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Tracing the Inflationary Effects of Energy Price Shocks in the EU

Evidence from a Structural VAR Approach

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Abstract
Recent geopolitical and structural developments have triggered a period of heightened volatility in European energy markets, with important implications for inflation dynamics. This thesis investigates how shocks to key energy prices – crude oil, natural gas, coal, diesel, gasoline, and electricity – affect both headline and core inflation in the European Union. Using a structural vector autoregression (SVAR) framework, we apply a hybrid identification strategy combining recursive ordering and heteroskedasticity-based methods to identify causal effects. In line with previous literature, we find that the overall pass-through to both headline and core inflation is relatively modest. However, substantial heterogeneity emerges across energy types and between headline and core measures of inflation. Our approach allows us to distinguish global demand-driven price movements from energy-specific cost shocks and offers a more granular understanding of inflation dynamics. The findings underscore the importance of disaggregating energy prices in inflation analysis and highlight the need for differentiated policy responses depending on the source of energy shocks.

Keywords: Energy price shocks, Inflation dynamics, Structural VAR, Pass-through, European Union
JEL codes: E31, Q43, C32

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1 Introduction

Recent global events have exposed the vulnerability of global and regional energy markets, and have reignited concerns about inflation dynamics. The Covid-19 pandemic disrupted energy supply chains and temporarily shifted demand patterns. This was followed by Russia's full-scale invasion of Ukraine in 2022, which triggered a severe energy crisis in Europe due to the region's reliance on Russian-imported natural gas (Eurostat 2023a). At the same time, the EU has been, and is still trying, to accelerate its green transition, aiming to reduce fossil fuel dependence while maintaining price stability and energy security. These recent developments have underscored the need to better understand how energy price shocks influence inflation.

This question is particularly relevant in the EU, where the contribution of the energy sector to inflation increased markedly after the Covid-19 pandemic (Yakut 2023). Volatile energy prices have supposedly been a key driver of headline inflation, being one of the key component of the Consumer Price Index, but they may also affect core inflation indirectly, as higher production and transportation costs are passed through to the price of other goods and services (European Central Bank 2024). Understanding these direct and indirect channels is essential for monetary policy, fiscal planning, and the design of long-term energy strategies.

More recently, energy costs have also become central in debates about Europe's long-term competitiveness. The Draghi report (Draghi 2024) published in late 2024 highlights how structurally higher energy prices in the EU, compared to the U.S. and China, pose a persistent challenge for households and industry. These concerns are magnified by rising geopolitical tensions. A return to protectionist trade policies under the new Trump administration could lead to new tariffs on energy-related goods, further increasing price volatility and disrupting global supply chains (New York Post 2025). In this environment, where energy markets are shaped by both structural and geopolitical factors, understanding how energy prices feed into inflation is not just timely — it is essential for informed policy.

In this thesis, we investigate how shocks to key energy prices – including crude oil, natural gas, diesel, gasoline, heating gas oil, coal, and electricity – affect headline and core inflation in the European Union. We estimate a structural vector autoregression (SVAR) model using a hybrid identification strategy that combines recursive ordering with heteroskedasticity-based methods, tailored to the structure of European energy markets. Building on the methodology developed by Kilian & Zhou (2022), we apply this approach to the EU context to explore how energy price shocks propagate through the economy and affect consumer prices.

Our findings suggest that the overall pass-through from energy price shocks to inflation is relatively modest. However, substantial heterogeneity emerges across energy types and between headline and core inflation measures. For instance, shocks to gasoline and natural gas tend to generate more persistent inflationary responses, while electricity shocks appear largely transitory. These results provide a more nuanced understanding of inflation dynamics and emphasize the importance of disaggregating energy sources in empirical analyses.

Thus, we contribute to the literature by applying a novel hybrid SVAR identification strategy to trace the inflationary effects of a broad set of energy shocks in the EU, providing new evidence on their differential impact in the EU context.

1.1 Research question

To what extent do different types of energy price shocks drive inflation in the EU, through both direct effects on headline inflation and indirect pass-through to core inflation?

1.2 Outline

The remainder of this thesis is structured as follows: Section 2 reviews relevant literature, Section 3 provides background on the EU energy mix, Section 4 describes the data, Section 5 outlines the methodology including the SVAR model and identification strategy, Section 6 presents results, Section 7 discusses limitations, and Section 8 concludes with policy recommendations. Appendices A–F provide formal test results, detail specific methodological procedures, describe the use of AI during the research process, and provide additional impulse response functions.

2 Literature Review

2.1 Understanding pass-through

Energy price shocks can influence inflation through both direct and indirect channels. The direct channel refers to the immediate impact on the prices of goods and services that include energy inputs, such as household heating or transportation fuel – this effect is captured in headline inflation. The indirect channel reflects how higher energy costs transmit through production chains and industries, increasing costs for goods and services that are not directly energy-related. This latter effect unfolds over time and is typically measured through core inflation, which excludes volatile components like energy (and sometimes food) (Neri et al. 2023).

To analyze these dynamics more precisely, Conflitti & Luciani (2019) distinguish between two mechanisms of transmission from an oil price shock: a common macroeconomic component and an idiosyncratic component. While this division overlaps with the direct/indirect distinction, it highlights different aspects of the underlying pass-through process. The common component represents broad, economy-wide effects – for instance, an energy shock that reduces real incomes may in turn lower aggregate demand, and one that raises production costs may increase prices across many sectors. These widespread pressures typically manifest in core inflation and develop more slowly as firms adjust prices and wages. The idiosyncratic component, by contrast, captures more localized effects of energy shocks on specific product categories (such as a spike in gasoline or heating oil prices) that are not representative of the entire economy. These category-specific impacts tend to be absorbed more quickly and appear in headline inflation.

Understanding this distinction is essential for policy makers. Central banks may be less concerned with idiosyncratic and transitory spikes in headline inflation, but more alert to persistent increases in the common component that signal broader inflationary pressure or unanchored inflation expectations. The insight from Conflitti & Luciani (2019) underscores why distinguishing the nature of an energy shock's impact (broad-based vs. item-specific) is crucial when formulating an appropriate policy response.

2.2 Empirical evidence

US and global evidence

Empirical research in the United States and other advanced economies has examined how energy price shocks transmit into inflation, often finding that the aggregate effects can be moderate due to offsetting factors. Gao, Kim & Saba (2014), for instance, investigate the pass-through of oil price shocks to different components of the US Consumer Price Index (CPI). Using a bivariate VAR on monthly data from 1974 to 2014, they disaggregate the CPI into energy-intensive vs. non-energy-intensive categories to analyze each segment's response to an oil shock.

Their findings reveal that inflationary effects of oil shocks are uneven across consumption categories: significant and persistent price responses are found only for energy-intensive components (such as transportation and household energy), whereas categories like food, apparel, and medical care show minimal or statistically insignificant reactions. The authors interpret this pattern through the lens of consumption reallocation. When oil prices rise and energy expenditures (e.g. for heating or fuel) remain inelastic due to their essential nature, households are forced to reduce spending on other goods and services. In other words, a larger share of the household budget goes to energy-related needs, while non-energy purchases are cut back or deferred, resulting in this offsetting effect on the aggregate. This demand reduction in non-energy sectors dampens price pressures, resulting in smaller inflation responses outside of energy-intensive goods.

In sum, although the overall CPI was found to exhibit a statistically significant increase following an oil price shock, the magnitude of the aggregate effect remains modest. The muted impact is driven by the fact that only certain categories (primarily those directly related to energy) experience large price changes, while others see offsetting declines in demand.

More recent work has emphasized that focusing on a single energy product can understate the total inflationary impact of energy shocks. Kilian & Zhou (2022) question earlier research that often examined only oil or gasoline prices in relation to inflation. They argue that it is crucial to account for the heterogeneity among energy sources: changes in refined product prices (such as gasoline, diesel, or jet fuel) do not necessarily mirror changes in crude oil prices, and not all energy types are oil-based.

To address these complexities, Kilian & Zhou (2022) employ a block recursive structural VAR model on US data from 1995 to 2022, allowing for multiple different energy price shocks. They incorporate not just gasoline but also diesel, jet fuel, natural gas, and electricity into their analysis of inflationary responses. This broader approach reveals that concentrating solely on gasoline underestimates the overall impact of energy price movements on inflation.

Kilian & Zhou (2022)'s results show that in the US context, an unexpected increase in gasoline prices does have a relatively large impact on both headline and core inflation compared to shocks in natural gas, diesel, jet fuel, or electricity. However, even these impacts are mostly temporary. The cumulative effect of a shock to any single energy component remains limited: energy price spikes tend to cause short-lived fluctuations in the inflation rate rather than sustained inflationary pressure. In other words, energy shocks on their own did not lead to persistently higher inflation in their analysis — a finding consistent with Gao, Kim & Saba (2014)'s observation that broader economic adjustments, such as shifts in household consumption or firm pricing behavior, temper the long-term effects on inflation.

Taken together, the US evidence suggests that examining a wide set of energy prices is important to capture the full inflationary impact of energy shocks. This is particularly relevant when considering the EU, where the energy mix is diverse and the dominant sources of energy differ from those in the US (for example, natural gas plays a larger role in Europe's energy costs). It is therefore crucial to move beyond a narrow focus on a single fuel when assessing inflationary risks. In addition, in an era of energy transition, and as electricity consumption increases (for instance, through the adoption of electric vehicles) the role of electricity in transmitting energy shocks to inflation is likely to grow, while the relative impact of gasoline prices may diminish (Kilian & Zhou 2022).

European evidence

In the European context, a number of recent studies have explored the inflationary effects of energy price shocks, especially in light of the pronounced energy price surges since 2021. Corsello & Tagliabracci (2023) analyze the pass-through of energy prices to inflation in the euro area during the period of sharply rising energy costs from mid-2021 onward. Using a standard VAR framework, they focus on how changes in the overall energy component of the Harmonized Index of Consumer Prices (HICP) feed into both headline and core inflation.

Notably, unlike Kilian & Zhou (2022) who disaggregate energy into multiple sub-components, Corsello & Tagliabracci (2023) treat energy as a single aggregate category. They also compare results across the four largest euro area economies (Germany, France, Italy, and Spain) to examine potential cross-country differences in this pass-through.

Their findings indicate that energy prices have exerted relatively small but statistically significant indirect spillover effects on core and food inflation. In normal times, the pass-through from energy to core inflation has been quite low in the euro area, but during the exceptional energy surge of 2021–2022, this indirect effect became more visible. Corsello & Tagliabracci (2023) estimate that, both through direct contributions to headline inflation and indirect effects on other components, energy price increases accounted for roughly 60 percent of headline inflation in the first nine months of 2022.

The magnitude of the impact differed by country, reflecting each economy's unique energy mix and government interventions (such as price caps or subsidies) to mitigate the shock. They caution that the lingering effects of recent energy shocks, combined with the gradual adjustment of core prices (and food prices) to higher energy costs, could prolong inflationary pressures beyond the initial shock. Given that monetary policy has limited influence over energy supply shocks, the analysis underscores the importance of monitoring indirect pass-through channels when assessing the inflationary impact of energy prices, with close attention to inflation expectations and wage dynamics to avoid second-round effects.

Earlier euro area research had already noted the limited but persistent influence of energy (especially oil) on core inflation. Building on the conceptual distinction discussed above, Conflitti & Luciani (2019) focus specifically on how oil price fluctuations affect euro area core inflation through the two channels (common vs. idiosyncratic) identified in their framework. Using a structural dynamic factor model for the period 1996–2016, they find that oil price changes influence core inflation exclusively via the broader macroeconomic channel, with essentially no direct idiosyncratic contribution from energy-specific price movements.

The effect on core inflation, while persistent, is relatively small in magnitude. For example, the steep drop in oil prices between mid-2014 and early 2016 is estimated to have lowered euro area core inflation by only a few tenths of a percentage point. Overall, Conflitti & Luciani (2019) conclude that the impact of oil price swings on underlying inflation is long-lasting yet modest, driven primarily by economy-wide factors rather than direct energy price pass-through into core non-energy items.

A complementary perspective is offered by Markowski & Kotliński (2023), who examine how energy shocks have contributed to divergent inflation trajectories across EU countries. This study underscores the role of cross-country heterogeneity: differences in national energy mixes (e.g., reliance on gas vs. oil), as well as varying fiscal responses to energy shocks, have led to some countries experiencing higher inflationary effects from energy than others.

While insightful, this cross-country angle is not the focus of our research. As we work with EU-wide aggregates, we do not attempt to capture country-level variation. We acknowledge that national factors matter significantly — indeed, Markowski & Kotliński (2023)'s findings suggest policy responses need to be tailored to country-specific circumstances — but we leave a detailed country-by-country analysis for future research. Accordingly, our analysis will concentrate on EU-wide inflation dynamics, treating the EU as a whole.

At the same time, this research underscores the importance of recognizing the distinct structure of the EU energy market, particularly in contrast to contexts such as the US. We therefore place particular emphasis on analyzing how the composition and characteristics of the EU energy mix shape inflationary transmission mechanisms.

It is worth noting that most of the euro area studies above consider energy as a single aggregate commodity (or focus only on oil), rather than distinguishing the effects of different types of energy shocks. In Corsello & Tagliabracci (2023), for example, the entire energy HICP is aggregated, and in Conflitti & Luciani (2019) the emphasis is on oil price changes. This points to a gap in the literature: the potentially distinct inflationary impacts of various energy sources (oil, natural gas, electricity, etc.) in the EU remain under-examined. Our study seeks to fill this gap by analyzing disaggregated energy price shocks within a unified framework for the EU.

2.3 Econometric approaches to identification

Apart from these empirical findings, the literature also varies in how it identifies energy price shocks in econometric models. Different identification strategies can lead to different conclusions about the impact of those shocks. We briefly review the main approaches used in the existing literature to set the stage for our own identification strategy.

Recursive identification

Many studies employ a recursive (Cholesky) identification in VAR models to estimate the dynamic effects of structural shocks. This approach, used for example by Corsello & Tagliabracci (2023) and Conflitti & Luciani (2019), imposes an ordering of variables such that those ordered first affect those coming later contemporaneously, but not vice versa. By assuming a particular causal ordering (often informed by economic theory), one can disentangle the specific impact of an energy price shock separate from other shocks. Recursive identification remains widespread in applied macroeconometrics due to its simplicity, transparency, and modest data requirements (Kilian & Zhou 2022). However, its validity depends on choosing a credible ordering in the context of energy and inflation, which is why we in the next section present a qualitative overview of the use of different energy sources in the EU.

Heteroskedasticity-based identification

Another strand of research exploits changes in volatility to achieve identification. Rigobon (2003) proposes that when the variances of underlying structural shocks shift between distinct regimes (for instance, calm vs. turbulent periods in energy markets), these natural experiments can be used to identify structural parameters without relying solely on other identification strategies such as imposing zero restrictions on contemporaneous relationships. The key intuition and assumption is that structural shocks affect observed variables with stable coefficients, so if the relative variance of one shock increases in a certain regime, the co-movement of variables in that regime will reveal which shock is driving them.

By comparing the covariance of residuals across high-volatility and low-volatility periods, one can recover information about the underlying structural impact matrix. This approach, known as identification through heteroskedasticity, uses statistical properties of the data rather than strong a priori assumptions. In the context of energy prices, one might leverage episodes of extreme energy market volatility (such as the 2021–2022 surge) to help identify the impact of energy shocks more cleanly.

Rigobon (2003) also notes that heteroskedasticity-based identification can be used alongside other strategies, such as recursive ordering. While recursive structures impose a specific causal ordering of shocks, variance shifts across regimes can provide testable implications that help assess whether such an ordering is consistent with the data. This is particularly relevant in models with many variables but few observable regimes, where combining theoretical assumptions with data-driven evidence can strengthen identification.

In our analysis, we thus draw inspiration from both the recursive identification commonly used in the literature and the heteroskedasticity-based approach. Details regarding our implementation of this hybrid identification strategy are provided in section 5.2.

2.4 Our contribution

We contribute to the literature in two main ways. First, we bring the disaggregated energy price approach of Kilian & Zhou (2022) into the EU context, applying it to European inflation where the energy mix and market structures differ substantially from those in the US. We thus extend prior euro area studies by explicitly modeling the effects of several energy components – rather than treating energy as a single aggregate index. This allows us to assess the heterogeneous impact of different energy shocks on inflation.

Second, we construct a hybrid identification strategy that combines recursive ordering with heteroskedasticity-based identification. This over-identified framework enables us to test the plausibility of our identifying assumptions and more reliably estimate the causal effect of energy price shocks on headline and core inflation.

