Carbon Emissions and the Transmission of Monetary Policy*

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November 5, 2025

Abstract

This paper investigates the dynamic causal effects of monetary policy on carbon emissions in the United States through a Structural Vector Autoregression (SVAR) model. I find that, contrary to conventional wisdom, a contractionary monetary policy shock leads to a significant *increase* in total carbon emissions from energy consumption, even as economic activity declines. The impact is sizeable, as a 25-basis-point tightening leads to a rise in emissions of about one percent. This countercyclical response is driven by contrasting sectoral dynamics: whereas emissions from the industrial sector decline as expected, emissions from non-industrial sectors rise significantly in the short run. A detailed analysis reveals that the channels of monetary policy transmission vary in strength and relevance across sectors and help explain these heterogeneous responses: while the conventional *aggregate demand* channel plays a central role in the response of industrial sector emissions, the evidence suggests a more significant role of *commodity price* and *energy reallocation* channels for the transmission of shocks to non-industrial sectors.

JEL classification: E32, E43, E62, Q43, Q54, Q58
Keywords: Monetary Policy, Carbon Emissions, Commodity Prices, Business Cycle Fluctuations, High-Frequency Identification.

*I would like to thank Jordi Galí, Davide Debortoli, Priit Jeenas, Barbara Rossi, Geert Mesters, Andresa Lagerborg, Francesca Loria, Kurt G. Lunsford, Jorge Miranda-Pinto, and participants at the 28th Conference "Theories and Methods in Macroeconomics" (T2M), the 1st Congress of LAERE, the 2024 European Winter Meeting of the Econometric Society, the 7th Annual Meeting of CEBRA's International Finance and Macroeconomics Program, the 8th Conference on the Econometric Models of Climate Change, the 6th QMUL Economics and Finance Workshop for PhD and Post-doctoral Students, the CREi Macroeconomics Lunch Workshop and the BSE PhD Jamboree 2024 for helpful discussions, comments and suggestions. I gratefully acknowledge financial support from the European Union through the Joan Oró FI Grant under the European Social Fund. Finally, I thank the School of Economics at the University of East Anglia for awarding me the Best Paper presented by a Junior Researcher at the 2nd edition of the UEA ECO Time Series Workshop. The views expressed in this manuscript are those of the authors and do not necessarily represent the views of Banco de España, or the Eurosystem. All errors are my own.

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1 Introduction

The increase in global carbon dioxide emissions and other greenhouse gases, alongside the resulting acceleration of climate change in recent decades, is considered one of the most critical threats to global economic prosperity and well-being. Addressing these challenges has become a priority on the public policy agenda, with carbon pricing, through carbon taxes and emissions trading systems, widely recognized as a key policy tool. However, while there is substantial consensus and evidence on the effectiveness of these policies in reducing emissions, there is less agreement on the potential role of complementary tools, such as monetary policy, in mitigating the drivers and impacts of climate change.

An ongoing debate centers on whether central banks should integrate climate change considerations into their monetary policy frameworks and adopt a more active role in addressing it. Key points in this discussion include the manner in which monetary policy should address climate change while adhering to its primary objective of price stability, the potential trade-offs between climate-related goals and these core objectives, and how these trade-offs should be managed given the range of policy instruments available to central banks (Ferrari and Nispi Landi, 2024; Nakov and Thomas, 2024). While this issue has sparked growing controversy, several institutions have already taken steps to incorporate climate change into their policy mandates.[1] However, despite these theoretical discussions and policy developments, important questions remain open regarding the actual capacity of monetary policy to influence environmental outcomes, and its effectiveness in addressing climate-related challenges.

This paper contributes to addressing these questions by providing novel empirical evidence on the response of carbon emissions and emission intensity metrics to monetary policy. More specifically, I estimate the impact of exogenous variations in monetary policy on aggregate and sectoral carbon emissions within a standard structural monetary policy vector autoregression (VAR) model. Following Gertler and Karadi (2015), Jarociński and Karadi (2020), Miranda-Agrippino and Ricco (2021), Bauer and Swanson (2023), and others, I identify the effects of monetary policy on the economy and carbon emissions using high-frequency changes in interest rate futures around Federal Open Market Committee (FOMC) announcements as an external instrument. I also employ the recent methodology of Jarociński and Karadi (2020), which disentangles monetary policy shocks from contemporaneous information shocks by analyzing the high-frequency co-movement of interest rates and stock prices in the narrow window around policy announcements. This approach seeks to isolate the 'pure' policy component of the announcements and allows for accurate, unbiased estimates of the responses of macroeconomic aggregates and carbon emission flows to monetary policy shocks.

[1] Notably, the Bank of England has explicitly integrated climate change considerations into its mandate. Similarly, the European Central Bank, following a recent review of its monetary policy strategy, has developed a comprehensive climate action plan. Additionally, the Network for Greening the Financial System, founded in 2017 with eight members, now includes 95 members and 15 observers, including all major central banks. The International Monetary Fund, which joined as an observer in 2019, further underscores the global recognition of the link between monetary policy and climate change mitigation.

The results indicate that monetary policy shocks have statistically and economically significant effects on both the macroeconomy and carbon emissions dynamics. Contrary to what one might expect, an unanticipated monetary tightening leads to a significant *increase* in carbon emissions from total energy consumption on impact, with emissions only returning to pre-contraction levels after approximately two quarters. The impact is sizeable, as a 25-basis-point tightening of the policy indicator leads to a rise in emissions of about one percent. On the other hand, consistent with established findings in the monetary VAR literature, such a tightening also leads to a significant and persistent decline in consumer prices and economic activity, along with tighter financial conditions and a sharp deterioration in commodity prices.

A detailed exploration of the factors behind this counterintuitive behavior—given the unconditional prociclicality of carbon emissions—reveals that the increase is primarily driven by the responses of *non-industrial* sector emissions (electric power, residential, and commercial), all of which rise significantly following the monetary tightening. Given the substantial contribution of these non-industrial sectors to aggregate emissions, this unusual aggregate response can largely be attributed to the behavior of these energy-consuming sectors.

Next, to explain these empirical findings, I study the effects of monetary policy across the different energy-consuming sectors of the economy. For the industrial sector, which broadly encompasses facilities and equipment used in manufacturing, agriculture, mining, and construction, the dominant channel appears to be what I define as the standard *aggregate demand* channel: higher interest rates reduce aggregate consumption and output. Since most consumer goods are produced in this sector, demand for labor and energy inputs declines sharply following the monetary tightening. The reduction in emissions for this sector, approximately 0.4 percent at its lowest point, almost mechanically follows from the decreased consumption of electricity and fossil fuels, mirroring the timing and pattern of the decline in economic activity discussed earlier.

In contrast, complementary evidence suggests that alternative transmission channels, namely *energy reallocation* and *commodity price* channels, play a more prominent role in non-industrial sectors. What I define as the *energy reallocation* channel, particularly relevant to the residential and commercial sectors, emerges as employment and leisure move in opposite directions over the typical business cycle, and at the onset of a downturn, involuntary accumulation of stocks and inventories occurs when demand falls faster than production can adjust. In the residential sector, increased leisure time during economic downturns leads to higher energy and electricity consumption as individuals spend more time at home, driving up emissions in this sector. Meanwhile, a similar pattern of increased energy demand arises in commercial buildings, where firms store inventories of goods, manufactured products, merchandise, and raw materials, further contributing to higher emissions. This heightened activity in residential and commercial facilities drives up energy and electricity consumption following a monetary contraction, resulting in substantial increases in carbon emissions of approximately 3 percent in the residential sector and 2 percent in the commercial sector. This effect also extends to the electric power sector, which must accommodate the rising electricity demand.

The second channel, the *commodity price* channel, arises as monetary policy actions by major central banks affect global economic activity and financial conditions, which are key drivers of commodity price fluctuations (Miranda-Pinto et al., 2023; Degasperi et al., 2023; Castelnuovo et al., 2024). This channel is particularly relevant to the electric power sector, which primarily generates electricity and heat for sale to other energy-using sectors. Large and heterogeneous commodity price responses to monetary policy shocks directly influence the marginal costs of electricity generation, pushing the sector toward more polluting, cheaper fuels, such as coal, in the short term, displacing cleaner but more expensive alternatives such as natural gas. Specifically, my findings indicate that, following an unexpected 25-basis-point monetary tightening, the average cost of coal declines by more than 4 percent relative to the cost of natural gas, prompting a shift in fuel use at the margin. This shift ultimately triggers a significant 1 percent increase in the electric power sector's emissions in the short run. Given the heavy dependence of both the commercial and residential sectors on electricity, the electric power sector's adjustment to tighter monetary policy has substantial implications for the indirect carbon dioxide emissions from these sectors.

To better understand the driving forces behind these divergent responses in energy commodity prices, which appear to trigger input substitution in the electric power sector, I examine the mechanisms through which monetary policy shocks may influence commodity prices, as suggested by Frankel (1986, 2008). Specifically, I focus on coal and natural gas, which together accounted for 65 percent of the energy consumed in this sector by 2023 (U.S. Energy Information Administration, 2024b) and represent the main sources of carbon emissions. My results suggest that the negative impact of a monetary policy tightening on the price of coal can be attributed to incentives for stock depletion and immediate extraction. In contrast, while there is some suggestive evidence of stock depletion for natural gas, the effect on extraction appears to be much less pronounced.

A comprehensive set of robustness and sensitivity checks confirms that my findings are consistent across various dimensions, including alternative constructions of the instrument, estimation techniques, model specifications, data sources, data transformations, and the sample period analyzed. In particular, the results are robust to the use of alternative instruments from the literature for identifying the structural monetary policy shock, employing local projections and an internal instrument approach to estimate the impulse responses, accounting for temperature anomalies in the emissions data, applying alternative transformations to the emissions series to account for potential noise, relying on different emissions data sources, and adjusting the start and end dates of the sample period under study.

Finally, I formalize the mechanisms uncovered in the empirical analysis through the lens of a New Keynesian model, extended with an energy block, similar to the frameworks of Olovsson and Vestin (2023), Ferrari and Nispi Landi (2024), and Nakov and Thomas (2024). The energy block features two key sectors: an electric power sector, which purchases *energy inputs* to produce and supply *energy services* (i.e., electricity) to households and intermediate goods firms, and an energy sector, consisting of representative firms that produce *energy inputs* (coal and natural gas) using labor. Households consume both goods and energy services, while intermediate goods firms combine labor and energy services to produce consumption goods. Importantly, household electricity consumption is modeled as complementary to leisure, meaning that more leisure time *increases* household demand for electricity (e.g., for entertainment, heating, or cooling). I calibrate the model using macro and micro moments from the data and drawing upon values previously used in the literature.

The model qualitatively captures the observed empirical responses to monetary policy shocks, demonstrating that these findings can be explained within a standard framework under reasonable assumptions and calibration. Specifically, it highlights the role of leisure in household electricity demand and the impact of fluctuations in relative energy input prices on the energy mix in the electric power sector. Additionally, the model is also able to replicate the unconditional procyclicality of emissions observed in the data through the dynamics generated by a technology shock. This reinforces the conclusion that monetary policy shocks, though impactful, contribute modestly to the overall fluctuations in both business cycles and emissions, aligning with findings that suggest a smaller yet non-negligible role for such shocks in driving short-term variations in industrial production and unemployment (Caldara and Herbst, 2019; Plagborg-Møller and Wolf, 2022).

Related literature and contribution — This paper contributes to several strands of literature. First, my empirical analysis relates closely to the extensive literature on monetary policy VARs and high-frequency identification (Stock and Watson, 2012; Gertler and Karadi, 2015; Ramey, 2016; Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023). I extend this literature by incorporating carbon emissions, energy consumption, energy prices, and emission intensity measures into the baseline monetary VAR. This allows for an exploration of the dynamic interaction between monetary policy and the environment, identification of the potential mechanisms driving this relationship, and an assessment of the role of different sectors in the response of aggregate carbon emissions to a surprise monetary tightening.

My findings suggest that the heterogeneous effects of monetary policy shocks on commodity prices, particularly energy inputs in the electric power sector, play a critical role in shaping carbon emissions from energy consumption in both the sector and the broader economy. In this respect, I contribute to the literature on the various transmission channels through which monetary policy influences energy and, more broadly, commodity prices (Barsky and Kilian, 2004; Frankel, 2008; Anzuini et al., 2013; Rosa, 2014; Miranda-Pinto et al., 2023; Degasperi et al., 2023; Castelnuovo et al., 2024). Building on this work, I reassess the transmission of monetary policy through commodity prices, extending the analysis to examine its role in the demand and consumption of different energy sources and the corresponding emissions response.

Additionally, my analysis contributes to the growing literature on the business cycle dynamics of carbon emissions (Khan et al., 2019; Jo and Karnizova, 2021; Känzig and Williamson, 2023; Moench and Soofi-Siavash, 2023; Känzig, 2023). Notably, Khan et al. (2019) provide the only other investigation into the causal effects of monetary policy on emissions, employing structural VARs to identify various demand and supply shocks that are well-documented drivers of output fluctuations. Their findings suggest that while anticipated investment technology shocks significantly influence emissions, demand shocks (e.g., monetary and fiscal policy) induce procyclical emissions-output comovements, though with statistically insignificant effects[2]. My approach diverges by using a state-of-the-art identification strategy (i.e., external instruments), longer-horizon policy indicators (potentially unconstrained during the ZLB period), higher-frequency data, and extends the analysis to include various energy indicators (carbon emissions, energy consumption, energy prices, and emission intensity). These refinements reveal that emissions behave countercyclically in response to monetary policy shocks, shedding light on a more complex and nuanced relationship between emissions and output than previously documented.

Roadmap — The remainder of the paper is organized as follows. In Section 2, I introduce the carbon emissions data and describe the empirical VAR analysis, including the high-frequency identification of monetary policy shocks and the econometric approach. Section 3 presents the baseline results on how carbon emissions from aggregate energy consumption respond to a monetary policy shock, along with the disaggregated responses across different energy-consuming sectors. In Section 4, I explore how different channels play heterogeneous roles in the transmission of monetary policy across sectors, conditioning the aggregate emissions response. Section 5 presents the model, calibration and simulation results, and discusses the mechanisms through which the model is able to qualitatively replicate the empirical results. Finally, Section 6 presents some concluding remarks and suggests directions for future research.

2 Data and Econometric Approach

2.1 Data on carbon dioxide emissions and energy consumption

One of the key data series in my analysis is total CO2 emissions from energy consumption, estimated by the U.S. Energy Information Administration (EIA). Understanding how emissions are measured in practice is crucial for interpreting the results of this paper. The EIA employs a bottom-up approach, beginning with energy consumption data disaggregated by fuel type (coal, natural gas, and oil products) and energy-use sectors[3]. Physical quantities for each fuel type are first converted to British thermal units (Btu) of heat[4], then multiplied by fuel-specific CO2 emissions coefficients provided by the U.S. Environmental Protection Agency, and finally summed across fuels and sectors to calculate total emissions

[2]Other studies have examined emissions responses to energy-efficiency shocks (Jo and Karnizova, 2021), energy-saving technology shocks (Känzig and Williamson, 2023), emission intensity shocks (Moench and Soofi-Siavash, 2023), and carbon policy shocks (Känzig, 2023).

[3]Defined by the EIA as *"A group of major energy-consuming components of U.S. society developed to measure and analyze energy use."*

[4]One Btu is the amount of heat required to raise the temperature of one pound of water from 39 to 40 degrees Fahrenheit.

(U.S. Energy Information Administration, 2024d).

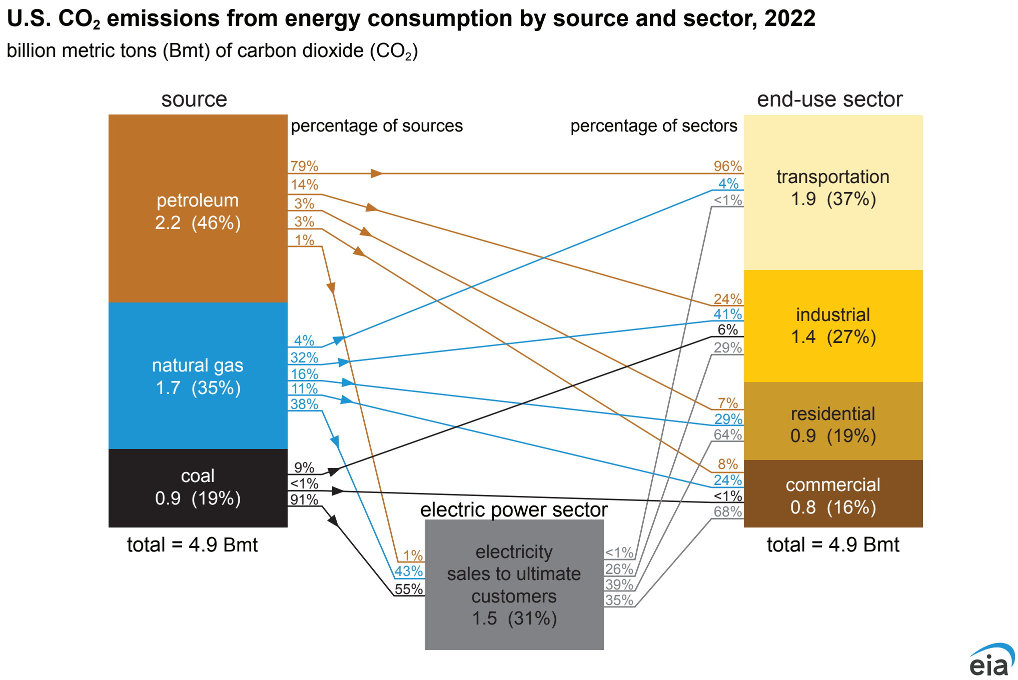

Figure 1: U.S. CO2 emissions from energy consumption by source and sector, 2022

Notes: The U.S. Energy Information Administration (EIA) chart on U.S. CO2 emissions from energy consumption by source and sector illustrates carbon dioxide (CO2) emissions from fossil fuel consumption in the United States, along with the relative contributions of sectors and sources. *Source*: U.S. Energy Information Administration (EIA), Monthly Energy Review (April 2023), Tables 11.1—11.6.

