The Unequal Economic Consequences of Carbon Pricing*

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Abstract

This paper studies how carbon pricing affects emissions, economic aggregates and inequality. Exploiting institutional features of the European carbon market and high-frequency data, I identify a carbon policy shock. I find that a tighter carbon pricing regime leads to a significant increase in energy prices, a persistent fall in emissions and an uptick in green innovation. This comes at the cost of a temporary fall in economic activity, which is not borne equally across society: poorer households lower their consumption significantly while richer households are less affected. Not only are the poor more exposed because of their higher energy share, they also experience a larger fall in their income. These indirect, general-equilibrium effects turn out to be quantitatively important. My results suggest that targeted fiscal policy can reduce the economic costs of carbon pricing and foster the public support of such policies – without compromising emission reductions.

JEL classification: E32, E62, H23, Q54, Q58

Keywords: Carbon pricing, cap and trade, emissions, macroeconomic effects, inequality, high-frequency identification

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1. Introduction

The looming climate crisis has put climate change at the top of the global policy agenda. Governments around the world have started to implement carbon pricing policies to mitigate climate change, either via carbon taxes or cap and trade systems. Yet, little is known about the effects of such policies in practice. Is carbon pricing effective at reducing emissions? What is the impact on output, employment and inflation, and who bears the economic costs of these policies?

To answer these questions, I propose a novel approach to identify the aggregate and distributional effects of carbon pricing, exploiting institutional features of the European carbon market and high-frequency data. The European Union Emissions Trading System (EU ETS) is the largest carbon market in the world, covering around 40 percent of the EU's greenhouse gas (GHG) emissions. The market was established in phases and the regulations have been updated frequently. Using an event study approach, I collect 126 regulatory update events concerning the supply of emission allowances. By measuring the change in the carbon futures price in a tight window around the regulatory news, I isolate a series of carbon policy surprises. Reverse causality can be plausibly ruled out because economic conditions are known and priced by the market prior to the regulatory news, and they are unlikely to change within the tight window I consider. Using the surprise series as an instrument, I estimate the dynamic causal effects of a carbon policy shock.

I find that carbon pricing has significant effects on both emissions and the economy. A carbon policy shock tightening the carbon pricing regime causes a strong, immediate increase in energy prices and a persistent fall in overall GHG emissions. Thus, carbon pricing is successful in achieving its goal of reducing emissions. However, this does not come without a cost. Consumer prices rise significantly and economic activity falls, as reflected in lower output and higher unemployment. Monetary policy leans against the inflationary pressures, likely exacerbating the effects on activity. Stock prices fall, but the shock does not appear to strongly transmit through financial markets. The main transmission channel appears to work through higher carbon prices, which passing through energy prices lead to a fall in income, and thus consumption and investment. Interestingly, the fall in activity turns out to be somewhat less persistent than the fall in emissions – improving the emissions intensity in the longer term. Consistent with that, I document a significant uptick in low-carbon patenting as carbon pricing creates an incentive for green innovation.

Carbon policy shocks also contribute meaningfully to historical variations in prices, emissions and macroeconomic aggregates. However, they did not account for the fall in emissions associated with the global financial crisis – supporting the validity of my identification strategy.

My results illustrate a trade-off between reducing emissions and the economic costs of climate policies. Importantly, these costs are not equally distributed across society. Using detailed household-level data, I document pervasive heterogeneity in the expenditure response to carbon policy shocks. While the expenditure of higher-income households only falls marginally, low-income households reduce their expenditure significantly and persistently. These households are more severely affected in two ways. First, they spend a larger share of their disposable income on energy and thus the higher energy bill leaves significantly fewer resources for other expenditures. Second, they experience a stronger fall in income, as they tend to work in sectors that are more impacted by the policy. Interestingly, these are not the sectors with the highest energy intensity but sectors that are more sensitive to changes in demand, producing more discretionary goods and services. Crucially, the magnitudes of the expenditure responses are larger than what can be accounted for by the direct effect through energy prices alone. This points to an important role of indirect, general equilibrium effects via income and employment. Based on my estimates, indirect effects can account for about two-thirds of the total effect on consumption.

My findings on the distributional impact of carbon pricing suggest that targeted fiscal policies could be an effective way to reduce the economic costs. To the extent that energy demand is inelastic, which turns out to be particularly the case for poorer households, this should not compromise emission reductions. This intuition is confirmed in a climate-economy model with nominal rigidities and heterogeneity in households' energy expenditure shares, income incidence and marginal propensities to consume (MPCs). The model can account for the observed empirical responses to carbon policy reasonably well. Using the model, I show that redistributing carbon revenues can mitigate the fall in aggregate consumption and reduce the regressive distributional consequences of carbon pricing, without compromising emission reductions to a significant extent. Finally, I provide some suggestive evidence that carbon pricing leads to a fall in the support for climate-related policies that is particularly pronounced among low-income households. Therefore, mitigating the distributional impact may also help to increase the public support for climate policy.

A comprehensive series of sensitivity checks indicate that the results are robust along a number of dimensions including the selection of event dates, the construction of the instrument, the estimation technique, the model specification, and the sample period. Importantly, the results are also robust to accounting for confounding news over the event window using an heteroskedasticity-based estimator.

Related literature and contribution. This paper contributes to a growing literature studying the effects of climate policy and carbon pricing in particular. While there is mounting evidence on the effectiveness of such policies for emission reductions (Martin, De Preux, and Wagner, 2014; Andersson, 2019, among others), less is known about the economic effects. A number of studies have analyzed the macroeconomic effects of the British Columbia carbon tax, finding no significant impacts on GDP (Metcalf, 2019; Bernard and Kichian, 2021). Metcalf and Stock (2020*a*,*b*) study the macroeconomic impacts of carbon taxes in European countries. They find no robust evidence of a negative effect of the tax on employment or GDP growth.[1] In a similar vein, Konradt and Weder di Mauro (2021) find that carbon taxes in Europe and Canada do not appear to be inflationary. In contrast, theoretical studies based on computable general equilibrium models tend to find contractionary output effects (see e.g. McKibbin et al., 2017; Goulder and Hafstead, 2018). I contribute to this literature by providing new estimates based on the EU ETS, the largest carbon market in the world.

A large literature has studied the macroeconomic effects of discretionary tax changes more generally. To address the endogeneity of tax changes, the literature has used SVAR techniques (Blanchard and Perotti, 2002) and narrative methods (Romer and Romer, 2010). The narrative approach points to large macroeconomic effects: a tax increase leads to a significant and persistent decline of output and its components (see also Barro and Redlick, 2011; Mertens and Ravn, 2013). However, it is unclear how much we can learn from these estimates with respect to carbon pricing, which is enacted to correct an externality and not because of past decisions or ideology. While the motivation behind carbon pricing is arguably long-term and thus more likely unrelated to the current state of the economy – similar to the tax changes considered in Romer and Romer (2010) – it is still perceivable that regulatory decisions also take economic conditions into account.

To address this potential endogeneity in carbon pricing, I propose a novel identification strategy exploiting high-frequency price variation. From a methodological viewpoint, my approach is closely related to the literature on high-frequency identification, which was developed in the monetary policy setting

[1] Metcalf and Stock (2020*a*,*b*) study the effects of national carbon taxes, which are present in many European countries and cover sectors that are not included in the EU ETS. A key difference is that European carbon taxes generally do not cover the power sector, which is part of the ETS.

(Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018, among others) and more recently employed in the global oil market context (Känzig, 2021). In this literature, policy surprises are identified using high-frequency asset price movements around policy events, such as FOMC or OPEC meetings. The idea is to isolate the impact of policy news by measuring the change in asset prices in a tight window around the events.

I contribute to this literature by extending the high-frequency identification approach to climate policy, exploiting institutional features of the European carbon market. A number of studies have used event study techniques to analyze the effects of regulatory news on carbon, energy and stock prices (Mansanet-Bataller and Pardo, 2009; Fan et al., 2017; Bushnell, Chong, and Mansur, 2013, among others). To the best of my knowledge, however, this paper is the first to exploit these regulatory updates to analyze the economic effects of carbon pricing. The approach is very general and could also be employed to evaluate the performance of other cap and trade systems.

Equipped with this novel identification strategy, I provide new evidence not only on the aggregate but also on the distributional consequences of carbon pricing. Among policymakers, there is growing consensus that the transition towards a low-carbon economy should involve fairness and equity considerations (European Comission, 2021). Against this backdrop, it is crucial to understand how carbon pricing affects economic inequality. I find that carbon pricing in the EU has been more regressive than commonly thought, burdening lower-income households substantially more than richer ones. This stands in contrast to existing studies, which tend to find a more modest regressive impact (Beznoska, Cludius, and Steiner, 2012; Ohlendorf et al., 2021). My findings illustrate the importance of accounting for indirect, general-equilibrium effects via income and employment; solely focusing on the direct effects via higher energy prices can understate the actual distributional impact.

Finally, I show that carbon-policy induced changes in energy prices transmit through a powerful demand channel that can outweigh the traditional cost channel. This has important implications for the transmission of energy price shocks more broadly and speaks to a growing literature studying the role of Keynesian supply shocks (see e.g. Guerrieri et al., 2022). The demand channel can be reinforced by the monetary policy reaction (Bernanke, Gertler, and Watson, 1997) and the unequal incidence on constrained households (Bilbiie, 2008; Auclert, 2019; Patterson, 2021). Thus, the distributional consequences do not only matter for inequality but also for the transmission of the policy to the macroeconomy. To formalize this in the context of carbon tax policy, I develop a climate-economy model (in spirit of Heutel, 2012; Golosov et al., 2014; Annicchiarico and Di Dio, 2015) with nominal rigidities and household heterogeneity. In this sense, I also contribute to an influential literature studying the role of heterogeneity in the transmission of fiscal policies (see e.g. Johnson, Parker, and Souleles, 2006; Kaplan and Violante, 2014; Cloyne and Surico, 2017, among many others).

Roadmap. The paper proceeds as follows. In the next section, I provide institutional background on the European carbon market and discuss the high-frequency identification strategy. Section 3 covers the econometric approach. Section 4 presents the results on the aggregate effects of carbon pricing, on emissions and the macroeconomy. Section 5 looks into the heterogeneous effects of carbon pricing, using detailed household-level data. I analyze the distributional impact, the relative importance of different transmission channels, and the role of redistributing carbon revenues. Section 6 looks beyond the short term and analyzes the impact on attitudes towards climate policies and the effects on green innovation. Section 7 concludes.

2. Institutional Background and Identification

2.1. The European carbon market

The European emissions trading system is the cornerstone of the EU's policy to combat climate change. It is the largest carbon market in the world and also has one of the longest implementation histories. Established in 2005, it covers more than 11,000 heavy energy-using installations and airlines, accounting for around 40 percent of the EU's greenhouse gas emissions.

The market operates under the cap and trade principle. Different from a carbon tax, a cap is set on the total amount of certain greenhouse gases that can be emitted by installations in the system. The cap is reduced over time so that total emissions fall. Within the cap, emission allowances are auctioned off or allocated for free among the companies in the system, and can subsequently be traded. Alternatively, companies can also use limited amounts of international credits from emission-saving projects around the world. Regulated companies must monitor and report their emissions. Each year, the companies must surrender sufficient allowances to cover their emissions. This is enforced with heavy fines. If a company reduces its emissions, it can keep the spare allowances for future needs or sell them to another company short of allowances (European Comission, 2020*a*).