In summary, our study builds directly on the insights of previous research and seeks to fill the gaps in it. By incorporating a broader set of energy prices and a novel identification approach, we provide a more comprehensive understanding of how energy price shocks propagate through the European economy and affect inflation. This contribution not only bridges the US-EU context divide, but also offers policymakers in Europe fresh evidence on the nuanced roles of different energy sources in driving inflation dynamics.

3 The EU Energy Mix

Understanding the composition and usage of different energy sources is essential to our analysis of how energy price shocks transmit through the European economy. The EU has a diverse energy mix that reflects both differences in infrastructure and evolving policy priorities aimed at achieving climate neutrality. Fossil fuels, particularly natural gas, refined petroleum products and coal, continue to play a significant role in meeting energy demand within the EU, despite the growing importance of renewables. Each of these sources enters the economy through distinct channels, serves different end-use sectors and is priced through separate markets. This leads to heterogeneous effects on production costs, consumer prices and thus inflation dynamics. This section reviews the structure and economic dynamics of the main energy sources in the EU, focusing on natural gas, crude oil (as well as refined oil products), coal, and electricity.

Natural gas is extracted often alongside oil, and is usually converted into liquefied natural gas (LNG) to enable transportation over long distances. Upon arrival, it is turned back into gas and fed into the national systems. In the EU, natural gas is used by consumers and firms both directly and indirectly. Approximately two-thirds of the total gas consumption is for direct use, primarily by households for heating and cooking, and by industry for energy-intensive processes such as the production of fertilizers, steel, and chemicals (Eurostat 2024a). The remaining one-third is used indirectly, mostly for electricity generation in gas-fired power plants and for central district heating. In 2022, around 22 percent of the electricity produced in the EU originated from natural gas, making it a significant, although not dominant, component of the electricity mix (Eurostat 2022). Domestic production of natural gas has steadily declined over the years, and by 2023, net imports accounted for as much as 88 percent. This dependence on imported natural gas creates vulnerability, which became especially evident after the Russian invasion of Ukraine. In response, the EU launched the REPowerEU Plan to diversify its energy supply and accelerate the transition to cleaner energy sources

(Eurostat 2024b).

Crude oil, in contrast, is extracted and transported to refineries where it is processed into a wide range of refined petroleum products. These include diesel fuel, motor gasoline (typically corresponding to Euro 95 in European markets), and heating gas oil, among others such as lubricants, asphalt, and petrochemical feedstocks such as ethane and propane. These refined products serve different end-uses: diesel is predominantly used in freight transport, private vehicles (although on the decline in Europe), and off-road machinery; motor gasoline is largely consumed in passenger cars; and heating oil continues to be used in residential heating, particularly in colder regions. In terms of output volume, diesel and gasoil together accounted for almost 49 percent of the EU's petroleum product output in 2022, while motor gasoline represented about 22 percent (Eurostat 2023b). These shares underscore the continued importance of diesel fuel in the EU context, where the vehicle fleet and freight sector remain more diesel-oriented than in other parts of the world. The overall oil supply in the EU has followed a slightly downward trend for many years, with an uptick observed in 2022 following the pandemic. To meet growing oil demand, the EU has been compensating with imports, while domestic production continues to decline steadily over time (Eurostat 2024b).

Coal, while declining in prominence due to environmental concerns and climate policy targets, is still used in the EU – primarily for electricity generation. As of 2021, around 60 percent of coal consumption in the EU was dedicated to power generation (International Energy Agency 2021) and it made up 12 percent of the EU electricity mix during 2023 (Ember 2024). Additional uses include industrial applications, notably in steel production where "coking coal" remains essential, as well as a limited role in district heating systems. Among fossil fuels, coal is the most carbon-intensive. When used for electricity generation, coal emits roughly twice as much carbon dioxide per unit of electricity produced compared to natural gas (International Energy Agency 2022). Due to coal's high emissions intensity, reducing its use has become a central priority in decarbonization strategies across the EU (Dialogue Earth 2024).

Electricity occupies a unique role within the EU energy system due to its position as both a final energy product and an intermediate input into a wide range of production processes. Unlike fossil fuels, electricity cannot be easily stored at scale, which makes real-time balancing of supply and demand crucial. The EU electricity market has undergone significant integration in recent decades, facilitated by cross-border interconnections and a shared market architecture. This integration is exemplified by the Internal Electricity Market (IEM), which aims to improve efficiency, ensure security of supply, and support the energy transition by enabling electricity to flow freely between member states (Eurostat 2024b). Prices in wholesale electricity markets are generally determined via the merit order system, where power plants are dispatched based on their short-run marginal cost – from the lowest one to the highest – until demand is met. As a result, the marginal "plant" (typically fossil-fuel-based) sets the market price, even when cheaper renewables provide the largest share of total generation. This makes electricity prices highly sensitive to fuel input costs, especially for natural gas, which remains a common marginal technology in many EU countries (Agency for the Cooperation of Energy Regulators 2023; Ember 2024). Electricity demand is also relatively inelastic in the short run, particularly in industrial sectors with continuous processes and for essential residential use. Consequently, price shocks in the electricity market can quickly translate into broader cost pressures across the economy.

4 Data

We construct our dataset using publicly available price data from several sources. All variables are converted to a monthly frequency and span the period from August 2007 to January 2025, except for European wholesale electricity prices, which are only available from January 2015. All variables are demeaned; the inflation series are expressed as year-over-year percentage changes, while all other price variables are expressed as year-over-year log differences. Our selection of variables is inspired by Kilian & Zhou (2022), adapted to suit the EU context (see Appendix A.1 for visual inspection of the series).

Overview of variables and sources

Table 1: Data sources for inflation and energy price variables

Variable	**Source**
HICP (Harmonised index of consumer prices)	Eurostat
HICP excluding energy	Eurostat
Diesel prices	European Commission
Euro-super 95 prices	European Commission
Heating gas oil prices	European Commission
Brent crude oil Europe prices	US EIA
Natural gas (Dutch TTF) prices	Refinitiv Eikon
Rotterdam coal futures prices	Investing.com
European wholesale electricity prices	Ember
German electricity prices (EEX strompreis phelix DE)	Business Insider

Table 2: Summary statistics of monthly variables (2007–2025)

Variable	**Obs.**	**Mean**	**SD**	**Min**	**Max**
Headline inflation, YoY growth	216	2.46	2.33	-0.50	11.50
Core inflation, YoY growth	216	2.26	1.79	0.50	9.10
Diesel (€/1,000L)	216	650.61	175.28	366.38	1259.06
Euro-super 95 (€/1,000L)	216	606.71	154.59	307.11	1222.42
Heating gas oil (€/1,000L)	216	604.71	172.37	328.03	1203.52
Brent crude oil (USD/barrel)	216	78.13	24.52	18.38	132.72
Dutch TTF natural gas (€/MWh)	216	28.41	28.85	3.50	231.30
Rotterdam coal futures (USD/ton)	216	101.86	58.58	38.50	388.00
European wholesale electricity (€/MWh)	122	77.10	67.20	18.60	420.83
German electricity price (€/MWh)	216	87.90	94.93	23.86	768.05

Energy price variables are monthly averages in euros or USD as indicated. Inflation variables are expressed as year-over-year percentage changes based on the Harmonised Index of Consumer Prices (HICP) EU average. SD is the standard deviation.

Inflation measures

We use EU aggregate inflation rates as our inflation response variables. The decision to focus on the EU as a whole, rather than the Euro Area or individual countries, is consistent with a strand of the literature that adopts a broader EU-wide perspective, such as Markowski & Kotliński (2023). Moreover, conducting this analysis on the EU level puts our results in the relevant policy context, particularly in light of the recommendations outlined in the highly topical Draghi (2024) report mentioned earlier. Thus, although it would be more straightforward to, for instance, draw conclusions related to monetary policy by focusing solely on the Euro Area, we see several advantages to analyzing the EU as a whole – particularly in terms of relevance for recent EU-level proposals concerning competitiveness and the green transition.

A country-level analysis would require generating a large number of IRFs (one for each energy source, each inflation measure, each country, and each combination of these) and would therefore exceed the scope of this paper. To conserve space and maintain a clear analytical focus, we analyze the effects at the EU level, allowing us to highlight the heterogeneous impact of different energy sources.[1]

We thus use Eurostat's composite index of harmonized consumer prices (the HCPI), which includes 27 EU countries between 2007 and 2013, 28 EU countries between 2013 and 2020 (when Croatia joined), and 27 countries between 2020 and 2025 (when the UK left). We use the main HCPI for our measure of headline inflation, and capture core inflation by taking the HICP excluding energy. The HCPI values are then used to calculate the year on year percentage changes.

While the conventional core inflation measure often excludes both energy and food, we retain the food component. Food prices are an important transmission channel

[1]Future research could build on this approach and conduct more granular, country-specific analyses as discussed in our concluding section.

for energy shocks, particularly through input costs in agriculture, transportation, and food production. Excluding food could miss relevant pass-through effects (Corsello & Tagliabracci 2023) (see appendix A.1 for further details on the inflation data series).

Refined products

Data for prices on diesel, Euro-super 95, and heating gas oil are retrieved from the European Commission's Weekly Oil Bulletin, which provides detailed and harmonized fuel price information across EU countries. The reported prices are weekly, denominated in euros per 1,000 litres, and exclude excise duties and VAT.

The reported prices on diesel, Euro-super 95, and heating gas oil reflect weighted EU averages derived from national prices, where weights correspond to annual fuel consumption per country. These weights are based on reported volumes (in 1,000 tonnes) for each fuel type and country, as provided in the Weekly Oil Bulletin. They are updated annually to ensure they reflect actual consumption patterns across member states. However, weights for the most recent period (from January 2024 onwards) are subject to revision as final consumption data becomes available (European Commission 2025).

- **Diesel** captures the retail price of automotive gas oil—known as diesel fuel—used in road transport by vehicles like cars, trucks, and buses.

- **Euro-super 95** (hereafter "Euro-95") captures the price of the most common petrol type in Europe, meeting standard EU fuel quality criteria.

- **Heating gas oil** represents the average price for residential and commercial heating oil. The reported prices are based on deliveries between 2,000–5,000 litres.

Crude oil

The Brent crude oil series (DCOILBRENTEU), sourced from the US Energy Information Administration (EIA) via FRED, reflects spot market prices in USD per barrel. Brent crude, extracted from the North Sea, serves as a global pricing benchmark. We use monthly averages of daily closing prices, as calculated by the EIA, which helps smooth short-term fluctuations(U.S. Energy Information Administration 2024).

Natural gas

We use monthly averages of the Dutch TTF Day-Ahead Future Contract (TRNLTTFD1), retrieved from Refinitiv Eikon, as our proxy for European natural gas prices. It represents next-day delivery prices at the Title Transfer Facility (TTF), a virtual hub operated by Gasunie Transport Services (GTS).

This variable is recognized as a benchmark for European gas prices across Europe (ICE Markets 2024).

Coal

Rotterdam Coal Futures (ATWMc1) are sourced from Investing.com and used as a proxy for coal prices in the EU. These one-month forward contracts are denominated in USD per metric ton and financially settled based on coal deliveries to major European ports (Investing.com 2025).

Electricity

We incorporate two electricity price series:

- The **German electricity price** is based on the EEX Strompreis Phelix DE futures contract, widely used as a benchmark for expected market prices.
- The **European wholesale electricity price** series from Ember, providing monthly

spot prices per country. These reflect the prices generators receive for selling electricity on the spot market.

While our preferred choice was the broader European series, it only spans from January 2015. Since our analysis requires a longer time frame, we use the German Phelix DE futures as a proxy. To validate this substitution, we created a GDP-weighted average of the Ember country-level prices and calculated the correlation. The two series are highly correlated, with a Pearson coefficient of 0.914 and Spearman rank correlation of 0.876. Based on this evidence, we consider the German futures data to be a reliable proxy for broader European electricity price trends (Ember 2024; Business Insider 2024).

5 Methodology

This study applies a structural vector autoregressive (SVAR) model identified through a combination of block-recursive ordering and heteroskedasticity-based methods to analyse how shocks to energy prices affect headline inflation, both directly and indirectly via core inflation. The methodology is inspired by Kilian & Zhou (2022), who extended previous work by incorporating a broader set of energy prices beyond gasoline, and by Rigobon (2003), who proposed using changes in shock variances across regimes to achieve structural identification. By combining a theoretically motivated recursive structure with a data-driven heteroskedasticity-based approach, we aim to achieve robust identification of the shocks and transmission mechanisms.

5.1 Model specification

The SVAR model consists of a set of variables capturing the relationship between energy price changes and inflation. Let Y_t be a vector containing the model variables:

$$Y_t = \begin{bmatrix} \Delta p_{\text{Energy1},t} \\ \Delta p_{\text{Energy2},t} \\ \Delta p_{\text{Energy3},t} \\ \Delta p_{\text{Energy4},t} \\ \Delta p_{\text{Energy5},t} \\ \Delta p_{\text{Energy6},t} \\ \Delta p_{\text{Energy7},t} \\ \pi_{\text{headline},t} \\ \pi_{\text{core},t} \end{bmatrix} \tag{1}$$

where:

- $\Delta p_{\text{Energy1},t}$ to $\Delta p_{\text{Energy7},t}$ are the growth rates of selected energy prices.

- $\pi_{\text{headline},t}$ and $\pi_{\text{core},t}$ represent headline and core inflation rates, respectively.

The structural VAR model is represented as:

$$B_0 Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{t-p} + W_t \tag{2}$$

where:

- B_0 represents the contemporaneous relationships between the variables: the structural impact matrix.
- $B_1, ..., B_p$ are the matrices of lagged coefficients.
- W_t is a vector of structural shocks, assumed to be mutually uncorrelated.

The reduced-form VAR is thus given by:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + U_t \tag{3}$$

where:

- $A_i = B_0^{-1} B_i$ for $i = 1, ..., p$.
- $U_t = B_0^{-1} W_t$ are the reduced-form residuals.

The lag order p is set to six months for our main model, to capture medium-term effects of energy price fluctuations on inflation (see Appendix A.3).

To be able to interpret the structural shocks W_t, additional identifying assumptions must be imposed. In the following section, we outline two complementary strategies used for identification: (i) a recursive ordering based on economic theory, and (ii) a heteroskedasticity-based approach exploiting changes in residual variances across regimes.

5.2 Identification

Our identification strategy combines a block-recursive structure with heteroskedasticity-based methods, resulting in an overidentified SVAR model. This hybrid approach allows us to (i) impose economically meaningful short-run restrictions, and (ii) validate model stability through regime-dependent volatility shifts.

First, we impose a contemporaneous ordering (as described above) which partially identifies the shocks via zero restrictions. Then, we exploit heteroskedasticity: specifically, we identify distinct high-volatility vs. low-volatility regimes in the data (e.g., before and after a certain date or event, see Appendix C.1 and C.2). We use changes in the covariance of VAR residuals between these regimes to pin down the remaining free elements of B_0, following the approach of Rigobon (2003) (see Appendix C.3).

We implement the identification using the `id.cv` function in R, which estimates the structural impact matrix B_0 under the assumption that structural variances differ across regimes while contemporaneous relationships remain constant (see Appendix C.3).

Recursive Ordering and Demand Shock Proxy

The recursive block structure follows Kilian & Zhou (2022) and is adapted for EU energy markets. We order energy prices based on their upstream-to-downstream relationship, economic exogeneity, and price-setting behavior. Inflation is ordered last and treated as a response variable.

Crude oil (1) is placed at the top of the hierarchy. Brent prices are assumed to reflect global market conditions and are minimally affected by short-run EU-specific factors (Edelstein & Kilian 2009). Importantly, we interpret oil price shocks as a proxy for *global aggregate demand shocks*, following the methodology of Kilian & Zhou (2022). This has implications for the interpretation of such shocks: inflationary responses to oil may reflect broader macroeconomic expansions, not purely supply shocks. All other energy variables are allowed to respond contemporaneously to crude oil, but not vice versa.

Refined fuels: Diesel (2), gasoline (Euro-95) (3), and heating gas oil (4) are treated as downstream refined oil products. Diesel is allowed to contemporaneously affect gasoline and heating oil, reversing the ordering in Kilian & Zhou (2022), consistent with diesel's larger role in transport specifically in the EU (Eurostat 2023b). Euro-95 is also allowed to affect heating gas oil, but not vice versa, reflecting the relatively larger size of the gasoline market. A shock to gasoline prices may influence the availability or pricing of crude oil inputs for heating oil production, while the reverse is unlikely given the smaller scale and declining use of heating gas oil in many EU markets.