To provide additional context on the nature and magnitude of these variables, Figure 1 presents aggregate CO2 emissions from energy consumption by source and sector in the U.S. In 2022, total carbon emissions from energy consumption reached nearly five billion metric tons (Bmt) of CO2. Petroleum consumption accounted for 2.2 Bmt, or about 46% of the U.S. total, while natural gas and coal contributed 1.7 Bmt (35%) and 0.9 Bmt (19%), respectively. Importantly, different fuels emit varying amounts of CO2 depending on their carbon content and the energy produced when burned[5]. The amount of CO2 emitted is determined by the fuel's carbon content, while the energy produced (or heat content) is influenced by both its carbon (C) and hydrogen (H) content. Natural gas, primarily composed of methane (CH4), has a higher energy content relative to other fuels and thus produces lower CO2 emissions per unit of energy. By contrast, coal is the most carbon-intensive of the major fossil fuels, emitting nearly twice as much CO2 per unit of energy as natural gas and approximately 33% more than oil.

Regarding energy-consuming sectors, although the industrial sector used the most energy in 2022 (including direct primary energy use[6] and electricity purchases from the electric

[5]Fossil fuels primarily consist of carbon and hydrogen. When burned, carbon combines with oxygen to form CO2, and hydrogen combines with oxygen to form water (H2O). These reactions release heat, which is used for energy.

[6]Primary energy sources include fossil fuels (petroleum, natural gas, coal), nuclear energy, and renewables.

power sector), the transportation sector emitted more CO2 due to its near-total reliance on petroleum fuels. Emissions from the electric power sector are allocated to each end-use sector based on their share of total annual retail electricity sales. Even with these adjustments, the transportation sector accounted for the largest share of U.S. energy-related CO2 emissions in 2022 (37%), followed by the electric power (31%) and industrial (27%) sectors.

2.2 High-frequency identification and econometric framework

Several recent studies have used high-frequency financial asset price changes around the Federal Reserve's Federal Open Market Committee (FOMC) announcements, or monetary policy "surprises", as an instrument to estimate the causal effects of monetary policy on macroeconomic variables in structural VARs (Cochrane and Piazzesi, 2002; Stock and Watson, 2012, 2018; Gertler and Karadi, 2015; Ramey, 2016; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023). To accurately measure these effects, it is crucial to control for the variation in economic fundamentals to which policy endogenously responds. Monetary policy surprises are particularly useful in these applications because focusing on price changes within a narrow window around FOMC announcements (usually a half-hour window starting 10 minutes before and ending 20 minutes after the announcement) plausibly rules out reverse causality and other endogeneity concerns.

However, recent literature has highlighted the importance of considering the *information effects* of monetary policy announcements. These studies suggest that announcements reveal not only information regarding policy actions but also the central bank's assessment of the broader economic outlook (Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023). In light of these considerations, I rely on the updated "pure" monetary policy shock series by Jarociński and Karadi (2020)[7], which decomposes the surprises by analyzing the high-frequency co-movement of financial assets and stock prices around the policy announcement. The intuition behind this decomposition is that, according to a wide range of theoretical models, a pure monetary policy tightening should lead to a decline in stock market valuations. Based on this argument, the authors compute the first principal component of the surprises in interest rate derivatives with maturities from one month to one year (MP1, FF4, ED2, ED3, ED4) and identify a monetary policy shock when interest rates and stock prices move in opposite directions. Conversely, if interest rates and stock prices co-move positively, this is interpreted as reflecting an *information shock*, where the central bank's announcement conveys new information about the economic outlook. This procedure isolates the structural monetary policy component of the announcements from the broader central bank information effect.

To study the causal impact of monetary policy on carbon emissions, I employ a structural vector autoregression (SVAR) model. Consider the following reduced-form VAR(p) model:

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{B}_1 \mathbf{Y}_{t-1} + \cdots + \mathbf{B}_p \mathbf{Y}_{t-p} + \mathbf{u}_t \tag{1}$$

Electricity is a secondary energy source generated from primary energy.

[7]Available at https://marekjarocinski.github.io/jkshocks/jkshocks.html

where $\mathbf{Y}_t$ is an $n \times 1$ vector of endogenous variables, $\mathbf{c}$ is a vector of constants, $\mathbf{u}_t$ is an $n \times 1$ vector of serially uncorrelated regression residuals with covariance matrix $\text{Var}(\mathbf{u}_t) = \Sigma$, $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices, and p represents the lag order.

I follow standard practice in assuming that the economy is driven by a set of serially and mutually uncorrelated structural shocks, $\boldsymbol{\varepsilon_t}$, with $\text{Var}(\boldsymbol{\varepsilon_t}) = \boldsymbol{\Omega}$, where $\boldsymbol{\Omega}$ is diagonal. Assuming the VAR is invertible, the reduced-form innovations, $\boldsymbol{u_t}$, can be expressed as linear combinations of the structural shocks:

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon_t} \tag{2}$$

where $\mathbf{S}$ is a non-singular, $n \times n$ structural impact matrix, and $\boldsymbol{\varepsilon_t}$ is an $n \times 1$ vector of structural shocks. From the linear mapping of the shocks, it follows that $\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$. We are interested in characterizing the causal impact of a single shock. Without loss of generality, let us denote the monetary policy shock as the first shock in the VAR, ε_{1t}. Our goal is to identify the structural impact vector $\mathbf{s}_1$, which corresponds to the first column of $\mathbf{S}$.

External instrument approach — Identification using external instruments (or "proxies") proceeds as follows. Suppose an external instrument, z_t, is available. In the application at hand, z_t represents the monetary policy surprise series. For z_t to be a valid instrument, the following conditions must hold:

$$\mathbb{E}[z_t \varepsilon_{1t}] = \alpha \neq 0 \tag{3}$$

$$\mathbb{E}[z_t \varepsilon_{2:nt}] = \mathbf{0} \tag{4}$$

where ε_{1t} is the structural monetary policy shock and ε_2 is an $(n-1) \times 1$ vector containing the other structural shocks. Assumption (3) refers to the relevance requirement, and assumption (4) ensures exogeneity. Together with the invertibility condition (2), these assumptions identify $\mathbf{s}_1$, up to sign and scale:

$$\mathbf{s}_1 \propto \frac{\mathbb{E}[z_t \mathbf{u}_t]}{\mathbb{E}[z_t u_{1t}]} \tag{5}$$

provided that $\mathbb{E}[z_t u_{1t}] \neq 0$. To estimate the elements in the vector $\mathbf{s}_1$ I proceed as follows: first, I obtain estimates of the vector of reduced form residuals from the ordinary least squares regression of the reduced form VAR in Equation 1, $\hat{\mathbf{u}}_t$. Then I implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\hat{\mathbf{u}}_t$ on $\hat{u}_{1t}$ using z_t as the instrument. To conduct inference, I employ a wild bootstrap, as proposed by Mertens and Ravn (2013).

2.3 Empirical specification

Studying the impact of monetary policy on carbon emissions requires modeling them jointly with the U.S. economy. The baseline specification consists of six variables. For the core macroeconomic variables, I follow the literature on monetary VARs and include monthly measures of industrial production, the personal consumption expenditures (PCE) price index, the Bloomberg Commodity Spot Price Index, the Gilchrist and Zakrajšek (2012) excess bond premium, and the one-year Treasury yield as the relevant monetary policy indicator, given that the economy was at the effective lower bound for the latter part of the sample period. In the baseline specification, I further extend the VAR by including a measure of aggregate carbon emissions from energy consumption in the U.S.[8] More information on the data and its sources can be found in Appendix B.

The data are monthly and span the period from 1973M1 to 2019M12. Following Gertler and Karadi (2015), I use a shorter sample for identification, specifically 1990M2 to 2019M12, as the futures data required to construct the instrument are only available for this period. The rationale for using the longer sample for estimation is to obtain more precise estimates of the reduced-form coefficients. However, restricting the sample to 1990-2019 produces very similar results. I end the sample in 2019 to avoid the dramatic swings in economic activity associated with the onset of the COVID-19 pandemic in the United States. Following Sims et al. (1990), I estimate the VAR in log levels. With the exception of the excess bond premium and the one-year rate, all variables are entered in log levels. The lag order is set to 12, and only a constant term is included as a deterministic component.

3 Empirical Results

3.1 Effects on carbon emissions and the macroeconomy

In this section, I examine the macroeconomic effects of monetary policy shocks through the lens of the baseline model. The main identifying assumption underlying the external instrument approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. Additionally, for standard inference to be valid, the instrument must be sufficiently strong. The F-statistic in the first stage is 13.31, which exceeds conventional critical values, allowing me to conclude that the instrument is strong enough to support standard inference.

Turning to the macroeconomic and environmental impacts of monetary policy shocks, Figure 2 presents the impulse responses to the monetary policy shock, normalized to increase the one-year rate by 25 basis points (bps) on impact. As most variables are in logs, the responses can be interpreted as elasticities. The solid black line in each panel shows the point estimates, while the dark and light-shaded regions represent 68 and 90 percent confidence bands, respectively, based on 2,000 bootstrap replications.

Turning to the effects on macroeconomic variables, a surprise monetary contraction results in a significant, immediate increase in the one-year government bond yield. This contraction slows down economic activity, as industrial production shows no immediate response but declines significantly in the following months. This has important implications for inflation and price dynamics, as the PCE price index shows little change on impact but begins to fall slowly and persistently afterward. Commodity prices, on the other hand, decrease

[8] To get rid of the seasonal variation, I seasonally adjust the carbon dioxide emissions and energy consumption data using the X-13ARIMA-SEATS method.

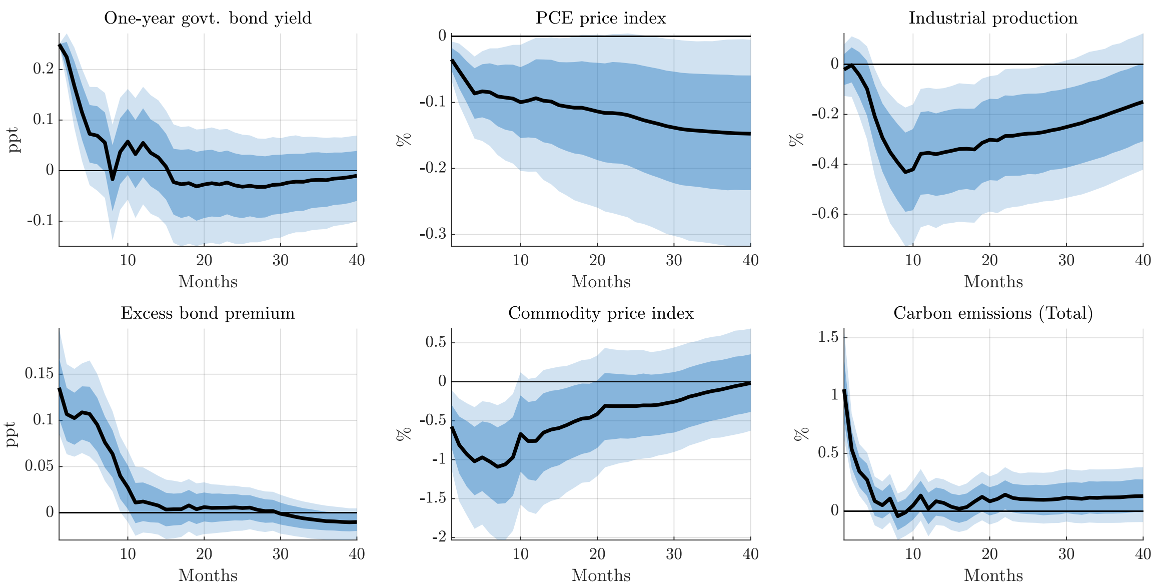

Figure 2: Impulse responses to a monetary policy shock: Aggregate variables

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

sharply on impact and continue to decline for about three quarters before slowly converging back to normal. Financial conditions also tighten, as reflected by the excess bond premium, which increases significantly on impact, remains elevated for several months, and then gradually returns to steady state.

In terms of magnitudes, the shock leads to a decline in industrial production of about 0.42 percent after a little less than one year. Consumer prices fall slightly on impact by 0.07 percent and then decline gradually over the following years, while commodity prices fall by 1 percent at the peak of the response. The excess bond premium rises by 13 basis points on impact and returns to normal after about one year. These responses are very similar to those from monetary policy VARs estimated by other authors in the literature (Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023) and are consistent with the aggregate economy weakening moderately and inflation falling slightly after a monetary policy tightening.

Turning to the last panel in Figure 2, carbon emissions from aggregate energy consumption in the U.S. significantly *increase* on impact by approximately 1 percent in response to the monetary policy tightening, gradually returning to steady state after about six months. These results are surprising, given the unconditional procyclicality of emissions documented in the economics literature (Heutel, 2012; Doda, 2014). However, recent studies such as Jo and Karnizova (2021) and Känzig and Williamson (2023) also document a negative correlation and decoupling between emissions and economic activity in recent years, exploring factors that influence emissions without necessarily leading to a trade-off between sustainability and economic performance.

To put the estimated one percent increase in carbon emissions into context, I perform some illustrative back-of-the-envelope calculations. Using 2022 annual emissions figures of approximately 4.9 billion metric tons of CO2, as per Figure 1, a 1 percent rise in monthly emissions translates, on average, to additional 4.1 million metric tons. This is a relevant figure: it is equivalent to the annual emissions from adding 890,000 passenger vehicles to circulation (with each vehicle emitting roughly 4.6 metric tons of CO2 per year), the annual electricity use of about 480,000 U.S. homes (each home emitting around 8.5 metric tons of CO2 from electricity), the monthly emissions of an additional large coal-fired power plant (each releasing approximately 4 million metric tons), or the emissions from 10,200 roundtrip transatlantic flights (e.g., NYC to London), with each Boeing 747 flight emitting approximately 400 metric tons of CO2. These comparisons underscore the significance of the estimated emission increases driven by monetary policy shocks.

Furthermore, to put the magnitude of these results in context, it is useful to compare my findings on the estimated impact of monetary policy shocks on carbon emissions with those from related studies. For instance, Känzig (2023) reports that greenhouse gas (GHG) emissions decline by around 0.6 percent following a restrictive carbon policy shock that raises the HICP energy component by one percent on impact, within the context of the European emissions trading system. In response to this shock, monetary policy appears to lean against inflationary pressures, with the two-year rate increasing by about 25 basis points. Additionally, Martin et al. (2014) estimate the effects of the Climate Change Levy (CCL) on manufacturing plants using panel data from the UK production census. Their findings show that the implementation of the CCL package led to a significant reduction in total CO2 emissions by 7.3 percent. In the case of Sweden, Andersson (2019) finds that after the introduction of a carbon tax and a value-added tax on transport fuel, carbon dioxide emissions from the transport sector declined by nearly 11 percent, with the majority of the reduction attributed to the carbon tax alone, relative to a synthetic control group constructed from a comparable set of OECD countries.

Hence, based on these findings in the literature, a 1 percent increase in emissions following a surprise monetary contraction, while smaller in magnitude compared to the effects of carbon taxes, still represents an economically significant impact. This suggests that the effect of monetary policy shocks on carbon emissions, though not directly comparable in magnitude to those of targeted environmental policies, should be considered by policymakers when assessing the broader implications of carbon reduction strategies, especially if such policies are implemented during periods of monetary tightening. A better understanding of how monetary policy might influence emissions could help ensure that climate objectives are not inadvertently undermined by macroeconomic stabilization efforts.

In Appendix C, I perform a comprehensive series of robustness checks on the identification strategy and empirical approach used to isolate the monetary policy shocks. In particular, I employ alternative instruments proposed by Gertler and Karadi (2015), Miranda-Agrippino and Ricco (2021) and Bauer and Swanson (2023) to identify the structural monetary policy shock. The results remain robust when using local projections and an internal instrument approach to estimate the impulse responses, although these responses are less precisely estimated. Additionally, I account for temperature anomalies in the emissions data by applying a "weather-normalization" procedure, and I test alternative transformations of the emissions series to mitigate potential noise, including smoothing the emissions series with a backward-looking moving average, isolating the cyclical component via a Hodrick-Prescott filter, and estimating a stationary VAR. I also verify the robustness of the findings by substituting the EIA emissions data with that from an alternative source: the European Commission's Emissions Database for Global Atmospheric Research (EDGAR). Finally, I demonstrate that the results remain consistent across different sample periods. Together, these checks confirm the robustness of the main findings across multiple dimensions.

While the aggregate increase in emissions following a monetary contraction offers an important macroeconomic perspective, understanding the full extent of this response requires a closer examination of sectoral dynamics. Different energy-consuming sectors may react differently to changes in monetary policy, contributing in various ways to the observed overall increase in emissions. To further explore these potential drivers, I rely on sectoral data on carbon emissions for each of the energy-consuming sectors depicted in Figure 1. By disaggregating emissions, my aim is to shed light on how different sectors contribute to the aggregate outcome and explain the seemingly counterintuitive response of carbon emissions to a monetary tightening.