A brief history of the EU ETS. The development of the EU ETS was divided into different phases. Figure 1 shows the evolution of the carbon price over the phases of the system. The first phase lasted three years, from 2005 to 2007. This period was a pilot phase to prepare for phase two, where the system had to run efficiently to help the EU meet its Kyoto targets. In this initial phase, almost all allowances were freely allocated at the national level. In absence of reliable emissions data, phase one caps were set on the basis of estimates. In 2006, the carbon price fell significantly as it became apparent that the total amount of allowances issued exceeded total emissions, and eventually converged to zero as phase one allowances could not be transferred to phase two.

Figure 1: The EU Carbon Price

Notes: The EU carbon price, as measured by the price of the first EUA futures contract over the different phases of the EU ETS.

The second phase ran from 2008 until 2012, coinciding with the first commitment period of the Kyoto Protocol where the countries in the EU ETS had concrete emission targets to meet. Because verified annual emissions data from the pilot phase was now available, the cap on allowances was reduced in this phase, based on actual emissions. The proportion of free allocation fell slightly, several countries started to hold auctions, and businesses were allowed to buy limited amounts of international credits. The commission also started to extend the system to cover more gases and sectors; in 2012 the aviation sector was included, even though this only applied for flights within the European Economic Area. Despite these changes, EU carbon prices remained at moderate levels. This was mainly because the 2008 economic crisis led to large fall in emissions. As this was not reflected in the way the caps were set, this led to a large surplus of allowances weighing down on prices.

The subsequent third phase began in 2013 and ran until the end of 2020. Learning from the previous phases, the system was changed in a number of key respects. In particular, the new system relies on a single, EU-wide cap on emissions in place of the previous national caps, auctioning became the default way of allocating allowances with harmonized allocation rules for the allowances still allocated for free, and the system covers more sectors and gases, in particular nitrous oxide and perfluorocarbons in addition to carbon dioxide. In 2014, the Commission postponed the auctioning of 900 million emission allowances to address the surplus of allowances that has built up since the Great Recession ('back-loading'). Later, the Commission introduced a market stability reserve, which became operative in January 2019. This reserve has the aim to reduce the current surplus of allowances and improve the system's resilience to major shocks by adjusting the supply of allowances. To this end, back-loaded and unallocated allowances were transferred to the reserve rather than auctioned in the last years of phase three.

The current, fourth phase spans the period from 2021 to 2030. The legislative framework for this trading period was revised in early 2018. To achieve the EU's 2030 emission reduction targets, the pace of annual reductions in total allowances is increased to 2.2 percent from the previous 1.74 percent and the market stability reserve is reinforced to improve the systems resilience to future shocks. More recently, the Commission has proposed to further revise and expand the scope of the EU ETS, with the aim to achieve a climate-neutral EU by 2050 (see European Comission, 2020*a*).

Regulatory events. Given its pioneering role, the establishment of the European carbon market has followed a learning-by-doing process. As illustrated above, since the start in 2005, the system has been expanded considerably and its institutions and rules have been continuously updated to address issues encountered in the market, improve market efficiency, and reduce information asymmetry and market distortions.

Building on the event study literature, I collect a comprehensive list of regulatory events in the EU ETS. These regulatory update events can take the form of a decision of the European Commission, a vote of the European Parliament or a judgment of a European court. Of primary interest in this paper are regulatory news regarding the *supply* of emission allowances. Thus, I focus on news concerning the overall cap in the EU ETS, the free allocation of allowances, the auctioning of allowances as well as the use of international credits. Going through the official journal of the European Union as well as the European Commission Climate Action news archive, I could identify 126 such events during the period from 2005 to 2019. The events as well as the sources are detailed in Table A.1 in the Appendix. There are only a few events that concern the setting of the overall cap in the system. In the first two phases, the key events concern decisions on the national allocation plans (NAP) of the individual member states, e.g. the commission approving or rejecting allocation plans or court rulings in legal conflicts about the free allocation of allowances. With the move to auctioning as the default way of allocating allowances, decisions on the timing and quantities of emission allowances to be auctioned became the most important regulatory news in phase three. Finally, starting from phase two, there were also a number of important events related to the use and entitlement of international credits.

The selection of events is a crucial factor in event studies. As the baseline, I use all of the identified events, however, in Appendix C.1, I study the sensitivity of the results with respect to different event types in detail.

Carbon futures markets. There exist several organized markets where EU emission allowances (EUAs) can be traded. An EUA is defined as the right to emit one ton of carbon dioxide equivalent gas and is traded in spot markets such as Bluenext in Paris, EEX in Leipzig or Nord Pool in Oslo. Furthermore, there exist also futures markets on EUAs, such as the EEX in Leipzig and ICE in London. In 2018, the cumulative trading volume in the relevant futures and spot markets was about 10 billion EUA (DEHSt, 2019). The most liquid markets to trade emission allowances are the futures markets. In this paper, I focus on data from the ICE, which has been found to dominate the price discovery process in the European carbon market (Stefan and Wellenreuther, 2020).

2.2. High-frequency identification

Since policies to fight climate change are long-term in nature, they are likely less subject to endogeneity concerns than other fiscal polices (Romer and Romer, 2010). However, to properly address the concern that regulatory decisions in the carbon market may take economic conditions into account, I adopt a high-frequency identification approach.

The institutional framework of the European carbon market provides an ideal setting in this respect. First, as discussed above, there are frequent regulatory updates in the market that can have significant effects on the price of emission allowances. Second, there exist liquid futures markets for trading allowances. This motivates the idea to construct a series of carbon policy surprises by looking at how carbon prices change around regulatory events in the carbon market. By measuring the price change within a sufficiently tight window around the event, reverse causality of the state of the economy can be plausibly ruled out because it is known and priced prior to the decision, and unlikely to change within the tight window.

Specifically, I compute the carbon policy surprise series as the change in the EUA futures price on the day of the regulatory event compared to the last trading day before the event. To account for the fact that carbon prices were close to zero at the end of the first phase, I measure the surprises as the EUR change in carbon prices relative to the prevailing wholesale electricity price on the day before the event:

$$CPSurprise_{t,d} = \frac{F^{carbon}_{t,d} - F^{carbon}_{t,d-1}}{P^{elec}_{t,d-1}}, \tag{1}$$

where d and t indicate the day and the month of the event, respectively, $F_{t,d}$ is the settlement price of the EUA futures contract, and $P^{elec}_{t,d-1}$ is the wholesale electricity price. This allows me to isolate some variation in the carbon price that is driven by the regulatory news, assuming that risk premia do not change over the narrow event window.[2] An alternative approach is to compute the surprise series as the percentage change in the carbon price around the event. Reassuringly, this produces very similar results, especially when excluding the second half of 2007 when carbon prices were approaching zero as the trial phase was coming to an end, see Appendix C for more details.

The daily surprises, $CPSurprise_{t,d}$, are then aggregated to a monthly series, $CPSurprise_t$, by summing over the daily surprises in a given month. In months without any regulatory events, the series takes zero value.

Figure 2 shows the resulting carbon policy surprise series. We can see that regulatory news can have a significant impact on carbon prices, with some news moving carbon prices by close to 1.5 percent, relative to wholesale electricity prices.[3] In the first phase, there were a number of significant events concerning the free allocation of allowances. For instance, in June 2005 the initial national allocation plans were finally completed, which lead to a significant increase in prices. The beginning of the second phase was characterized by only few regulatory news. This changed dramatically from the second half of phase two through the first years of phase three, which were marked by many significant carbon policy surprises. For example, carbon prices jumped up in March 2011 after the Commission proposed to start the auctioning of allowances earlier than originally

[2]While futures prices are in general subject to risk premia, there is evidence that these premia vary primarily at lower frequencies (Piazzesi and Swanson, 2008; Hamilton, 2009; Nakamura and Steinsson, 2018).

[3]Carbon prices, per se, turn out to be more volatile, with some announcements moving prices in excess of 40 percent, see Appendix C.1.

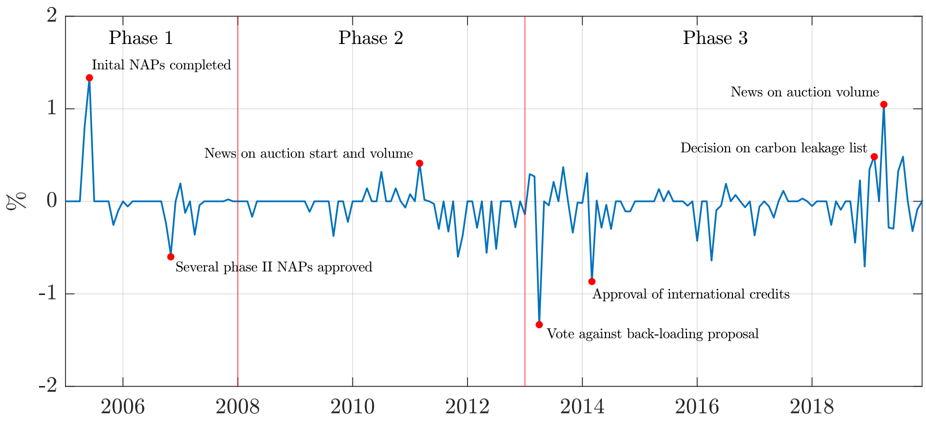


Figure 2: The Carbon Policy Surprise Series

Notes: The carbon policy surprise series, constructed as the change of the EUA futures price around regulatory policy events concerning the supply of EU emission allowances relative to the prevailing wholesale electricity price.

planned. On April 16, 2013 the European Parliament voted against the Commission's back-loading proposal, which led to a massive fall in carbon prices. And in March 2014, the Commission approved two batches of international credit entitlement tables, causing a significant fall in prices, just to name a few. There were also a number of significant surprises towards the end of phase three. In February 2019, carbon prices jumped up following news on the adoption of a stricter carbon leakage list, and in April 2019, carbon prices increased further, after an update on auction volumes in EFTA countries contributing to bullish sentiment in the market.

Construction choices and diagnostics. A crucial choice in high-frequency identification concerns the size of the event window. There is a trade-off between capturing the entire response to the announcement and the threat of other news confounding the response, so-called background noise (Nakamura and Steinsson, 2018). To give markets enough time to respond to the regulatory news, I use a daily event window. Using a tighter, intraday window is complicated by the fact that exact release times of the regulatory events are mostly unavailable. However, to mitigate concerns about background noise when using a daily window, I also present results from a heteroskedasticity-based approach that allows for background noise in the surprise series (see Appendix C.2).

Another choice concerns the maturity of the futures contract. I focus here on the front contract (the contract with the closest expiry date) for two reasons. First, it is the most liquid contract and thus gives the best price signal. Second, near-dated contracts also tend to be less sensitive to risk premia (Baumeister and

Kilian, 2017; Nakamura and Steinsson, 2018). Thus, focusing on the front contract helps to further mitigate concerns about time-varying risk premia.

To be able to interpret the resulting series as carbon policy surprises, it is crucial that the events do not release other information such as news about the demand of emission allowances or economic activity in the EU more generally. To address these concerns, I select only regulatory update events that were specifically about changes to the supply of emission allowances in the European carbon market and do not include broader events such as outcomes of Conference of the Parties (COP) meetings or other international conferences. In a series of sensitivity checks, I also show that the results are not driven by a particular subset of events. In particular, the results are robust to excluding events from the first trial phase or excluding event days in periods of economic distress, such as the Great Recession or the European debt crisis (see Appendix C.1).