Natural gas (5) prices respond to oil and heating fuels, reflecting partial substitution and co-movement during major disruptions (Su et al. 2023; Szafranek & Rubaszek 2024). Gas prices are shaped by regional factors such as weather, storage levels, and geopolitical tensions (Su et al. 2023). While the historic oil-gas link has weakened in the EU, we allow oil to affect gas prices contemporaneously to capture the possible co-movement during large global shocks (Szafranek & Rubaszek 2024).

Coal (6) responds to oil and natural gas, consistent with its marginal role in power generation.

Electricity (7) prices in the EU follow the marginal pricing model (Merit Order), with gas often setting the clearing price – approximately 55 percent of the time, according to recent estimates (Gasparella, Koolen & Zucker 2023). Coal also remains important in EU electricity generation – making up approximately 12 percent of the energy mix (Ember 2024). We thus allow electricity to respond to both gas and coal shocks contemporaneously.

Despite possible co-movements over time, we do not allow diesel or gasoline to affect natural gas, coal or electricity prices within the same period, given the limited short-run substitutability with refined fuels (Eurostat 2022). Since gas is used in electricity production, and electricity might substitute gasoline in vehicle fuel – we consider this to be a more long-term substitution. Heating gas oil is however allowed to affect both natural gas, coal, and electricity, reflecting limited household substitution across heating systems (Eurostat 2023b).

Inflation (8, 9) – core and headline – are ordered last. Energy prices are treated as predetermined with respect to inflation, a standard assumption in SVAR models examining price pass-through.

The recursive ordering is implemented via a lower triangular B_0 matrix, with specific zero restrictions imposed on cross-variable contemporaneous effects:

$$B_0 = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 & 0 & 0 & 0 & 0 \\ b_{51} & 0 & 0 & b_{54} & b_{55} & 0 & 0 & 0 & 0 \\ b_{61} & 0 & 0 & b_{64} & b_{65} & b_{66} & 0 & 0 & 0 \\ b_{71} & 0 & 0 & b_{74} & b_{75} & b_{76} & b_{77} & 0 & 0 \\ b_{81} & b_{82} & b_{83} & b_{84} & b_{85} & b_{86} & b_{87} & b_{88} & 0 \\ b_{91} & b_{92} & b_{93} & b_{94} & b_{95} & b_{96} & b_{97} & b_{98} & b_{99} \end{bmatrix}$$

In non-technical terms, the structural impact matrix above tells us how different types of energy price shocks directly influence each other and inflation **at the moment the shock occurs** (i.e in the same month). Each row represents one variable in the system, and each column represents a different shock to each of these variables. A zero in the matrix means that a particular shock does not have an immediate effect on that variable, while a non-zero entry (represented here as b_{ij}) indicates a possible immediate impact.

We group the nine variables into three blocks:

1. **Oil and refined fuels**: Brent, diesel, gasoline (Euro95), heating oil
2. **Other energy prices**: natural gas, coal, electricity
3. **Inflation measures**: core and headline inflation

The structure reflects the logical economic ordering defined above: oil shocks can affect all other variables immediately; refined fuels respond to oil and each other in sequence; gas, coal, and electricity respond to oil, and to each other in sequence contemporaneously. Inflation is assumed to react within the month to all energy shocks, but not influence them in return.

This setup helps us isolate the impact of specific energy shocks on inflation while remaining consistent with typical energy market dynamics.

Identification via Heteroskedasticity

To complement the recursive ordering, and estimate the remaining non-zero parameters, we also apply heteroskedasticity-based identification (Rigobon 2003). This is a data-driven method (rather than relying solely on economic rationale) and exploits regime-dependent changes in the variances of structural shocks.

For instance, if natural gas prices experienced an exogenous volatility shock in 2022, significantly larger than other shocks, this covariance shift would help isolate the pure 'gas shock' from other energy price shocks. With seven energy-related shocks, pure recursive ordering requires strong assumptions about contemporaneous relationships among all energy prices. The heteroskedasticity-based method complements the recursive ordering by using regime-dependent variance shifts to identify additional shocks and to test the robustness of the recursive assumptions, as we can test for parameter stability after estimating the model (see Appendix C.5).

Let the reduced-form VAR residuals U_t relate to the structural shocks ε_t as:

$$U_t = B_0 \varepsilon_t, \quad \text{with } \mathbb{E}[\varepsilon_t \varepsilon_t'] = \Sigma_\varepsilon^{(r)}, \quad \text{for regime } r \in \{1, 2\}$$

Then, the residual covariance matrices are:

$$\Sigma_U^{(1)} = B_0 \Sigma_\varepsilon^{(1)} B_0', \quad \Sigma_U^{(2)} = B_0 \Sigma_\varepsilon^{(2)} B_0'$$

If (1) the structural variances change non-proportionally across regimes ($\Sigma_\varepsilon^{(1)} \neq \lambda \Sigma_\varepsilon^{(2)}$), and (2) B_0 remains constant, these matrices allow identification of the structural impact matrix by diagonalizing both systems jointly. We thus check for these two conditions.

Regime Detection and Assumptions Using Bai–Perron tests, we detect potential structural breaks in residual variances around observation 150 (August 2020), coinciding with the COVID-19 pandemic and subsequent energy market disruptions. Thus, we define two volatility regimes accordingly. We treat August 2020 onward as a high-volatility regime for energy prices, and earlier periods as a lower-volatility regime. By verifying a significant increase in variance for certain energy price residuals in the later period, this provides extra equations to identify the model (see Appendix C.2).

To check for the second condition, we validate the time-invariance of B_0 by:

- Re-estimating the model on sub-samples and confirming similar impulse responses across regimes.
- Referencing previous literature such as Kilian & Zhou (2022) who estimated their model without post-covid data and retained similar results.
- Examining the residual correlation matrices across the two regimes, and finding that pairwise correlations remain relatively stable (see Appendix C.4)

- Additionally confirming the stability of our parameters by conducting a CUSUM test (see Appendix C.5)

5.3 Summary of method

To summarize our method: We estimate a structural vector autoregressive (SVAR) model to identify and trace the effects of energy price shocks on headline and core inflation. The model is estimated in its reduced form, capturing the dynamic interactions among nine variables — seven energy price series and two inflation measures — based on their lagged values.

To recover economically interpretable structural shocks, we impose an identification strategy that combines recursive block ordering with heteroskedasticity-based restrictions. The recursive structure relies on the assumed upstream-to-downstream relationship in energy markets, as argued for earlier, and treats inflation as a response variable, responding only to contemporaneous shocks in energy prices. This ordering is implemented via zero restrictions in the structural impact matrix B_0.

To strengthen identification and allow for overidentifying restrictions, we complement the recursive strategy with heteroskedasticity-based identification to identify the remaining free parameters. Specifically, we exploit changes in the variances of structural shocks across two regimes – a low-volatility regime (pre-August 2020) and a high-volatility regime (post-August 2020). Assuming that structural variances shift while contemporaneous relationships remain stable (see Appendix C for testing and validity of this method given our data), this approach enables us to uniquely identify the elements of B_0 by jointly diagonalizing the residual covariance matrices across the high- and low volatility regimes.

After identification, we compute impulse response functions (IRFs) to quantify the dynamic effects of each identified structural shock on all variables in the system. These IRFs provide a time profile (over many months) of how headline as well as core inflation respond to specific energy price shocks, allowing us to distinguish between direct and indirect transmission channels, and transmission differences between price shocks in different energy variables.

5.4 Robustness checks

To ensure the reliability of our results, we conduct an extensive set of robustness checks addressing both model specification and underlying assumptions. These include unit root tests (ADF, PP, and KPSS) to assess stationarity (see Appendix A.2), as well as information criteria (AIC and BIC) to aid in lag length selection (see Appendix A.3). We test for structural breaks and heteroskedasticity using Bai–Perron and ARCH tests (see Appendices C.2 and C.1), and evaluate model stability through eigenvalue analysis (see Appendix B1). Residual diagnostics include Portmanteau tests for autocorrelation and Jarque–Bera tests for normality (see Appendices B.2 and B-3). We further test the stability of our estimated VAR parameters with a CUSUM test (see Appendix C.5).

In addition to diagnostic tests, we explore alternative model specifications. Specifically, we estimate the model using both 2 and 6 lags, but set the lag length of the main model to $p = 6$ (months), based on a balance of statistical criteria and economic judgment (see Appendix A). We also compare results under different identification schemes: recursive ordering only, heteroskedasticity-based identification only, and the combined baseline specification. While point estimates and impulse responses differ slightly across specifications, the general shape and economic interpretation of the results remain robust. We highlight any deviations in the discussion below and provide full details of the robustness checks as well as plots from alternative models in Appendices A–B and F.

6 Results

This section presents the impulse response functions (IRFs) from our baseline SVAR specification with six lags. A shorter two-lag version is also estimated, but only discussed when it materially affects the dynamics. Impulse response plots for all specifications can be found in Appendix F. Inflation is expressed in demeaned year-over-year percentage changes, so each IRF represents the expected deviation in inflation – measured in percentage points –from a scenario with no shock, at each month (horizon) following the shock.

In general, all energy price shocks raise inflation to some extent, but the timing, magnitude, and persistence of these effects differ by energy type. As expected, headline inflation responds more strongly and immediately than core inflation, given that energy is directly included in the HICP headline index but excluded from the core. In contrast, core inflation effects are typically more gradual, reflecting second-round channels such as production costs, wage setting, and expectations.

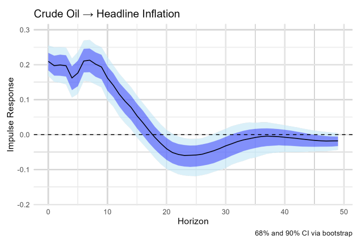
We structure the results in three parts: (1) Transmission of the most prominent energy prices: This section analyzes how inflation responds to shocks in the most important energy prices. (2) Transmission of refined fuel prices: We examine how shocks to refined fuel prices (diesel and gasoline) transmit to inflation. (Heating gas oil is excluded due to insignificant relevance and results.) (3) Electricity price transmission: This section explores how shocks to crude oil, natural gas, and coal influence electricity prices.

The first section addresses our main research question. The second and third provide insight into underlying transmission mechanisms and driving dynamics that help explain the inflationary patterns observed in (1). We focus on the most relevant IRFs and highlight differences that might offer valuable insights. These sections are then followed by a discussion that provides further intuition behind the results.

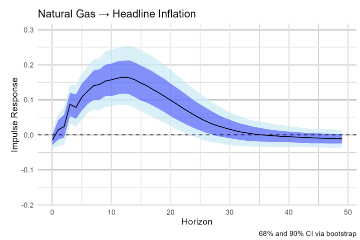
6.1 Presentation of results

6.1.1 Energy shocks and inflation: six-lag model

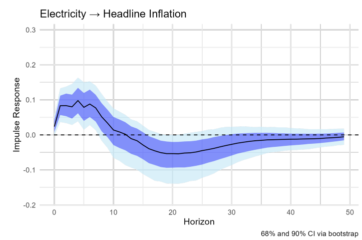
See Appendix F for IRFs from the two-lag model.



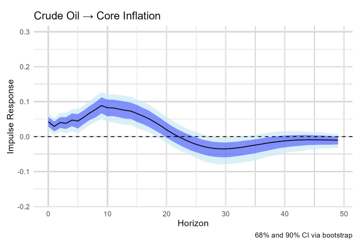
(a) Brent → Headline



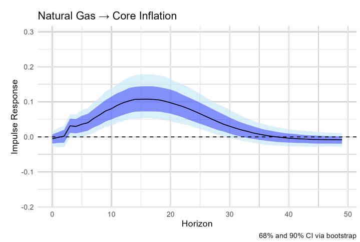
(b) Dutch TTF → Headline



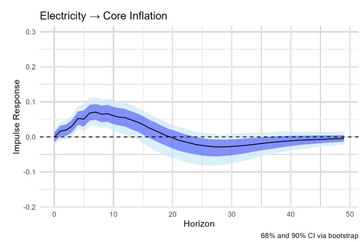
(c) Electricity → Headline



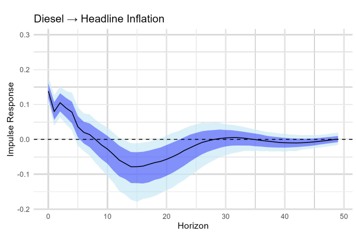
(d) Brent → Core



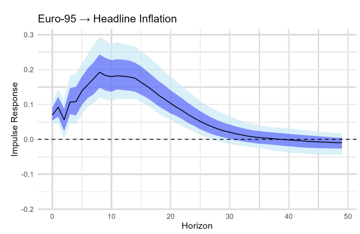
(e) Dutch TTF → Core



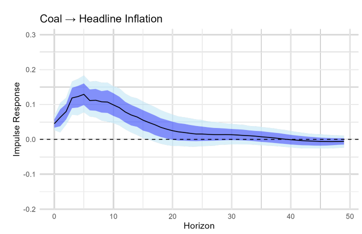
(f) Electricity → Core



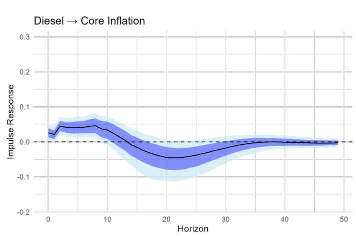
(g) Diesel → Headline



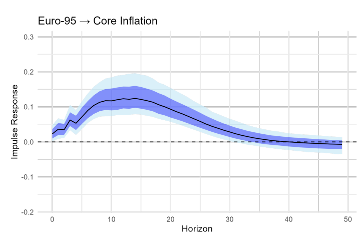
(h) Euro95 → Headline



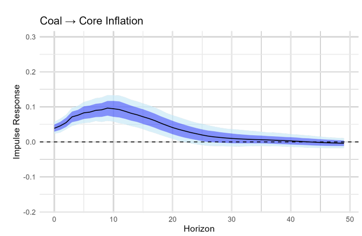
(i) Coal → Headline



(j) Diesel → Core

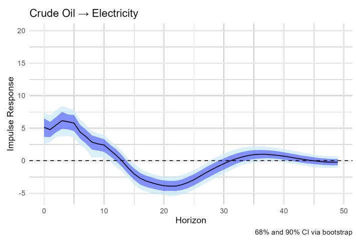


(k) Euro95 → Core

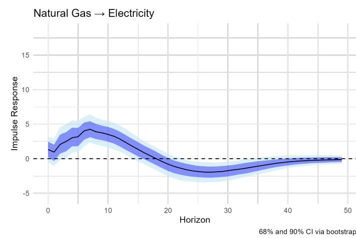


(l) Coal → Core

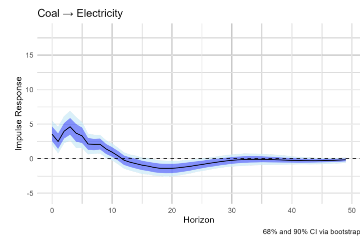
Figure 1: Impulse response functions from energy price shocks to headline and core inflation. Headline is shown on top of each pair.



(a) Brent → Electricity



(b) Dutch TTF → Electricity



(c) Coal → Electricity

Figure 2: Impulse response functions from price shocks in crude oil and energy sources used for electricity generation to electricity prices

Headline inflation

Figure 1 panels (a)–(c) and (i) display headline inflation responses to Brent crude oil, Dutch TTF natural gas, coal and electricity price shocks.

Crude oil shocks (Panel 1a) produce an immediate and pronounce rise in headline inflation, peaking between month 0 and 8 slightly above 0.2. The effect steadily declines and becomes somewhat negative after month 18, before fading into insignificance around month 30–35.

Natural gas shocks (Panel 1b) exhibit a slower more gradual build-up, with the response peaking between months 10 and 15 at approximately 0.17. The effect then declines slowly and remains statistically significant until around month 25, after which it becomes insignificant for the remainder of the forecast horizon. This indicates a slower direct pass-through to inflation compared to oil (our demand shock proxy).

Electricity shocks (Panel 1c) generate a short-lived and moderately sized inflationary response. The IRF peaks between months 2 and 7 at about 0.1 and returns to insignificance by month 8. The decline from peak is relatively sharp, falling from 0.1 to near zero between months 7 and 11, suggesting a contained and quickly reversing shock impact. Like with oil, there is also a period of negative effect after the fall. For electricity, this negative effect is however only significant on the 68 percent level.

A coal price shock (Panel 1i) also induces an increase in headline inflation. In particular, headline peaks around month 5 at approximately 0.12 with statistical significance up until month 15-20. Thereafter, the effect dissipates relatively fast, indicating a moderately transitory influence of coal prices on overall inflation.

