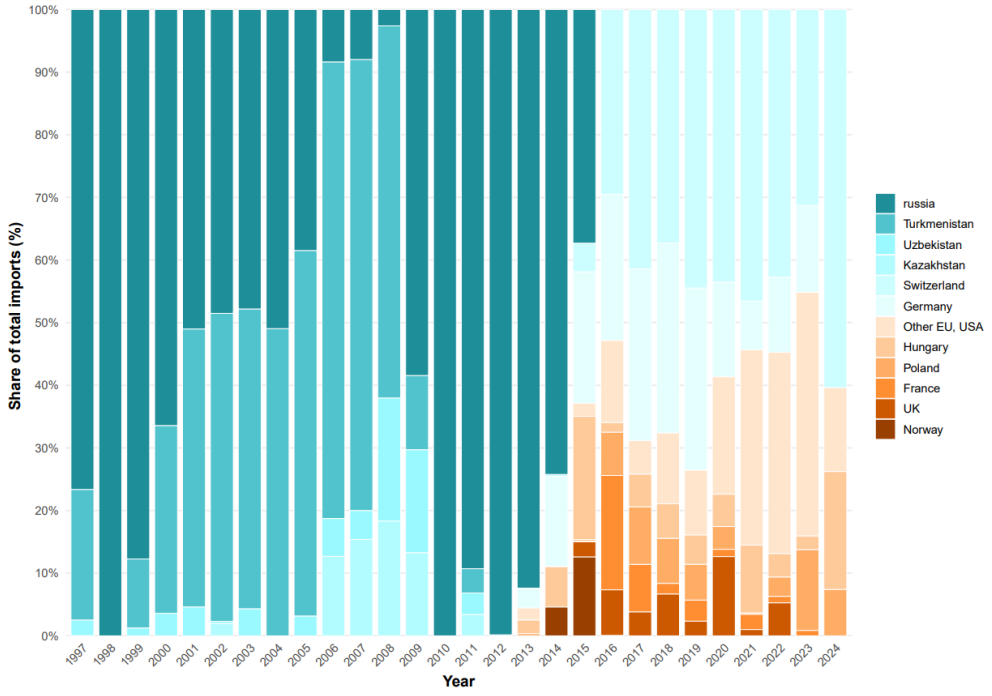


Figure 16. Ukraine's natural gas import structure by supplier, 1997–2024

Note: Natural gas refers to natural gas in gaseous state (HS-6: 271121). Shares are based on import quantities.

Source: own calculations and visualization based on trade data from the World Integrated Trade Solution (WITS)