3.2 Effects on sectoral carbon emissions

The results in the previous section suggest that, despite the unconditional procyclicality of emissions, they exhibit countercyclical dynamics in response to a monetary tightening when conditioned on a monetary policy shock. However, to fully understand this response, a closer examination of sectoral dynamics is necessary. The Energy Information Administration (EIA) divides energy use into five economic sectors—residential, commercial, transportation, industrial, and the electric power sector—in order to make reasonable estimates of potential future prices, supply, and energy demand, as well as accurate calculations of carbon emissions from energy consumption, as mentioned in Section 2.

To analyze how emissions from each of these sectors respond to a monetary policy shock, I extend my baseline six-variable monetary VAR. Including all five sectors at once would introduce too many parameters, leading to overfitting and imprecise estimates. Therefore, I follow the approach of Gertler and Karadi (2015) and Graves et al. (2024), extending the baseline VAR by adding one sectoral emissions variable at a time. The results for each sector are presented in Figure 3. Each panel in Figure 3 corresponds to a separate seven-variable VAR, comprising the six original variables from the baseline VAR along with the sectoral emissions variable listed at the top of each panel[9]. The emissions measure for each end-use sector (residential, commercial, industrial, and transport) encompasses both the emissions from direct energy consumption in each sector and the estimated indirect emissions asso-

[9]For space considerations, the IRFs for the five baseline macroeconomic variables are not shown in Figure 3, as they closely resemble the responses reported in Figure 2.

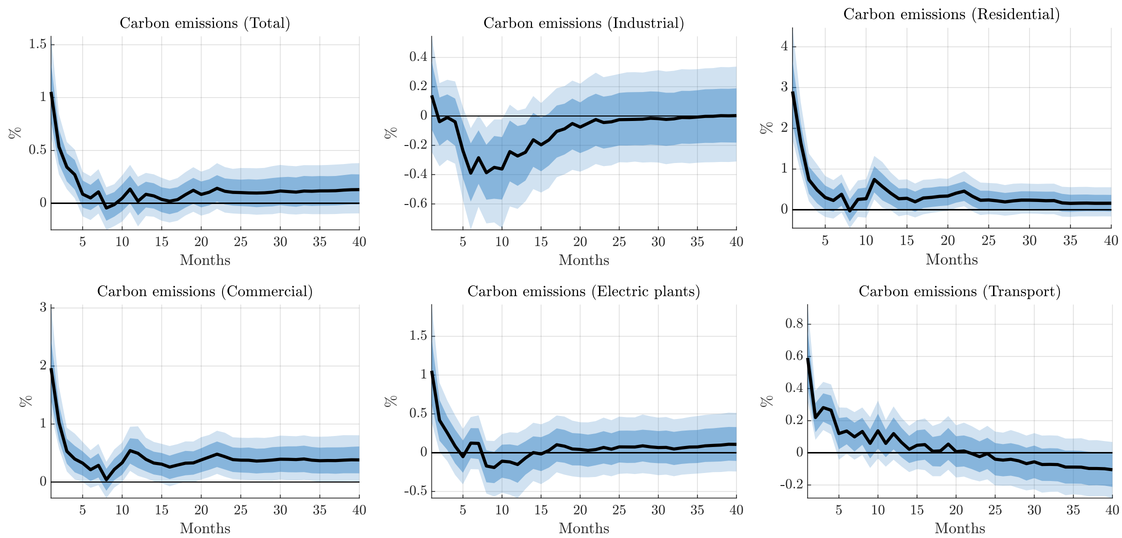

Figure 3: Impulse responses to a monetary policy tightening: Sectoral emissions

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are computed by appending the given sectoral emissions variable to the baseline VAR from Figure 2. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

ciated with electricity sales to ultimate consumers within each sector[10].

Regarding the interpretation of the results in Figure 3, consistent with the aggregate evidence, a 25-basis-point monetary policy tightening leads to an *increase* in emissions from the residential, commercial, transportation, and electric power sectors—collectively referred to as the *non-industrial* sectors due to their similar dynamics. These emissions rise on impact and gradually return to their steady states, with the residential and commercial sectors exhibiting the most persistent responses. In terms of economic magnitude, carbon emissions from energy consumption in the residential sector increase by approximately 3 percent, while emissions from the commercial sector rise by nearly 2 percent. Importantly, emissions from the electric power sector also increase by around 1 percent, but with a lower degree of persistence, returning to normal within a few months. In contrast, emissions from the transportation sector rise by about 0.6 percent but show greater persistence, only returning to steady state after nearly one year. Finally, emissions from the industrial sector are the only ones that exhibit the "expected" behavior, declining significantly by about 0.4 percent at the trough of the response. The emissions response from this sector closely mirrors the fluctuations in economic activity documented in the previous section, aligning with the contraction in industrial output typically associated with a monetary tightening.

To put these percentage changes into context, consider the emissions data for 2022 in Figure 1. Out of the 4.9 billion metric tons of carbon dioxide emitted from energy consumption that year, the residential sector contributed 0.9 billion metric tons (19 percent), the commercial sector added 0.8 billion metric tons (16 percent), the transportation sector accounted for 1.9 billion metric tons (37 percent), and the industrial sector emitted 1.4 billion metric tons

[10]The EIA allocates the consumption-weighted average CO2 emissions from electricity sales proportionally to the national electricity sales sold to each end-use sector.

(27 percent). Taking these values as a baseline, a 2.8 percent increase in residential emissions translates to an additional 25.2 million metric tons of CO_2, while a 1.9 percent rise in commercial emissions adds about 15.2 million metric tons. Similarly, the 0.55 percent increase in transportation emissions corresponds to around 10.5 million metric tons. Together, the emissions increase from the residential, commercial, and transportation sectors totals roughly 50 million metric tons of CO_2, aligning with the aggregate increase previously discussed. Notably, these sector-specific volumes already incorporate the indirect emissions linked to electricity consumption, which made up 31 percent of total emissions and increase by approximately 1 percent following the monetary contraction.

Based on the findings from this section, the empirical evidence suggests that the four *non-industrial* sectors (residential, commercial, transportation, and electric power) are the primary drivers of the aggregate carbon emissions response to a monetary contraction. The sharp and persistent increases in emissions from the residential and commercial sectors, along with the notable but more short-lived responses from the electric power and transportation sectors, indicate that non-industrial patterns play a crucial role in shaping the overall emissions response. In contrast, emissions from the *industrial* sector decline in line with reduced output, aligning predictably with the contraction in economic activity following the monetary policy shock. This divergence between *industrial* and *non-industrial* sectors highlights the sector-specific nature of monetary policy's transmission.

These results suggest the need for a deeper investigation into the mechanisms driving these sectoral responses. In the next section, I explore key variables related to energy consumption, energy prices, and emission intensity across sectors. This analysis aims to uncover the channels through which monetary policy affects energy use and emissions dynamics, shedding light on the differential impacts observed between *non-industrial* and *industrial* sectors.

4 The Heterogeneous Transmission Channels of Monetary Policy

The results in the previous section suggest that monetary policy plays a relevant role in shaping the dynamics of carbon emissions, both at the aggregate and sectoral levels, at business cycle frequencies. However, with the exception of the industrial sector, the response of emissions to a surprise monetary tightening appears puzzling, going in the opposite direction of what conventional wisdom would predict. To better understand the drivers behind this increase in emissions following a monetary contraction, and to gain further insight into how monetary policy shocks transmit through different sectors of the economy, I examine the responses of key sector-specific variables. These include metrics such as energy consumption, energy prices, and emission intensity (that is, emissions per unit of energy consumed) following a monetary policy shock. The five energy-use sectors vary considerably in both their primary energy uses and their dominant energy sources, as summarized in Figure A.1. For instance, residential and commercial buildings use energy mainly for heating, cooling, lighting, and operating appliances, whereas the industrial sector uses energy both as a direct production input (feedstock) and to power machinery.

In terms of energy sources, the residential and commercial sectors predominantly rely on electricity and natural gas, while the transportation sector is heavily dependent on motor gasoline. This marked heterogeneity in energy usage and sources could help explain the wide range of responses reported in Figure 3.

4.1 Industrial sector

The industrial sector encompasses all facilities and equipment used for producing, processing, or assembling goods. Formally, it includes manufacturing (NAICS codes 31-33); agriculture, forestry, fishing, and hunting (NAICS code 11); mining, including oil and gas extraction (NAICS code 21); and construction (NAICS code 23). In 2022, this sector accounted for nearly 35 percent of total U.S. end-use energy consumption and 27 percent of total U.S. carbon dioxide emissions (Figure 1).

Regarding energy consumption patterns, the industrial sector's needs vary from using energy products as direct inputs to produce goods such as plastics and chemicals, to employing electricity for operating industrial motors, machinery, lighting, computers, and office equipment, as well as for facility heating, cooling, and ventilation (U.S. Energy Information Administration, 2024e). Figure A.2 illustrates the relative importance and evolution of energy sources consumed in the industrial sector over time, including primary energy sources (natural gas, oil, coal, renewables) and electricity. Natural gas and petroleum products, such as distillate and residual fuel oils and hydrocarbon gas liquids (HGLs), represent the largest share of energy consumption in the sector, while the electricity share has remained fairly consistent at around 15 percent over the years. To understand the behavior of emissions in this sector following a surprise monetary contraction, as reported in the top middle panel of Figure 3, it is essential to consider the response of sectoral activity and the consumption of these key energy sources.

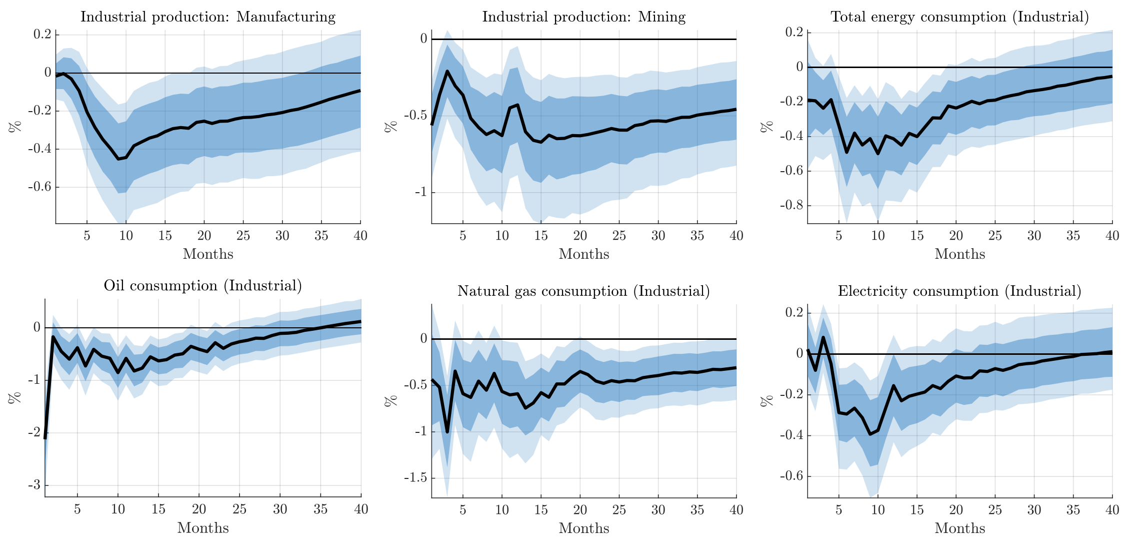

Figure 4: Impulse responses to a monetary policy tightening: Industrial energy and activity

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are computed by appending the given sectoral variables to the baseline VAR from Figure 2. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure 4 presents the impulse responses of several variables related to economic activity and energy consumption in the industrial sector to the identified monetary policy shock. Specifically, I estimate the responses of the manufacturing (NAICS 31–33) and mining (NAICS 21) components of industrial production, as well as natural gas, oil, and electricity consumption, which by 2022 represented about 87 percent of the sector's energy needs, as well as total energy consumption. The data on consumption of the different energy sources comes from the Energy Information Administration's Monthly Energy Review[11]. As with the aggregate index of industrial production, both the manufacturing and mining components behave as expected: following a monetary contraction, economic activity weakens moderately, and responds to the tightening with a slight lag. Notably, the response of mining activity is highly persistent, remaining well below the steady-state level even three years after the shock. In contrast, the response of manufacturing activity mirrors the behavior of the overall industrial production index, plotted in the top right panel of Figure 2, peaking at around -0.4 percent approximately one year after the shock.

This decline in industrial activity results in a corresponding drop in total energy consumption in the sector, as shown in the top right panel of Figure 4. Lower production mechanically leads to reduced demand for inputs, with energy being a key component in the production process. Furthermore, the three bottom panels in Figure 4 corroborate this trend: consumption of oil, natural gas, and electricity all decrease in line with reduced production, reflecting a decline in the sector's energy needs. These responses align with the behavior of carbon emissions illustrated in Figure 3, indicating a strong, positive relationship between economic activity, energy demand, and emissions within the industrial sector.

Overall, the responses of the industrial sector's activity and energy consumption measures in Figure 4 suggest that monetary policy operates on this sector through its effect on real economic activity, which I label the *aggregate demand* channel. This result is consistent both with the unconditional procycality of emissions as well as with key assumptions in the macro-environmental literature, namely that emissions are positively correlated and proportional to output (Heutel, 2012; Golosov et al., 2014; Doda, 2014; Annicchiarico and Di Dio, 2015; Nakov and Thomas, 2024). However, as noted earlier, industrial emissions account for only about a third of U.S. CO2 emissions from energy consumption. To fully understand the overall emissions response to a monetary policy shock, it is crucial to analyze the dynamics in the remaining sectors.

4.2 Residential and commercial sectors

The residential sector is defined by the EIA as the energy-consuming sector consisting of living quarters for private households[12]. In contrast, the commercial sector comprises service-providing facilities and equipment used by businesses; federal, state, and local governments; and other private and public organizations, such as religious, social, or fraternal groups. Both sectors, commonly referred to as the *buildings sector* due to their similar energy

[11]Table 2.4. *Industrial sector energy consumption*

[12]It excludes institutional living quarters, which are included in the commercial sector.

uses, together accounted for 35 percent of U.S. carbon emissions from energy consumption (Figure 1) and nearly 30 percent of U.S. energy consumption (Figure A.1) in 2022.

Energy used in the residential and commercial sectors provides a variety of services, including space and water heating, air conditioning, lighting, refrigeration, cooking, and the operation of various appliances. Figure A.3 shows the evolution of energy consumption profiles for these two sectors over time. The figure highlights a key similarity between the residential and commercial sectors: their heavy reliance on electricity as a major energy source. By 2022, electricity sales from the electric power sector accounted for 43 percent of the residential sector's energy consumption and 49 percent for the commercial sector. This reliance on electricity has increased in recent years, gradually displacing fossil fuels such as coal and oil. Consequently, the energy mix used in electricity generation plays a critical role in determining the indirect emissions of these two sectors, as nearly half of their energy needs are met by electricity.

Natural gas is also a significant energy source for both sectors, representing 43 percent of residential and 39 percent of commercial end-use energy consumption in 2022. In the residential sector, about 60 percent of U.S. homes use natural gas for space and water heating, cooking, and drying clothes. In the commercial sector, natural gas is used not only for heating and cooling but also as a fuel for generating electricity and in combined heat and power systems.

To understand the dynamics of emissions generated by the residential and commercial sectors following a surprise monetary contraction, and to identify the underlying drivers of the increases observed in Figure 2, I examine the responses of various measures of energy consumption in these sectors. Figure 5 presents the impulse responses of overall sectoral energy use to the monetary policy shock. I focus on the responses of electricity and natural gas consumption, as these two sources together account for nearly 90 percent of end-use energy consumption in both sectors. Consistent with the findings in Figure 3, a 25-basis-point monetary policy tightening leads to an *increase* in total energy consumption in both the residential and commercial sectors, with the effect gradually dissipating over time. In terms of economic magnitude, total energy consumption in both sectors increases by about 2.5 and 2 percent, respectively. Both electricity and natural gas consumption increase following the monetary contraction, by about 0.6 and 3.5 percent in the residential sector and 0.5 and around 3 percent in the commercial sector, respectively, explaining the overall rise in energy demand across these two sectors. In all cases, the dynamics closely mirror those of sectoral emissions in Figure 3, with energy consumption and emissions increasing significantly on impact and gradually returning to steady state in the subsequent months.