Core inflation

Panels (d)–(f) and (l) display the corresponding effects on core inflation. All panels exhibit a later peak compared to the headline case, which showcases the slower pass-through via common macroeconomic channels into core inflation. The shape of each panel from each of the energy price shocks appear similar as the case of headline inflation.

However, crude oil appears to have a relatively smaller peak (around 0.08-0.09), whereas natural gas peaks slightly above 0.1. This indicates that the pass-through to core inflation is relatively stronger for natural gas compared to oil shocks. Worth noting is that the estimated response to a crude oil shock is notably larger in the 2-lag model, with a peak around 0.14 (see Figure 13 in Appendix F). This may reflect our treatment of crude oil as a proxy for aggregate demand shocks – which could plausibly influence a broader range of energy prices and generate more immediate upward pressure on headline inflation.

For electricity, the decline following the peak (approximately 0.07) is slower than in the headline case. The trajectory and magnitude of the response closely resemble that of oil on core, though the electricity response is slightly smaller. Interestingly, the magnitude of the peak is fairly similar in the core and headline responses to an electricity shock. This stands in contrast to the shocks in crude oil and natural gas which appear to exhibit greater differences between the core and headline peak responses.

Another interesting result is the immediate response in core inflation to a coal price shock. It peaks around 0.1 followed by a relatively slow and gradual decline back.

Thus coal shocks exhibit a relatively large inflationary impact, comparable to the other energy variables.

6.1.2 Refined fuel shocks

Figure 1 panels (g) and (h) compare the effects of diesel and Euro-95 shocks on headline inflation. Diesel shocks (Panel 1g) induce an immediate positive response but which quickly decays and turns negative after about 8 months, before returning toward zero. Euro-95 shocks (Panel 1h) show a different pattern, generating a gradual increase in inflation, peaking after around 8 months, and declining slowly over the following two years.

6.1.3 Fossil fuels on electricity

Figure 2, panels (a)–(c), show the responses of electricity prices to shocks in crude oil, natural gas, and coal. Crude oil shocks (Panel 2a) lead to the largest increase in electricity prices, followed by coal and then natural gas. All responses gradually return to zero between month 10-20, with some episodes of negative responses before stabilizing again near zero around month 40. Among the three, natural gas has the weakest direct effect on electricity prices, with a more gradual build-up. All responses remain statistically significant until approximately month 30.

6.2 Interpretation of results

6.2.1 Pass-through to inflation

Crude oil shocks generate rapid but relatively short-lived effects on headline inflation, consistent with the direct and immediate role of oil in transport and heating costs. This aligns with previous evidence showing that oil price fluctuations pass through to inflation quickly and almost fully via the energy component Meyler (2009), typically resulting in a sharp but temporary rise and fall in inflation. As noted by Kilian & Zhou (2023), this pattern suggests that the response to a crude oil shock is transitory rather than persistent, producing only a temporary blip in the inflation rate.

Regarding the effect on core inflation, several studies have suggested that the pass-through from crude oil prices has steadily declined since the mid-1980s, to such an extent that it is now considered negligible or even absent. Our estimated results align with this view, showing that the response of core inflation is relatively small and delayed. This finding is also in line with Conflitti & Luciani (2019), who emphasize a limited yet persistent pass-through from oil price shocks to core inflation.

Our crude oil findings should also be interpreted through a demand-side perspective, following the logic of Gao, Kim & Saba (2014). When oil prices rise, and energy demand is relatively inelastic, households must reduce their consumption of other goods and services to compensate for the higher energy expenditures. This shift in spending lowers demand in less energy-intensive sectors, which in turn limits the price pressure in those categories. As a result, inflationary effects tend to concentrate in sectors directly linked to energy use, while broader consumer prices – especially those captured in core inflation – respond less intensely. This mechanism helps explain why oil price shocks show asymmetric inflation responses, with relatively stronger effects in energy-heavy categories and more muted impacts elsewhere.

The response to a natural gas shock builds more gradually and persists longer, particularly in core inflation. This persistence potentially reflects several structural features of the European gas market – such as lower substitutability and flexibility as well as high degree of import dependence. Natural gas plays a central role in heating, industrial processes, and electricity generation in many EU countries, and short-term alternatives remain limited due to constrained LNG terminal capacity and existing pipeline networks. As Bachmann et al. (2024) highlights, the EU has historically relied heavily on Russian gas, and short-run substitution away from this dependence has proven challenging.

Electricity shocks tend to be short-lived, with their effects dissipating relatively fast. This pattern may reflect protective mechanisms within the EU – such as fixed consumer contracts, regulatory price caps, and temporary subsidies. The muted response in core inflation further supports the notion that electricity shocks are buffered by institutional factors, limiting their spillover into broader price-setting behavior. The relatively small difference between the core and headline inflation responses to electricity shocks suggests that transmission may occur primarily through indirect channels rather than direct impacts on consumer prices. This, in turn, implies a relatively stronger pass-through to core inflation compared to other types of energy shocks. The estimated results may also reflect the diverse energy mix of the EU, with a substantial share of the electricity being generated from renewables, which contributes to a greater resistance to inflation. Indeed, many EU countries did implement price caps or subsidies on electricity during the 2021–2022 crisis, which would blunt the immediate CPI impact of an electricity market shock (Bruegel 2024).

The inflationary response to a coal price shock is immediate and pronounced, consistent with the findings of Guo, Zheng & Chen (2016), who study the case of China and show that coal price increases lead to sharp but short-lived surges in inflation. While their analysis focuses on a highly coal-dependent economy, the comparison remains informative. In contrast, the EU's energy mix has shifted significantly in recent years, with coal steadily being phased out in favor of cleaner alternatives (Dialogue Earth 2024). Still, the comparison highlights that coal can continue to exert significant inflationary pressure during periods of constrained energy supply – even in economies where its role is diminishing. The EU's declining reliance on coal, along with stricter climate policies, will likely dampen long-term pass-through effects.

Nevertheless, our results indicate that coal price shocks still trigger a rapid and direct inflationary response in the EU, particularly via electricity markets where coal remains marginal but non-negligible. It is important to note, however, that our estimates are based on futures prices for coal. If spot price data had been used instead, the timing or magnitude of the inflationary response might have differed. This caveat underscores the need for cautious interpretation.

Refined fuel shocks

Our impulse response functions indicate that diesel price shocks induce a stronger and more immediate increase in inflation than Euro-95 shocks. In the baseline 6-lag specification, headline inflation peaks in the same month as the diesel shock, with a smaller but parallel effect on core inflation. The inflationary impact of diesel then fades rapidly and turns slightly negative between months 12 and 30, consistent with a potential demand-side correction. In contrast, Euro-95 shocks produce smoother and more persistent inflation paths, with both headline and core inflation peaking around 12 months after the initial shock.

This contrast highlights the importance of fuel type in inflation transmission. Diesel, while often associated with freight and commercial use, is also widely consumed by private users in the EU, particularly in rural and long-distance commuting contexts. Its dual role — as both an industrial input and final consumption good — helps explain the faster and more concentrated pass-through observed in the short run.

Our results also align with recent findings by Gkatzoglou, Papadimitriou & Gogas (2024), who show that diesel prices are more synchronized across EU member states. This synchronization may lead firms to interpret diesel price shocks as systemic and persistent, thereby prompting faster and more coordinated price adjustments across supply chains.

In contrast, Euro-95 is primarily used in household vehicles. Its price shocks may have more persistent, but slower-moving effects on inflation. While Euro-95 directly enters headline CPI, its broader inflationary impact likely operates through consumer expectations and wage-setting behavior. Persistent and unexpected increases in household fuel costs may contribute to sustained upward pressure on inflation expectations. This, in turn, can influence wage-setting and downstream consumer pricing with a lag, leading to a more gradual but enduring pass-through.

In addition, we observe that the inflationary impulse response to diesel shocks becomes negative around 12–18 months after the initial shock. This could reflect a demand-side correction mechanism as discussed in Gao, Kim & Saba (2014): higher energy costs initially raise prices, but subsequently suppress real incomes and aggregate consumption demand, thereby moderating inflation. These reversal dynamics are consistent with the mechanism also discussed by Edelstein & Kilian (2009), where demand responses counteract the initial impact of energy price shocks.

Notably, robustness checks using a 12-lag specification reveal that while diesel shocks remain highly front-loaded, they also exhibit a large and delayed effect after almost 3 years. This could signal that some industry pass-through effects come into effect much later. However, the extended lag structure introduces greater volatility and substantially wider confidence intervals, which limits the interpretability of these results. We therefore retain the 6-lag model as the baseline. Nonetheless, the possibility of longer-term transmission from diesel shocks cannot be entirely ruled out, though these late responses should be interpreted with caution given their statistical fragility.

6.2.2 Electricity price responses

The positive and immediate response of electricity prices to crude oil shocks likely reflects oil's role as a proxy of global economic activity, rather than a direct input in electricity generation, which is minimal in the EU. This interpretation aligns with the view of oil price shocks as signals of broader global demand conditions, as emphasized by Edelstein & Kilian (2009). In this sense, oil acts less as a cost-push driver of electricity inflation and more as a signal of rising economic activity across sectors. This increase in aggregate demand can raise electricity consumption, especially in energy-intensive industries and services. As electricity demand increases, prices may rise accordingly

– particularly in marginal cost-driven markets like the EU, where prices may adjust quickly. Thus, even though oil itself is not a major input in EU power generation, an oil demand shock in our model may indirectly raise electricity prices via higher demand for electricity as a production input. As can be observed in Figure 2 Panel a, this effect seems to be quite significant.

Natural gas shocks exhibit a direct and substantial effect on electricity prices, consistent with the fuel's role as the most common marginal price-setter in EU power markets. Under the merit-order pricing system, wholesale electricity prices are typically set by the most expensive unit needed to meet demand – often a gas-fired plant. This mechanism explains both the strength and immediacy of the gas-to-electricity transmission channel. The results underscore the EU's exposure to gas market volatility and confirm that electricity inflation is closely tied to fluctuations in natural gas prices.

Coal shocks also produce a clear and immediate increase in electricity prices, albeit somewhat less pronounced than gas. This effect would be particularly relevant in coal-intensive regions where coal remains a key marginal fuel, despite general decarbonisation efforts in the EU (Dialogue Earth 2024). This significant pass-through into electricity prices highlights coal's continuing role in shaping direct and input costs – and may thus partly explain the significant effect of coal shocks on inflation.

Taken together, the results in Figure 2 illustrate the structural dependencies embedded in the EU's electricity pricing system. Crude oil shocks affect electricity prices indirectly by signaling stronger aggregate demand, which increases electricity consumption and price pressure. In contrast, natural gas and coal shocks operate via direct cost-push channels, as they often set the marginal generation cost in wholesale electricity markets. These findings highlight how both demand-side signals and fuel-specific cost pressures interact in shaping electricity price dynamics – placing particular emphasis on natural gas as the dominant transmission channel for upstream energy shocks.

In summary, a significant energy price shock (on the scale observed in our sample) typically translates into at most a 0.2–0.25 percentage point increase in headline inflation, and much less in core, with effects usually dissipating within 1–2 years. While the peak effects are modest, many shocks exhibit persistent inflation responses lasting up to 18–24 months, highlighting the importance of tracking energy shocks over time.

The evidence consistently points to natural gas playing a central role in transmitting energy market disturbances to both electricity prices and broader inflation. Gas shocks not only have relatively large and persistent direct effects on inflation (especially core), but they also indirectly drive inflation via the electricity price channel. In contrast, shocks to other energy commodities either dissipate faster or are absorbed by market mechanisms such as price regulations and policy.

Our findings imply that second-round effects (energy influencing core inflation) are present but limited. Core inflation responses are an order of magnitude smaller than headline responses for all shocks, and they materialize with delays of 6–12 months. This suggests that while energy shocks can seep into underlying inflation (via expectations or cost spillovers), the magnitude is relatively contained (peaking around 0.1–0.2 points for gas, and less for others).

7 Limitations and Future Research

This analysis is conducted at the aggregate EU level, which limits the ability to account for cross-country heterogeneity in inflation responses. Member states differ significantly in terms of energy mix, market structures, and fiscal responses – factors that may shape the transmission of energy price shocks in different ways. A more granular and country-specific approach could provide valuable insights into these varying dynamics which would also improve the policy relevance of the findings.

Second, the empirical framework used relies on a standard structural VAR (SVAR) model with identification achieved through recursive ordering and heteroskedasticity-based methods. While this approach is effective and incorporates economically meaningful restrictions, it may be less suited to small-sample environments or settings where prior information is uncertain or difficult to encode using classical identification schemes. In such cases, a Bayesian SVAR (BSVAR) could offer advantages by allowing more flexible and formally structured priors, potentially leading to more robust inference and more sensitivity to parameter uncertainty.

Lastly, the stability of the reduced-form model is assessed using a cumulative sum (CUSUM) test (see Appendix C.5), which indicates that the VAR coefficients remain stable within the 95% confidence interval over the full sample period. However, toward the end of the sample – coinciding with the COVID-19 pandemic, the 2022 energy crisis, and the Russian full-scale invasion of Ukraine – the CUSUM function approaches the upper confidence bound. While this does not constitute a formal rejection of parameter stability, it may signal the emergence of structural changes. Future research should keep this in mind and could build on our framework by explicitly modeling such breaks in the transmission mechanism, for instance through time-varying parameter VARs or regime-switching models.

Together, these limitations and considerations point to several promising avenues for further research: analyzing country-level dynamics, adopting a Bayesian estimation framework, and incorporating structural shifts in the transmission mechanism over time.

8 Conclusions and Policy Suggestions

This thesis has explored how shocks to various energy prices — including crude oil, natural gas, coal, diesel, gasoline, and electricity — affect both headline and core inflation in the EU. Using a structural vector autoregression (SVAR) framework with a hybrid identification strategy combining recursive ordering and heteroskedasticity-based identification, we find that energy price shocks are a key driver of inflation dynamics in the short-run, albeit with modest effects, and with insignificant effects in the long-run. However their effects vary substantially across energy types and inflation components.

8.1 Summary of Main Findings

We find that although the direction and timing of effects differ by energy type, the magnitude of inflationary responses is modest across the board, typically peaking below 0.25 percentage points.

- **Crude oil shocks** cause immediate increases in headline inflation, but the effects are short-lived and fade within a year. Core inflation reacts weakly and with a lag.
- **Natural gas shocks** produce slower, more persistent responses – especially in core inflation – though the maximum effect remains below 0.25.
- **Electricity shocks** trigger brief and limited inflation responses, likely buffered by regulatory mechanisms and price caps.
- **Coal shocks** lead to a visible headline inflation response, and a slightly slower and dampened one in core inflation, likely reflecting coal's marginal role in electricity pricing.
- **Diesel shocks** generate immediate and relatively strong headline effects, but these remain modest and dissipate quickly, turning negative for a period of time.

- **Euro-95 shocks** show more gradual but persistent impacts, particularly in core inflation.

- **Electricity price responses** to upstream energy shocks reinforces that natural gas is the key driver of power price fluctuations; however, even large electricity price swings translate to only limited inflation changes, likely thanks to market interventions and the structure of retail pricing.

In sum, while energy price shocks contribute to short-run inflation volatility, they do not appear to drive large or lasting inflationary pressure in the EU. This finding supports a cautious, non-reactive policy stance toward transitory energy shocks.

8.2 Monetary Policy

Our results support the view that monetary policy responses to energy shocks must differentiate between temporary, idiosyncratic price movements and broader, persistent inflationary pressures. Central banks may justifiably "look through" transient spikes in headline inflation – such as those driven by oil – if core inflation remains stable. However, persistent shocks to gas or euro-95 gasoline, which may signal second-round effects or shifts in expectations, might warrant some monetary tightening to avoid de-anchoring inflation expectations.

In this context, forward guidance and policy communication are essential. Tolerating short-term inflation deviations may be prudent, but policy must also remain alert to structural changes in energy pass-through dynamics.

8.3 Role of Fiscal and Regulatory Policy

Several EU member states responded to recent energy crises with price caps, tax reductions, or subsidies (Bruegel 2024). While such measures can temporarily shield consumers from high prices and moderate headline inflation, they may also delay necessary adjustments or put pressure on government budgets over time. More targeted interventions – focused on especially vulnerable households – combined with measures that encourage consumers to reduce or shift their energy use, may better balance inflation management and social equity concerns.

Additionally, the EU electricity market's reliance on marginal pricing (i.e. natural gas as the most common price-setter) suggests that regulatory reform – including capacity markets or mechanisms that decouple electricity prices from gas – may reduce the inflationary sensitivity of electricity prices.