Finally, I perform a number of additional diagnostic checks on the surprise series as proposed in Ramey (2016), in particular with regards to autocorrelation, forecastability and correlation with other structural shocks. I find no evidence that the series is serially correlated. The p-value for the Q-statistic that all autocorrelations are zero is 0.97. I also find no evidence that macroeconomic or financial variables have any power in forecasting the surprise series. For all variables considered, the p-values for the Granger causality test are far above conventional significance levels, with the joint test having a p-value of 0.93. Finally, I show that the surprise series is uncorrelated with other structural shock measures from the literature, including oil demand, uncertainty, financial, fiscal and monetary policy shocks. Overall, this evidence supports the validity of the carbon policy surprise series. The corresponding figures and tables can be found in Appendix B.1.

3. Econometric Approach

As illustrated above, the carbon policy surprise series has many desirable properties. Nonetheless, it is only an imperfect measure of the shock of interest because it may not capture all relevant instances of regulatory news in the carbon market and could be measured with error (see also Stock and Watson, 2018).

Therefore, I do not use it as a direct shock measure but as an *instrument*. Provided that the surprise series is correlated with the carbon policy shock but uncorrelated with all other shocks, we can use it to estimate the dynamic causal effects of a carbon policy shock. Because of the short sample at hand, I rely on VAR techniques for estimation. For identification, I rely on the external instrument approach (Stock, 2008; Stock and Watson, 2012; Mertens and Ravn, 2013). While this approach tends to be very efficient, it provides biased estimates if the VAR is not invertible. Thus, I also present results from an internal instrument approach (Ramey, 2011; Plagborg-Møller and Wolf, 2019), which includes the instrument in the VAR and is robust to problems of non-invertibility.

An alternative strategy would be to estimate the dynamic causal effects using local projections (see Jordà, Schularick, and Taylor, 2015; Ramey and Zubairy, 2018). However, this approach is quite demanding given the short sample, as it involves a distinct IV regression for each impulse horizon. Importantly, Plagborg-Møller and Wolf (2019) show that the internal instrument VAR and the LP-IV rely on the same invertibility-robust identifying restrictions and identify, in population, the same relative impulse responses. In Appendix B.2, I compare the LP-IV to the internal instrument VAR responses in the sample at hand. Reassuringly, the responses turn out to be similar, even though the LP responses are more jagged and less precisely estimated.

3.1. Framework

Consider the standard VAR model

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{2}$$

where p is the lag order, $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form innovations with covariance matrix $\text{Var}(\mathbf{u}_t) = \mathbf{\Sigma}$, $\mathbf{b}$ is a $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices.

Under the assumption that the VAR is invertible, we can write the innovations $\mathbf{u}_t$ as linear combinations of the structural shocks $\boldsymbol{\varepsilon}_t$:

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t. \tag{3}$$

By definition, the structural shocks are mutually uncorrelated, i.e. $\text{Var}(\boldsymbol{\varepsilon}_t) = \mathbf{\Omega}$ is diagonal. From the invertibility assumption (3), we get the standard covariance restrictions $\mathbf{\Sigma} = \mathbf{S}\mathbf{\Omega}\mathbf{S}'$.

We are interested in characterizing the causal impact of a single shock. Without loss of generality, let us denote the carbon policy shock as the first shock in the VAR, $\varepsilon_{1,t}$. Our aim 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 works as follows. Suppose there is an external instrument available, z_t. In the application at hand, z_t is the carbon policy surprise series. For z_t to be a valid instrument, we need

$$\mathbb{E}[z_t \varepsilon_{1,t}] = \alpha \neq 0 \tag{4}$$

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \tag{5}$$

where $\varepsilon_{1,t}$ is the carbon policy shock and $\boldsymbol{\varepsilon}_{2:n,t}$ is a $(n-1) \times 1$ vector consisting of the other structural shocks. Assumption (4) is the relevance requirement and assumption (5) is the exogeneity condition. These assumptions, in combination with the invertibility requirement (3), identify $\mathbf{s}_1$ up to sign and scale:

$$\mathbf{s}_1 \propto \frac{\mathbb{E}[z_t \mathbf{u}_t]}{\mathbb{E}[z_t \mathrm{u}_{1,t}]}, \tag{6}$$

provided that $E[z_t \mathrm{u}_{1,t}] \neq 0$.[4] To facilitate interpretation, we scale the structural impact vector such that a unit positive value of $\varepsilon_{1,t}$ has a unit positive effect on $\mathrm{y}_{1,t}$, i.e. $\mathrm{s}_{1,1} = 1$. I implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\hat{\mathbf{u}}_t$ on $\hat{\mathrm{u}}_{1,t}$ using z_t as the instrument. To conduct inference, I employ a residual-based moving block bootstrap, as proposed by Jentsch and Lunsford (2019).

Internal instrument approach. To address potential problems of non-invertibility, I also employ an internal instrument approach. For identification, we have to assume in addition to (4)-(5) that the instrument is orthogonal to leads and lags of the structural shocks:

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{t+j}] = \mathbf{0}, \quad \text{for } j \neq 0. \tag{7}$$

In return, we can dispense of the invertibility assumption underlying equation (3). Under these assumptions, 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, $\bar{\mathbf{s}}_1 = [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{.,1} / [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{1,1}$. As Plagborg-Møller and Wolf (2019) show, this approach consistently estimates the relative impulse responses even if the instrument is contaminated with measurement error or if the shock is non-invertible.

[4] To be more precise, the VAR does not have to be fully invertible for identification with external instruments. As Miranda-Agrippino and Ricco (2018) show, it suffices if the shock of interest is invertible in combination with a limited lead-lag exogeneity condition.

3.2. Empirical specification

Studying the macroeconomic impact of carbon policy requires modeling the European economy and the carbon market jointly. The baseline specification consists of eight variables. For the climate block, I use the energy component of the HICP as well as total GHG emissions.[5] To proxy the state of the economy, I include the headline HICP, industrial production, and the unemployment rate. Given that the economy was at the effective lower bound for most of the sample period, I use the two-year rate as the relevant monetary policy indicator. However, using the shadow rate or other longer-term rates produces similar results. Finally, I include a stock market index and the Brent crude oil price, deflated by the HICP, as financial indicators. More information on the data and its sources can be found in Appendix A.2.

The sample period starts in January 1999, when the euro was introduced, and runs until December 2019, stopping before the outbreak of the Covid pandemic. Recall that the carbon policy surprise series is only available from 2005 when the carbon market was established. To deal with this discrepancy, the missing values in the surprise series are censored to zero (see Noh, 2019, for a formal justification of this approach). The motivation for using a longer sample is to increase the precision of the estimates. However, restricting the sample to 2005-2019 produces very similar results.[6]

Following Sims, Stock, and Watson (1990), I estimate the VARs in levels. Apart from the unemployment and the two-year rate, all variables enter in log-levels. As controls I use six lags of all variables and in terms of deterministics only a constant term is included. However, the results turn out the be robust with respect to all of these choices (see Appendix C.3).

4. The Aggregate Effects of Carbon Pricing

4.1. The impact on emissions and the macroeconomy

In this section, we study how carbon policy shocks affect the macroeconomy through the lens of the baseline model. Recall, the main identifying assump-

[5]Unfortunately, GHG emissions are only available at the annual frequency. Therefore, I construct a monthly measure of emissions using the Chow-Lin temporal disaggregation method with indicators from Quilis's (2020) code suite. As the relevant monthly indicators, I include the HICP energy and industrial production. The results are robust to extending the list of indicators used.

[6]Note that while the carbon market was only established in 2005, the EU agreed to the Kyoto protocol in 1997 and started planning on how to meet its emission targets shortly after. The directive for establishing the EU ETS came into force in October 2003 (Directive 2003/87/EC).

tion behind the external instrument approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. However, to be able to conduct standard inference, the instrument has to be sufficiently strong. To analyze whether this is the case, I perform the weak instruments test by Montiel Olea and Pflueger (2013).

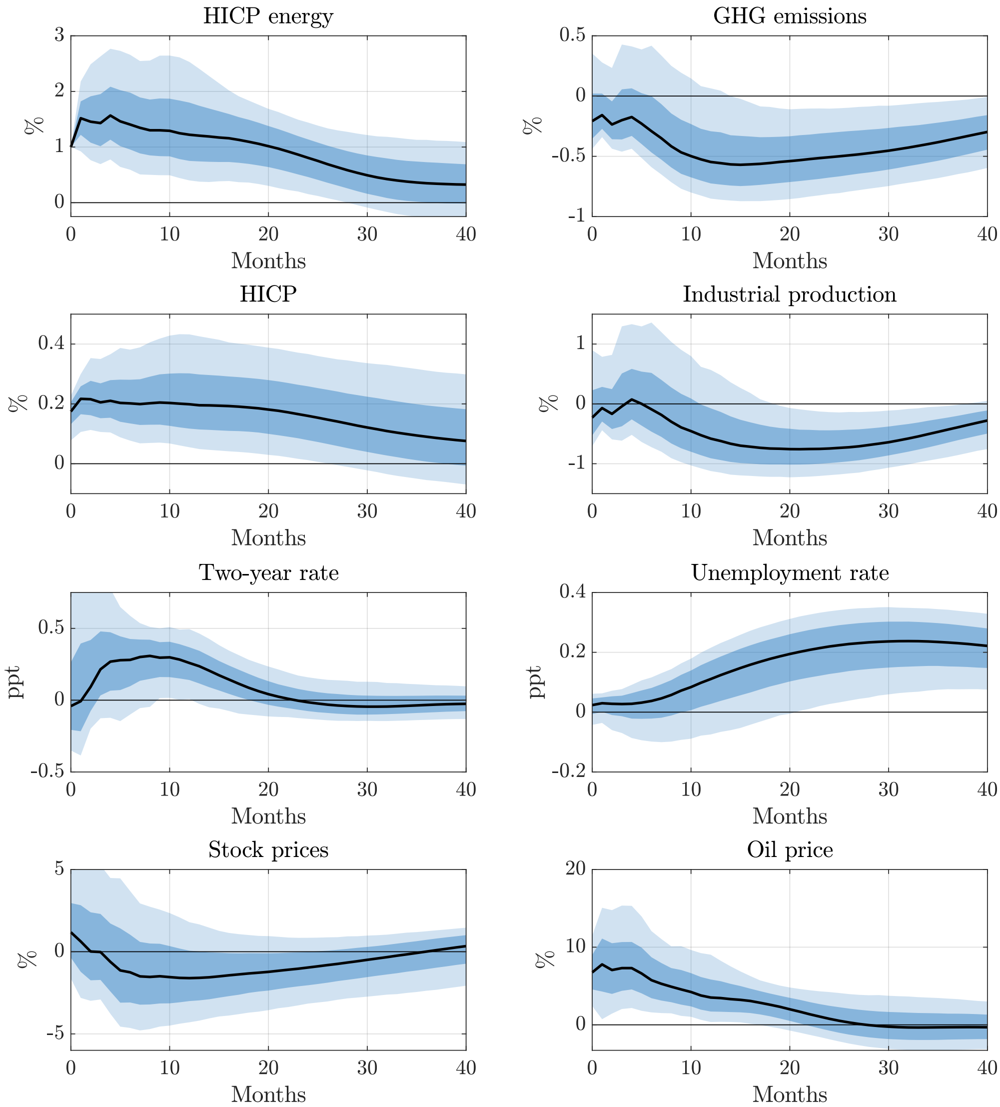
The carbon policy surprise series turns out to be a strong instrument. The heteroskedasticity-robust F-statistic in the first stage is 17.43. As this is clearly above conventional critical values, we conclude that the instrument appears to be sufficiently strong to conduct standard inference.