APPENDIX B

DATA EXPLORATION

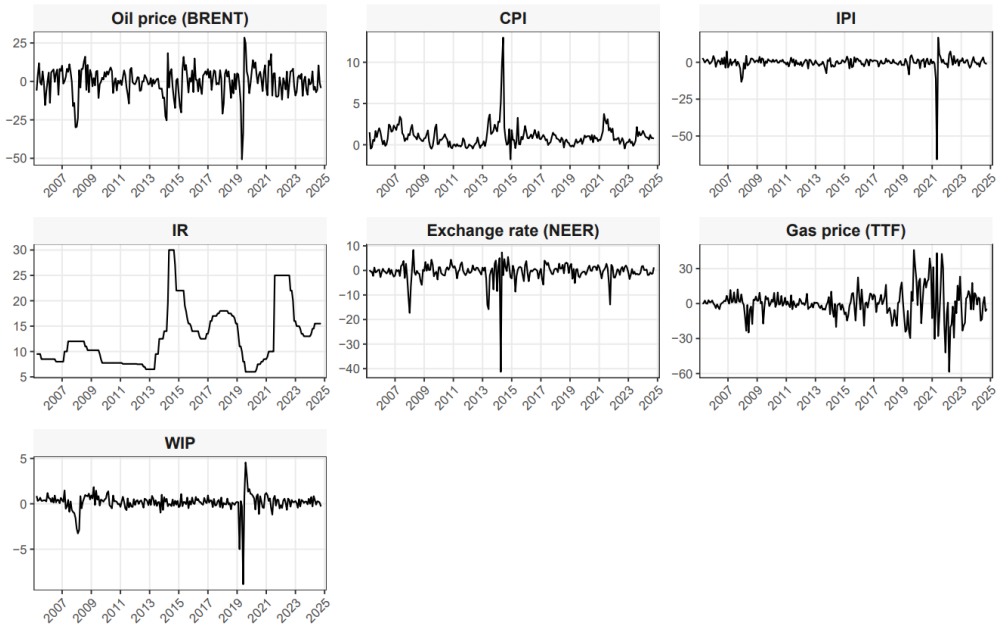


Figure 17. The developments in main variables

Note: sample: 2006m2 – 2025m8. For the variables' definitions and applied transformations, see Table 1.

Table 9. Descriptive statistics for the extended sample

Variable	Obs.	Mean	Std. Dev	Min	Max
Domestic inflation rate (CPI)	236	206	130	52	502
Heating CPI subindex (Heating)	236	363	279	25	711
Electricity CPI subindex (Electricity)	236	358	298	64	1004
Natural gas CPI subindex (NGAS)	236	607	537	24	1394
Domestic economic activity (IPI)	236	106	23	47	151
Exchange rate (NEER)	236	0.53	0.24	0.26	1.1
Interest rate (IR)	236	13	5.8	6	30
Global oil price (BRENT)	236	0.32	0.11	0.091	0.61
Global gas price (TTF)	236	0.043	0.029	0.006	0.24
Global economic activity (WIP)	236	125	13	100	150
COVID dummy	236	0.068	0.25	0	1
WAR dummy	236	0.18	0.39	0	1

Note: untransformed (raw) data; based on full sample: 2006m1 – 2025m8.

Table 10. Correlation matrix of continuous variables

Variable	Domestic inflation rate (CPI)	Domestic economic activity (IPI)	Exchange rate (NEER)	Interest rate (IR)	Global oil price (BRENT)	Global gas price (TTF)	Import price (IMPORT)	Global economic activity (WIP)
Domestic inflation rate (CPI)	1							
Domestic economic activity (IPI)	-0.85***	1						
Exchange rate (NEER)	-0.74***	0.67***	1					
Interest rate (IR)	0.22***	-0.45***	-0.43***	1				
Global oil price (BRENT)	-0.37***	0.27***	0.74***	-0.26***	1			
Global gas price (TTF)	0.22***	-0.40***	0.05	0.13	0.41***	1		
Import price (IMPORT)	0.20**	-0.30***	0.08	0.08	0.41***	0.73***	1	
Global economic activity (WIP)	0.95***	-0.80***	-0.69***	0.20**	-0.22***	0.31***	0.30***	1

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Sample: Jan 2013 – Aug 2025.

APPENDIX C

CONSTRUCTION OF THE NATURAL GAS IMPORT PRICE SERIES

This appendix describes the procedure regarding the construction of a monthly series of Ukraine's average import price of natural gas. This derived series is used as a proxy of gas price for robustness checks.

The underlying monthly data on trade flows of natural gas imports to Ukraine was sourced from the International Trade Center (ITC) and the State Statistics Service of Ukraine (SSSU). The data is disaggregated by exporting partner and contains two key indicators: 1) trade value in (thousand USD); 2) physical quantity (in kilograms). To construct the series of average natural gas import price for Ukraine I perform the following steps:

1. Constructing an implicit import price for each partner country i in month t. Formally, it can be defined as unit value:

$$P_{i,t} = \frac{V_{i,t}}{Q_{i,t}} \tag{22}$$

where $V_{i,t}$ denotes import value and $Q_{i,t}$ represents import quantity.

2. The relative importance of each supplying country was captured through quantity-based weights:

$$w_{i,t} = \frac{Q_{i,t}}{\sum_j Q_{j,t}} \tag{23}$$

where the denominator denotes total imports across all European partner countries in month t.