8.4 Energy Resilience

Over the long term, accelerating the green energy transition – particularly investments in renewables and grid infrastructure – can reduce exposure to volatile fossil fuel markets. As electricity demand rises, ensuring that additional capacity is met with stable, and preferably domestically sourced generation is critical for price stability.

Our findings thus reinforce the argument that energy policy and macroeconomic stability are increasingly intertwined. Policymakers must coordinate fiscal, regulatory, and monetary responses to maintain resilience in a world of volatile energy geopolitics. The growing energy needs of AI technologies, climate risks from global warming, resurgence of protectionist trade policies, and persistent geopolitical conflicts – such as the Ukraine war – all underscore the need for coordinated and forward-looking economic policy responses with energy considerations at its core.

8.5 Final Remarks

This thesis contributes to the literature by demonstrating the heterogeneous inflationary effects of energy price shocks in the EU and by applying a novel hybrid identification strategy. Future work could extend the analysis to country-level heterogeneity, nonlinear dynamics, or the evolving role of renewables in inflation transmission. For now, we have identified a central main message: energy price shocks are not all alike – and policy must not treat them as such.

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A Pre-estimation Tests

A.1 Visual inspection of series

We begin by visually inspecting the annualized changes in energy prices and inflation rates over the sample period.

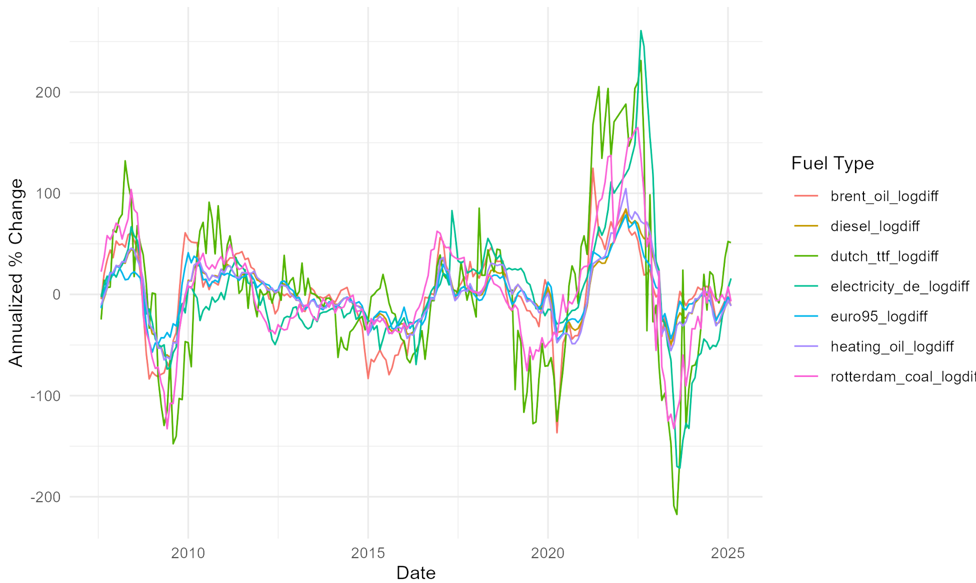


Figure 3: Annualized Change in Energy Prices Over Time, log-differenced

Our price data is expressed as year-over-year log-differences. Overall, the data shows a relatively stable mean over time, with distinct spikes during certain periods. There is clear co-movement across all of the energy price series, although the degree of volatility varies. Some series display sharp, localized spikes that are not mirrored in others.

Our inflation data is expressed as year-over-year changes in the Harmonized Index of Consumer Prices (HICP), with the mean removed to focus on deviations from the average trend. We employ a core inflation measure that excludes energy prices but retains food prices. This choice diverges from approaches like that of Kilian & Zhou (2022), who exclude both energy and food. We include food because its prices can be significantly affected by energy shocks, particularly through increased transportation and production costs. For instance, higher diesel prices can raise the cost of distributing food products, thereby impacting food prices and overall inflation (Corsello & Tagliabracci 2023).

The inflation data exhibits a relatively stable mean over time, punctuated by fluctuations and a pronounced peak around 2023. This spike aligns with the broader inflationary trends observed across Europe during that period, driven by factors such as energy price surges and supply chain disruptions.

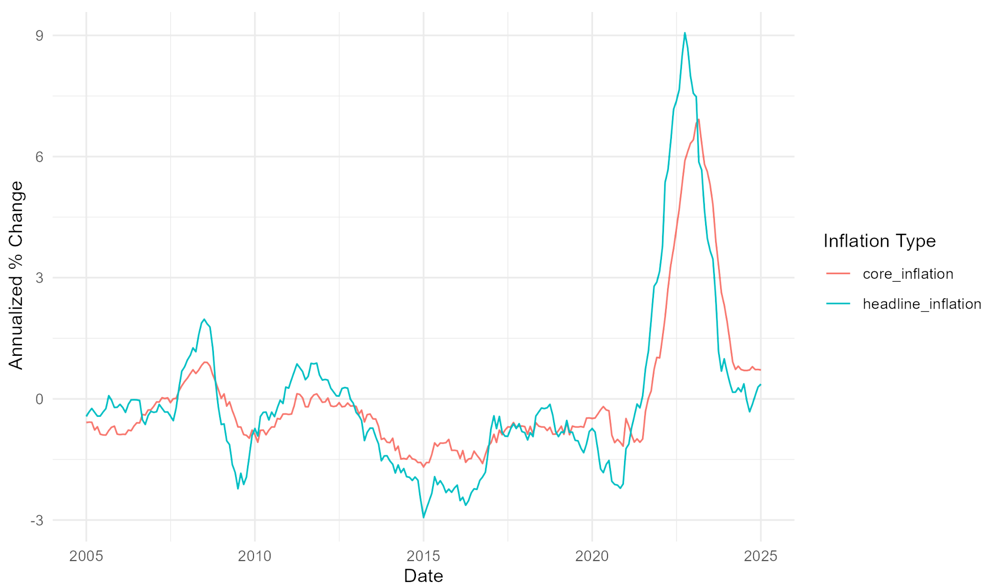


Figure 4: Annualized Demeaned Inflation Rate Over Time (Seasonally Adjusted)

A.2 Stationarity tests

A fundamental assumption in structural vector autoregression (SVAR) modeling is that the included variables are stationary. If a time series is non-stationary, standard inference methods may lead to spurious relationships and unreliable impulse response functions. To formally assess stationarity, three complementary tests are employed: the Augmented Dickey-Fuller (ADF), the Perron's (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. These tests differ in their null hypotheses, with the KPSS test assuming stationarity and the ADF as well as PP test assuming non-stationarity.

Conducting the tests provides a robust assessment of whether a series satisfies the stationarity requirement for SVAR estimation (Enders 2015: 103–106).

The ADF test assesses the presence of a unit root, which is indicative of non-stationarity. The test is based on the regression equation:

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{4}$$

where $\Delta Y_t = Y_t - Y_{t-1}$ is the first difference of the series, α is a constant, γ is the coefficient of interest, p is the number of lags included to control for serial correlation, and ε_t is a white noise error term. The null hypothesis of the ADF test is $H_0 : \gamma = 0$, implying that Y_t has a unit root and is therefore non-stationary. If the test statistic is sufficiently negative, H_0 is rejected, indicating that the series is stationary (Enders 2015: 106–108).

We conduct Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests to assess stationarity.

	ADF	PP	KPSS
diesel_logdiff	0.01	0.07	0.10
euro95_logdiff	0.02	0.04	0.10
heating_oil_logdiff	0.01	0.07	0.10
brent_oil_logdiff	0.01	0.02	0.10
dutch_ttf_logdiff	0.02	0.02	0.10
rotterdam_coal_logdiff	0.01	0.09	0.10
electricity_de_logdiff	0.03	0.12	0.10
headline_inflation	0.04	0.67	0.01
core_inflation	0.01	0.74	0.01

Table 3: p-values from stationarity tests (ADF, PP, KPSS)

A.2.1 ADF Test Results and Interpretation

The ADF test results show p-values below 0.05 for all series, indicating rejection of the null hypothesis of a unit root at the 5% level. This suggests that all series are stationary in their log-differenced form.All test statistics were more negative than the 5% critical value, supporting rejection of the null hypothesis.

A.2.2 PP Test

While the ADF test provides initial evidence for stationarity, it may have limited power (the ability to correctly identify a false null hypothesis). Time-series data might also exhibit structural breaks or non-linear trends. This means that even if a series is trend-stationary, the ADF test may fail to reject the null hypothesis of a unit root, especially when large shocks or regime shifts are present in the data (Enders 2015: 235). To address these potential pitfalls, we complement the ADF results with the PP test.

The PP test provides further support for the conclusion that the log-differenced series are stationary, and is more robust than ADF to serial correlation and heteroskedasticity.

A.2.3 KPSS Test

The KPSS test decomposes a time series Y_t into a deterministic trend, a random walk component, and a stationary error term:

$$Y_t = \beta t + R_t + \varepsilon_t \tag{5}$$

where βt represents a deterministic trend, R_t follows a random walk, and ε_t is a stationary error term. The hypothesis of stationarity is tested by examining whether the variance of R_t is zero. The null hypothesis (H_0) states that R_t is constant, implying that Y_t is stationary around a deterministic trend, whereas the alternative hypothesis (H_1) suggests that R_t exhibits stochastic behavior, implying non-stationarity. If the

KPSS test statistic exceeds the critical value, H_0 is rejected, indicating that the series is non-stationary (Enders 2015: 109–110).

A.2.4 Implications for the SVAR Model

The combined evidence suggests that the log-differenced transformations applied to the energy price variables do appropriately induce stationary, and thus make them suitable for inclusion in the SVAR model (Enders 2015).

Stationarity is particularly important for the identification of structural shocks in the SVAR framework. Since the variance-covariance matrix of residuals Σ_u is assumed to be time-invariant, non-stationarity in any variable could lead to biased estimates of impulse response functions (Enders 2015: 245–247). The rejection of the unit root hypothesis ensures that the estimated shocks can be interpreted as structurally meaningful disturbances rather than artifacts of stochastic trends.

For the inflation series, the stationarity tests yield mixed results. While ADF tests suggest stationarity, the PP and KPSS tests raise doubts. However, in our model, these variables are never used to identify structural shocks; they only appear as response variables in the impulse response analysis. As such, the strict requirement for stationarity is relaxed. Since the inflation series are detrended and their means removed, they still serve as meaningful outcome variables without biasing the structural interpretation of the upstream shocks.

Overall, the results confirm that the log-differenced transformations applied to the energy price variables appropriately induce stationarity, making them suitable for the SVAR model. This finding allows for a valid interpretation of the dynamic interactions between energy price shocks and inflation in our main analysis.

A.3 Lag Length Selection

We use information criteria to guide our selection of the lag length in the SVAR model. Specifically, we compute the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Hannan–Quinn Criterion (HQC) in R. These criteria balance model fit against the number of parameters, with AIC typically favoring more lags and BIC imposing a stronger penalty for complexity and thus favoring less lags.

The optimal lag is chosen by minimizing the value of the information criterion. As shown in Table 4, the AIC suggests a much higher lag length (up to 15 months), while the BIC favors a more parsimonious model with only one lag. This discrepancy is common in small- to medium-sized macroeconomic datasets, where AIC may overfit and BIC may underfit the true lag dynamics (Enders 2015).

	1	2	3	13	14	15
AIC(n)	22.79	21.81	21.52	18.06	17.27	16.34
HQ(n)	23.41	22.99	23.26	25.41	25.18	24.81
SC(n)	24.32	24.73	25.82	36.21	36.80	37.26

Table 4: Information criteria for selected lag lengths

To evaluate the trade-off empirically, we estimate the model with 2, 6, and 12 lags. The 2-lag model yields impulse response functions (IRFs) that appear stable, but that seem to underestimate the magnitude of several key effects. In contrast, the 12- and 14-lag models produce unstable and erratic IRFs, and when bootstrapping the confidence intervals yield essentially no significant results, likely due to overfitting and reduced degrees of freedom considering our limited data. The 6-lag specification offers a more stable middle ground.

This choice is also supported by previous research. Edelstein & Kilian (2009) and Kilian & Zhou (2022) use six lags to account for delayed effects of energy shocks on macroeconomic variables, noting that shorter lag lengths may fail to capture the gradual pass-through through supply chains and pricing decisions. Although their work is based on US data, we find the logic applicable to the Euro area, where monetary and trade integration implies similar transmission patterns.

We therefore adopt a 6-lag specification as our baseline model. It strikes a balance between theoretical plausibility, empirical performance, and robustness across lag structures. This choice is further supported by model stability tests (see Section B.1), which confirm that all characteristic roots lie within the unit circle, indicating dynamic stability of the system. While we detect significant residual autocorrelation (see Section B.2), the instability of longer lag structures leads us to retain the 6-lag specification. To address potential inference issues arising from autocorrelated residuals, we rely on bootstrapped impulse response functions and report the median responses to ensure robust inference (see Section D) (Enders 2015: 300-301).

B Residual Diagnostics

B.1 Roots Stability Test

To ensure that the system of equations behaves in a stable and predictable manner, we assess whether small shocks dissipate over time or lead to explosive dynamics. This is done by examining the eigenvalues (or characteristic roots) of the companion matrix associated with the VAR model. If all roots lie strictly inside the unit circle, the system is considered dynamically stable, meaning that any deviations from equilibrium caused by shocks will eventually fade. Conversely, if one or more roots lie on or outside the unit circle, the system may be unstable, and the resulting impulse response functions become unreliable.

Note that even if each of the variable is stationary individually, their dynamic interaction in the VAR system can still lead to instability. In our case, the model satisfies the stability condition, as all roots lie strictly within the unit circle, as shown in Figure 5.

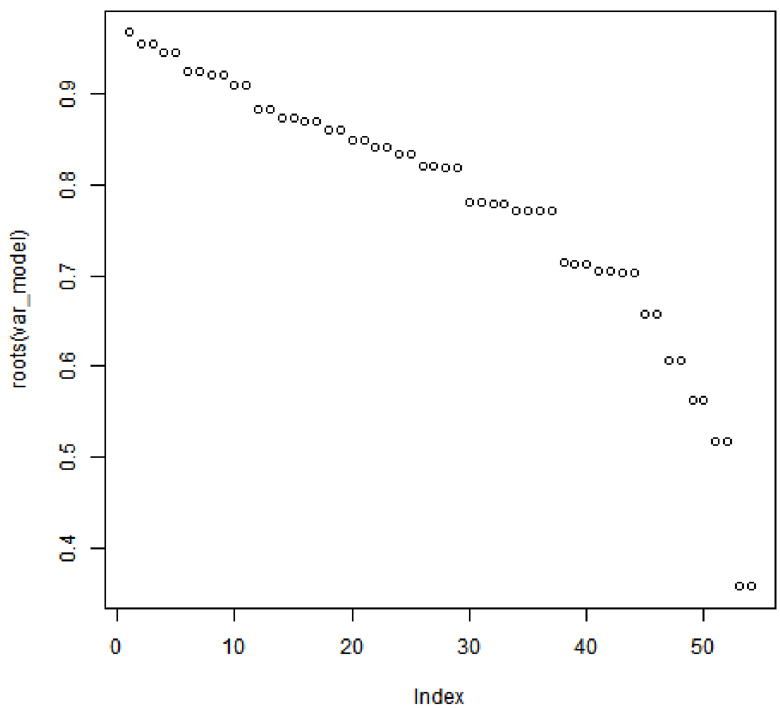


Figure 5: Roots of the VAR Characteristic Polynomial

B.2 Serial Correlation Test

To check whether the residuals from the estimated VAR model are free from autocorrelation, we use a Portmanteau test. This test evaluates whether there is any significant correlation still in the residuals across additional lags. Ideally, a well-specified model will produce residuals that only resemble "white noise", indicating that all the dynamics of the data has been adequately captured in the model.

We conduct the test using 12 lags, which exceeds the 6 lags used in the VAR model and ensures valid degrees of freedom. The result yields a test statistic of $\chi^2 = 797.73$ with 486 degrees of freedom and a p-value less than 2.2×10^{-16}, leading to a rejection of the null hypothesis of no autocorrelation.

However, we find that this rejection persists even when increasing `lags.pt` to 20 or 30. This suggests that the test may be overly sensitive to minor and economically insignificant autocorrelation when many lags are included – especially in a high-dimensional VAR with many parameters and limited sample size such as ours. It is possible that the rejection of the null hypothesis is influenced by the relatively large number of variables and parameters, combined with a limited sample. As noted by Enders (2015: 305), the Portmanteau test may tend to over-reject in such settings. We therefore interpret the result with some caution and consider it alongside other diagnostics and robustness checks.