What drives the increased energy demand in the residential and commercial sectors following a monetary contraction? When examining the household side, the literature on monetary policy transmission has primarily focused on households' financial positions and how these shape the transmission of monetary policy (Kaplan et al., 2018; Debortoli and Galí, 2024). However, some strands of literature have explored how business cycles affect household energy demand. For instance, Cicala (2023) documents an increase in residen-

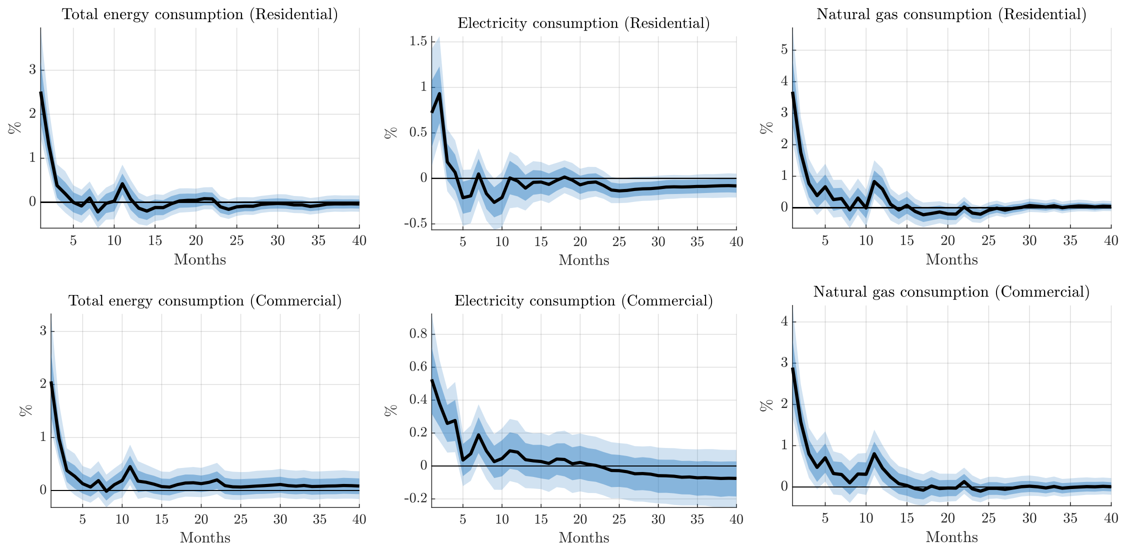

Figure 5: Impulse responses to a monetary policy tightening: Residential and commercial energy

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are computed by appending the given sectoral variables to the baseline VAR from Figure 2. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

tial electricity consumption in the U.S. during the COVID-19 pandemic, linked to the rise in remote work. Similarly, during an economic downturn, households may substitute activities typically performed outside the home for more home-based activities due to falling incomes. Additionally, rising unemployment or reduced working hours following a contractionary shock might leave people at home for longer periods during the day, thereby increasing energy consumption in residential buildings. This is consistent with the typical business cycle dynamic in which employment and leisure (and/or home production) move in opposite directions (Aguiar and Hurst, 2007; Ramey, 2009; Aguiar et al., 2013).

In the commercial sector, while commonly associated with retail and wholesale activity, the largest share of energy consumption comes from warehouses and storage buildings, both in terms of quantity and total square footage (U.S. Energy Information Administration, 2018). These buildings are primarily used to store goods, manufactured products, raw materials, and personal belongings (e.g., self-storage). Following an economic downturn, as sales decline, inventories are likely to increase, driving up energy demand in these facilities as storage and stockpiling grow.

To empirically analyze the validity of these intuitive mechanisms underlying the increase in energy demand from the residential and commercial sectors following a monetary contraction, Figure 6 presents the impulse responses of certain activity metric for the residential and commercial sector. Following a surprise monetary tightening, unemployment rises with a lag and hours worked fall unequivocally, both in the short and the medium run. This response supports the hypothesis of substitution between in-home and out-of home activities, under which energy demand in the residential sector would increase following an economic downturn, pushing electricity and natural gas demand. The same is evidenced in the commercial sector, as a measure of inventories over sales increases in the short run,

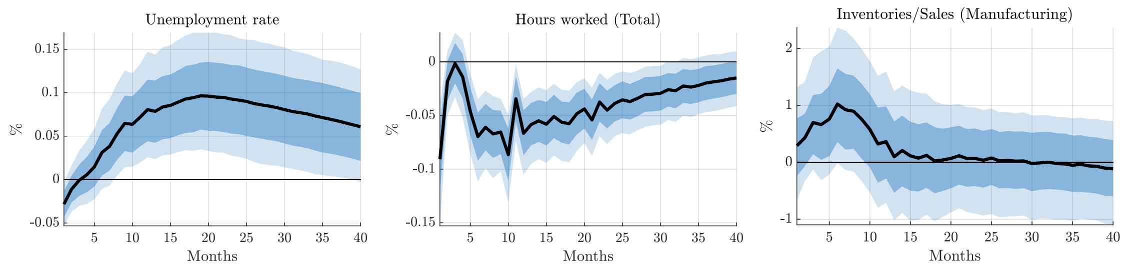

Figure 6: Impulse responses to a monetary policy tightening: Residential and commercial activity

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are computed by appending the given sectoral variables to the baseline VAR from Figure 2. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

supporting the hypothesis of an increase in energy demand from warehouses and storage buildings following the monetary contraction.

4.3 Electric power sector

The electric power sector is defined by the EIA as an energy-consuming sector consisting of electricity-only and combined-heat-and-power (CHP) plants, whose primary business is to sell electricity or electricity and heat to the public. These plants are classified under Code 22 in the North American Industry Classification System (NAICS). In 2022, this sector accounted for 31 percent of U.S. carbon emissions from energy consumption (Figure 1) and nearly 35 percent of U.S. energy consumption (Figure A.1).

The energy profile for U.S. electricity generation has shifted dramatically over time, particularly in recent years. Natural gas and renewable energy sources have gained a growing share of electricity generation, while coal-fired generation has steadily declined. In 1990, coal-fired power plants accounted for approximately 52 percent of total electricity generation. By the end of 2023, coal's contribution had dropped to about 16 percent. In contrast, the share of natural gas-fired electricity generation more than tripled, rising from 12 percent in 1990 to 43 percent in 2023 (U.S. Energy Information Administration, 2024a). This growth has been primarily driven by technological advances in horizontal drilling and multistage hydraulic fracturing (fracking), which have unlocked vast natural gas deposits in shale formations, significantly increasing production and reducing market prices (Holladay and LaRiviere, 2017; Knittel et al., 2019; Acemoglu et al., 2023). Figure A.4 illustrates the evolution of primary energy sources used by the electric power sector over time.

To fully understand the dynamics of emissions from the electric power sector, it is essential not only to examine its evolving energy profile but also to consider how the sector operates in practice. The U.S. electric power grid is a vast and interconnected network of generators, transformers, transmission lines, and distribution systems that spans the lower 48 states, with connections to Canada and Mexico (U.S. Energy Information Administration, 2024a). This system ensures that electrical energy is reliably available for residential, commercial, and industrial use. The electric power industry consists of three main components: generation, transmission, and distribution. *Generation* refers to the actual production of electrical energy at power stations. *Transmission* involves the transportation of electricity over long distances at high voltages, while *distribution* refers to the delivery of electricity to customers at usable voltages on local networks. Since electricity cannot be economically stored in large quantities, the grid faces the constant challenge of balancing electricity generation and demand in real time. To maintain this balance, operators of the grid dispatch power plants to generate the exact amount of electricity needed at every moment (United States Environmental Protection Agency, 2024). Figure A.5 provides a simplified representation of this system.

Carbon emissions from the electric power sector are primarily produced during electricity generation when fossil fuels are burned. These emissions vary depending on the energy source and the type and efficiency of the power plants. The amount of CO2 produced per kilowatt-hour (kWh) fluctuates according to the energy mix being used at a given time, as well as seasonal and daily changes in electricity demand (U.S. Energy Information Administration, 2024c). Thus, electricity-related carbon emissions can vary significantly on an hourly, daily, monthly, and annual basis. To understand the behavior of emissions from this sector following a surprise monetary contraction, as shown in the bottom middle panel of Figure 3, it is essential to consider how sectoral activity and the consumption of key energy sources respond to the shock.

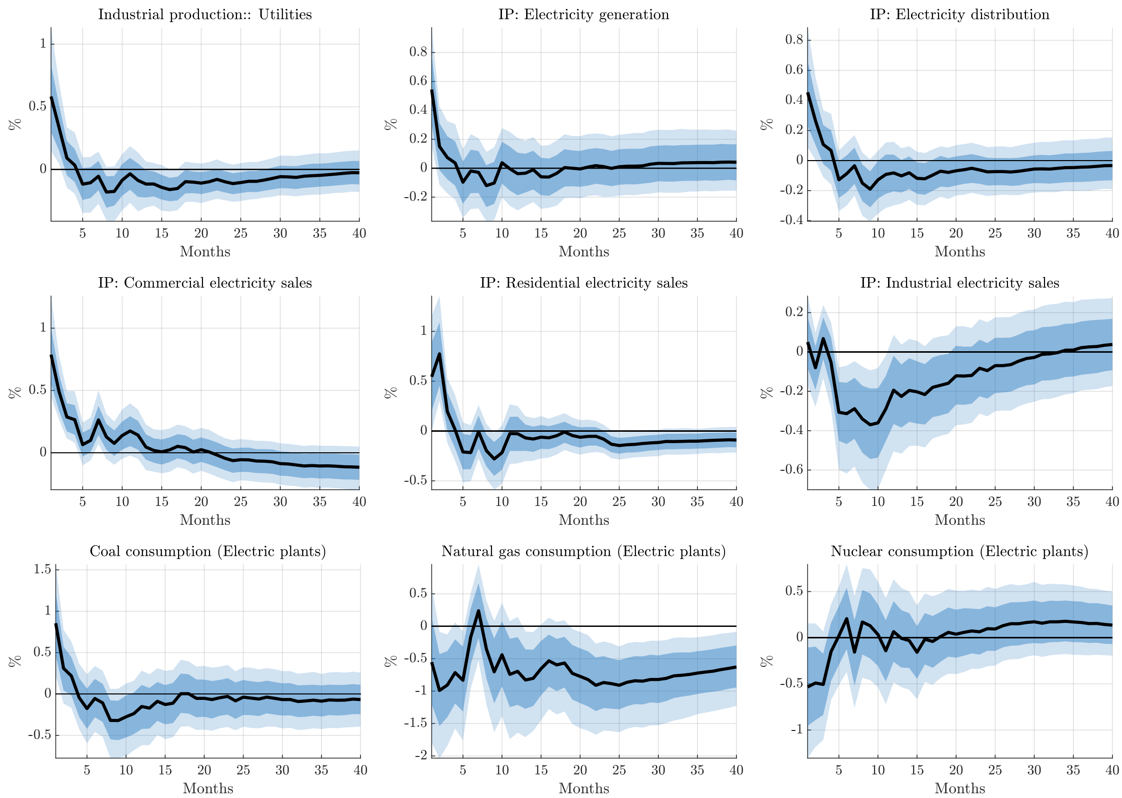

Figure 7: Impulse responses to a monetary policy tightening:: Electricity generation and sales

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are computed by appending the given sectoral variables to the baseline VAR from Figure 2. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Figure 7 presents the impulse responses of several variables related to sectoral activity and energy consumption following the identified monetary policy shock. Specifically, I estimate the responses of the utilities subcomponent of industrial production (NAICS 2211,2), the series associated with electric power generation (NAICS 22111), and electric power transmission, control, and distribution (NAICS 22112). In addition, I include responses for commercial and other electricity sales, industrial electricity sales, and residential electricity sales (NAICS 22112pt.). I also estimate the responses for natural gas, coal, and nuclear energy consumption in the sector, which together accounted for nearly 90 percent of the sector's energy needs in 2022.

Following a surprise monetary tightening, activity in the electric power sector *expands*, as captured by increases in the associated industrial production indices. Electricity sales to the commercial and residential sectors also rise after the monetary tightening, increasing by approximately 0.8 percent and 0.5 percent, respectively, consistent with heightened economic activity and electricity demand in these sectors, as discussed in the previous section. Conversely, industrial electricity sales decline by about 0.4 percent, with a lagged response to the shock, reinforcing the observed trends in industrial sector activity and emissions.

Finally, regarding energy sources, the increased economic activity in the sector is not uniformly supported by a rise in all energy sources. Coal consumption rises by approximately 0.3 percent, while the consumption of natural gas and nuclear energy declines by about 0.5 percent and 0.2 percent, respectively. This suggests some substitution between energy sources within the sector following the monetary contraction, which may further contribute to fluctuations in emissions. Hence, the increase in emissions from the electric power sector, as shown in Figure 2, appears to be driven not only by increased activity in electricity supply for the commercial and residential sectors but also by a temporary shift toward more polluting energy sources.

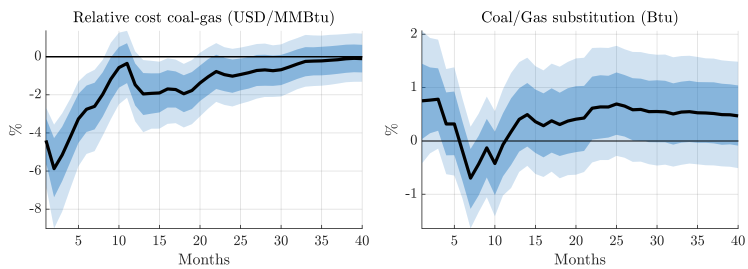

Figure 8: Impulse responses to a monetary policy tightening: Electricity generation and input relative costs

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are computed by appending the given sectoral variables to the baseline VAR from Figure 2. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Building on the evidence of fuel substitution in the electric power sector following a monetary contraction, I estimate the responses of both input costs and electricity generation following a monetary policy shock. Figure 8 shows the impulse responses of relative input costs, as well as the corresponding changes in coal and gas-fired electricity generation. In response to the tightening, coal prices fall significantly by approximately 4 percent on impact relative to natural gas prices, decreasing an additional 1 percent in the first quarter before gradually recovering over the following years. This substantial decline in coal prices relative to natural gas drives increased coal-fired electricity generation, rising by about 0.7 percent relative to natural gas-fired generation. This pattern persists over the long run, despite a brief deviation in trajectory approximately one year after the shock.

These results align with the findings of Miranda-Pinto et al. (2023), who, using U.S. data from 1990M2 to 2019M5 and employing a local projections approach, show that a large fraction of commodity prices decline following a U.S. monetary tightening. In particular, storable and industrial commodities exhibit the strongest responses. They report that coal futures (API2 and API4) experience the largest negative responses to a 10-basis-point monetary contraction, with peak declines of approximately 6.5 percent and 4.5 percent, respectively, within 24 days. By contrast, benchmark U.S. natural gas prices (Henry Hub) exhibit no response to monetary shocks in their baseline analysis, although they note that Henry Hub prices became more responsive to monetary policy during the 2016-2019 period.

Furthermore, these results can be interpreted in the context of the dynamic and immediate nature of the electric power sector's operations. As previously noted, grid operators dispatch power plants based on the lowest-cost generation available to meet demand. According to the Federal Energy Regulatory Commission (2023), this process typically begins with day-ahead market commitments, followed by real-time updates as needed. Dispatch decisions are based on the cost of generation, with the least expensive resources dispatched first and higher-cost resources dispatched last. For any given level of demand, the lowest marginal cost generators are dispatched until the market clears, with the wholesale price of electricity set by the marginal cost of the last generator used to meet demand (Fell and Kaffine, 2018). Given this structure, the observed decline in coal prices relative to natural gas makes coal-fired plants more competitive in the short run, driving an increase in coal-fired electricity generation and, consequently, a rise in emissions.

Overall, the findings in this section indicate that the increase in emissions from the electric power sector following a monetary contraction can be attributed to both higher sectoral activity and a shift towards more carbon-intensive energy sources like coal. This shift suggests the operation of an additional transmission channel of monetary policy, the *commodity price* channel, previously examined in the literature, particularly in relation to oil prices (Frankel, 2008; Anzuini et al., 2013; Rosa, 2014; Miranda-Pinto et al., 2023). Notably, my results suggest that this channel operates with different intensities across energy commodities, with coal prices showing a more pronounced response compared to natural gas, which drives down its relative price and makes coal-fired plants more competitive at the margin. To fully understand the forces behind these heterogeneous responses, it would be important to explore the underlying drivers that differentiate the impact of monetary policy on energy commodity prices.

4.4 The impact of monetary policy shocks on energy commodity prices

Building on the seminal work of Frankel (1986), who extended exchange rate overshooting models to commodities, this section investigates how monetary policy shocks influence energy prices, with a particular focus on coal and natural gas. While a broad body of literature has examined the relationship between commodity price fluctuations and macroeconomic variables, far less attention has been given to how monetary conditions drive these fluctuations, with most studies focusing predominantly on oil in both cases. Conceptually, changes in interest rates can affect energy prices through several channels, extending beyond the traditional supply-and-demand dynamics (Hamilton, 2009). This section explores these transmission mechanisms to better understand the factors driving the heterogeneous responses of energy commodities observed in the previous section.

According to Frankel (1986, 2008), monetary policy can influence commodity prices through several key channels. First, changes in interest rates affect the cost of holding inventories (*inventory channel*). Higher rates discourage storage, as the funds tied up in inventories could be invested to earn higher returns, reducing the demand for holding storable commodities. Second, higher rates incentivize the extraction of exhaustible commodities by increasing the opportunity cost of leaving them "in the ground". Producers are more likely to extract and sell now, reinvesting the proceeds at higher rates, which increases supply in the short term (*supply channel*). Finally, higher interest rates make speculative activity in commodity markets less attractive (*financial channel*). Investors face increased borrowing costs or higher opportunity costs for maintaining speculative positions in futures contracts, leading to a reduction in speculative demand. This reduction in demand pushes down futures prices, and by arbitrage, spot prices fall as well, further dampening commodity prices.

Following Anzuini et al. (2013), I assess the empirical relevance of these alternative channels in the context of coal and natural gas, which together accounted for nearly 60 percent of the electric power sector's energy needs in 2022. As highlighted earlier, these commodities exhibit divergent responses to a surprise monetary tightening, which has significant implications for carbon emissions dynamics in the sector. To investigate these channels, I estimate the impulse responses of coal and natural gas inventories, as well as metrics of extraction and production for both commodities in the U.S. For inventories, I use data on total coal stocks (in thousand short tons) and working natural gas in underground storage (in billion cubic feet)[13]. For extraction, I use data on total coal and dry natural gas production[14]. The data are sourced from the Energy Information Administration's Monthly Energy Review[15].