3. A single monthly import price for Ukraine was constructed as a weighted average of partner-specific prices:

$$P_t = \sum_i w_{i,t} \times P_{i,t} \quad (24)$$

The resulting monthly series contains four missing observations which correspond to months with no recorded imports of natural gas to Ukraine. Therefore, 3 alternative imputation methods were considered to reconstruct the series:

1. Linear interpolation
2. Kalman filter with a structural time series model
3. Kalman filter based on an ARIMA model

To determine the most appropriate imputation method I conducted an out-of-sample validation where a subset of observed datapoints was randomly removed from the data and treated as artificially missing. Then, I applied each imputation method to reconstruct missing values. Model performance was evaluated using two standard accuracy metrics: root mean squared error (RMSE) and mean absolute error (MAE). Results are summarized in Table 11 and show that all the methods perform relatively closely, suggesting that all considered approaches capture the dynamics of import price series well. I select Kalman filter based on a structural time series as the baseline to reconstruct missing observations since it treats the observed series as a stochastic process with latent components (e.g. trend and level).

Table 11. Performance comparison of selected imputation methods based on RMSE and MAE

Method	RMSE	MAE
Linear	0.1594	0.0770
Kalman StructTS	0.1567	0.0788
Kalman Arima	0.1567	0.0788

Figure 18 demonstrates the reconstructed series of average natural gas import price for Ukraine and how it compares to the European natural gas price at the Dutch TTF hub as well as gas price for households in Ukraine.

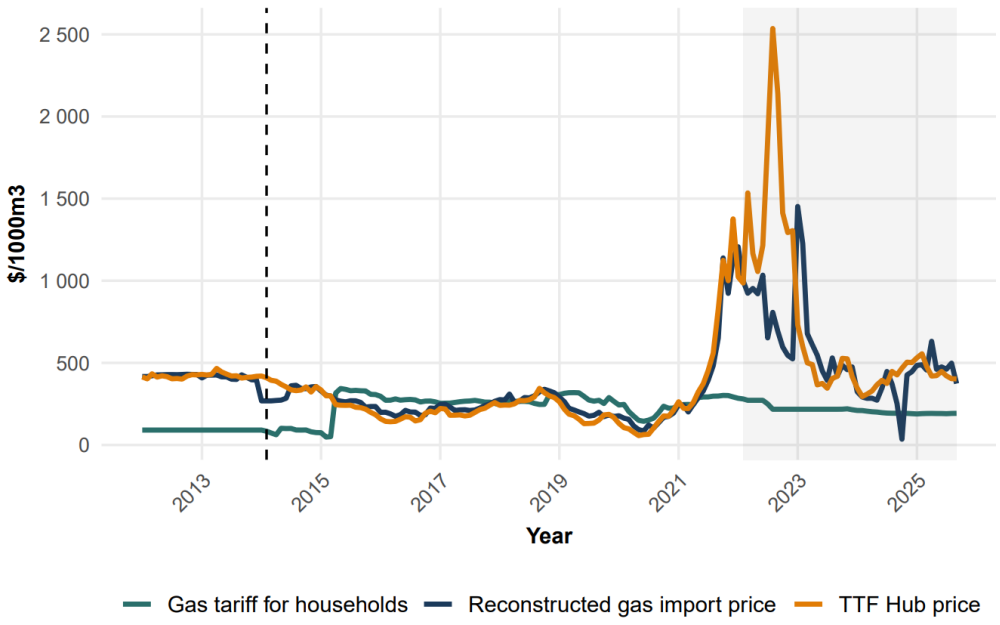


Figure 18. Monthly dynamics of natural gas price series, 2012–2025

Note: Black dashed line reflects the russian invasion in Crimea in 2014. Grey shaded are represents the period of full-scale russian invasion in Ukraine. The data on gas tariff for households is sourced from Minfin.com.ua.