Since increasing the lag length in the VAR itself results in unstable impulse responses (see Appendix A.3), we retain the 6-lag model. To ensure valid inference despite the presence of autocorrelated residuals, we use bootstrap-based confidence intervals. Specifically, we implement a moving block bootstrap procedure that resamples residuals in blocks within each regime, preserving the autocorrelation structure. This method does not rely on the assumption of white noise residuals and is therefore suited for situations with autocorrelation or conditional heteroskedasticity (see Kilian & Lütkepohl 2017: p. 88–90) (see Appendix D).

B.3 Normality Test

To evaluate the distributional properties of the residuals from the VAR model, we apply a multivariate Jarque–Bera test. This test assesses whether the residuals deviate significantly from a joint normal distribution, considering both skewness and excess kurtosis.

The results indicate a clear rejection of the null hypothesis of joint normality, with a test statistic of $\chi^2 = 462.55$, 18 degrees of freedom, and a p-value below 2.2×10^{-16}. Both components of the test contribute to this result: skewness ($\chi^2 = 56.82$, df $= 9$, $p = 5.47 \times 10^{-9}$) and kurtosis ($\chi^2 = 405.73$, df $= 9$, $p < 2.2 \times 10^{-16}$).

This outcome suggests that the residuals are not normally distributed, which may undermine the validity of standard inference procedures which rely on asymptotic normality. While non-normal residuals do not invalidate the model specification itself, they may highlight the need for robust inference methods. As such (and as mentioned above), we rely on bootstrap-based confidence intervals for impulse response analysis, which are better suited to models with non-Gaussian error distributions (see Appendix D) (Kilian & Lütkepohl 2017: 88).

C Regimes and Structural Stability

C.1 Evidence of Heteroskedasticity

Our identification strategy relies on the assumption that the structural shocks exhibit conditional heteroskedasticity across regimes. To test this, we conduct univariate ARCH LM tests on the residuals from each equation in the VAR model. These tests examine whether past squared residuals help explain the variance of current residuals, which is an indication of time-varying volatility.

The results indicate significant ARCH effects in some of the energy price variables, including Brent oil, Dutch TTF gas, and Rotterdam coal, as well as in core inflation. For example, the Brent oil residuals yield a test statistic of $\chi^2 = 72.79$ (df = 12, $p < 1 \times 10^{-10}$), clearly rejecting the null of constant variance. This supports the presence of conditional heteroskedasticity in key shock-generating variables. In contrast, variables such as diesel, Euro95, and headline inflation show no such effects—consistent with the assumption that the source of heteroskedasticity is concentrated in the upstream block. These findings also provide empirical support for the use of heteroskedasticity-based identification, but further testing is needed to ensure that the parameters of interest for the structural impact matrix are time invariant.

Variable	Test_Statistic	P_Value
brent_oil_logdiff	49.12	0.00
diesel_logdiff	3.41	0.76
euro95_logdiff	7.16	0.31
heating_oil_logdiff	5.89	0.44
dutch_ttf_logdiff	8.71	0.19
rotterdam_coal_logdiff	16.67	0.01
electricity_de_logdiff	7.24	0.30
headline_inflation	0.57	1.00
core_inflation	2.48	0.87

Table 5: ARCH Test Results for Residual Heteroskedasticity

C.2 Tests for Structural Change

To support the assumption that the volatility of structural shocks varies across regimes, we perform structural break tests on the residuals of the VAR model. Specifically, we apply the Iterative Cumulative Sum of Squares (ICSS) test to detect sudden shifts in the variance of each residual series over time.

The ICSS test identifies multiple breakpoints in several of the upstream energy residuals, including Dutch TTF and Rotterdam coal. These shifts coincide with periods of known geopolitical and energy market disruptions, such as the Covid-19 pandemic and Russian invasion of Ukraine.

Variable	Num_Breaks	Breakpoints
brent_oil_logdiff	2	145, 163
diesel_logdiff	0	
euro95_logdiff	0	
heating_oil_logdiff	1	146
dutch_ttf_logdiff	1	124
rotterdam_coal_logdiff	2	29, 162
electricity_de_logdiff	1	172
headline_inflation	1	168
core_inflation	1	153

Table 6: ICSS Detected Breakpoints in Residual Variance

The presence of such variance breaks suggests that the assumption of a constant error variance over the full sample is unlikely to hold. This reinforces the justification for modeling the system under different volatility regimes and using identification strategies that exploit such structural heteroskedasticity in the data.

We also consider the Bai–Perron test for multiple structural breaks in the mean or variance of the residuals. Where applicable, break dates are consistent with those inferred from the ICSS procedure. Overall, the results support the presence of regime shifts in the data-generating process.

Variable	Num_Breaks	Breakpoints
brent_oil_logdiff	2	143, 173
diesel_logdiff	1	168
euro95_logdiff	0	
heating_oil_logdiff	1	168
dutch_ttf_logdiff	1	124
rotterdam_coal_logdiff	1	167
electricity_de_logdiff	0	
headline_inflation	0	
core_inflation	1	153

Table 7: Bai-Perron Breakpoints for Variance Changes

C.3 Changes in Covariance Matrix

A central assumption of the heteroskedasticity-based identification strategy is that the structural impact matrix B_0 remains time-invariant across regimes (the pass-through of the shocks is the same in both periods), while the variance–covariance matrix of the structural shocks changes. To test this, we estimate the residual covariance matrices separately for each regime and then examine their properties.

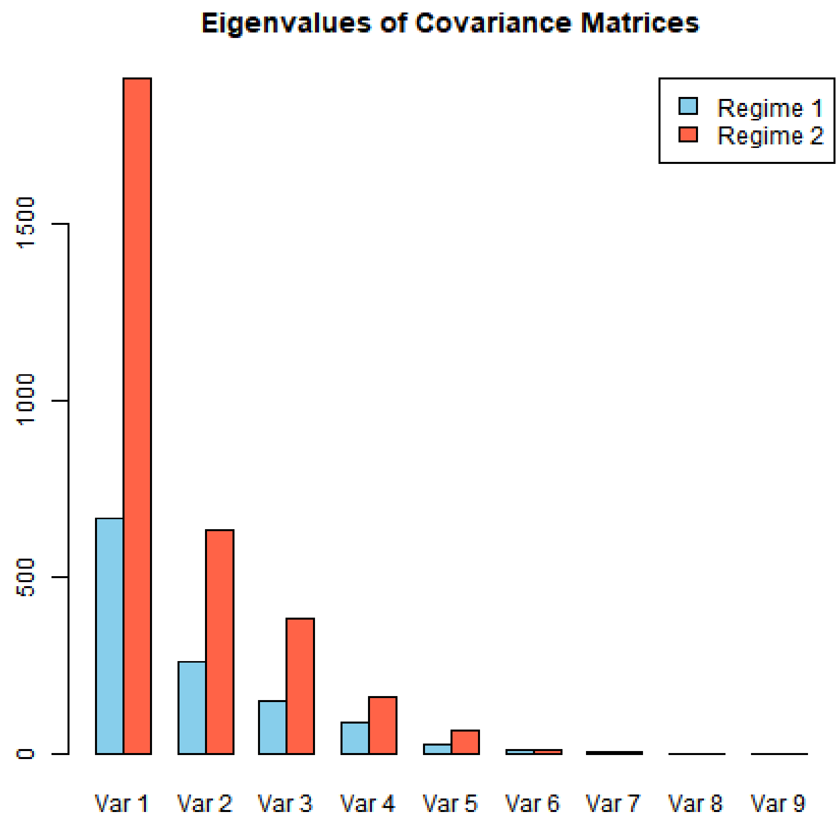


Figure 6: Eigenvalues of residual covariance matrices across regimes

Figure 6 shows that the eigenvalues of the covariance matrices differ in a significant way between the two regimes, particularly for upstream energy variables such as oil. These differences suggest a shift in the variance structure of the underlying shocks.

To formally test whether the covariance matrices differ, we apply Box's M test. The null hypothesis of equal covariance matrices across regimes is rejected at the 1% level, confirming that the variance–covariance structure is not stable over time.

Test_Statistic	DF	P_Value
216.07	45.00	0.00

Table 8: BoxM Test for Equality of Covariance Matrices

Table 8 reports the test results. The significant change in covariance supports the core requirement of conditional heteroskedasticity-based identification.

C.4 Correlation Matrix Comparison

To further assess the stability of the contemporaneous structural relationships, which is a core assumption for our identification strategy, we compare the residual correlation matrices across regimes. Since correlation matrices remove differences in scale by standardizing variances, they help isolate changes in the relationships between variables. Stable correlations across regimes support the assumption that the underlying structural impact matrix remains unchanged, even if variances shift. In other words, while changes in the covariance matrix may simply reflect increased volatility in individual variables, the correlation matrix tells us whether the co-movement between variables such as Brent oil and core inflation— remains stable across regimes, regardless of their individual variances.

We find that most pairwise correlations change only modestly, typically within ± 0.10, and only a few exceed ± 0.20. These exceptions appear to be idiosyncratic and are not systematically concentrated in any specific block. The off-diagonal structure remains visually and statistically similar across regimes, suggesting that the contemporaneous impact matrix B_0 is invariant – meaning our identification strategy is valid.

Additionally, Kilian & Zhou (2022) remove the post-2020 data and re-estimate their SVAR model to test for structural stability. They find no meaningful change in results, suggesting that the structural impact matrix remained invariant and that the underlying pass-through dynamics were unaffected by the volatility regime shift.

These results collectively support the assumption of regime-varying shock variances combined with a stable structural transmission matrix. However, considering that some pairwise correlations were slightly higher, we also conduct a CUSUM test after estimating the model, to check for parameter stability.

C.5 Parameter Stability Testing

A key assumption of heteroskedasticity-based identification is that structural relationships – particularly the structural impact matrix B_0 – remain invariant across regimes, while variances of structural shocks change. Although B_0 is not directly testable, stability of the reduced-form VAR coefficients is a necessary precondition.

To assess this, we conduct a recursive CUSUM test on the VAR residuals. The test tracks the cumulative sum of recursive residuals over time and compares it to the 95% confidence bounds under the null hypothesis of parameter stability.

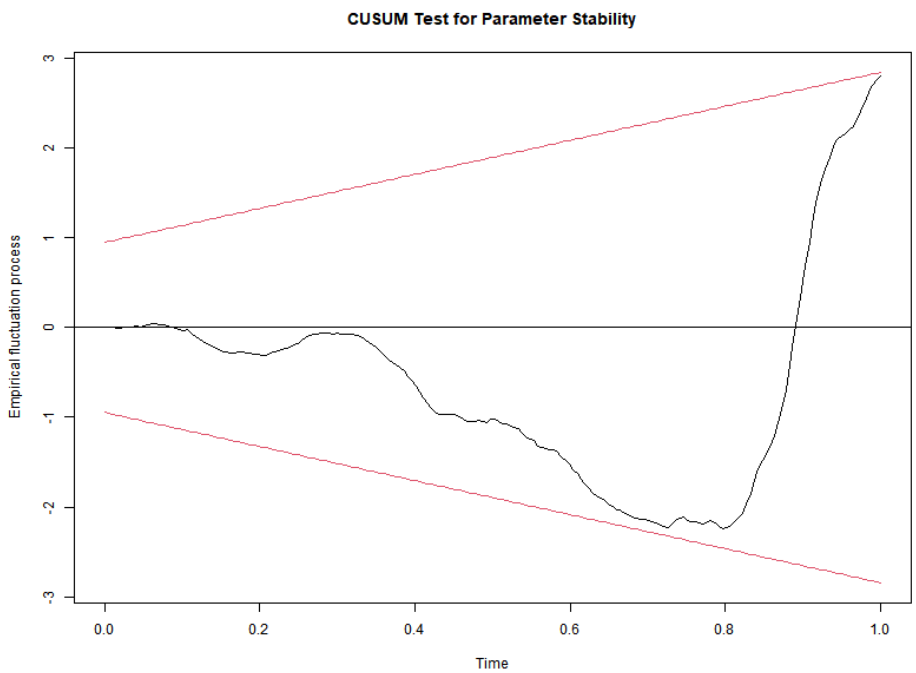


Figure 7: CUSUM test for parameter stability. The empirical fluctuation process remains within the 95% confidence bounds.

As shown in Figure 7, the CUSUM process remains within the confidence bounds throughout the sample, indicating that the null hypothesis of stable reduced-form parameters cannot be rejected. This supports the plausibility of treating B_0 as time-invariant for identification purposes.

Toward the end of the sample, the process approaches the boundary, suggesting that structural changes may be emerging. While our framework assumes stability of B_0, future work could explore extensions using time-varying or regime-switching structural models to capture evolving transmission mechanisms.

Overidentification Test

Since our model imposes additional restrictions beyond those required for identification via heteroskedasticity – namely both recursive ordering and exclusion restrictions – it is overidentified. To assess whether these restrictions are consistent with the data, we conduct a likelihood ratio test comparing our restricted SVAR to a more general baseline model identified solely through heteroskedasticity, without any structural zero restrictions.

Test Component	**Value**
Likelihood Ratio (LR) statistic	16.91
Degrees of freedom	42
p-value	0.9998

Table 9: Likelihood Ratio Test for Overidentifying Restrictions

As shown in Table 9, the test yields a high p-value, indicating that the imposed restrictions are not rejected at any conventional significance level. This suggests that the recursive and exclusion restrictions used in our main model are statistically valid and compatible with the identifying information provided by the regime-based variance shifts.

Overall, the test supports the view that our SVAR model is not misspecified due to the imposed recursive structure, and that the hybrid identification strategy is internally coherent.

D Confidence Interval Construction

D.1 Our method

In the presence of heteroskedasticity, autocorrelation, and non-Gaussian residuals (as shown in Appendix B), traditional asymptotic inference may lead to misleading confidence intervals. Bootstrap techniques offer a more robust alternative by empirically re-sampling the data and capturing the true distribution of impulse responses – and constructing the confidence intervals and IRF function thereafter.

We manually build and employ a moving block bootstrap (MBB) in R that resamples residuals in fixed-length blocks while preserving the identified structural break at observation 150. This regime-aware procedure maintains the heteroskedasticity pattern required for identification and preserves temporal dependencies within each block. Residuals are drawn separately for each regime, and then re-combined with the fitted values from the original VAR to simulate new datasets.

For each bootstrap iteration, the VAR is re-estimated, and the SVAR is identified using the same hybrid strategy as in the baseline: a combination of recursive ordering and zero restrictions alongside volatility shifts (via the `id.cv` function). This process is repeated 1000 times to generate bootstrap distributions for each impulse response function (IRF).

We report percentile-based confidence intervals at the 68% and 90% levels, along with the bootstrap median as the central estimate. This choice is motivated by the fact that the original "true" IRF from the full-sample model can occasionally lie outside the empirical confidence region generated by bootstrap resampling, particularly in small samples or when residuals are non-Gaussian (as in our case). So, instead, the bootstrap median provides a robust alternative that always lies within its own confidence interval, offering a more reliable estimate of the central tendency under empirical uncertainty

(Kilian & Lütkepohl 2017: 88–90).

The resulting confidence intervals are often asymmetric – which is an expected feature of bootstrap-based inference, particularly when responses are skewed or horizon-dependent. We construct the confidence intervals non-parametrically from the empirical distribution, without assuming symmetry. This approach allows the shape of the intervals to be determined entirely by the data.

D.2 Alternative methods

We also experimented with alternative resampling methods, including wild bootstrap procedures such as `wild.boot` in the `svars` package. While this is convenient for recursive identification, the wild bootstrap schemes do not easily accommodate hybrid models as they don't preserve the regime-dependent volatility structure essential to our identification strategy. For these reasons, we rely on the regime-preserving moving block bootstrap as our preferred method for inference.

E Use of AI

In this thesis, the generative AI tool ChatGPT (developed by OpenAI) was used as support in different parts of the process. The AI helped mainly with three things: searching for articles and data, improving the language in the writing, and helping with coding in R and Overleaf Latex.

At the start of the project, ChatGPT was used to get suggestions for relevant academic papers, reports, and datasets. It helped speed up the early stages of finding material, but all sources were carefully reviewed and chosen by the authors. No references were included based only on AI suggestions.

ChatGPT was also used to improve the language and structure of parts of the thesis. It helped by suggesting clearer wording and making the text flow better. Importantly, however, all ideas, arguments, and interpretations were written independently by the authors, and the AI was only used to aid in polishing the writing, not to create content.