Figure 9 presents the impulse responses to a monetary policy shock. Following a surprise monetary contraction, coal and natural gas inventories both respond in line with Frankel (2008)'s predictions and decline by approximately 1 percent and 3 percent, respectively, providing evidence for the relevance of the *inventory channel*, as higher interest rates dis-

[13]Due to its chemical properties, natural gas is stored in large underground facilities such as salt domes, depleted oil or gas fields, or aquifers capped by impermeable rock. These facilities contain both *Base Gas* (needed to maintain reservoir pressure) and *Working Gas* (available for withdrawal).

[14]Results are nearly identical when using industrial production components for coal (NAICS 2121) and natural gas (NAICS 21113) mining.

[15]Table 6.3. *Coal stocks by sector*, Table 4.4. *Natural gas underground storage*, and Table 1.2. *Primary energy production by source*.

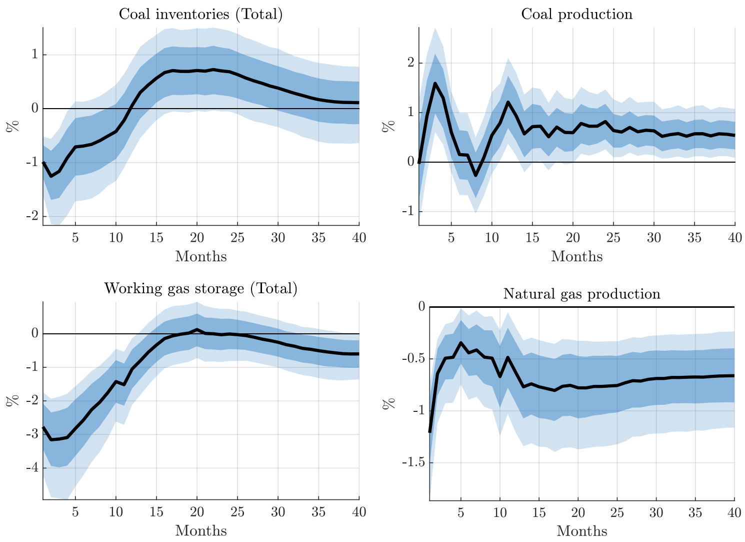

Figure 9: Impulse responses to a monetary policy tightening: Production and stocks of coal and natural gas

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are computed by appending the given sectoral variables to the baseline VAR from Figure 2. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

courage the storage of these energy commodities. Furthermore, coal extraction increases, remaining about 0.7 percent above its previous level in the long run, consistent with the *supply channel*. In contrast, the same pattern does not hold for natural gas as production falls by more than 1 percent after the monetary contraction and remains permanently below its previous levels, diverging from the expected pattern under higher interest rates.

These results suggests that while the *inventory channel* appears relevant for both commodities, the *supply channel* behaves counter to expectations in the case of natural gas. This discrepancy underscores the need for further investigation into how these channels function across different commodities, although such analysis lies beyond the scope of this paper. Nevertheless, these findings provide suggestive evidence of the underlying forces driving the heterogeneous price responses for coal and natural gas, and help explain the relative fall in the price of coal compared to gas and the corresponding implications for carbon emissions in the electric power sector documented in the previous section.

5 Model

In this section, I develop a New Keynesian model extended with an energy block to formalize the mechanisms uncovered in the empirical analysis. The model builds on frameworks from Olovsson and Vestin (2023), Ferrari and Nispi Landi (2024), and Nakov and Thomas (2024), incorporating two key sectors: an *energy sector*, which produces energy inputs (coal and natural gas), and an *electric power sector*, which purchases these inputs to produce and supply *energy services* (electricity). Households and intermediate-goods firms consume these energy services, while the production of energy inputs relies on labor. This structure allows for a detailed exploration of sectoral dynamics and the interplay between monetary policy, energy demand, and carbon emissions.

5.1 Households

The economy is assumed to be inhabited by a large number of identical households. The representative household seeks to maximize the following objective function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma} - 1}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) \tag{6}$$

where C_t is the quantity consumed of the single good available in the economy, N_t denotes hours of work or employment, $\beta \in (0,1)$ is the discount factor, σ is the inverse of the intertemporal elasticity of substitution, and φ represents the inverse of the Frisch elasticity of labor supply.

Maximization of (6) is subject to a sequence of flow budget constraints given by:

$$P_t C_t + P_t^E E_t^H + Q_t B_t = B_{t-1} + W_t N_t + D_t \tag{7}$$

where P_t is the price of the consumption good, W_t denotes the nominal wage per hour, D_t represents dividends from ownership of intermediate-goods-producing firms, and B_t denotes the quantity of one-period nominal riskless bonds purchased in period t. Each bond pays one unit of money at maturity, with Q_t as its price. Departing from the standard model, households allocate their income not only between consumption and savings but also towards electricity usage, which directly influences their utility from leisure. P_t^E is the price of electricity, and E_t^H is the household's demand for it.

More specifically, households allocate their fixed time between labor (N_t) and leisure (L_t), constrained by $1 = N_t + L_t$. Importantly, in this framework, electricity consumption is a *complementary* good to leisure: more leisure time increases household demand for electricity (e.g., for entertainment, heating/cooling):

$$E_t^H = \Xi(1 - N_t) \tag{8}$$

where the parameter Ξ captures how strongly electricity consumption depends on leisure time. Based on this framework, the optimality conditions for the household's problem are standard and can be expressed as:

$$\frac{W_t}{P_t} = N_t^{\varphi} C_t^{\sigma} \tag{9}$$

$$1 = \beta \mathbb{E}_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \frac{I_t}{\Pi_{t+1}} \right] \tag{10}$$

with $I_t = Q_t^{-1}$ the gross yield on the one-period bond and $\Pi_{t+1} = \frac{P_{t+1}}{P_t}$ the gross inflation rate in period $t+1$.

5.2 Final-good firm

The representative and perfectly competitive final-good firm uses the following CES aggregator to produce the final good, Y_t:

$$Y_t = \left(\int_0^1 Y_t(i)^{\frac{\epsilon-1}{\epsilon}} \, di \right)^{\frac{\epsilon}{\epsilon-1}} \tag{11}$$

where $Y_t(i)$ is an intermediate input produced by intermediate-goods firm i, whose price is $P_t(i)$, and $\epsilon > 1$ is the constant elasticity of substitution across intermediate goods. The firm maximizes profits, taking $P_t(i)$ and P_t as given. The solution to this problem yields the final-good firm's demand schedule for intermediate good i:

$$Y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} Y_t \tag{12}$$

where

$$P_t = \left(\int_0^1 P_t(i)^{1-\epsilon}\, di\right)^{\frac{1}{1-\epsilon}} \tag{13}$$

is the aggregate price index.

5.3 Intermediate-goods firms

A continuum of monopolistically competitive firms indexed by $i \in [0, 1]$ produces differentiated goods using the following production function:

$$Y_t(i) = A_t \left(E_t^Y(i)\right)^{\alpha} \left(N_t^Y(i)\right)^{1-\alpha} \tag{14}$$

where $E_t^Y(i)$ and $N_t^Y(i)$ are the quantities of *energy services* (electricity) and labor used by the generic firm i as inputs in production, and A_t is a common, exogenous technology factor that evolves over time as:

$$\log(A_t) = \rho_a \log(A_{t-1}) + v_t^a \tag{15}$$

with $\rho_a \in (0, 1)$ and $v_t^a \sim \mathcal{N}(0, \sigma_a^2)$ an i.i.d. technology shock. Firms are not freely able to adjust prices so as to maximize profits each period, but will always act to minimize costs. Hence, each firm solves an intratemporal problem to choose the optimal input combination and an intertemporal problem to set the price.

The intermediate-goods firms take electricity prices P_t^E and wages W_t as given, since they are price-takers with respect to both inputs in production. The intratemporal problem, which consists in minimizing costs subject to a given level of production is given by:

$$\min_{N_t^Y(i), E_t^Y(i)} W_t N_t^Y(i) + P_t^E E_t^Y(i) \tag{16}$$

subject to (14). The solution of this optimization problem yields the following demand functions for labor and electricity:

$$N_t^Y(i) = \frac{(1-\alpha) MC_t Y_t(i)}{W_t} \tag{17}$$

$$E_t^Y(i) = \frac{\alpha MC_t Y_t(i)}{P_t^E} \tag{18}$$

$$MC_t = \frac{1}{A_t}\left(\frac{P_t^E}{\alpha}\right)^{\alpha}\left(\frac{W_t}{1-\alpha}\right)^{1-\alpha} \tag{19}$$

where MC_t is the (nominal) marginal cost in period t.

As mentioned above, firms operate in monopolistic competition, setting prices subject to the final-good firm's demand (12). However, they cannot freely adjust prices so as to maximize profits each period. I follow the literature and assume Calvo (1983) pricing, under which each firm may reset its price only with probability $1-\theta$ in any given period, independent of the time elapsed since it last adjusted its price. Thus, in each period a measure $1-\theta$ of producers reset their prices, while a fraction θ keep their prices unchanged.

A firm reoptimizing in period t will choose the price $P_t^\star$ that maximizes the current market value of the profits generated while that price remains effective,

$$\max_{P_t^\star} \quad \sum_{k=0}^{\infty} \theta^k \mathbb{E}_t \left\{ \Lambda_{t,t+k} \left(\frac{1}{P_{t+k}} \right) \left(P_t^\star Y_{t+k|t} - \mathcal{C}_{t+k}(Y_{t+k|t}) \right) \right\} \tag{20}$$

subject to a sequence of demand constraints:

$$Y_{t+k|t}(i) = \left(\frac{P_t^\star}{P_{t+k}} \right)^{-\epsilon} Y_{t+k} \tag{21}$$

where $\Lambda_{t,t+k} \equiv \beta^k \frac{C_{t+k}^{-\sigma}}{C_t^{-\sigma}}$ is the stochastic discount factor, $\mathcal{C}(\cdot)$ is the (nominal) cost function, and $Y_{t+k|t}$ denotes output in period $t+k$ for a firm that last reset its price in period t.

After some manipulation, the optimality condition associated with the problem above takes the form:

$$\sum_{k=0}^{\infty} \theta^k \mathbb{E}_t \left\{ \Lambda_{t,t+k} Y_{t+k|t} \left(\frac{1}{P_{t+k}} \right) \left(P_t^* - \mathcal{M} MC_{t+k|t} \right) \right\} = 0 \tag{22}$$

where $MC_{t+k|t} \equiv \mathcal{C}'_{t+k}(Y_{t+k|t})$ denotes the (nominal) marginal cost in period $t+k$ for a firm which last reset its price in period t and $\mathcal{M} \equiv \frac{\epsilon}{\epsilon-1}$. Furthermore, solving for $P_t^\star$, we get the following condition:

$$P_t^\star = \frac{\epsilon}{\epsilon-1} \frac{\mathcal{K}_{1t}}{\mathcal{K}_{2t}} \tag{23}$$

where

$$\mathcal{K}_{1t} = Y_t C_t^{-\sigma} P_t^{\epsilon} \frac{MC_t}{P_t} + \theta\beta \mathbb{E}_t \mathcal{K}_{1t+1} \tag{24}$$

$$\mathcal{K}_{2t} = Y_t C_t^{-\sigma} P_t^{\epsilon-1} + \theta\beta \mathbb{E}_t \mathcal{K}_{2t+1} \tag{25}$$

Therefore, intermediate-goods firms that are able to reoptimize choose a price that reflects their desired markup over a weighted average of current and expected future marginal costs. This setup also implies that aggregate price dynamics can be described by:

$$\Pi_t^{1-\epsilon} = \theta + (1-\theta) \left(\frac{P_t^\star}{P_{t-1}} \right)^{1-\epsilon} \tag{26}$$

5.4 The electric power sector

The electric power sector consists of a representative competitive firm that combines coal and natural gas (*energy inputs*) to produce *energy services* (electricity), which are used in the production of the intermediate goods and by households. This representative firm combines the two energy inputs in the following fashion:

$$E_t = A_t^E \left(X_t^G\right)^\gamma \left(X_t^C\right)^{1-\gamma} \tag{27}$$

where X_t^G and X_t^C are the quantities of natural gas and coal used in energy services production, and $E_t = E_t^H + E_t^Y$ is the total electricity supply in the economy. The profit maximization problem for the representative firm in the electric power sector is given by:

$$\max_{X_t^G, X_t^C} \quad P_t^E E_t - P_t^G X_t^G - P_t^C X_t^C \tag{28}$$

subject to the Cobb-Douglas aggregator in (27). Given this framework, the optimality conditions for the firm in the sector are respectively given by:

$$P_t^G X_t^G = \gamma P_t^E E_t \tag{29}$$

$$P_t^C X_t^C = (1-\gamma) P_t^E E_t \tag{30}$$

where P_t^G and P_t^C are the price of natural gas and coal inputs, respectively.

5.5 Energy firms

Each type of energy is produced by a representative firm and is sold in a perfectly competitive market at price P_t^j, with $j \in \{G, C\}$. Distancing from the setups in Golosov et al. (2014), Nakov and Thomas (2024), and Olovsson and Vestin (2023), which define production in both energy sectors as linear in labor, I assume that the production of energy inputs exhibits *decreasing* returns to scale, with differing labor shares. This assumption not only aims to capture the distinct levels of labor utilization in the production and extraction of these energy commodities, as documented in the data, but also seeks to reflect other important factors related to the influence of fixed costs in the extraction of each commodity, which are not captured explicitly under this formulation. Accordingly, the representative natural gas and coal firms produce the total supply of each energy input using the following functions, respectively:

$$X_t^G = A_t^G \left(N_t^G\right)^{1-\eta} \tag{31}$$

$$X_t^C = A_t^C \left(N_t^C\right)^{1-\zeta} \tag{32}$$

with η and $\zeta \in (0,1)$ pinning down the corresponding labor shares in each sector, N_t^G and N_t^C denoting the quantities of labor employed by the firms as input in the production of natural gas and coal, respectively, and A_t^G, A_t^C referring to sector-specific exogenous productivity factors. Given this setup, the profit maximization problems for the natural gas and coal energy sectors are, respectively, given by:

$$\max_{X_t^G} \quad P_t^G X_t^G - W_t N_t^G \tag{33}$$

$$\max_{X_t^C} \quad P_t^C X_t^C - W_t N_t^C \tag{34}$$

subject to (31) and (32). Hence, the optimal demand for labor in the two energy sectors is given by:

$$(1-\eta)P_t^G X_t^G = W_t N_t^G \tag{35}$$

$$(1-\zeta)P_t^C X_t^C = W_t N_t^C \tag{36}$$

5.6 Monetary policy

The Central Bank sets the nominal short-term interest rate by responding to deviations of inflation and output from their steady state values, according to the following Taylor rule:

$$\frac{I_t}{\bar{I}} = \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi^\pi} \left(\frac{Y_t}{\bar{Y}}\right)^{\phi^y} \exp(v_t^m) \tag{37}$$

where $\bar{I}, \bar{Y}, \bar{\Pi}$ are steady state values for the nominal interest rate, the output gap and the inflation target, respectively, ϕ^π and ϕ^y are the non-negative inflation- and output-response coefficients chosen by the monetary authority, and v_t^m is an exogenous monetary policy shock that evolves according to the following AR(1) process

$$v_t^m = \rho_v v_{t-1}^m + e_t^v \tag{38}$$

with $\rho_v \in [0, 1]$. A positive (negative) realization of e_t^v should be interpreted as a contractionary (expansionary) monetary policy shock, leading to a rise (decline) in the nominal interest rate, given inflation and output.

5.7 Emissions

For simplicity and without loss of generality, I assume that emissions are directly proportional to total electricity use in the economy, $CO_2 = E_t$. This assumption abstracts from the varying emissions intensities of the different energy inputs, related to the fact of coal being twice as polluting as natural gas due to its higher carbon content. Notably, accounting for these differences would only strengthen the results presented in the analytical section. Unlike some papers in the related literature, I also abstract from feedback effects and climate externalities, which are common in macro-environment models (Golosov et al., 2014), as they are not essential to replicate the empirical findings here[16]. Nevertheless, incorporating these dimensions in future research could provide valuable insights.

5.8 Aggregation and market clearing

Market clearing in the goods market requires that the quantity produced of each good matches the quantity demanded. In the stylized model analyzed here, consumption is the

[16] In the models in Heutel (2012) and Golosov et al. (2014), industrial CO2 emissions are an increasing function of production. Higher emissions increase carbon in the atmosphere, which is also fueled by carbon in the oceans and exogenous non-industrial emissions. Higher values of atmospheric carbon raise the mean surface temperature, which in turn reduces total factor productivity. In these frameworks, this is modelled by asumming that TFP $A_t = (1 - D_t(x_t))a_t$, where $D_t(x_t)$ is the damage function, which is increasing in atmospheric carbon (pollution) x_t (Ferrari and Nispi Landi, 2024).

only source of demand for goods. Letting aggregate output be defined as in (11), it follows that $Y_t = C_t$. Similarly, the energy services and labor market clearing conditions are respectively given by:

$$N_t = \int_0^1 N_t^Y(i)di + N_t^G + N_t^C = N_t^Y + N_t^G + N_t^C \tag{39}$$

$$E_t = \int_0^1 E_t^Y(i)di + E_t^H = E_t^Y + E_t^H \tag{40}$$

Since markets are complete and consumers who have access to financial markets are identical, government bonds are always in zero net supply: $B_t = 0$.