APPENDIX D

MONTHLY ESTIMATES

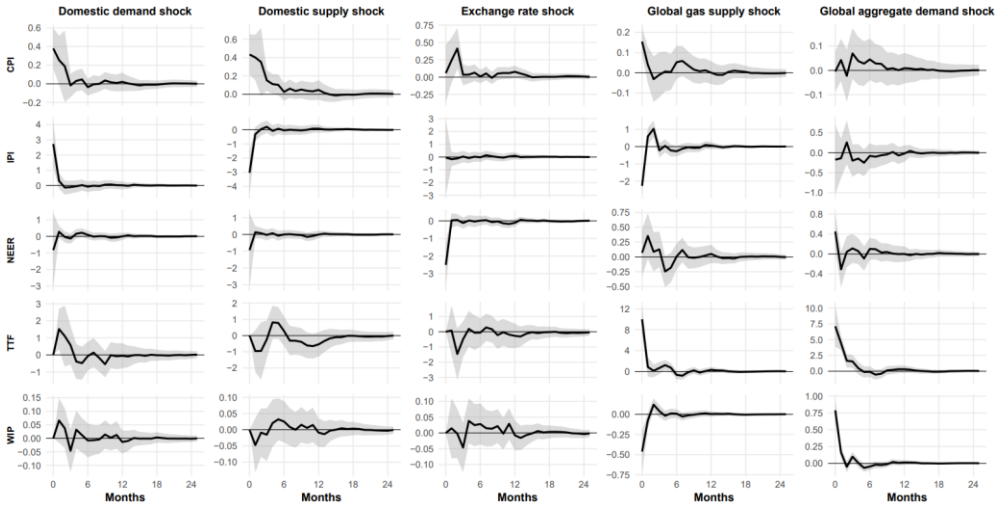


Figure 19. Resulting IRFs for baseline BSVAR: month-on-month estimates

Note: The figure shows impulse responses from the estimated posterior distribution. Model is identified with the combination of sing and zero restrictions (see Table 3 for details on identification strategy). Columns represent shocks and rows denote the response variables. All results are measured in percentage points (pp). The shocks are normalized to represent the magnitude of one standard deviation. The black solid lines indicate the median of impulse responses. Grey shaded areas (ribbons) correspond to the 68% probability bands.

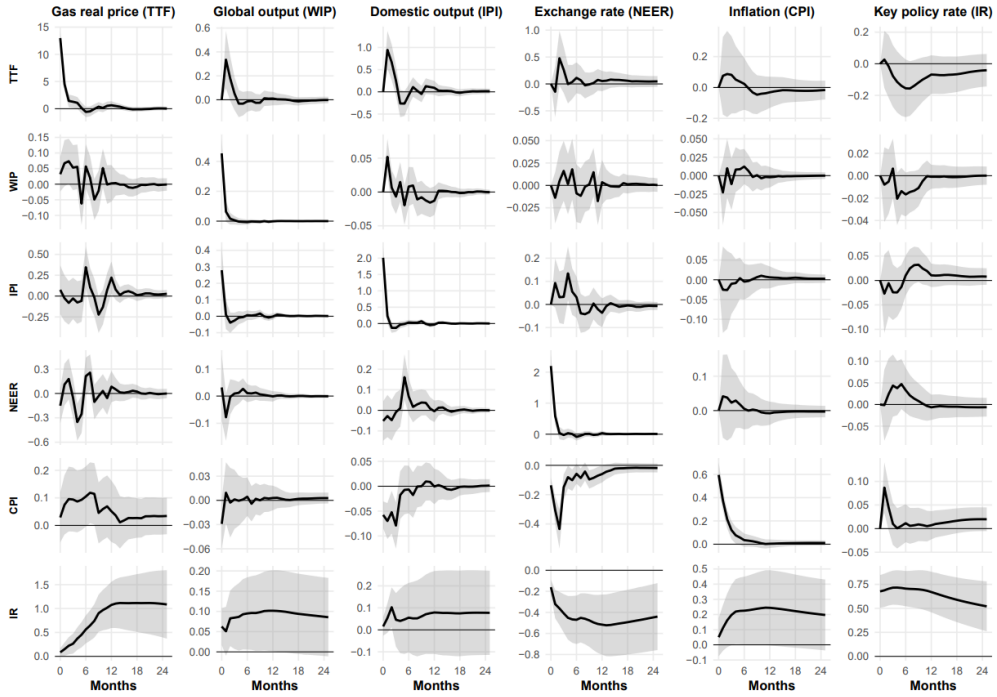


Figure 20. Resulting IRFs for BSVAR with stochastic volatility (SV): month-on-month estimates