Finally, during the empirical work, ChatGPT helped with coding by suggesting relevant packages, ways to fix minor mistakes and errors, and improvements to the structure of the code used for the econometric model in R. Even though the AI made coding faster and easier at times, all key methodological decisions, model building, and interpretation of results were done by the authors themselves. Additionally, AI was used to help convert references to Latex-format, and for faster input of plots and graphs into Overleaf.

Before using AI, approval was obtained from the thesis supervisor.

E.1 How AI helped improve the thesis

The use of AI mainly helped save time and made the work process smoother. It simplified the process of finding relevant research materials, especially at the start of the thesis process, and improved the clarity and style of the written text by fixing typos and refining sentences. Importantly, the suggestions from the AI were sometimes wrong, or written in unnecessarily complex language – in which case the suggestions were disregarded.

When coding, AI support additionally helped to (i) identify the most relevant R packages and functions to use for testing and model building, and (ii) solve technical problems faster, allowing more focus on researching and determining the most suitable methodology, as well as properly analyzing the results. Additionally, it helped speed up the process of importing references, tables and plots into Overleaf by providing the necessary code for integrating these objects into the document(s).

E.2 Risks of using AI

Using AI also comes with some risks. For example, the information suggested by ChatGPT was sometimes wrong or unreliable, the language was sometimes too informal to the extent that it was unclear, or not academic enough to the extent that it did not retain all the information initially provided. To handle these risks:

1. All suggested sources were manually checked and evaluated before being used.
2. Language improvements suggested by the AI were always reviewed and adjusted to meet academic writing standards.
3. No parts of the thesis were copied directly from ChatGPT without changes or careful checking.
4. Screenshots of some important AI interactions and commonly used prompts were saved to make the process more transparent. These are provided below in figures 6 and 7:

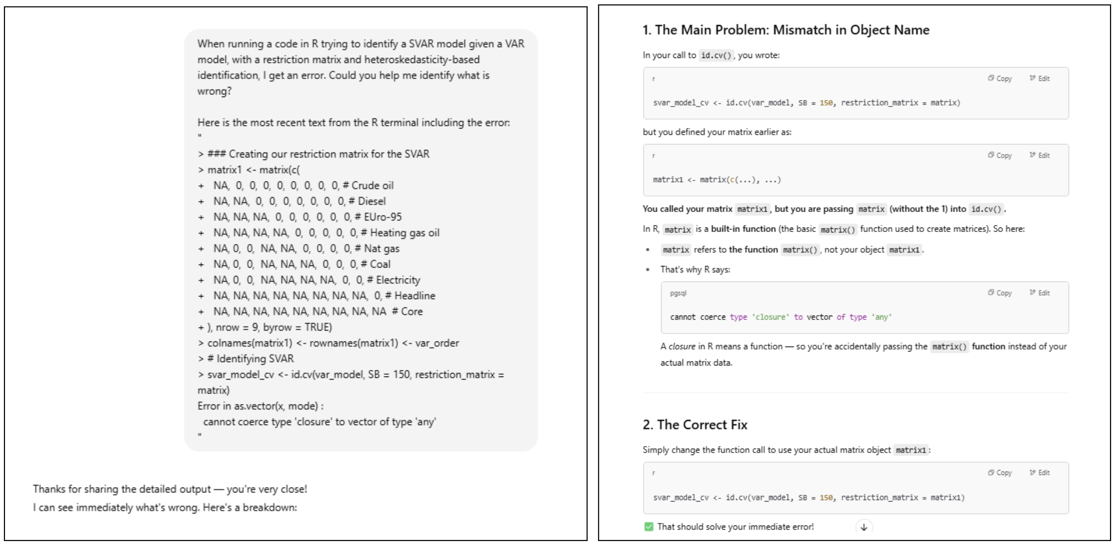


Figure 8: AI prompt often used for minor errors in code

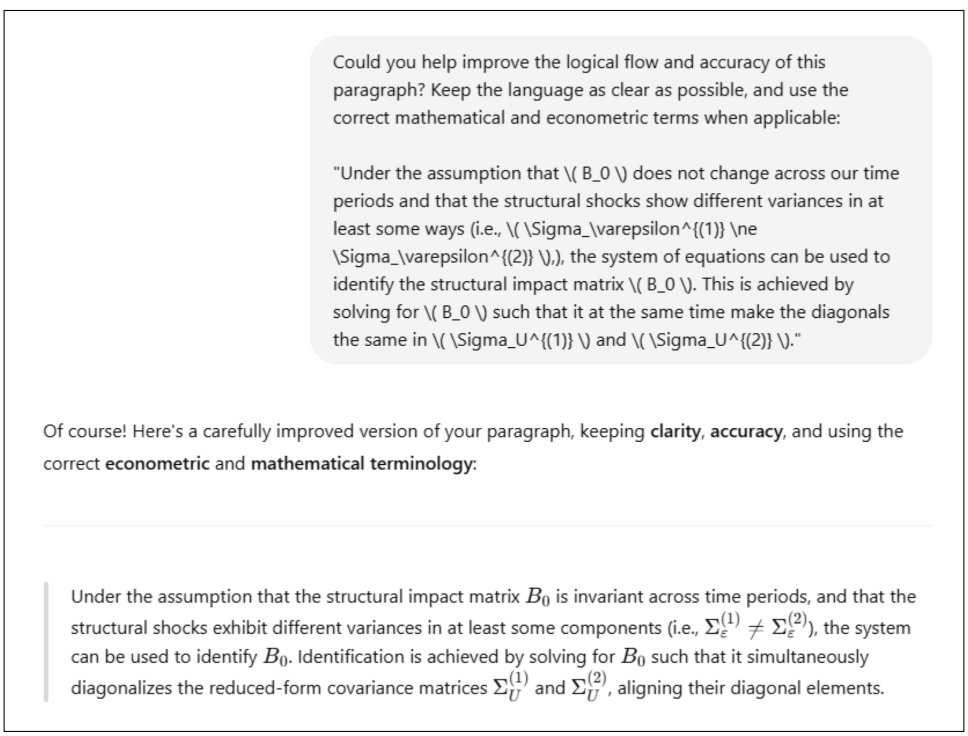
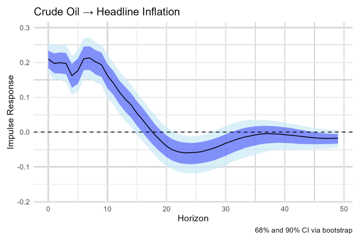


Figure 9: AI prompt used to improve language and terminology for specific paragraphs

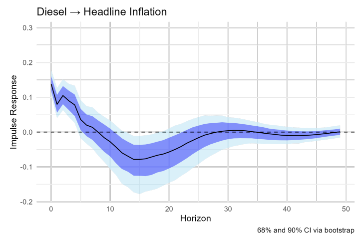
E.3 What we learned from using AI

Using AI gave helpful support in the writing and coding process, but it also showed clearly that AI should only be used with care. It made several tasks faster and helped identify minor problems and polish the final text, but critical thinking, decision-making, and academic responsibility always had to come from the authors. AI can be a useful tool when used thoughtfully, but cannot replace real academic work.

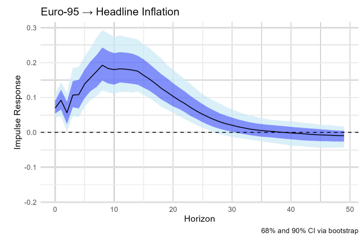
F Impulse Response Functions



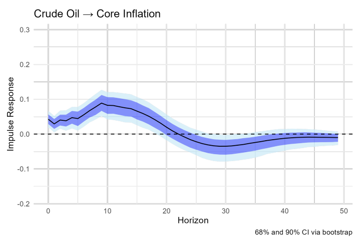
(a) Brent → Headline



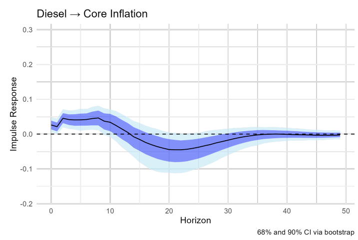
(b) Diesel → Headline



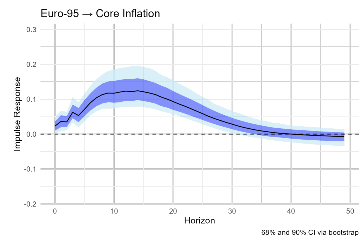
(c) Euro95 → Headline



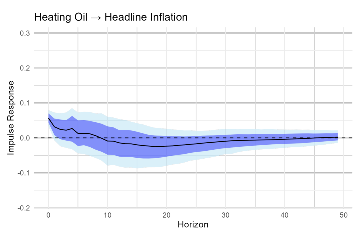
(d) Brent → Core



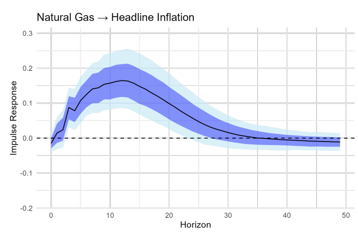
(e) Diesel → Core



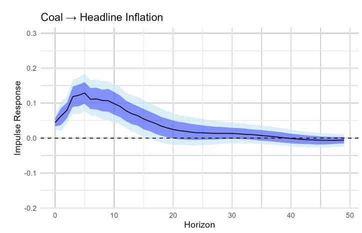
(f) Euro95 → Core



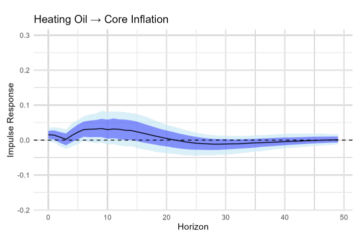
(g) Heating Oil → Headline



(h) Dutch TTF → Headline



(i) Coal → Headline



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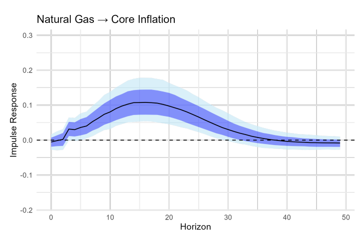
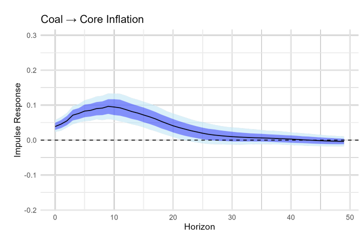
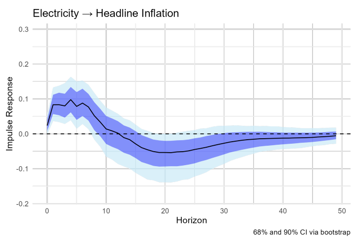


(k) Dutch TTF → Core

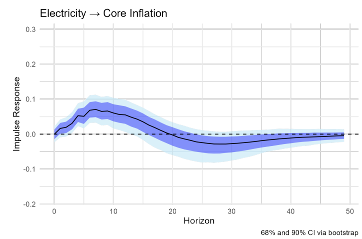


(l) Coal → Core

Figure 10: Impulse response functions from energy shocks to headline and core inflation. 6 lag model.

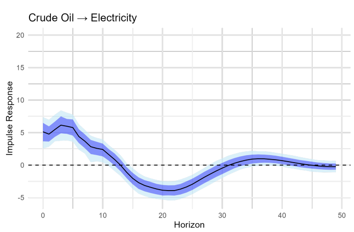


(a) Electricity → Headline

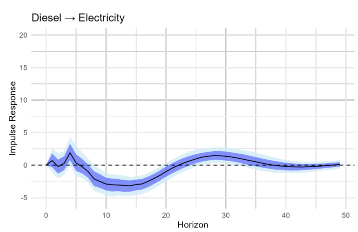


(b) Electricity → Core

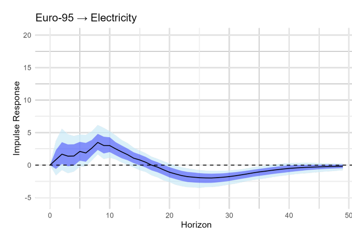
Figure 11: Impulse response functions from energy shocks to headline and core inflation. 6 lag model.



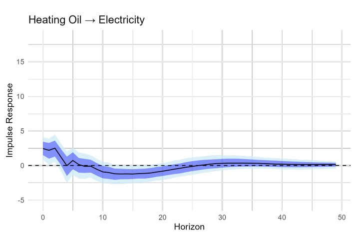
(a) Brent → Electricity



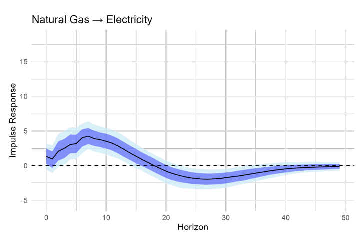
(b) Diesel → Electricity



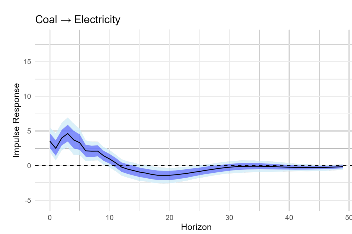
(c) Euro-95 → Electricity



(d) Heating oil → Electricity

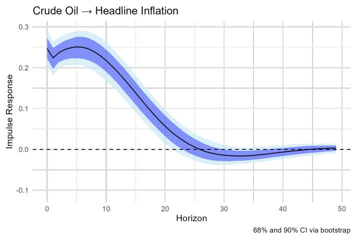


(e) Dutch TTF → Electricity

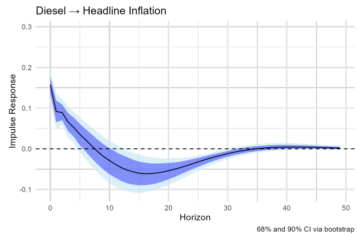


(f) Coal → Electricity

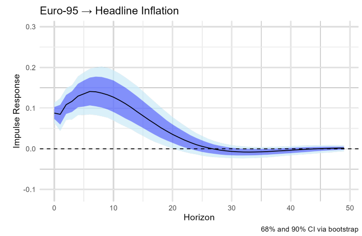
Figure 12: Impulse response functions from energy shocks to electricity prices. 6 lag model.



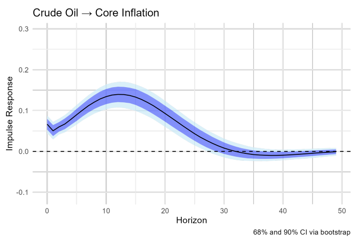
(a) Brent → Headline



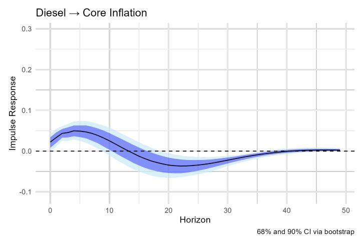
(b) Diesel → Headline



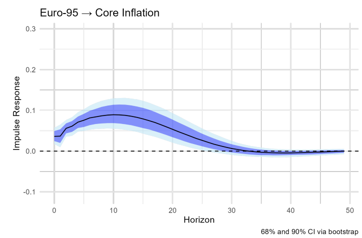
(c) Euro95 → Headline



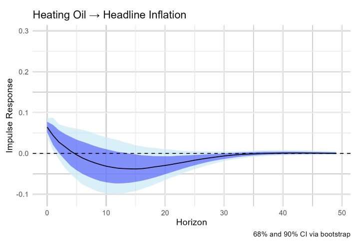
(d) Brent → Core



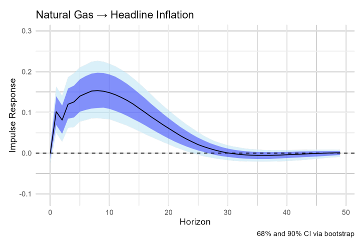
(e) Diesel → Core



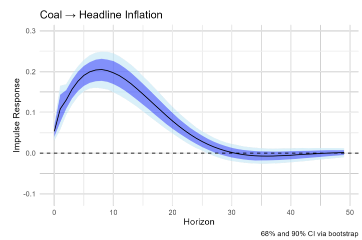
(f) Euro95 → Core



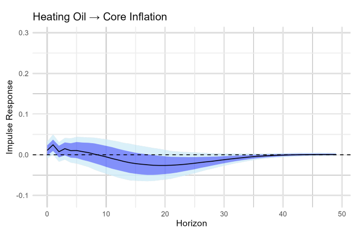
(g) Heating Oil → Headline



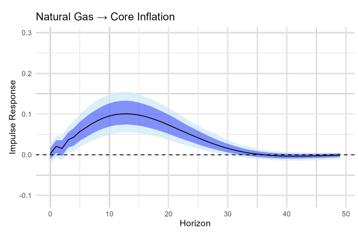
(h) Dutch TTF → Headline



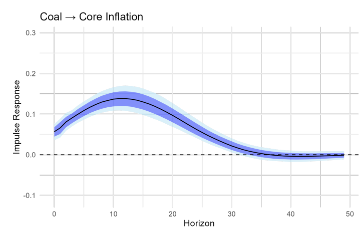
(i) Coal → Headline



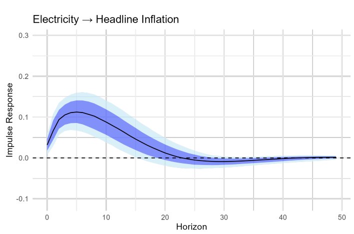
(j) Heating Oil → Core



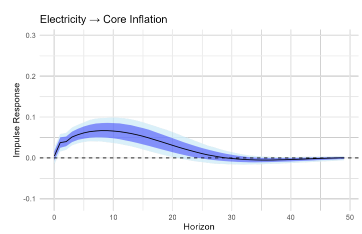
(k) Dutch TTF → Core



(l) Coal → Core

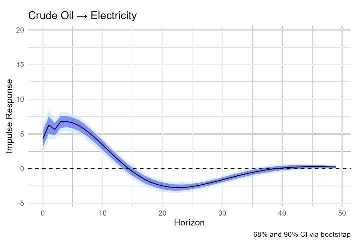


(m) Electricity → Headline

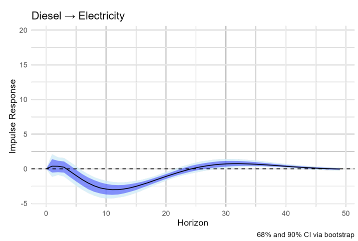


(n) Electricity → Core

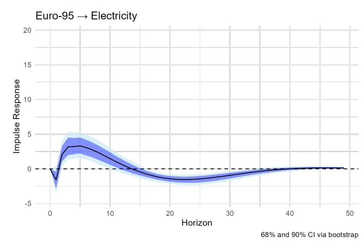
Figure 13: Impulse response functions from energy shocks to headline and core inflation. Headline is shown on top of each pair. 2 lag model.