Based on the former market clearing conditions, an aggregate formulation of the production function (14) can be written as:

$$Y_t\Delta_t = A_t\left(E_t^Y\right)^{\alpha}\left(N_t^Y\right)^{1-\alpha} \tag{41}$$

where $\Delta_t \equiv \int_0^1 (P_t(i)/P_t)^{-\epsilon}\, di$ is a measure of price (and, hence, output) dispersion across firms, with law of motion:

$$\Delta_t = (1-\theta)\left(\frac{P_t^\star}{P_t}\right)^{-\epsilon} + \theta\left(\frac{P_t}{P_{t-1}}\right)^{\epsilon}\Delta_{t-1} \tag{42}$$

Equation (41) implies that relative price dispersion increases the amount of labor and energy services needed to satisfy a certain level of aggregate consumption demand.

5.9 Calibration

All quantitative results in this section are based on calibrations that take each period in the model to correspond to a quarter. In the baseline calibration of the model's I set the preference parameter $\beta = 0.99$, which implies a steady state real (annualized) return on financial assets of about 4 percent. I also set $\sigma = 1$ (log utility), $\varphi = 5$ (which implies a Frisch elasticity of labor supply of 0.2), and $\epsilon = 9$ (implying $\mathcal{M} = 1.125$, i.e., a steady state markup of a 12.5 percent). These are values broadly similar to those found in the business cycle literature.

In addition, I set the Calvo parameter $\theta = 0.75$, such that prices change on average once a year, a value consistent with much of the empirical evidence. As to the interest rate rule coefficients, it is assumed $\phi^\pi = 1.5$ and $\phi^y = 0.5/4$, in a way consistent with Taylor's original rule. Finally, following Galí (2015), I set the persistence of the exogenous processes $\rho_a = 0.9$ and $\rho_v = 0.5$.

In terms of the parameters associated with energy and emissions in the model, as in Golosov et al. (2014), I set $\alpha = 0.04$, which corresponds approximately with the energy share of World GDP. For calibrating the share of natural gas in electricity production (γ) I rely on data from the Energy Information Administration (EIA). In 2022, natural gas and coal use in the electric power sector accounted for 38 and 27 percent of the energy needs in the sector

(Figure A.1). Assuming this represents all of the energy used in the sector, in line with the assumptions of the model, I set $\gamma = 0.59$. In terms of the calibration of the labor shares in the natural gas and coal sectors, $1 - \eta$ and $1 - \zeta$, I rely on data from the U.S. Bureau of Economic Analysis (BEA) on *Value Added by Industry* and *Compensation of Employees by Industry* for the *Oil and gas extraction* (Natural gas) and *Mining, except oil and gas* (Coal) industries and compute the labor sahres as the ratio between compensation and total value added for each industry. Based on the averages between 1998-2022, I set $1-\eta = 0.15$ and $1-\zeta = 0.33$. Finally, following Olovsson and Vestin (2023), turning to the production parameters, I abstract from technical change in the energy sectors and set $A_t^E = A^E = 1$, $A_t^G = A^G = 1$ and $A_t^C = A^C = 1$. The whole set of calibrated parameters are presented in Table 1.

Parameter	Description	Value	Notes
σ	Inverse intertemporal elasticity of substitution	1	Galí (2015)
φ	Inverse Frisch elasticity of labor supply	5	Galí (2015)
β	Discount factor	0.99	Galí (2015)
Ξ	Intensity of household electricity consumption	1	For now
α	Electricity share in production	0.04	Golosov et al. (2014)
ϵ	Elasticity of substitution btw diff. goods	9	Galí (2015)
θ	Calvo parameter	0.75	Galí (2015)
γ	Share of natural gas in electricity production	0.59	EIA data
A^E	TFP in electricity sector	1	Olovsson and Vestin (2023)
A^G	TFP in natural gas sector	1	Olovsson and Vestin (2023)
A^C	TFP in coal sector	1	Olovsson and Vestin (2023)
$1-\eta$	Share of labor in natural gas production	0.15	BEA and BLS data
$1-\zeta$	Share of labor in coal production	0.33	BEA and BLS data
ϕ^π	Monetary policy response to inflation	1.5	Galí (2015)
ϕ^y	Monetary policy response to output	0.125	Galí (2015)
ρ_a	Persistence technology shock	0.9	Galí (2015)
ρ_m	Persistence monetary policy shock	0.5	Galí (2015)

Table 1: Calibrated parameters

5.10 The effects of a monetary policy shock

The focus in this section is to assess the economy's response to a shift in v_t^m, holding $v_t^a = 0$ for all t. Figure 10 illustrates the dynamic effects of a contractionary monetary policy shock on several macroeconomic variables, with the shock modeled as a 25-basis-point increase in e_t^v.

This policy shock generates an increase in both the nominal (I_t) and real (R_t) interest rates, leading to decreases in inflation (Π_t), output (Y_t), and employment (N_t). This decline in total employment drives up household electricity consumption (E_t^H), resulting in increased total electricity usage (E_t) in the economy, even though electricity use by intermediate-goods firms (E_t^Y) declines due to the output contraction. Consequently, the overall increase in electricity demand leads to a proportional rise in carbon emissions $(CO2_t)$, replicating the main result from the empirical analysis. Furthermore, given the assumption on proportionality of emissions and electricity use, the model is also able to replicate the sectoral

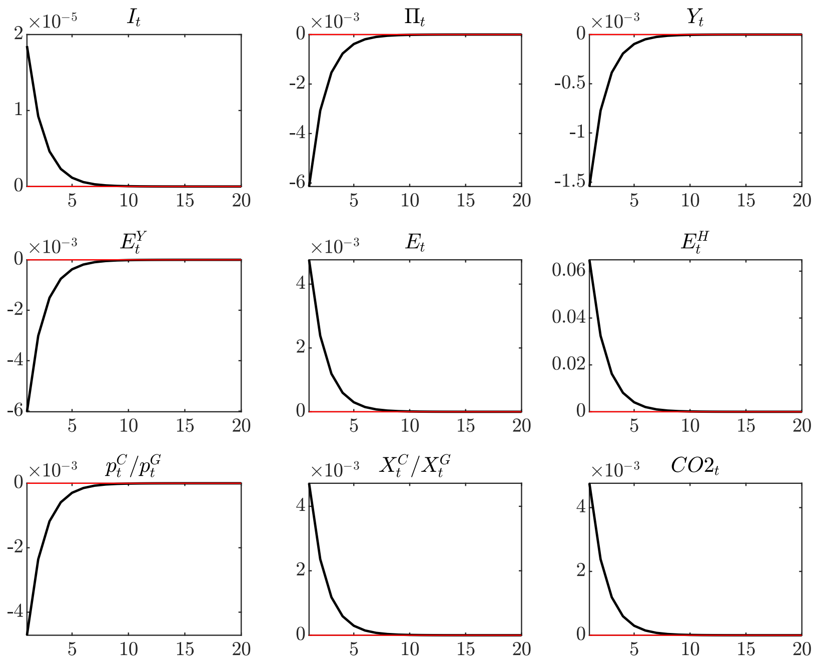

Figure 10: Dynamic responses to a monetary policy shock: Interest rate rule

results, under which emissions in the industrial sector behave as expected and fall following the monetary contraction, closely tracking output fluctuations, whereas emissions in the residential sector surge given increased energy use at home due to higher leisure time.

In the electric power sector, the heightened electricity demand increases the demand for energy inputs, thereby driving up employment in the natural gas (N_t^G) and coal (N_t^C) sectors. As a result, total employment in the model falls by less than it would in a standard framework, with the rise in energy sectors employment partially offsetting the decline. Due to the sector's Cobb-Douglas production structure, demand for both coal (X_t^C) and natural gas (X_t^G) *increases* following the contraction. However, differing labor shares lead to heterogeneity in the magnitude of the responses, resulting in a decrease in the price of coal relative to natural gas (p_t^C/p_t^G). This shift encourages the electric power sector to increase its relative use of coal in electricity production (X_t^C/X_t^G), replicating the empirical findings on the *commodity price* channel's role in the sector's emissions.

Finally, as mentioned earlier, the economics literature has documented the unconditional procycality of carbon emissions (Heutel, 2012; Doda, 2014). Notably, this model formulation, and under the same calibration, is able to replicate this empirical fact through the dynamics generated by a positive technology shock (v_t^a). The impulse responses to this shock are presented in Figure D.1 in the Appendix. Moreover, by capturing these broader empirical patterns, the model not only replicates the sector-specific and aggregate dynamics of carbon emissions observed in response to monetary policy shocks but also highlights the crucial role of energy price fluctuations and households' energy demand—factors that have been largely overlooked in assessments of monetary policy's implications for climate change. These insights contribute to a deeper understanding of how monetary policy may influence emissions and energy use, providing a framework that aligns with existing models while incorporating often-overlooked channels and highlighting their potential role in shaping carbon emissions dynamics over the business cycle.

6 Concluding Remarks

Addressing climate change is one of the most pressing challenges of our time. While carbon pricing is widely regarded as the most appropriate tool, practical concerns regarding implementation, uneven economic impacts, and limited public support (Känzig, 2023) open the door to complementary measures such as monetary policy. However, despite increasing theoretical discussions and policy developments signaling central banks' interest in contributing to this endeavor, little is known about the unintended and nuanced effects of monetary policy interventions on the key determinants of climate change. This paper provides new empirical evidence of a sizable response of carbon emissions to monetary policy. In particular, I show that a monetary policy tightening, contrary to conventional wisdom, leads to a significant *increase* in emissions. Importantly, this increase masks substantial heterogeneity across energy-consuming sectors, with the non-industrial sectors driving most of the rise.

This analysis uncovers alternative and novel channels that have not been previously considered in the literature on the relationship between monetary policy and emissions. In particular, the transmissions of this shock entails energy demand shifts from industry to residential and commercial sectors as unemployment rises and storage needs increase. Furthermore, heterogeneous responses of energy commodity prices to monetary policy have significant implications for the energy mix in the electric power sector, driving it toward more polluting energy generation in the short run. I capture and rationalize these novel channels in a simple model, aiming to clarify the trade-offs that arise from monetary policy interventions by incorporating factors such as the role of leisure in household energy consumption and the impact of fluctuations in relative energy input prices for electricity generation.

The normative question of whether central banks should incorporate climate change considerations into their policy frameworks is not only highly relevant but also increasingly complex. These unintended repercussions of monetary policy interventions should be considered by policymakers when evaluating the broader implications of carbon-reduction strategies, ensuring that climate objectives are not inadvertently undermined by economic stabilization efforts. Future research should shed more light on how monetary, fiscal, and climate policies can be better aligned to avoid unintended trade-offs and contribute to a successful transition to a low-carbon economy.

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Appendices

A Additional Figures

In this Appendix, I present additional tables and figures that complement the analysis in the main body of the paper.

A.1 Energy consumption by source and sector

As mentioned in the paper, the five energy-use sectors vary considerably in both their primary energy uses and their dominant energy sources. Figure A.1 presents this information for year 2022. The chart illustrates energy that is consumed (used) in the United States. The data are from EIA's Monthly Energy Review (MER) and include the relatively small amount of electricity net imports, not shown separately. The chart does not show energy production, nor the losses associated with energy production.

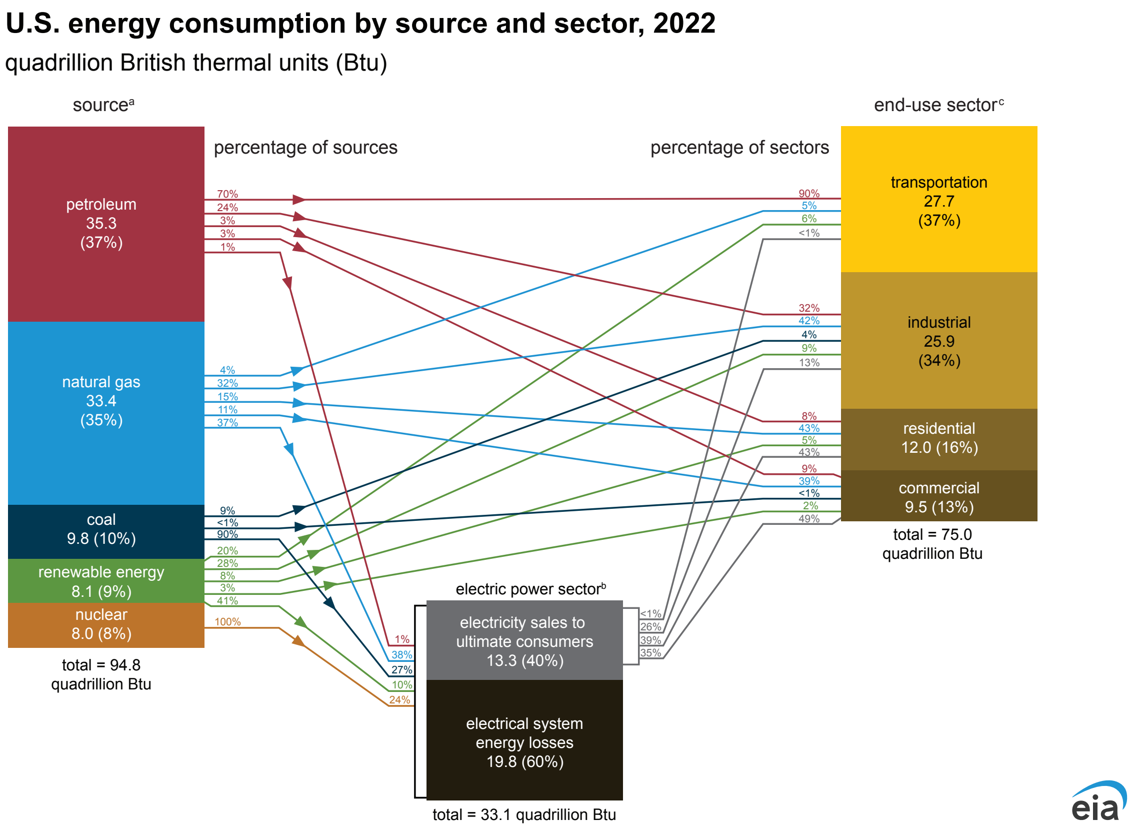

Figure A.1: U.S. energy consumption by source and sector, 2022

Notes: The U.S. Energy Information Administration's (EIA) chart shows the types and amounts of primary energy consumed in the U.S., energy use by the electric power and end-use sectors, and electricity sales to end-use sectors. *Source*: U.S. Energy Information Administration (EIA), Monthly Energy Review (April 2023), Tables 1.3, 1.4c, and 2.1a-2.6.

On the other hand, Figures A.2, A.3 and A.4 present the same information for each specific sector, for all the years since the data is available. The charts illustrate energy that is consumed (used) in the United States in the different sectors and its evolution across time. The underlying data is monthly and, to control for seasonality, all data are seasonally adjusted. Energy sources are measured in different physical units: liquid fuels in barrels or gallons, natural gas in cubic feet, coal in short tons, and electricity in kilowatthours. EIA converts each source into common British thermal units (Btu) to allow comparison among different types of energy.

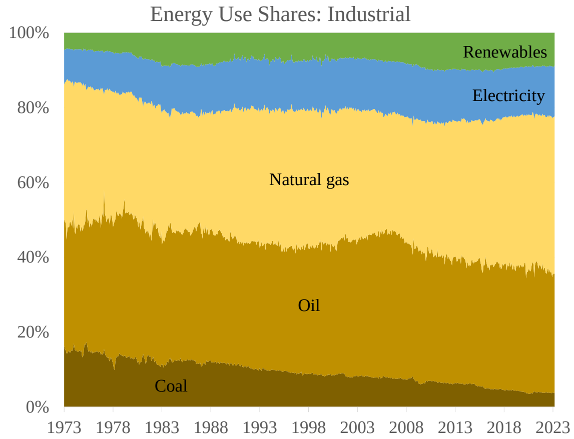

Figure A.2: Energy consumption by source and year: Industrial sector

Notes: Monthly industrial sector energy consumption by source. Includes energy used as feedstocks in manufacturing products. *Electricity* reflects retail sales to the sector and excludes electric system energy losses associated with these sales. Data are seasonally adjusted. *Source*: U.S. Energy Information Administration (EIA), Monthly Energy Review (April 2023), Table 2.4.

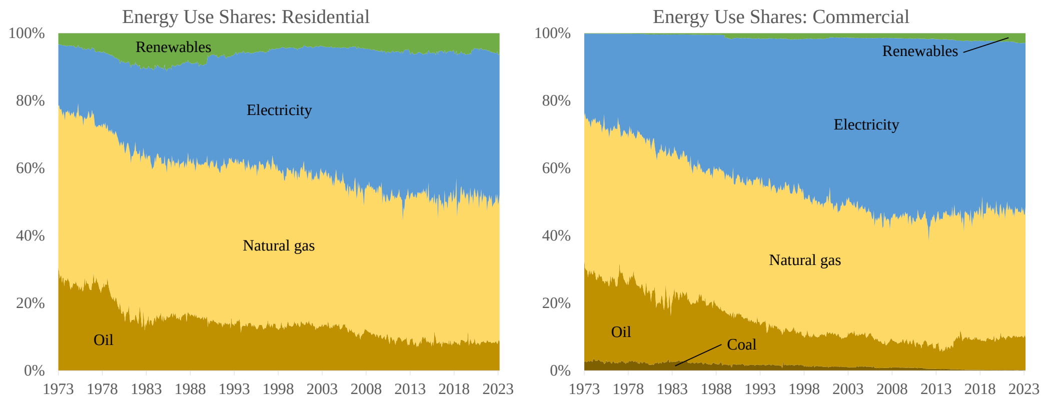

Figure A.3: Energy consumption by source and year: Residential and commercial sectors

Notes: Monthly residential and commercial sectors energy consumption by source. *Electricity* reflects retail sales to the sectors and excludes losses in generation and delivery. *Oil* includes heating oil, liquefied petroleum gas (propane), and kerosene. *Renewables* encompass wood, geothermal energy, and solar energy. Data are seasonally adjusted. *Source*: U.S. Energy Information Administration (EIA), Monthly Energy Review (April 2023), Tables 2.2. and 2.3.