Having established that the carbon policy surprise series is a strong instrument, we can now turn to the discussion of the macroeconomic and environmental impacts of carbon policy shocks. Figure 3 shows the impulse responses to the identified carbon policy shock, normalized to increase the HICP energy component by one percent on impact. The solid black lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands based on 10,000 bootstrap replications.

A restrictive carbon policy shock leads to a strong, immediate increase in energy prices and a significant and persistent fall in GHG emissions. Thus, carbon pricing appears to be successful at reducing emissions and mitigating climate change by increasing the cost of emitting. Turning to the macroeconomic variables, we can see that the fall in emissions does not come without cost. Industrial production falls and the unemployment rate rises significantly. The labor market response turns out to be particularly pronounced. Consumer prices, as measured by the HICP, increase. The pass-through is strong for headline, however, core consumer prices tend to increase as well but the response is more short-lived (see Figure B.4 in the Appendix). Monetary policy appears to lean against the inflationary pressures, which likely exacerbates the effects on activity. Stock prices do not respond significantly on impact but then tend to fall, anticipating the fall in activity. However, the response is imprecisely estimated. Oil prices on the other hand increase significantly, reflecting the fact that European oil producers and refineries are also covered by the emissions trading scheme.[7]

In terms of magnitudes, the shock leads to an increase in energy prices of about 1.6 percent at peak. GHG emissions and industrial production decline by around 0.6 percent, the unemployment rate rises by about 0.2 percentage points and consumer prices increase by slightly more than 0.2 percent. The two-year

[7]The EU ETS covers emissions associated with exploration and drilling, production and processing, transportation, and refining of oil. This includes energy use associated with these activities and gas flaring, and may thus also affect crude oil prices. In addition, substitution away from coal-fired electricity could put further upward pressure on oil prices.



First stage regression: F-statistic: 17.43, R^2: 2.85%

Figure 3: Impulse Responses to a Carbon Policy Shock

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

rate increases by about 25 basis points, stock prices fall by over 1.5 percent and oil prices increase by around 8 percent – all measured at the peak of the responses. Thus, the responses are not only statistically but also economically significant. While the price impacts materialize rather quickly, economic activity and GHG emissions only fall with a substantial lag. The implied price elasticity of emissions lies in the ballpark of the estimates in Metcalf (2019). It is also interesting to observe that the fall in output appears to be less persistent than the fall in emissions – implying an improvement in the emissions intensity at longer horizons. We will revisit this finding in Section 6, where I study the effects of carbon pricing on green innovation.

The results from the internal instrument model turn out to be very similar, see Appendix B.2. The signs are all consistent and the responses are of similar shape and magnitude. Only the estimated response of the two-year rate is somewhat less stable. The pre-test for invertibility by Plagborg-Møller and Wolf (2019) can also not reject the null of invertibility at the 10 percent level. Overall, these findings suggest that the results are robust to relaxing the assumption of invertibility.

To summarize, the above findings clearly illustrate the policy trade-off between reducing emissions and thus the future costs of climate change and the current economic costs associated with climate change mitigation policies. It is useful to contrast these results to Metcalf and Stock (2020*a*), who study the economic and environmental impact of European carbon taxes. They find that these taxes were successful at reducing emissions but had no robust negative effect on output and employment.

A crucial difference is that European carbon taxes do not include the power sector, which is covered by the EU ETS, and plays a crucial role for the macroeconomic effects that I estimate. In fact, in terms of magnitudes my results are consistent with previous evidence on energy price shocks, such as oil shocks (see e.g. Kilian, 2009; Baumeister and Hamilton, 2019; Känzig, 2021). Furthermore, in many European countries, carbon taxes were implemented as part of a broader tax reform which often included other changes to the tax code to cushion the impact of carbon taxes. As we will discuss in Section 5.5, the distribution of carbon revenues plays an important role in the transmission of carbon policy shocks. Finally, given that the EU is a monetary union, we would not expect a monetary response to national carbon tax policies. By contrast, monetary policy seems to lean against the inflationary pressures from the EU ETS, which also helps explain the larger economic impacts (Bernanke, Gertler, and Watson, 1997).

In Appendix C, I perform a comprehensive series of robustness checks on the identification strategy and empirical approach used to isolate the carbon policy shock. These checks indicate that the results are robust along a number of dimensions including the selection of event dates, the construction of the instrument, the estimation technique, the model specification, and the sample period.

4.2. Historical importance

In the previous section, we have seen that carbon policy shocks can have significant effects on emissions and the economy. An equally important question is how much of the historical variation in the variables of interest can carbon policy account for? To this end, I perform a historical decomposition exercise.

Figure 4 shows the historical contribution of carbon policy shocks to GHG emissions growth. We can see that carbon policy shocks have contributed meaningfully to variations in GHG emissions in many episodes. Importantly, however, they cannot account for the significant fall in emissions after the global financial crisis. This suggests that the high-frequency approach is not mistakenly picking up demand-related disturbances, as the fall in emissions during the Great Recession was clearly driven by lower demand and not supply-specific factors in the European carbon market.

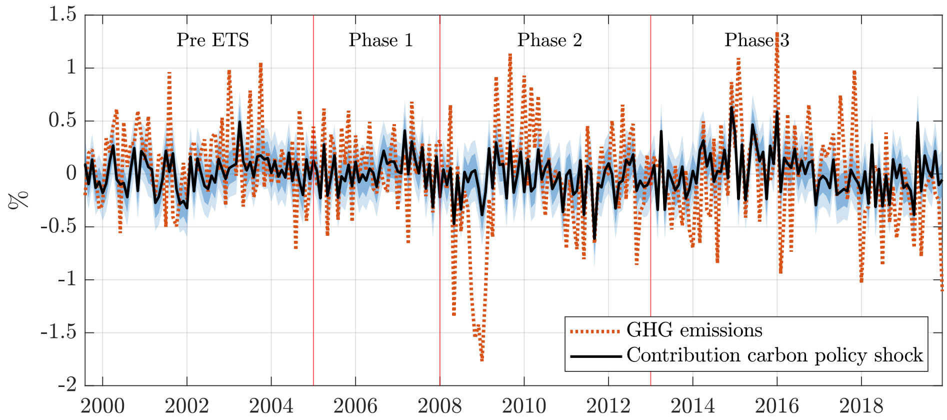


Figure 4: Historical Decomposition of GHG Emissions Growth

Notes: The figure shows the cumulative historical contribution of carbon policy shocks over the estimation sample for GHG emissions growth against the actual evolution of emissions growth. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

On average, carbon policy shocks account for close to a quarter of the variations in emissions at horizons up to two years. Furthermore, carbon policy shocks also explain a non-negligible share of the variations in energy prices and other macroeconomic and financial variables (see the variance decomposition in Appendix B.2).

4.3. Wider effects and propagation channels

The above results suggest that energy prices play an important role in the transmission of carbon policy shocks. Power producers seem to pass through the emission costs to energy prices to a significant extent, as can be seen from the strong energy price response. This is in line with previous empirical evidence (see e.g. Fabra and Reguant, 2014).

To get a better understanding of how carbon policy shocks transmit to the economy, I analyze the effects on a wider range of macroeconomic and financial variables. To compute the impulse responses, I extract the carbon policy shock from the monthly VAR as $CPShock_t = \mathbf{s}_1'\mathbf{\Sigma}^{-1}\mathbf{u}_t$ (for a derivation, see Stock and Watson, 2018) and estimate the effects using simple local projections:

$$y_{i,t+h} = \beta^i_{h,0} + \psi^i_h CPShock_t + \beta^i_{h,1} y_{i,t-1} + \ldots + \beta^i_{h,p} y_{i,t-p} + \xi_{i,t,h}, \tag{8}$$

where ψ^i_h is the effect on variable i at horizon h. Importantly, we can also use this approach to estimate the effects on variables that are only available at the quarterly or even annual frequency. In this case, we aggregate the shock $CPShock_t$ by summing over the respective months before running the local projections. Using the shock series directly in the local projections instead of the high-frequency surprises increases the statistical power of these regressions, as the shock series is consistently observed and spans the entire sample. Note, however, that this comes at the cost of assuming invertibility. Throughout the paper, I normalize the responses to have the same peak effect on HICP energy as in the baseline model to facilitate comparison of the results. The confidence bands are computed using the lag-augmentation approach (Montiel Olea and Plagborg-Møller, 2020).[8]

Figure 5 shows the impulse responses of real GDP, consumption, investment, and wages. Consistent with the monthly evidence, we find that the shock leads to a significant fall in real GDP. Looking at the different components, we can see that the fall in activity appears to be driven by lower consumption and investment. The consumption response turns out to be particularly pronounced.

Higher energy prices can affect the economy via both direct and indirect channels. They directly affect households and firms by reducing their discretionary income. Given that energy demand is considered to be inelastic, consumers and firms have less money to spend and invest after paying their energy bills (see e.g. Hamilton, 2008; Edelstein and Kilian, 2009). Energy prices also affect the economy indirectly through the general equilibrium responses of prices and wages and hence of income and employment.

Interestingly, the magnitudes of the effects are much larger than what can be accounted for by the direct effect through higher energy prices alone. If energy demand is completely inelastic, the direct price effect is bounded by the energy share in expenditure, which is around 10 percent in Europe. Given the shock magnitude, we would thus expect a direct impact on consumption of around 15 percent. However, the estimated consumption response is substantially larger than that, suggesting indirect effects play an important role in the transmission of carbon policy shocks. In fact, the significant fall in wages coupled with the em-

[8]As controls in the local projections, I use 7 lags for monthly variables, 3 lags for quarterly variables and 1 lag for annual variables.

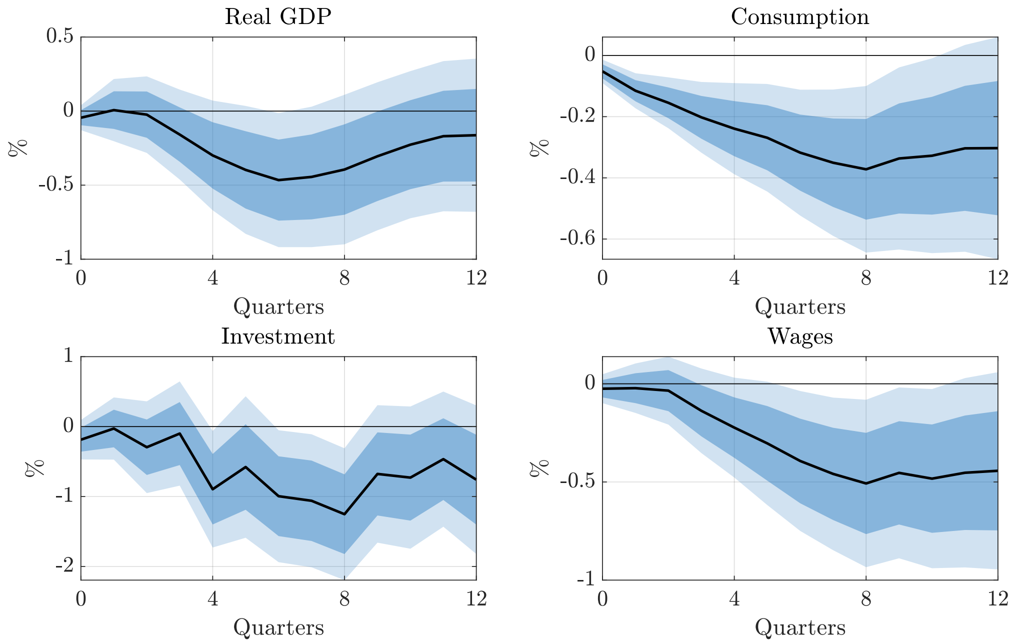


Figure 5: Effect on GDP, Consumption, Investment and Wages

Notes: Impulse responses of a selection of quarterly variables estimated using local projections on the carbon policy shock. The responses are normalized to have the same peak effect on HICP energy as in the baseline model.

ployment effects documented in Section 4.1 strongly supports this notion. The mechanism works as follows. After a carbon policy-induced energy price increase, the direct decrease in households' and firms' consumption and investment expenditure leads to lower output and exerts downward pressure on employment and wages. At the same time, interest rates increase as monetary policy leans against the inflationary pressures coming from higher energy prices, further exacerbating these effects. The additional fall in aggregate demand induced by lower employment and wages lies at the core of the indirect effect.