Note: The figure shows impulse responses from the estimated posterior distribution. Model is identified with lower triangular factorization (6 variables, 12 lags). Columns represent shocks and rows denote the response variables. All results are measured in percentage points (pp). The shocks are normalized to represent the magnitude of one standard deviation. The black solid lines indicate the median of impulse responses. Grey shaded areas (ribbons) correspond to the 68% probability bands.

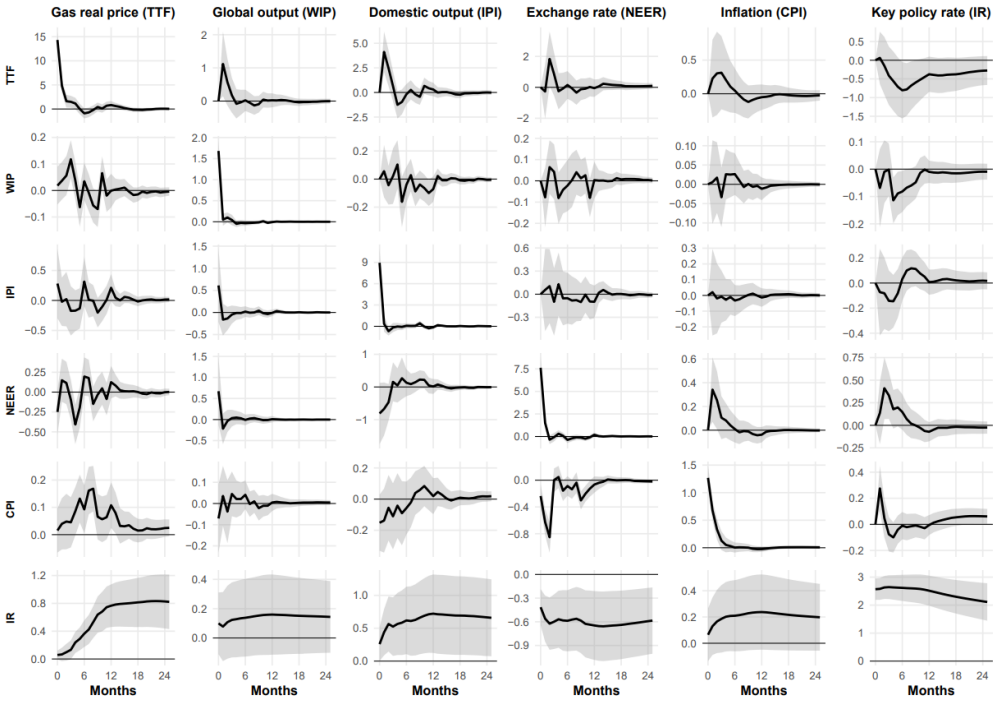


Figure 21. Resulting IRFs for BSVAR with Markov-switching heteroskedasticity (MSH): month-on-month estimates

Note: The figure shows impulse responses from the estimated posterior distribution. Model is identified with lower triangular factorization (6 variables, 12 lags). Columns represent shocks and rows denote the response variables. All results are measured in percentage points (pp). The shocks are normalized to represent the magnitude of one standard deviation. The black solid lines indicate the median of impulse responses. Grey shaded areas (ribbons) correspond to the 68% probability bands.

Table 12. Results of Savage-Dickey density ratio test for Markov-switching heteroskedasticity model

Shocks	log(SDDR)	NSE	Pr[H0|data]	Pr[H1|data]
TTF shock	0.674	0.191	0.662	0.338
WIP shock	-74.944	4.789	0.000	1.000
IPI shock	-125.175	4.532	0.000	1.000
NEER shock	-84.146	5.911	0.000	1.000
CPI shock	-19.251	7.952	0.000	1.000
IR shock	-79.065	13.297	0.000	1.000

Note: log(SDDR) denotes the logarithm of Bayes factor. NSE stands for numerical standard errors. Pr[H0|data] and Pr[H1|data] are the implied posterior probabilities of the homoskedasticity and heteroskedasticity hypotheses respectively.