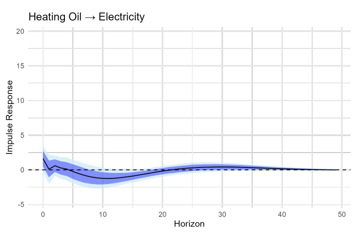
(a) Brent → Electricity



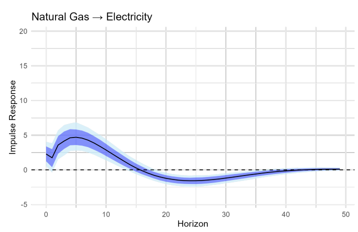
(b) Diesel → Electricity



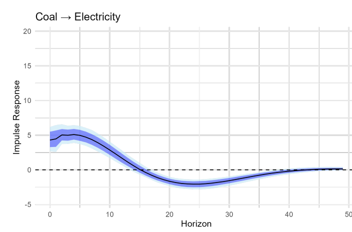
(c) Euro-95 → Electricity



(d) Heating oil → Electricity

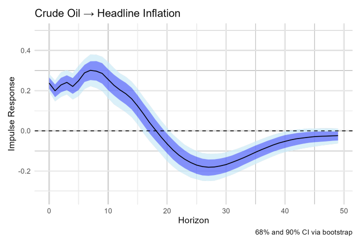


(e) Dutch TTF → Electricity

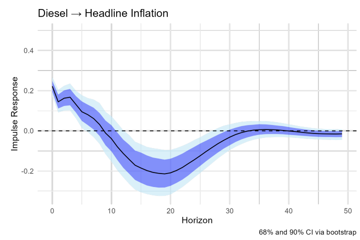


(f) Coal → Electricity

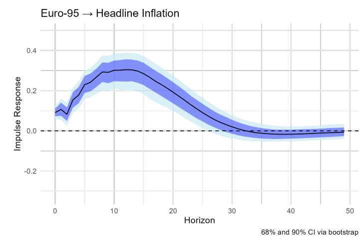
Figure 14: Impulse response functions from energy shocks to electricity prices. 2 lag model.



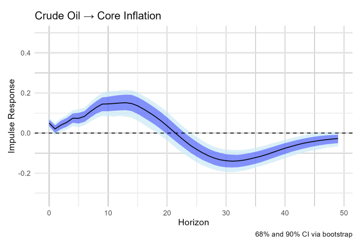
(a) Brent → Headline



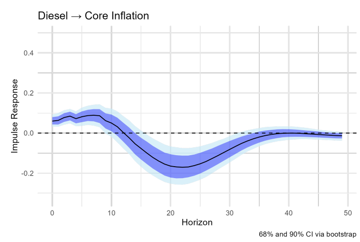
(b) Diesel → Headline



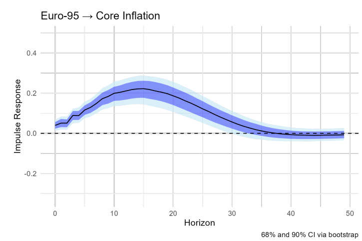
(c) Euro95 → Headline



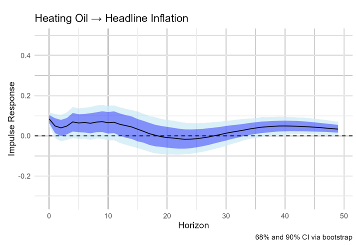
(d) Brent → Core



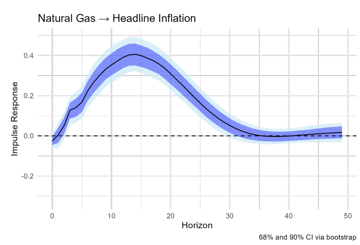
(e) Diesel → Core



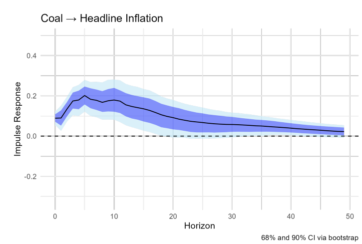
(f) Euro95 → Core



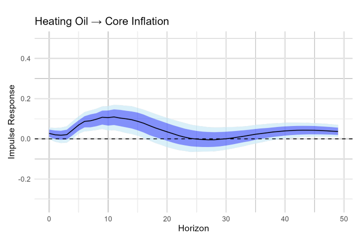
(g) Heating Oil → Headline



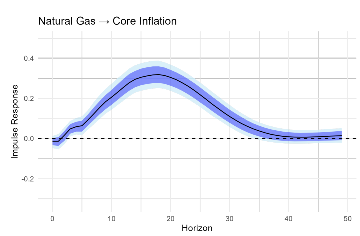
(h) Dutch TTF → Headline



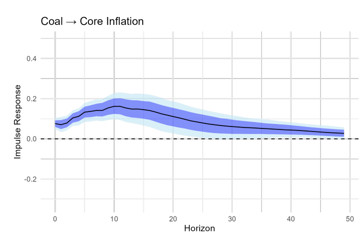
(i) Coal → Headline



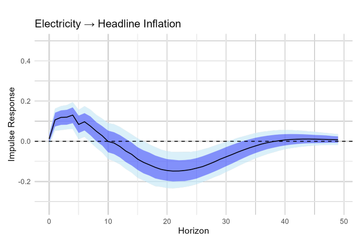
(j) Heating Oil → Core



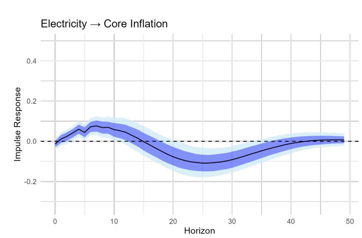
(k) Dutch TTF → Core



(l) Coal → Core

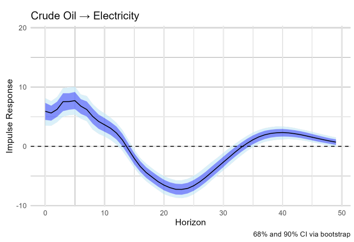


(m) Electricity → Headline

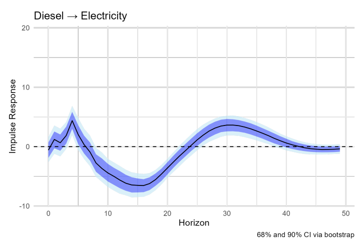


(n) Electricity → Core

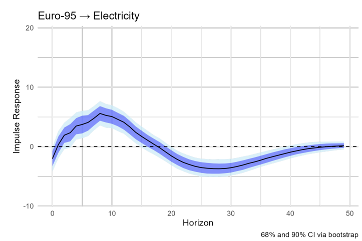
Figure 15: Impulse response functions from energy shocks to inflation using the id.chol function with only recursive ordering. Headline is shown on top of each pair.



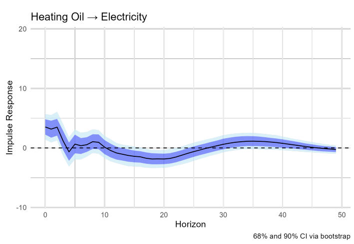
(a) Brent → Electricity



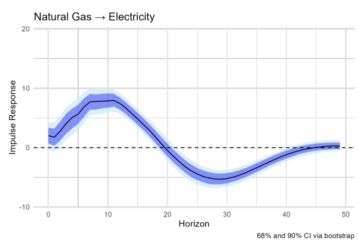
(b) Diesel → Electricity



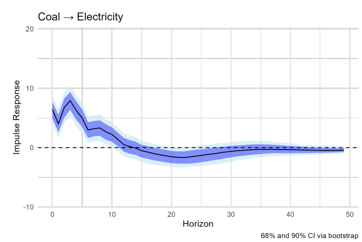
(c) Euro-95 → Electricity



(d) Heating oil → Electricity

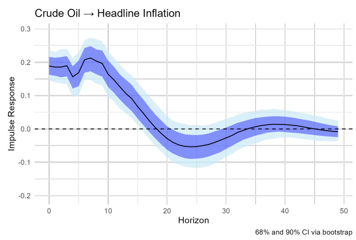


(e) Dutch TTF → Electricity

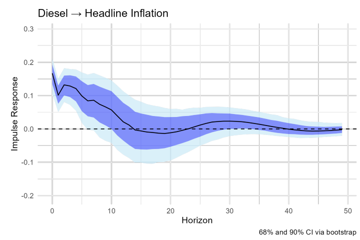


(f) Coal → Electricity

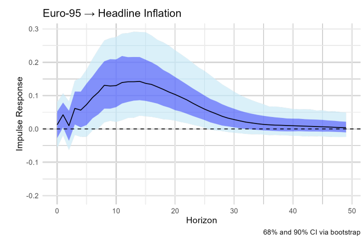
Figure 16: Impulse response functions from energy price shocks to electricity prices using the id.chol function with recursive ordering



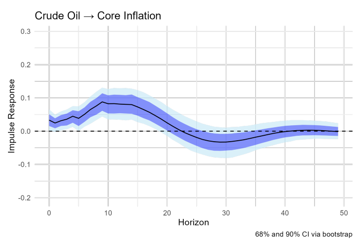
(a) Brent → Headline



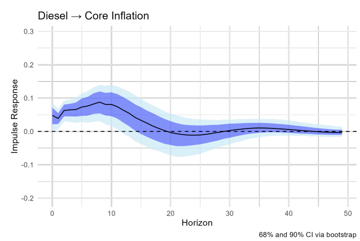
(b) Diesel → Headline



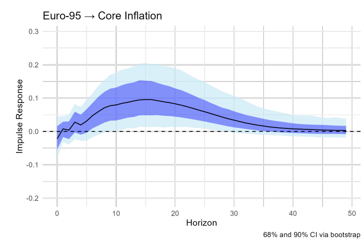
(c) Euro95 → Headline



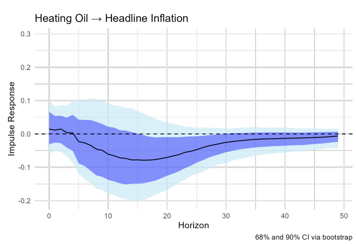
(d) Brent → Core



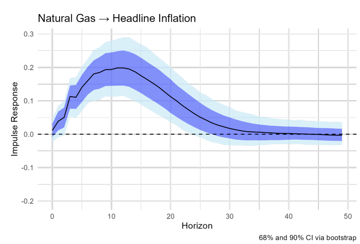
(e) Diesel → Core



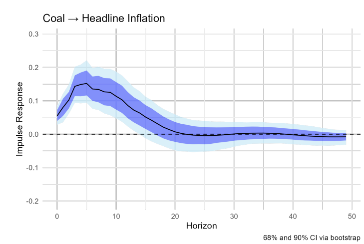
(f) Euro95 → Core



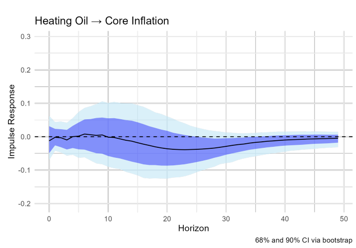
(g) Heating Oil → Headline



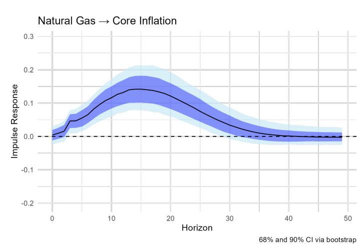
(h) Dutch TTF → Headline



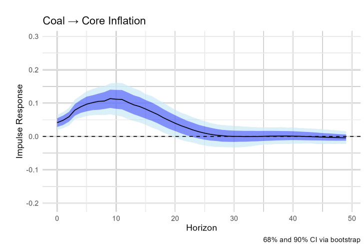
(i) Coal → Headline



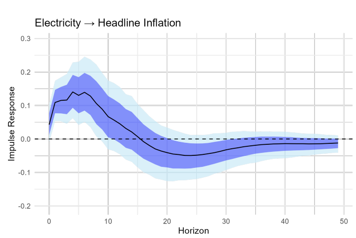
(j) Heating Oil → Core



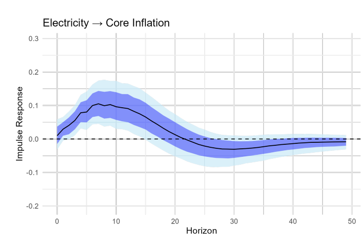
(k) Dutch TTF → Core



(l) Coal → Core

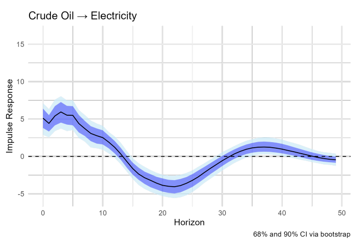


(m) Electricity → Headline

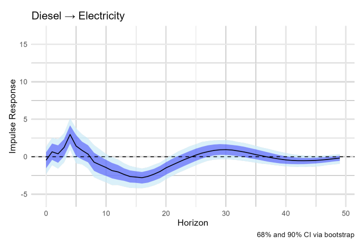


(n) Electricity → Core

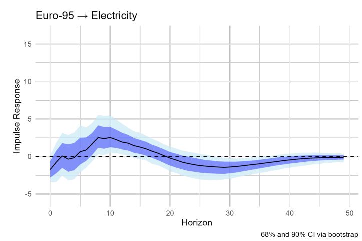
Figure 17: Impulse response functions from energy shocks to headline and core inflation using heteroskedasticity-based identification, without recursive ordering. Headline is shown on top of each pair.



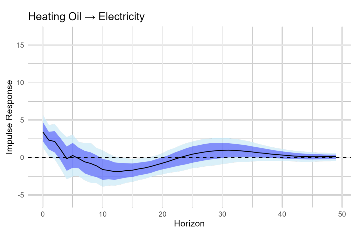
(a) Brent → Electricity



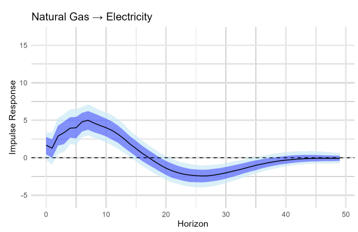
(b) Diesel → Electricity



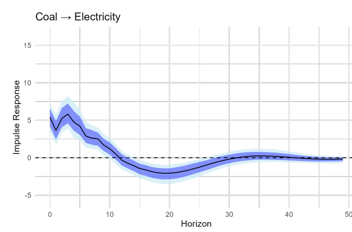
(c) Euro-95 → Electricity



(d) Heating oil → Electricity



(e) Dutch TTF → Electricity



(f) Coal → Electricity

Figure 18: Impulse response functions from energy shocks to electricity prices using heteroskedasticity-based identification, without recursive ordering.