There is little evidence that carbon policy shocks strongly transmit through financial channels or elevated uncertainty. As we have seen, the stock market displays a muted response and measures of financial conditions such as credit spreads do not respond significantly as well. Similarly, there is no significant response of uncertainty measures (see Figure B.5 in the Appendix). Thus, these alternative channels are unlikely to play a dominant role in the transmission of carbon policy.

Finally, there are also transmission channels that work through the supply side of the economy. Baqaee and Farhi (2019) focus on the input-output structure of firms. They show that the centrality of the power sector can amplify the effects of energy shocks in the presence of non-linearities. However, given that the sample of interest was characterized by relatively small shocks, we would not expect non-linearities to play a major role. In the next section, I shed more light on the role of different transmission channels using detailed household micro data.

5. The Heterogeneous Effects of Carbon Pricing

Recently, there has been a big debate in Europe on energy poverty and the distributional effects of climate policy amid the European Green Deal (European Comission, 2021). The situation has since been exacerbated by the Russian invasion of Ukraine, which led to a substantial increase in energy bills.

Against this backdrop, it is crucial to better understand the distributional impact of the EU ETS. If certain groups are left behind, this could ultimately undermine the success of climate policy. To this end, I study the heterogeneous effects of carbon pricing on households. This will help to get a better picture on how carbon pricing affects economic inequality. Furthermore, looking into potential heterogeneities in the consumption responses helps to better understand the transmission channels at work. There is reason to believe that there are important heterogeneities at play. First, the direct effect through energy prices crucially depends on the energy expenditure share, which is highly heterogeneous across households. Second, households can also be affected differently in indirect ways, as they may face different impacts on their incomes. As poorer households tend to have a higher energy share and their income tends to be more cyclical, we expect the impact to be regressive.

5.1. Household survey data

To be able to analyze the heterogeneous effects of carbon policy shocks on households, we need detailed micro data on consumption expenditure and income at a regular frequency for a sample spanning the last two decades. Unfortunately, such data does not exist for most European countries let alone at the EU level. Therefore, I focus here on the UK which is one of the few countries that has such data as part of the Living Costs and Food Survey (LCFS).[9]

The LCFS is the major survey on household spending in the UK and provides high-quality, detailed information on expenditure, income, and household characteristics. The survey is fielded in annual waves with interviews being con-

[9]The UK was part of the EU ETS until the end of 2020. Over the sample of interest, the aggregate effects in the UK are comparable to the ones documented at the EU level, see Figure B.6 in the Appendix. To further mitigate concerns about external validity, I show that the results for other European countries are comparable, using similar survey data for Denmark and Spain, see Figure B.18.

ducted throughout the year and across the whole of the UK. I compile a repeated cross-section based on the last 20 waves, spanning the period from 1999 to 2019. Each wave contains around 6,000 households, generating over 120,000 observations in total. To compute measures of income and expenditure, I first express the variables in per capita terms by dividing household variables by the number of household members. In a next step, I deflate the variables by the (harmonized) consumer price index to express them in real terms. For more information, see Appendix A.3.

Ideally, we would like to observe how individual consumption expenditure and income evolve over time. Unfortunately, the LCFS being a repeated cross-section has no such panel dimension. To construct a pseudo-panel, it is common to use a grouping estimator in the spirit of Browning, Deaton, and Irish (1985).

A natural dimension for grouping households is their income. However, as the income may endogenously respond to the shock of interest, we cannot use the current household income as the grouping variable. Luckily, the LCFS does not only collect information about current household income but also about *normal* household income. This can be thought of as a proxy for permanent income.[10] Based on normal disposable household income, I group households into three pseudo-cohorts: low-income, middle-income, and high-income households. Following Cloyne and Surico (2017), I assign each household to a quarter based on the date of the interview, and create the group status as the bottom 25 percent of the normal disposable income distribution for low-income, the middle 50 percent for middle-income, and the top 25 percent for high-income in every quarter of a given year. The individual variables are then aggregated using survey weights to ensure representativeness of the British population.

Table 1 presents some descriptive statistics, overall and by income group. We focus here on expenditure excluding housing, however, the results including housing turn out to be similar. We can see that quarterly household expenditure is increasing in income. While low-income households spend a large part of their budget on non-durables, richer households spend more on durables. Importantly, poorer households spend a significantly higher share of their expenditure on energy: the energy share stands at almost 10 percent for low-income, just above 7 percent for middle-income, and around 5 percent for high-income households. Thus, to the extent that energy demand is inelastic, poorer households are more exposed to increases in energy prices.

[10] I have verified that normal income does not respond significantly to the carbon policy shock. In contrast, current income falls significantly and persistently, as shown in Figure B.12 in the Appendix. Alternatively, I group households by an estimate of permanent income obtained from a Mincerian-type regression. The results again turn out to be robust, see Appendix B.3.

Table 1: Descriptive Statistics on Households in the LCFS

	Overall	By income group		
		Low-income	Middle-income	High-income
Income and expenditure				
Normal disposable income	6,748	3,740	6,807	10,866
Total expenditure	4,458	3,025	4,444	6,238
Energy share	7.2	9.5	7.2	5.2
Non-durables (excl. energy) share	81.5	81.6	81.6	81.3
Durables share	11.2	8.9	11.2	13.5
Household characteristics				
Age	51	47	54	49
Education (share with post-comp.)	34.0	25.7	29.7	51.2
Housing tenure				
Social renters	20.8	46.9	17.4	3.7
Mortgagors	42.3	25.5	41.3	60.0
Outright owners	36.9	27.7	41.3	36.4

Notes: The table shows descriptive statistics on quarterly household income and expenditure (in 2015 pounds), the breakdown of expenditure into energy, non-durable goods and services excl. energy, and durables (as a share of total expenditure) as well as a selection of household characteristics, both over all households and by income group. For variables in levels such as income, expenditure and age the median is shown while the shares are computed based on the mean of the corresponding variable. The expenditure shares are expressed as a share of total expenditure excluding housing, and semi-durables are subsumed under the non-durable category. Age corresponds to the age of the household reference person and education is proxied by whether a household member has completed a post-compulsory education.

The different income groups turn out to be comparable in terms of their age. Higher-income households tend to be better educated, and are more likely to be homeowners, either by mortgage or outright.

5.2. Heterogeneity by household income

We are now in a position to study how households' expenditure and income respond to carbon policy shocks and, more importantly, how the response varies by income group. Figure 6 shows the responses of total household expenditure and current income for the three income groups we consider.[11] The solid black lines are again the point estimates and the dark/light shaded areas are 68 and 90 percent confidence bands.

[11] To eliminate some of the noise inherent in survey data, I smooth the expenditure and income measures with a backward-looking (current and previous three quarters) moving average, as in Cloyne, Ferreira, and Surico (2020). The results are robust to using the raw series instead (even though the responses become more jagged and imprecise) or using smooth local projections as proposed by Barnichon and Brownlees (2019), see Figure B.10 in the Appendix. To flexibly control for seasonal and trending behavior, I include a set of quarterly dummies and a linear trend.

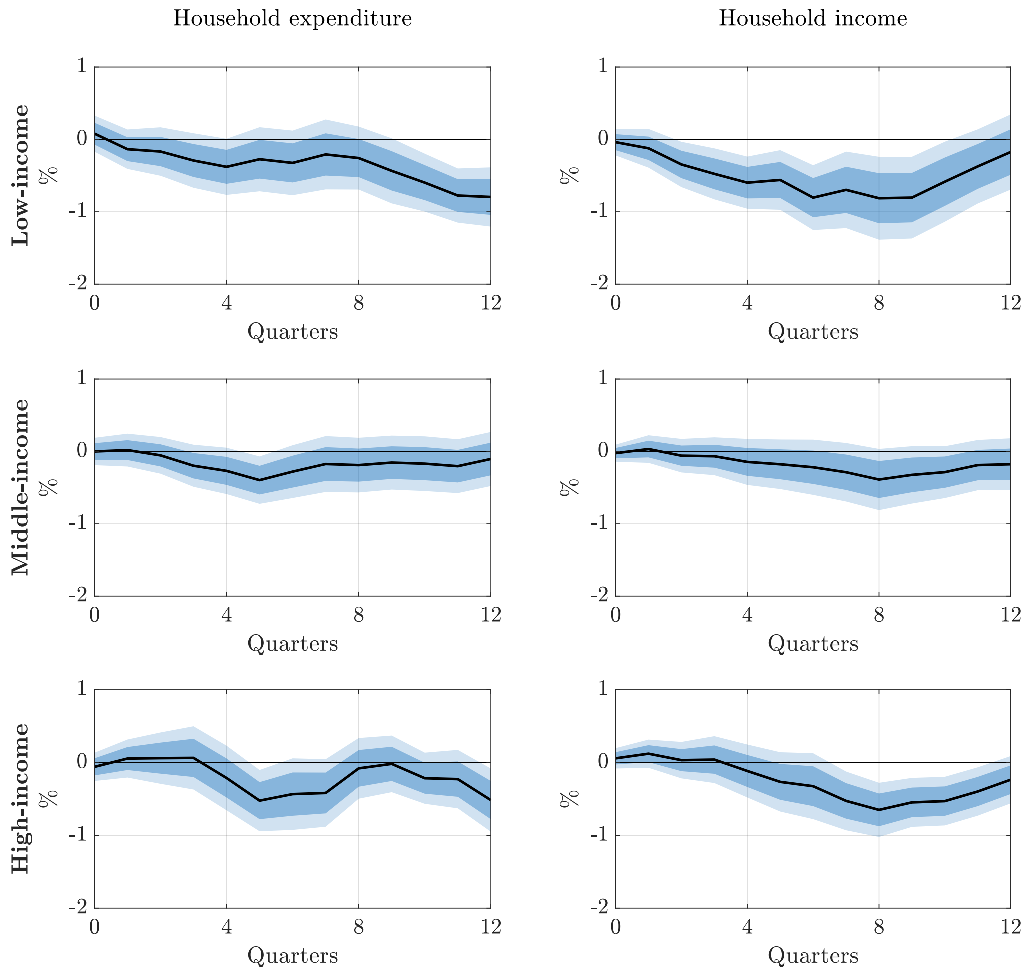


Figure 6: Household Expenditure and Income Responses by Income Group

Notes: Impulse responses of total expenditure (excluding housing) and current total disposable household income for low-income (bottom 25 percent), middle-income (middle 50 percent) and high-income households (top 25 percent). The households are grouped by total normal disposable income and the responses are computed based on the median of the respective group.