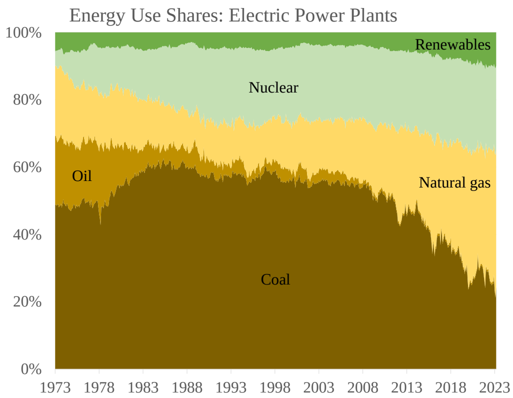

Figure A.4: Energy consumption by source and year: Electric power sector

Notes: Monthly electric power sector energy consumption by source. Includes electricity generation from power plants with at least 1,000 kilowatts of electric generation capacity (utility-scale). *Renewables* encompass wind, hydropower, solar, biomass, and geothermal. Data are seasonally adjusted. *Source*: U.S. Energy Information Administration (EIA), Monthly Energy Review (April 2023), Table 2.6.

A.2 The electric power grid

As mentioned in the main text, the electric grid is a complex machine in which electricity is generated at centralized power plants and decentralized units and is transported through a system of substations, transformers, transmission lines and distribution lines that deliver the product to its end user, the consumer. Since large amounts of electricity cannot be stored, it must be produced as it is used.

According to the U.S. Energy Information Administration (EIA), the U.S. power grid is made up of over 7,300 power plants, nearly 160,000 miles of high-voltage power lines, and millions of miles of low-voltage power lines and distribution transformers, connecting 145 million customers throughout the country. Figure A.5 provides a simplified represetation of the mains stages and actors of this system.

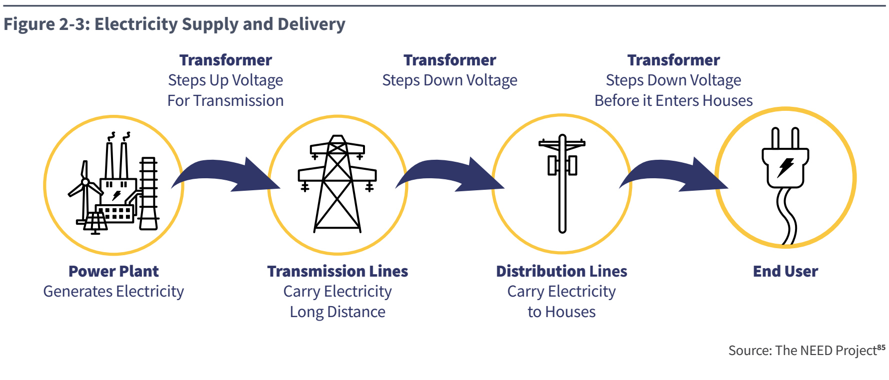

Figure A.5: The electric power grid

Source: Federal Energy Regulatory Commission (2023), adapted from the National Energy Education Development Project, Electricity, at 56 (2017), `http://www.need.org/Files/curriculum/infobook/Elec1S.pdf`.

B Data

B.1 Data sources

In this Appendix, I provide details on the macroeconomic data used in the paper, including information on the data source and coverage.

Table B.1: Data Description, Sources, and Coverage

Variable	Description	Source	Sample
Instrument			
mp_median	Monetary Policy Shocks obtained with the median rotation that implements the sign restrictions	Jarociński and Karadi (2020) / Jarociński's website	08/02/1990-31/12/2019
Baseline variables			
dgs1	Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity, End of Month	FRED	1973M1-2019M12
pcepi	Personal Consumption Expenditures: Chain-type Price Index	FRED	1973M1-2019M12
indpro	Industrial Production: Total Index	FRED	1973M1-2019M12
ebp_gz	Excess Bond Premium	Gilchrist and Zakrajšek (2012) / Fed's website	1973M1-2019M12
crbpi	Commodity Research Bureau's (CRB) Commodity Price Index	Bloomberg	1973M1-2019M12
co2_a	Carbon Dioxide Emissions From Energy Consumption: Total (Mmt of Carbon Dioxide)	EIA Monthly Energy Review	1973M1-2019M12
Additional variables			
co2_i	Carbon Dioxide Emissions From Energy Consumption: Industrial Sector (Mmt of Carbon Dioxide)	EIA Monthly Energy Review	1973M1-2019M12
co2_r	Carbon Dioxide Emissions From Energy Consumption: Residential Sector (Mmt of Carbon Dioxide)	EIA Monthly Energy Review	1973M1-2019M12
co2_c	Carbon Dioxide Emissions From Energy Consumption: Commercial Sector (Mmt of Carbon Dioxide)	EIA Monthly Energy Review	1973M1-2019M12
co2_t	Carbon Dioxide Emissions From Energy Consumption: Transportation Sector (Mmt of Carbon Dioxide)	EIA Monthly Energy Review	1973M1-2019M12
co2_ep	Carbon Dioxide Emissions From Energy Consumption: Electric Power Sector (Mmt of Carbon Dioxide)	EIA Monthly Energy Review	1973M1-2019M12
ipman	Industrial Production: Manufacturing (NAICS)	FRED	1973M1-2019M12
ipmine	Industrial Production: Mining: Mining (NAICS = 21)	FRED	1973M1-2019M12
totenergy_i_btu	Industrial Sector Energy Consumption: Total (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
oil_i_btu	Industrial Sector Energy Consumption: Total Petroleum (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
ngas_i_btu	Industrial Sector Energy Consumption: Natural Gas (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
elec_i_btu	Industrial Sector Energy Consumption: Electricity (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
ngas_r_btu	Residential Sector Energy Consumption: Natural Gas (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
elec_r_btu	Residential Sector Energy Consumption: Electricity (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
totenergy_r_btu	Residential Sector Energy Consumption: Total (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
ngas_c_btu	Commercial Sector Energy Consumption: Natural Gas (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
elec_c_btu	Commercial Sector Energy Consumption: Electricity (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
totenergy_c_btu	Commercial Sector Energy Consumption: Total (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
unrate	Unemployment rate	FRED	1973M1-2019M12
awhman	Average Weekly Hours of Production and Nonsupervisory Employees, Manufacturing	FRED	1973M1-2019M12
iputil	Industrial Production: Utilities: Electric and Gas Utilities (NAICS = 2211,2)	FRED	1973M1-2019M12
ipg22111s	Industrial Production: Utilities: Electric Power Generation (NAICS = 22111)	FRED	1973M1-2019M12
ipg22112s	Industrial Production: Utilities: Electric Power Transmission, Control, and Distribution (NAICS = 22112)	FRED	1973M1-2019M12
ipn22112ms	Industrial Production: Utilities: Industrial Electricity Sales (NAICS = 22112pt.)	FRED	1973M1-2019M12
ipn22112rs	Industrial Production: Utilities: Residential Electricity Sales (NAICS = 22112pt.)	FRED	1973M1-2019M12
ipn22112cs	Industrial Production: Utilities: Commercial and Other Electricity Sales (NAICS = 22112pt.)	FRED	1973M1-2019M12
coal_ep_btu	Electric Power Sector Sector Energy Consumption: Coal (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
ngas_ep_btu	Electric Power Sector Sector Energy Consumption: Natural Gas (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
nucl_ep_btu	Electric Power Sector Sector Energy Consumption: Nuclear Electric Power (Trillion Btu)	EIA Monthly Energy Review	1973M1-2019M12

Table B.2: Data Description, Sources, and Coverage (continued)

Variable	Description	Source	Sample
Additional variables			
costcoalngas_ep	Cost of Coal Receipts at Electric Generating Plants Relative to Natural Gas (Dollars per Million Btu, Including Taxes)	EIA Monthly Energy Review	1973M1-2019M12
netgen_coal_ngas	Electricity Net Generation from Coal Relative to Natural Gas (Million Kwh)	EIA Monthly Energy Review	1973M1-2019M12
stock_coal_a	Coal Stocks by Sector: Total (Thousand Short Tons)	EIA Monthly Energy Review	1973M1-2019M12
stock_ngas_a	Natural gas in Underground Storage, End of Period: Working Gas (Billion Cubic Feet)	EIA Monthly Energy Review	1973M1-2019M12
coal_p_btu	Primary Energy Production by Source: Coal (Quadrillion Btu)	EIA Monthly Energy Review	1973M1-2019M12
ngas_p_btu	Primary Energy Production by Source: Natural Gas (Dry) (Quadrillion Btu)	EIA Monthly Energy Review	1973M1-2019M12

C Sensitivity Analysis

In this Appendix, I perform a number of robustness checks on the identification strategy and the empirical specification used to isolate the monetary policy shocks, as discussed in Section 3 of the paper. Throughout, I report the point estimate as the solid black line and 68 and 90 percent confidence bands as dark and light shaded areas, respectively.

C.1 Alternative instruments

Over the past decade, high-frequency financial asset price changes around Federal Reserve Federal Open Market Committee (FOMC) announcements—referred to as monetary policy surprises—have become a central tool for identifying the effects of monetary policy on asset prices and the macroeconomy. These surprises are particularly appealing because their focus on financial assets price changes within a narrow window around FOMC announcements plausibly mitigates concerns about reverse causality and other endogeneity issues (Bauer and Swanson, 2023).

The monetary policy surprises proposed by Jarociński and Karadi (2020) represent just one of several high-frequency instruments used in the literature on monetary policy VARs. The seminal work of Gertler and Karadi (2015) introduced three-month-ahead federal funds futures (FF4) as an external instrument, advocating for their strong performance in VAR analysis for the period from January 1991 to June 2012. Building on this foundation, Nakamura and Steinsson (2018) highlighted the dual signaling and policy effects of monetary actions, which motivated subsequent empirical efforts to disentangle these channels.

Jarociński and Karadi (2020) advanced the literature by employing a high-frequency identification strategy that leverages the co-movement of interest rates and stock prices around monetary policy announcements. Using sign restrictions in a structural VAR framework, they distinguish conventional monetary policy shocks (negative co-movement) from central bank information shocks (positive co-movement). Expanding on this approach, Miranda-Agrippino and Ricco (2021) incorporate the Federal Reserve's internal Greenbook forecasts to develop an instrument that corrects for informational rigidities and signaling effects, isolating purely exogenous policy shocks. More recently, Bauer and Swanson (2023) refine these high-frequency methods by regressing these surprises on publicly available economic and financial data pre-dating the meetings, in order to address endogeneity and bias concerns, further enhancing the robustness of identified shocks.

To assess the robustness of my results, I employ these alternative instruments to estimate the dynamic causal effects of monetary policy on carbon emissions, using the same baseline specification as in Figure 2. Specifically, I use the following instruments:

- *GK (2015): FF4* – Monetary policy surprises based on changes in three-month-ahead (FF4) federal funds futures, as introduced by Gertler and Karadi (2015).

- *Alt. JK (2020): Poor man's* – Surprises constructed as the first principal component of high-frequency changes in interest rate derivatives (e.g., MP1, FF4, ED2–ED4) and the S&P 500 index within a 30-minute window around FOMC announcements, following Jarociński and Karadi (2020). Under the *poor man's* framework, surprises are classified as instruments for monetary policy shocks when the stock price surprise has the opposite sign of the interest rate derivative surprise (and zero otherwise). The remaining observations serve as proxies for central bank information shocks.

- *MAR (2021): Info. robust* – High-frequency surprises in FF4, aggregated monthly and orthogonalized to the Fed's Greenbook forecasts, per Miranda-Agrippino and Ricco (2021).[17]

- *BS (2023): PC1 [ED1-ED4]* and *Orthogonal BS (2023)* – Surprises derived from changes in Eurodollar futures rates (ED1–ED4), with *orthogonalized* surprises computed as residuals from regressing conventional surprises on a robust set of predictors, per Bauer and Swanson (2023).[18]

The impulse responses to a monetary policy shock using the alternative instruments, alongside the first-stage F-statistic for each them, are presented in Figure C.1. The results do not change materially, and in all cases the responses are very similar, both qualitatively and quantitatively. By employing these diverse instruments, I ensure that my findings are not driven by any specific methodology or underlying assumptions, thereby enhancing the credibility of the estimated causal effects on carbon emissions.

[17]These surprises are computed by regressing high-frequency FF4 changes on Greenbook forecasts and revisions. The residuals reflect only variation orthogonal to the Fed's information set, isolating purely exogenous shocks. To address autoregressive components, these residuals are further regressed on their own lags.

[18]The orthogonal surprise is, by construction, uncorrelated with pre-FOMC macroeconomic and financial data, ensuring its exogeneity. In this exercise I only use data based on FOMC meetings, given availability.

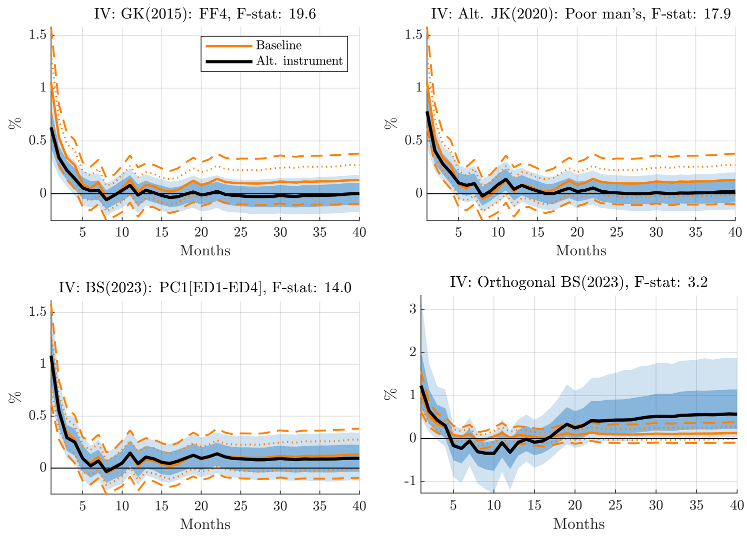

Figure C.1: Response of total carbon emissions to a surprise monetary tightening: Alternative instruments

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are estimated based on the baseline VAR specification, using alternative instruments for the structural monetary policy shock. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

C.2 Alternative estimation techniques

A key advantage of the external instruments approach lies in its efficiency. However, this efficiency comes at the cost of assuming (partial) invertibility. If the invertibility assumption is not satisfied, the results may be biased (Li et al., 2024). To address this concern, I also present results using the internal instruments approach (Ramey, 2011; Plagborg-Møller and Wolf, 2021), which is robust to non-invertibility. Under this method, we can estimate the dynamic causal effects by augmenting the VAR with the instrument ordered first, $\bar{\mathbf{y}}_t = [z_t, \mathbf{y}_t']'$, and computing the impulse responses to the first orthogonalized innovation,

$$\bar{s}_1 = \frac{[\text{chol}(\boldsymbol{\Sigma})]_{\cdot,1}}{[\text{chol}(\boldsymbol{\Sigma})]_{1,1}} \tag{43}$$

As shown by Plagborg-Møller and Wolf (2021), this approach consistently estimates the relative impulse responses even if the instrument is contaminated with measurement error or if the shock is non-invertible.

An alternative approach is to estimate the dynamic causal effects using local projections on the surprise series. However, directly estimating the macroeconomic effects of high-frequency surprises poses challenges. As noted by Nakamura and Steinsson (2018), the clean identification provided by the high-frequency approach often comes at the cost of lower statistical power. This is because macroeconomic variables several months or years out are influenced by a multitude of shocks, which can dilute the effects of the monetary policy surprise. Furthermore, the limited availability of high-frequency surprise series reduces the effective sample size, further compounding the loss of power. The VAR framework mitigates this issue by enabling the estimation of the reduced form over a longer sample, even if the instrument is available for only part of the sample, thus improving efficiency at all horizons. In contrast, the local projections framework offers less scope for enhancing efficiency (Stock and Watson, 2018).

Despite these challenges, I also present results from a local projections-instrumental variable (LP-IV) approach. The responses are estimated by running the following set of IV regressions:

$$y_{j,t+h} = \beta_0^j + \gamma_h^j i_t + \beta_h^j x_{t-1} + \xi_{i,t,h} \tag{44}$$

using the monetary policy surprise series z_t as an instrument for the one-year government bond yield, i_t, where $y_{j,t+h}$ is the outcome variable of interest (e.g., emissions in this case), and x_{t-1} is a vector of controls. Here, γ_h^j denotes the impulse response of variable j to the monetary policy shock at horizon h.

Figure C.2 compares the results of the internal instrument and the LP-IV approaches with those of the baseline external instrument approach. While the responses under the internal instrument approach are less precisely estimated, the differences are not statistically significant. In fact, the point estimate for the impact effect is larger than the one for the case of external instruments. Additionally, the internal instrument estimates exhibit wider confidence bands, reflecting lower precision. Nonetheless, the findings indicate that the results remain robust even when relaxing the invertibility assumption. The figure demonstrates that both methods yield qualitatively and quantitatively similar results.