APPENDIX E

OUTCOMES OF THE ROBUSTNESS CHECKS

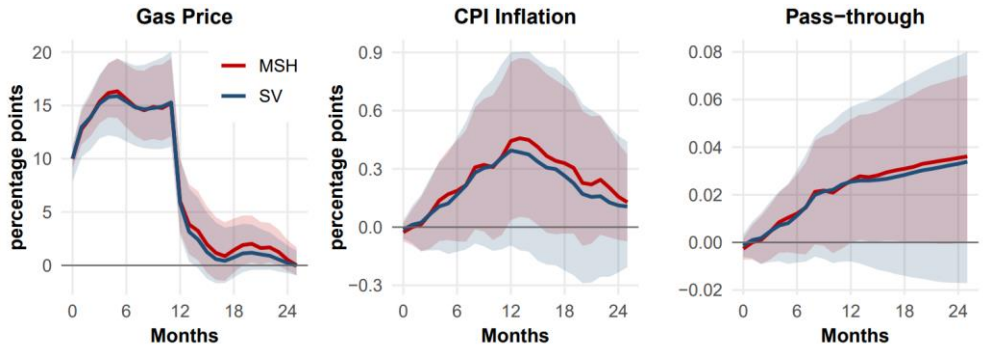


Figure 22. Gas price pass-through to Ukrainian consumer inflation: results for an extended sample (Jan 2006-Aug 2025)

Note: The figure demonstrates structural impulse response functions (IRFs) to a 10% increase in the price of natural gas price (TTF hub). The CPI response is a flow (annualized inflation at a given month), while pass-through (right-hand side panel) is a cumulative stock (total price-level effect relative to the size of the shock). Solid blue and red lines indicate median responses. Shaded areas (ribbons) correspond to the 68% probability bands.