We can see that there is pervasive heterogeneity in the expenditure response across income groups. Low-income households reduce their expenditure significantly and persistently. In contrast, the expenditure response of higher-income households is rather short-lived and only barely statistically significant. This result is even more stark when we separate between different types of expenditure. Figure 7 shows the responses of energy, non-durable goods and services excluding energy, and durable goods expenditure. We can see that poor households substantially lower their non-durable expenditure while higher-income households display an insignificant response. For durable expenditures, the pattern is less clear cut. While low-income household cut durable expenditure, high-income households also display a significant response. Therefore, the heterogeneity in

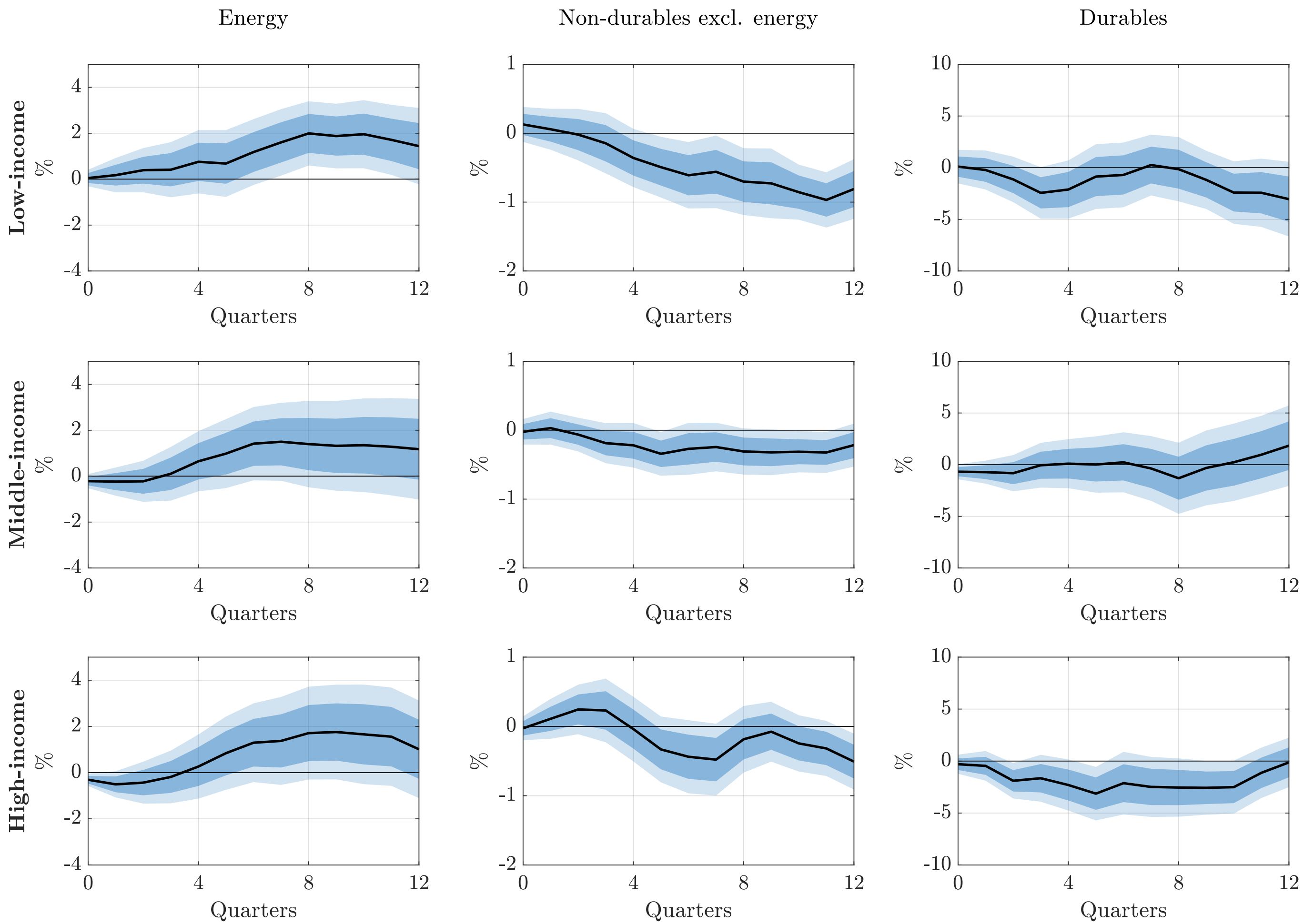


Figure 7: Energy, Non-durables and Durables Expenditure Responses by Income Group

Notes: Impulse responses of energy, non-durables excluding energy and durables expenditure for low-income (bottom 25 percent), middle-income (middle 50 percent) and high-income households (top 25 percent). The households are grouped by total normal disposable income and the responses are computed based on the median of the respective group.

the total expenditure responses appears to be driven by the non-durable expenditure component. Note that these group-specific differences are not only economically but also statistically significant (see the responses of the group differences in Figure B.11 in the Appendix).

Low-income households are more affected in two ways. First, they face a larger and more significant increase in their energy bill. This is consistent with the fact that these households have a higher energy share to start with and their energy demand is particularly inelastic, for instance because of financial constraints. Second, looking at the income responses, we can also see that they face a more significant and substantial fall in their income. As we will see in Section 5.4, this appears to be driven by the fact that they tend to work in sectors that are more affected by the carbon policy shock. Taken together, the shock leads to a substantial reduction in discretionary income, which forces poorer households, who are also more likely to be financially constrained, to cut their expenditure by more.

At this stage, it is worth discussing a potential concern about grouping households concerning selection. The assignments into the income groups are not random and some other characteristics may, potentially, be responsible for the heterogeneous responses I document. To mitigate these concerns, I group the households by a selection of other grouping variables, including age, education and housing tenure. The results are shown in Figures B.14-B.16 in the Appendix. While there is not much heterogeneity by age, less educated households tend to respond more than better educated ones and social renters tend to respond more than homeowners. However, none of the alternative grouping variables can account for the patterns uncovered for income, suggesting that we are not spuriously picking up differences in other household characteristics.

5.3. Direct versus indirect effects

We have seen that there is substantial heterogeneity in the households' expenditure response to carbon policy shocks: while richer households change their expenditure only marginally, low-income households lower their expenditure significantly and persistently. Furthermore, indirect, general equilibrium effects via income and employment seem to play an important role in the transmission of the policy. To shed more light on the role of direct and the indirect effects, it is instructive to convert the responses into an equivalent pound change in income and expenditure over the three-year impulse horizon. This can be interpreted as the overall short-run monetary adjustment following the change in carbon policy.

Table 2 shows the results, overall and by income group. We can see that energy expenditure increases for all income groups, but only low-income households display a strong and significant increase. These households also cut their expenditure significantly, while the adjustment for higher-income households is less pronounced and not statistically significant. Importantly, the increase in energy bills cannot account for the large fall in non-energy expenditure. Note, however, that the shock also leads to a substantial fall in households' incomes, which is again particularly pronounced for low-income households. Coupled with the fact that these households are more likely to be financially constrained (see e.g Jappelli and Pistaferri, 2014), this helps explain the significant expenditure response.

Table 2: Cumulative Monetary Changes over Impulse Horizon

	Overall	By income group		
		Low-income	Middle-income	High-income
Expenditure				
Energy	23.88	28.36	22.53	22.11
	[-16.93, 64.69]	[8.21, 48.51]	[-18.02, 63.07]	[-0.96, 45.17]
Non-durables excl. energy	-103.75	-134.76	-92.33	-95.60
	[-212.38, 4.87]	[-241.21, -28.32]	[-192.67, 8.02]	[-279.87, 88.67]
Durables	-6.95	-2.92	-0.44	-23.99
	[-56.09, 42.20]	[-20.75, 14.92]	[-10.37, 9.50]	[-71.44, 23.45]
Income				
	-203.70	-214.90	-138.65	-322.60
	[-387.13, -20.27]	[-376.38, -53.41]	[-301.82, 24.52]	[-635.44, -9.77]

Notes: The table reports the overall pound change in expenditure and income over the three-year period following a carbon policy shock (in 2015 pounds). Bootstrapped 90 percent confidence intervals are reported in brackets. The overall pound change is computed as the present discounted value of the impulse response, multiplied by the corresponding average quarterly expenditure/income.

By contrast, high-income households also display a significant fall in their income, however, their expenditure responses turn out to be insignificant, consistent with the notion that these households are less financially constrained and thus better able to cushion the adverse effects on their income. Overall, these results point to an important role of indirect effects via income and employment. My estimates suggest that the direct effect through energy prices accounts for less than a third of the aggregate consumption response, as proxied by the increase in energy bills relative to the overall fall in expenditure (23.88/86.82).

The expenditure heterogeneity uncovered in this section is striking, especially against the backdrop that low-income households have much lower levels of expenditure to start with (see in Table 1). Put differently, low-income households account for over 30 percent of the aggregate effect of carbon pricing on consumption, despite the fact that they make up for a much smaller share of consumption in normal times (around 15 percent). Accounting for indirect, general equilibrium effects turns out to be crucial to correctly assess the distributional impact of carbon pricing. Focusing on the direct effect via the energy share alone can understate the actual distributional effects considerably.

The distributional consequences also likely play an important role for the magnitude of the aggregate expenditure response. My findings are consistent with a literature that emphasizes the role of MPC heterogeneity in combination with unequal income incidence for the transmission of aggregate demand shocks (Bilbiie, 2008; Auclert, 2019; Patterson, 2021, among others). These studies show in the context of aggregate-demand policies that the aggregate impact can be amplified when the policy disproportionately affects the incomes of individuals whose consumption is more sensitive. My results suggest that such a mechanism is also at play in the transmission of carbon pricing, following the initial fall in non-energy expenditure. Thus, even though low-income households only make up for a relatively small portion of the population, they play an important role for the transmission of the policy to the macroeconomy.

Alternative channels. Thus far, I focused my analysis on the direct effect via energy prices and the indirect, general-equilibrium effect via income. While there may also other channels at work, I briefly discuss here why these alternative channels are unlikely to play an important role in the transmission of carbon policy. First, carbon pricing may also have an effect on the prices of other goods via substitution effects, which may in turn affect households' budgets. However, as shown in Section 4.1, the response of core consumer prices is much more muted and only barely significant; therefore this channel does likely not play a major role. Second, there may be a number of channels that work through the response of durable expenditure, for instance because of uncertainty or precautionary motives, or via a reduction in durables that are complementary in use with energy (see also Edelstein and Kilian, 2009). However, the overall response of durable expenditure is quantitatively too small to play a dominant role in the transmission of carbon policy. Furthermore, in Section 4.3 I did not find any significant change in aggregate uncertainty after the shock. Finally, households may also adjust their saving behavior as interest rates increase in response to the shock. However, this channel is particularly relevant for higher-income households, which contribute relatively less to the aggregate consumption response.

5.4. What drives the income response?

We have seen that there is significant heterogeneity in the households' income responses. This section aims to shed light on what is driving the income incidence by household group. There are at least two potential sources of heterogeneity. First, households may differ in their labor income, for instance because they work in sectors that are differentially affected by the policy. Second, households may differ in their income composition, as some households also have substantial sources of financial income. I will focus here on the former, which is more relevant to understand the heterogeneity at the lower-end of the income distribution. In Appendix B.3, I also study the role of the household income composition.