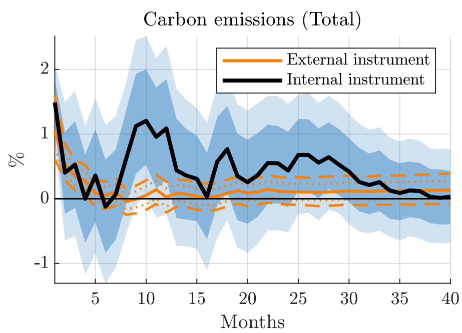

Figure C.2: Response of total carbon emissions to a surprise monetary tightening: Alternative methodologies

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are estimated based on the baseline VAR specification, using alternative methodologies for computing the impulse responses of carbon emissions. The solid lines are the point estimates for the internal instrument VAR, the LP-IV and the external instrument VAR, and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

C.3 Alternative data transformations and sources

C.3.1 Weather normalization

An important issue in VAR models is the selection and transformation of appropriate indicators. As mentioned in the main body of the paper, one of the key data series in my analysis is total CO2 emissions from energy consumption, estimated by the U.S. Energy Information Administration (EIA). The raw emissions data from the EIA, however, are not seasonally adjusted, which presents challenges given the pronounced seasonal patterns in energy use and emissions. To address this, I apply the standard Census X-13ARIMA-SEATS seasonal adjustment procedure commonly used for macroeconomic data. This process removes regular seasonal fluctuations and calendar effects, providing a clearer view of underlying trends and cyclical components in the series.

However, as highlighted in some recent reports by the Dutch Statistics Office (van Rossum and Schenau, 2010) and the Australian Department of Climate Change and Energy Efficiency (Australian Government and Efficiency, 2011), conventional seasonal adjustment processes fail to account for "weather-related effects." These refer to irregular deviations from average seasonal conditions, such as unusually hot summers or cold winters, which can significantly influence demand for heating, cooling, and consequently, emissions. Such weather-related anomalies represent fluctuations around seasonal temperatures that conventional seasonal adjustment cannot fully address.

To further refine the analysis, I incorporate an additional weather normalization step using temperature anomaly data, following the methodology proposed by the Australian Department of Climate Change and Energy Efficiency. Temperature anomalies measure deviations in average daily temperatures relative to thresholds typically associated with heating (18°C) or cooling (24°C) demand. Using data on heating degree days (HDDs) and cooling degree days (CDDs) provided by the EIA[19], I project the seasonally adjusted emissions data on these anomalies to correctly account for weather-related effects. This step delivers as a residual a new measure of weather-normalized emissions that controls for abnormal variations in temperatures and their potential effects on energy demand by different sectors.

In addition to the raw anomaly measures, I also compute a "censored" version of the anomalies, as proposed by Australian Government and Efficiency (2011), which assigns non-zero values only to months where heating or cooling demand is expected. For instance, heating degree anomalies are calculated only for December to March (winter months), while cooling degree anomalies are calculated exclusively for June to September (summer months).

[19]Degree days are measures of how cold or warm a location is. A degree day compares the mean (the average of the high and low) outdoor temperatures recorded for a location to a standard temperature, usually 65° Fahrenheit (F) in the United States. The more extreme the outside temperature, the higher the number of degree days. A high number of degree days generally results in higher energy use for space heating or cooling. Heating degree days (HDDs) provide a measure of how cold the temperature was on a given day or during a period of days, while Cooling degree days (CDDs) are a measure of how hot the temperature was on a given day or during a period of days (U.S. Energy Information Administration, 2023).

This adjustment ensures that temperature anomalies reflect realistic seasonal energy use patterns without introducing noise from periods with negligible heating or cooling requirements.

Figure C.3 presents the impulse responses of total carbon emissions to a surprise monetary tightening using these alternative, seasonally adjusted, and weather-normalized measures. The results remain consistent with those in Figure 2, showing a significant increase in emissions on impact. Interestingly, emissions rise by nearly 2 percent and 4 percent for the raw and censored anomaly adjustments, respectively, but the effects are shorter-lived compared to the baseline results.

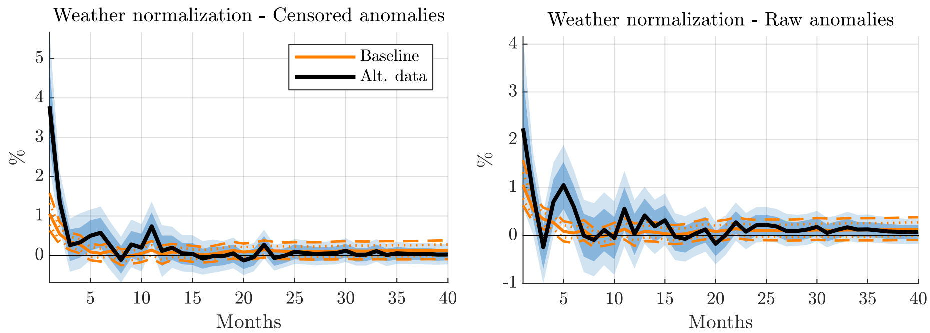

Figure C.3: Response of total carbon emissions to a surprise monetary tightening: Weather normalization

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are estimated based on the baseline VAR specification, for alternative weather normalizations of total emissions from energy consumption. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

C.3.2 Smoothing emissions data

Another potential concern involves background noise in the carbon emissions series, which could lead to unreliable inference and overstate the statistical precision of the estimates. Specifically, residual high-frequency movements or calendar effects may introduce noise, even after the seasonal adjustment applied in the baseline estimation. To address this concern, I explore alternative transformations of the emissions data and apply additional smoothing techniques and time series filtering to account for potential anomalies.

In particular, I smooth the seasonally adjusted emissions series using a backward-looking moving average (spanning the current and previous three months) and by applying the Hodrick-Prescott filter to extract the cyclical component of the series as the measure of emissions and re-estimate the baseline model using these alternative measures instead. Additionally, I also estimate a stationary VAR including PCE inflation, industrial production growth, commodity price inflation, and the month-over-month change in emissions.

The results of these sensitivity analysis exercises are presented in Figure C.4. As shown, the impulse responses remain remarkably consistent across all specifications, both qualitatively and quantitatively, further reinforcing the robustness of the baseline findings.

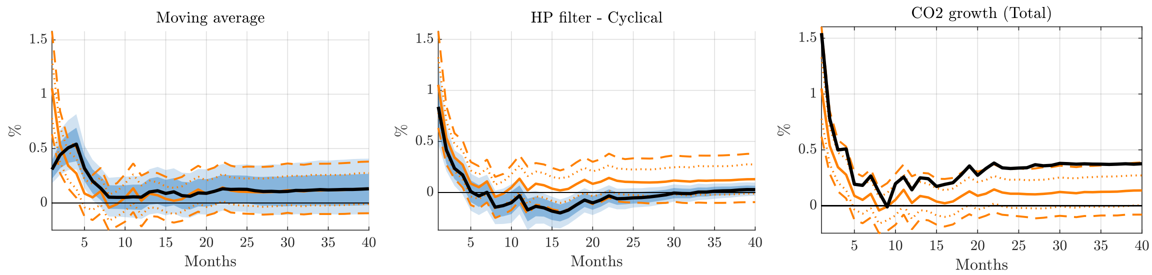

Figure C.4: Response of total carbon emissions to a surprise monetary tightening: Smoothing

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are estimated based on the baseline VAR specification, for alternative transformations of the data on total emissions from energy consumption. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

C.3.3 Alternative emissions measures

The U.S. Energy Information Administration (EIA) collects data through both supply and consumption surveys, each providing unique insights but also presenting certain limitations. Supply surveys measure the quantities of energy products supplied at various points in the supply chain, while consumption surveys capture the actual fuel quantities used by end-users. This distinction is critical because fuels (excluding electricity) can be stored, meaning that the supply recorded for a sector in a given period may not correspond to the actual consumption during that time. Additionally, supply and consumption surveys differ in sectoral coverage due to methodological decisions aimed at balancing statistical rigor with practical constraints, such as survey costs and respondent burden. These differences do not imply inaccuracies but instead highlight the trade-offs inherent in large-scale data collection. Understanding these nuances is essential for selecting appropriate indicators and considering potential adjustments to address limitations in the raw data from EIA surveys (U.S. Energy Information Administration, 1995).

The monthly data used in this study to measure total energy consumption, sourced from the EIA's Monthly Energy Review, are derived from supply surveys, in the interest of data availability, continuity over time, and consistency. Since emissions are calculated using these consumption estimates alongside annual CO2 emissions factors, in principle they may reflect fossil fuels supplied to end-use sectors but not necessarily consumed within the period. This issue is particularly relevant for storable energy sources, such as coal and oil.

To address these potential concerns and evaluate the robustness of my findings, I assess the sensitivity of the results to an alternative emissions measure from the Emissions Database for Global Atmospheric Research (EDGARv8.0) (European Commission, Joint Research Centre (JRC) and International Energy Agency (IEA), 2023) as a substitute for the EIA data. Specifically, I reestimate the baseline model, replacing the emissions variable with the seasonally-adjusted EDGARv8.0 series. Figure C.5 presents the impulse responses for the EDGAR series, as well as its cyclical component derived using the Hodrick-Prescott filter, alongside the baseline responses. The results remain robust across these alternative emissions variables, showing consistent qualitative and quantitative patterns, though some cyclicality appears before the responses taper off. These findings reinforce the robustness of the baseline estimates and strengthen confidence in the key conclusions of the analysis.

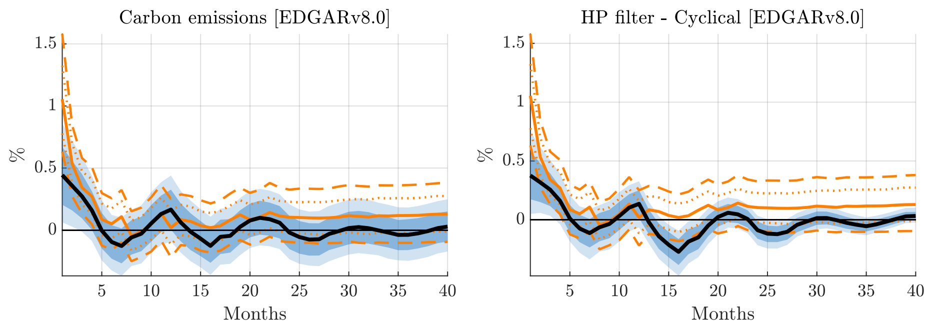

Figure C.5: Response of total carbon emissions to a surprise monetary tightening: EDGARv8.0

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are estimated based on the baseline VAR specification, for alternative data sources for total emissions from energy consumption. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

C.4 Alternative samples

Structural relationships may have evolved over the relatively long sample period, potentially influencing the results. To account for this, I estimate the model across different subsamples. Specifically, in Figure C.6, I present results based on shorter estimation windows starting in 1980M1, 1990M2 (coinciding with the instrument's starting date), and 2000M1, as well as ending in 2000M12, 2007M12, and 2015M12. While the responses are somewhat weaker in certain cases, the qualitative findings remain largely consistent. Additionally, I demonstrate that excluding the Great Recession or the Shale Gas revolution (Knittel et al., 2019; Acemoglu et al., 2023), starting around 2007, does not materially alter the results.

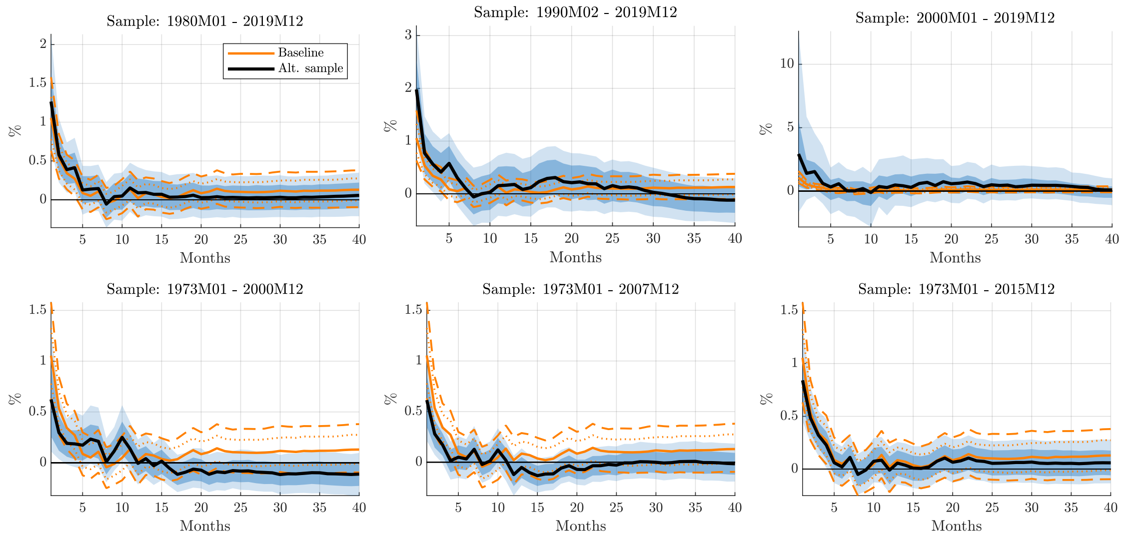

Figure C.6: Response of total carbon emissions to a surprise monetary tightening: Alternative samples

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are estimated based on the baseline VAR specification, for alternative samples. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

C.4.1 Excluding the transportation sector

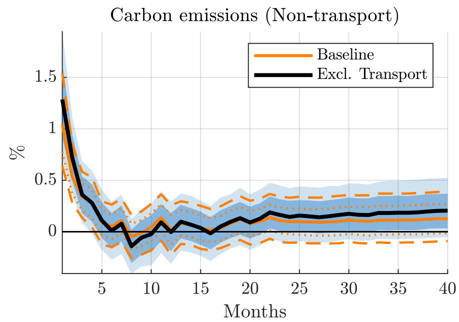

Figure C.7: Response of total carbon emissions to a surprise monetary tightening: Excluding transport

Notes: Impulse responses to a monetary policy shock, normalized to increase the one-year govt. bond yield by 25 basis points on impact. These IRFs are estimated based on the baseline VAR specification, for an alternative measure of emissions that excludes the transportation sector. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

D Additional Model Results

D.1 Impulse responses to a technology shock

As mentioned in the main body of the text, the economics literature has documented the unconditional procycality of carbon emissions (Heutel, 2012; Doda, 2014). Notably, this model formulation, and under the same calibration, is able to replicate this empirical fact through the dynamics generated by a positive technology shock (v_t^a). The impulse responses to this shock are presented in Figure D.1.

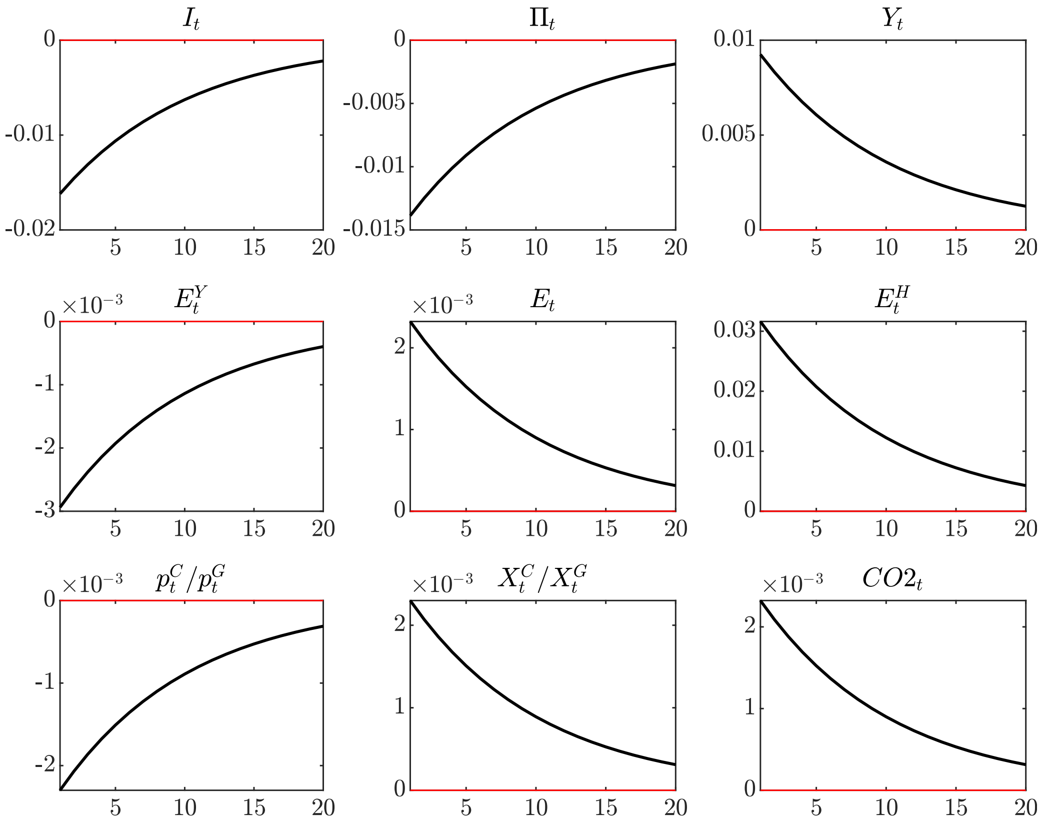

Figure D.1: Dynamic responses to a technology shock: Interest rate rule