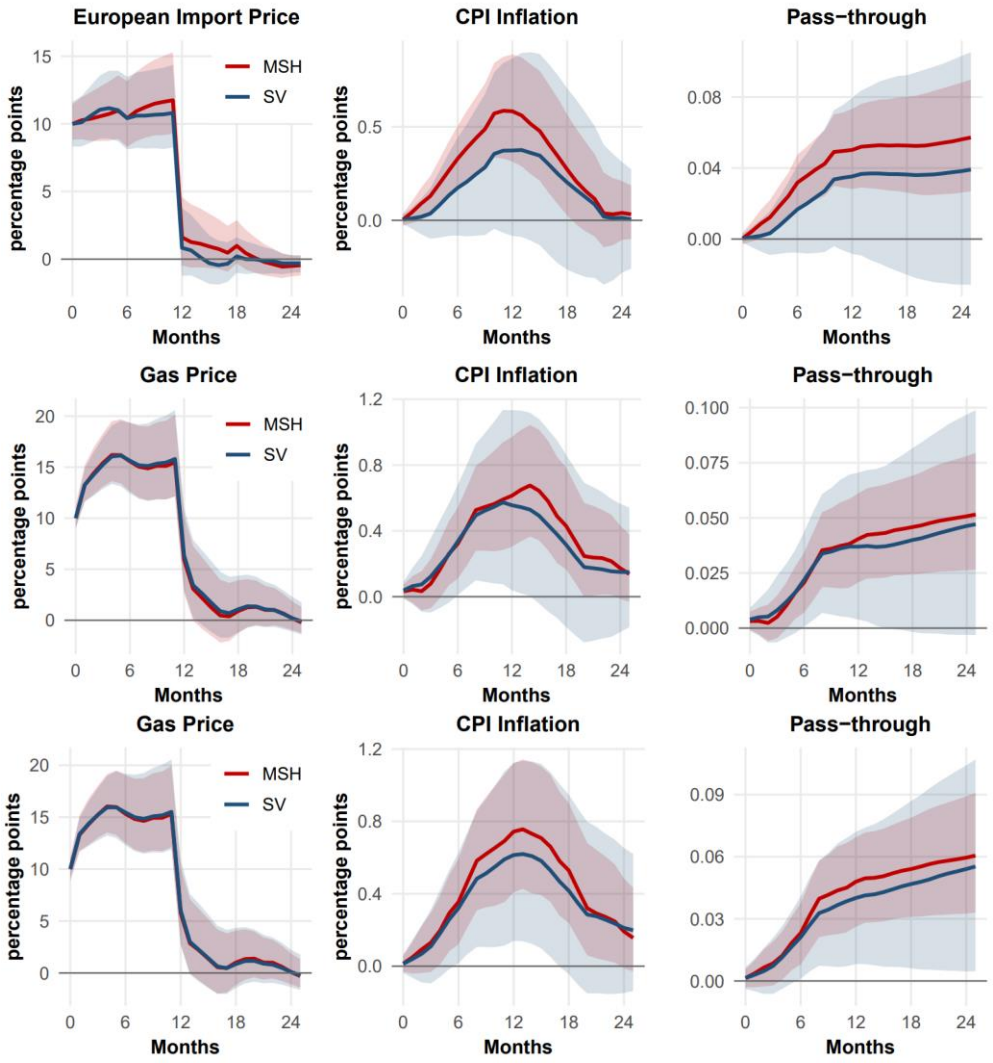


Figure 23. Gas price pass-through to Ukrainian consumer inflation: robustness checks for heteroskedastic models

Note: (a) upper panel uses developed import price series as a proxy for gas price; (b) middle panel presents the results of alternative ordering: $WIP \rightarrow TTF \rightarrow IPI \rightarrow NEER \rightarrow CPI \rightarrow IR.$; (c) bottom panel presents the results of alternative ordering: $TTF \rightarrow WIP \rightarrow IPI \rightarrow CPI \rightarrow NEER \rightarrow IR$. The figure demonstrates structural impulse response functions (IRFs) to a 10% increase in the price of natural gas price (TTF hub). The CPI response is a flow (annualized inflation at a given month), while pass-through (right-hand side panel) is a cumulative stock (total price-level effect relative to the size of the shock). Solid blue and red lines indicate median responses. Shaded areas (ribbons) correspond to the 68% probability bands. Sample: January 2013 to August 2025.

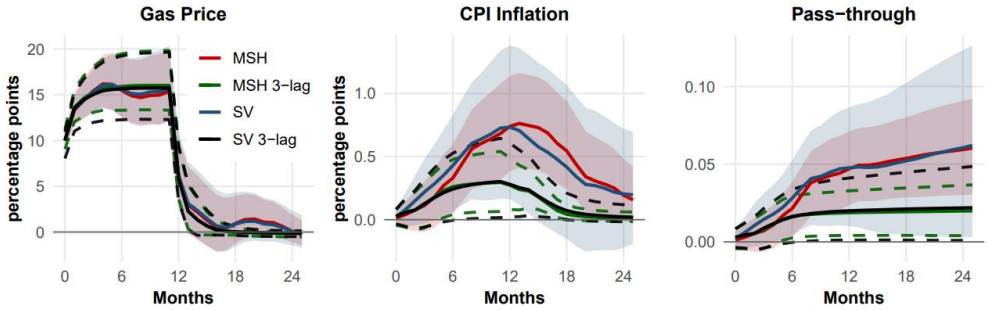


Figure 24. Gas price pass-through to Ukrainian consumer inflation: comparison to models with alternative number of lags

Note: The figure demonstrates structural impulse response functions (IRFs) to a 10% increase in the price of natural gas price (TTF hub). The CPI response is a flow (annualized inflation at a given month), while pass-through (right-hand side panel) is a cumulative stock (total price-level effect relative to the size of the shock). Solid lines indicate median responses. Shaded areas (ribbons) and dashed lines correspond to the 68% probability bands. Sample: January 2013 to August 2025.