To investigate into potential heterogeneities in labor income, I study how the responses vary by the sector of employment using data from the UK Labour Force Survey (LFS).[12] I consider two dimensions to group sectors. First, I group sectors by their energy intensity to gauge the role of the conventional cost channel. Second, I group sectors by how sensitive they are to changes in aggregate demand.[13]

Table 3: Sectoral Distribution of Employment

Sectors	Overall	By income group		
		Low-income	Middle-income	High-income
Energy-intensity				
High	21.6	9.8	25.6	25.8
Lower	78.4	90.2	74.4	74.2
Demand-sensitivity				
High	30.5	49.0	27.2	18.1
Lower	69.5	51.0	72.8	81.9

Notes: The table depicts the sectoral employment distribution of households in the LFS, both overall and by income group. I group sectors along two dimensions: their energy intensity and their demand sensitivity. The energy-intensive sectors include agriculture, utilities, transportation, and manufacturing. The demand-sensitive sectors include construction, wholesale and retail trade, hospitality, and entertainment and recreation.

Table 3 presents descriptive statistics on the sectoral distribution of households, both overall and by income group. We can see that only few low-income households work in sectors with a high energy intensity such as utilities or man-

[12] Unfortunately, the LCFS does not include any information on the sector of employment. Therefore, I use data from the LFS which provides detailed information on employment sector and income. For more information on the LFS, see Appendix A.3.

[13] I measure the demand-sensitivity by estimating the elasticity of sectoral labor income to changes in aggregate income. Sectors that produce more 'discretionary' goods and services turn out to be more demand-sensitive. See Appendix B.3 for more information.

ufacturing. Thus, the sectors' energy intensity is unlikely to explain the heterogeneous income responses that we observe. A more relevant dimension of heterogeneity appears to be the sectors' demand sensitivity: low-income households work disproportionally in sectors that tend to be more sensitive to aggregate fluctuations, such as retail or hospitality, while a large majority of higher income households work in less demand-sensitive sectors.

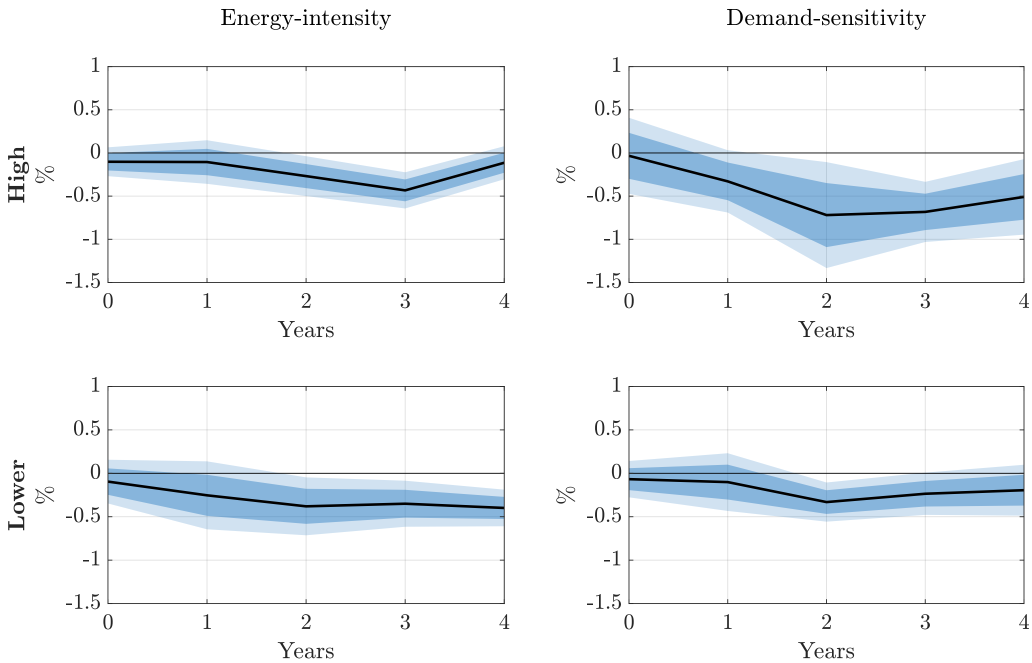


Figure 8: Income Response by Sector of Employment

Notes: Impulse responses of income (pay from main and second job net of deductions and benefits) in different sectors, grouped by their energy-intensity and demand-sensitivity. The response is computed based on the median income in the respective group of sectors. The sector groups are described in detail in Table 3.

Figure 8 shows how the median income across different sectors changes after a carbon policy shock. While sectors with a high energy intensity display a somewhat stronger fall in incomes than sectors with a lower intensity, the differences are not that large quantitatively. By contrast, there is significant heterogeneity by the sectors' demand-sensitivity: households working in demand-sensitive sectors experience the largest and most significant fall in their income while households in less-demand sensitive sectors display more muted income responses. This helps explain the observed heterogeneity in the income responses. In response to a carbon policy shock, these sectors face a stronger decrease in demand, also because households cut expenditure more in these sectors, and thus react by laying off employees and cutting compensation. As low-income households are overrepresented in these sectors, they are disproportionally affected.

These results further support the notion that carbon policy shocks strongly transmit to the economy not only through the traditional cost channel but also through the demand side of the economy, in line with previous evidence by Kilian and Park (2009) on the transmission of energy price shocks. A novel insight is that in the presence of household heterogeneity, the demand channel may be even stronger. This result speaks directly to a growing literature on the role of Keynesian supply shocks (see e.g. Guerrieri et al., 2022; Cesa-Bianchi and Ferrero, 2021).

5.5. The role of redistributing carbon revenues

We have seen that the economic costs of carbon pricing are borne unequally across society. Low-income households are the most affected, having to reduce their expenditures the most, and are contributing disproportionally to the aggregate response. A key question in this context is how the distribution of carbon revenues matters for the transmission of the policy. Since auctioning became the default way of allocating allowances, the system produces a growing share of auction revenues. However, there is no direct redistribution scheme in place that could offset the distributional effects on households that I document.[14] The large majority of revenues are earmarked and used for climate and energy related purposes.

While using the carbon revenues for climate purposes may help to further propel emission reductions, my results indicate that redistributing part of the revenues to the most affected groups in society could mitigate the distributional effects and reduce the economic costs of climate policy. To the extent that energy demand is inelastic, which turns out to be particularly the case for low-income households, this should not compromise the reductions in emissions.

A heterogeneous-agent climate-economy model. To study the role of redistributing carbon revenues more formally, I build a climate-economy model. The aim is to obtain a framework that can account for the empirical findings and can be used as a laboratory for policy experiments. The model belongs to the dynamic stochastic general equilibrium (DSGE) class. It augments the climate-economy structure by Golosov et al. (2014) with nominal rigidities and household hetero-

[14]For the period from 2012-2020, the revenues generated by the member states of the EU ETS exceeded 57 billion euros (European Comission, 2020*b*). The current ETS does not feature a direct redistribution scheme, however, there are certain other, indirect solidarity measures in place, e.g. via the Cohesion Fund or the Just Transition Fund. Only in the recent 'Fit for 55' plan, the European Commission takes a step in this direction by proposing a Social Climate Fund for the new ETS in transportation and buildings.

geneity, as in Bilbiie, Känzig, and Surico (2021), to allow for the demand channels identified in the data. I will only sketch the relevant parts of the model here, a full description can be found in Appendix D.

The household sector consists of a continuum of infinitely lived households. Households have identical preferences and derive utility from consumption x and disutility from labor h. The consumption good is a composite of an energy and a non-energy good. To retain tractability, I consider a model with limited heterogeneity. There are two types of households: a share λ of households are *hand-to-mouth* (H) and a share $1-\lambda$ are *savers* (S) who choose their consumption intertemporally. Apart from the difference in MPC, households differ in their energy expenditure share and income incidence. Consistent with the data, I assume that the hand-to-mouth have a higher energy share and that their income is more elastic to changes in aggregate income than savers'.

Households face idiosyncratic risk as they switch exogenously between types. I assume that only bonds are liquid and can be used to self-insure. There is limited asset market participation. Only savers are able to self-insure themselves using liquid bonds.[15] They choose their consumption intertemporally, according to the following Euler equation:

$$\frac{U_x(x_{S,t}, h_{S,t})}{p_{S,t}} = \beta \mathbb{E}_t \left[\frac{R_t^b}{\Pi_{t+1}} \left(s \frac{U_x(x_{S,t+1}, h_{S,t+1})}{p_{S,t+1}} + (1-s) \frac{U_x(x_{H,t+1}, h_{H,t+1})}{p_{H,t+1}} \right) \right], \quad (9)$$

where $x_{i,t}$ is total consumption of household i, $h_{i,t}$ is labor supply, U_x is the marginal utility, $\frac{R_{t-1}^b}{\Pi_t}$ is the real risk-free rate, $p_{i,t}$ is the price index of the household's consumption basket, and $1-s$ is the transition probability of becoming hand-to-mouth. The demand for non-energy and energy goods is given by the following schedules: $c_{S,t} = a_{S,c} \left(\frac{1}{p_{S,t}} \right)^{-\epsilon_x} x_{S,t}$ and $e_{S,t} = a_{S,e} \left(\frac{p_{e,t}}{p_{S,t}} \right)^{-\epsilon_x} x_{S,t}$, where ϵ_x is the elasticity of substitution between non-energy and energy goods. Savers also invest in capital k_t and supply labor $h_{S,t}$. The corresponding optimizing equations are standard and relegated to the Appendix. Savers receive labor income, financial income from dividends and capital returns, and transfers $\omega_{S,t}$ from the government.

Hand-to-mouth households have no assets and thus consume all of their income in every period: $p_{H,t} x_{H,t} = y_{H,t}$. Their income $y_{H,t}$ consists of labor income plus government transfers, $\omega_{H,t}$. The non-energy and energy demand functions, and labor supply equation are analogous to the expressions for the savers.

[15] This is a tractable way of introducing idiosyncratic risk and liquidity in spirit of full-blown HANK models à la Kaplan, Moll, and Violante (2018), see Bilbiie (2020) and Bilbiie, Känzig, and Surico (2021) for a detailed discussion.

The firm block of the model consists of two sectors: energy and non-energy producers. Energy firms produce energy using labor as an input, and can adjust their prices flexibly. Their production technology is given by

$$e_t = a_{e,t} h_{e,t}, \tag{10}$$

as in Golosov et al. (2014). I assume that there is only a single source of energy (e.g. coal) that is available in approximately infinite supply. Without loss of generality, energy is measured in terms of carbon content. Energy firms are subject to a carbon tax τ_t. This conforms well with my empirical analysis, where I study the impacts of plausibly exogenous changes in carbon prices. The optimal energy supply is characterized by $w_t = (1-\tau_t)p_{e,t}\frac{e_t}{h_{e,t}}$.

The non-energy sector consists of standard New Keynesian firms that produce non-energy goods using capital, energy, and labor as inputs and set prices subject to nominal rigidities. Their production technology is given by

$$y_t = e^{-\gamma s_t}\left[(1-\nu)^{\frac{1}{\epsilon_y}}\left(a_t k_t^{\alpha} h_{y,t}^{1-\alpha}\right)^{\frac{\epsilon_y-1}{\epsilon_y}} + \nu^{\frac{1}{\epsilon_y}}\left(e_{y,t}\right)^{\frac{\epsilon_y-1}{\epsilon_y}}\right]^{\frac{\epsilon_y}{\epsilon_y-1}}, \tag{11}$$

where $e^{-\gamma s_t}$ captures climate damages, modeled as a function of the atmospheric carbon concentration s_t. The cost-minimization problem gives rise to the factor demands for capital $r_t = \alpha v_{1,t} mc_t \frac{y_t}{k_t}$, labor $w_t = (1-\alpha)v_{1,t} mc_t \frac{y_t}{h_{y,t}}$ and energy $p_{e,t} = v_{2,t} mc_t \frac{y_t}{e_{y,t}}$, where mc_t are real marginal costs and $v_{1,t}$ and $v_{2,t}$ are auxiliary terms given in the Appendix. The price setting problem gives rise to a standard Phillips curve, which in log-linear form reads $\hat{\pi}_t = \kappa \hat{mc}_t + \beta E_t \hat{\pi}_{t+1}$, where hatted variables denote log-deviations from steady state.

As in Golosov et al. (2014), the current level of atmospheric carbon concentration is a function of current and past emissions, $s_t = (1-\varphi)s_{t-1} + \varphi_0 e_t$, where φ_0 captures the share of emissions that do not immediately exit the atmosphere, and $1-\varphi$ measures how emission decay over time.

The government runs a balanced budget in every period, i.e. all transfers are financed by tax revenues. We consider the following transfer policy

$$\lambda\omega_{H,t} = \mu\tau_t p_{e,t} e_t \quad \text{and} \quad (1-\lambda)\omega_{S,t} = (1-\mu)\tau_t p_{e,t} e_t. \tag{12}$$

The distribution of carbon tax revenues are governed by the parameter μ. As the baseline, I assume that all carbon revenues accrue to the savers $\mu = 0$. Later, we will study alternative transfer policies. Carbon taxes τ_t are set according to the following rule: $\tau_t = (1-\rho_\tau)\tau + \rho_\tau \tau_{t-1} + \epsilon_{\tau,t}$. Finally, the monetary authority follows a standard Taylor rule, targeting headline inflation. I calibrate the model using macro and micro moments from the data and drawing on values previously used in the literature. I discuss the calibration in detail in Appendix D.7.

Model evaluation. The impulse responses to a carbon policy shock, normalized to match the estimated peak energy price response, are shown in Figure 9. In what follows, we focus on the peak responses, as the model is not designed to match the hump-shaped responses in the data. We can see that the model is successful in generating consumption and income responses, overall and by household group, that are in the same order of magnitude as the estimated responses in Section 5. As in the data, consumption and income are more responsive to carbon policy shocks for the low-income, hand-to-mouth households. In contrast, the responses of high-income savers are much less pronounced.

The monetary response turns out to be an important factor for the transmission of carbon policy shocks. Recall that we assume that monetary policy targets headline inflation and thus leans against the inflationary pressures emerging from the increase in carbon prices, consistent with the monetary policy response estimated in the data. If we assume that monetary policy targets core inflation instead, the effects of carbon policy are attenuated. Household heterogeneity acts as a further amplifying channel through the unequal income incidence of the shock linked to the heterogeneity in MPCs. Without these demand channels, it is difficult to match the empirical magnitudes unless the energy share is set to implausibly high levels, see Appendix B.4.

Redistributing carbon revenues. We are now in a position to study how different carbon revenue redistribution schemes affect the transmission of carbon policy shocks. Figure 9 compares the baseline case when all carbon revenues accrue to the savers (blue line) to the case where the revenues are distributed equally across households $\mu = \lambda$ (red dashed line).

We can see that redistributing carbon revenues has important consequences: the aggregate effect on consumption and income is much smaller than in the baseline case of no redistribution. In contrast, redistributing revenues has a smaller impact on the response of emissions, see Appendix B.4. The intuition is that the redistribution scheme stabilizes the income of the hand-to-mouth which translates into a significantly smaller consumption response as they have a high MPC. Savers, on the other hand, face a somewhat more prolonged fall in their income but the effect on their consumption is more muted as they are able to smooth the effects of the shock. Thus, redistributing carbon revenues also leads to a reduc-

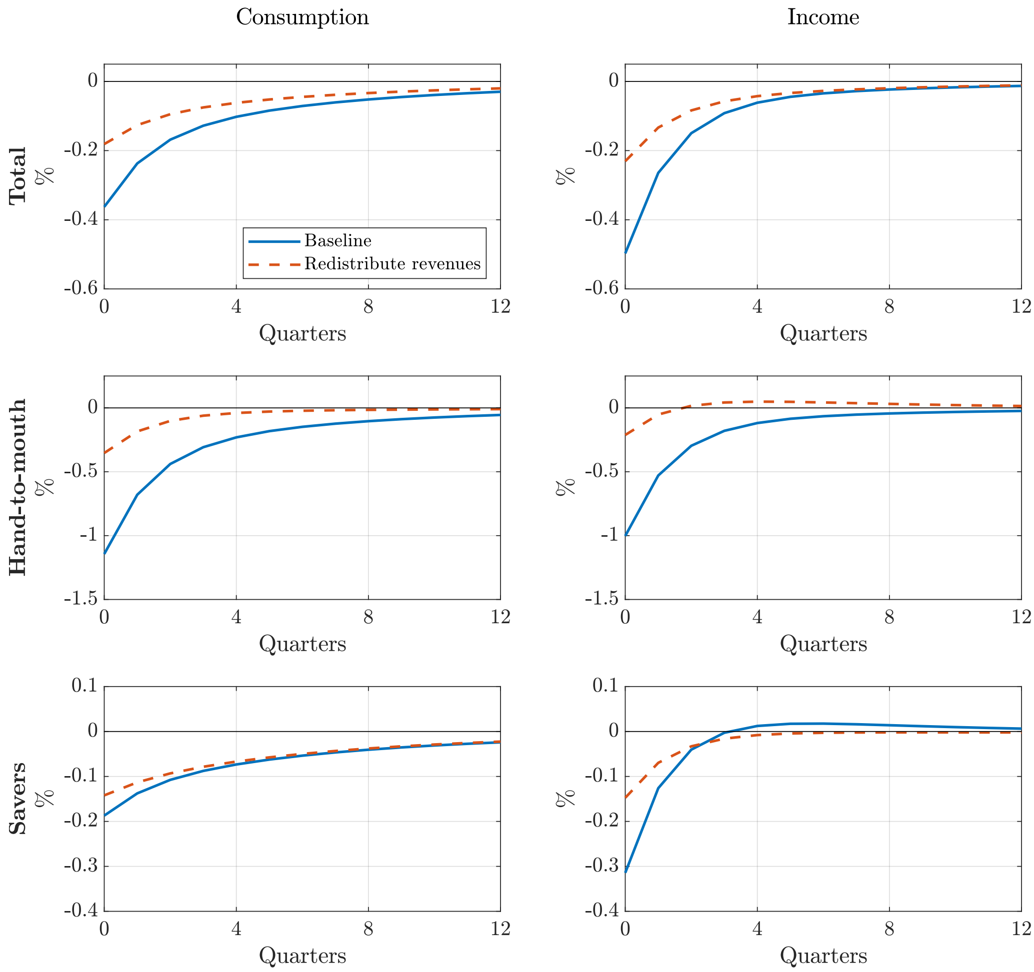


Figure 9: Model Responses for Consumption and Income

Notes: Impulse responses of consumption and income, in the aggregate as well as for hand-to-mouth and savers, to a carbon policy shock normalized to match the peak energy price response in the data. The blue line is the baseline response when carbon revenues solely accrue to the savers; the red dashed line is the response when carbon revenues are redistributed equally among hand-to-mouth and savers.

tion in consumption inequality. Emissions on the other hand change by less as low-income households' energy demand is particularly inelastic and they make up only a small share of aggregate emissions to start with.

The above findings speak directly to the recent debate on carbon pricing and inequality in Europe. The model confirms the intuition that redistributing carbon revenues could mitigate the effect on aggregate consumption and alleviate the distributional impact without compromising emission reductions to a significant extent. An interesting case in point in this context is the carbon tax in British Columbia. Contrary to the EU ETS, the tax was introduced alongside substantial reductions in income taxes and direct subsidies to the most affected households. The existing empirical evidence finds that the tax also reduced emissions significantly but the effects on economic activity turn out to be smaller (see Metcalf, 2019; Bernard and Kichian, 2021) – consistent with the predictions of my model.

6. Beyond the Short Term

We have seen that carbon pricing is successful in reducing emissions but this comes at an economic cost, at least in the short term. This section aims to shed light on some of the longer-term implications, specifically the impact of carbon pricing on public attitudes towards climate policy and the effects on green innovation.

Attitudes toward climate policies. An important argument for cushioning the distributional impact is that a successful transition to a low-carbon economy requires public support. If certain groups feel left behind, this could undermine the success of climate policy as the yellow vest movement in France, which started as a protest against higher fuel taxes, has shown for instance (Knittel, 2014).

To analyze this question, I use data from the British social attitudes (BSA) survey. The BSA is an annual survey that asks about the attitudes of the British population towards a wide selection of topics and is an important barometer of public attitudes in the UK. To proxy attitudes towards climate policy, I rely on a question that elicits the approval rate for environmentally-motivated fuel taxes (see Appendix B.3 for more information).

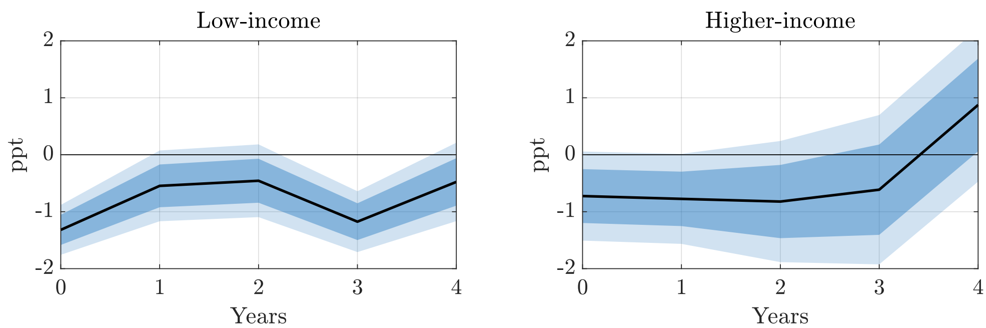


Figure 10: Effect on Attitude Towards Climate Policy

Notes: Impulse responses of public attitude towards climate policy for low- and higher-income groups. The public attitude towards climate policy is proxied by the share of households in the British social attitudes survey that express support for environmentally-motivated fuel taxes. Low-income correspond to the bottom 25 percent and higher-income to the other 75 percent of the income distribution.

Figure 10 shows the response of the approval rate of environmentally-motivated tax policies to a carbon policy shock across income groups. While the response of higher-income households is barely significant and even turns positive at longer horizons, low-income households display a significant and persistent fall in the support of climate policies. Recall, these households are also the ones that are most adversely affected by carbon policy shocks. These results suggest that compensating the most affected households may help increase the public support of climate change mitigation policies – consistent with recent evidence by Anderson, Marinescu, and Shor (2019) and Dechezleprêtre et al. (2022).

The impact on green innovation. A key motivation behind carbon pricing is to create an incentive for directed technical change. In fact, part of the vision for the EU ETS is to promote investment in clean, low-carbon technologies (European Comission, 2020*a*). Innovation in low-carbon technologies will be crucial to sustain emission reductions without permanently lowering output.

To analyze this channel empirically, I study how the patenting activity in climate change mitigation technologies changes in response to carbon policy shocks. I use data on patent applications from the European Patent Office (EPO), which has developed specific classification tags for patents in climate change mitigation technologies.

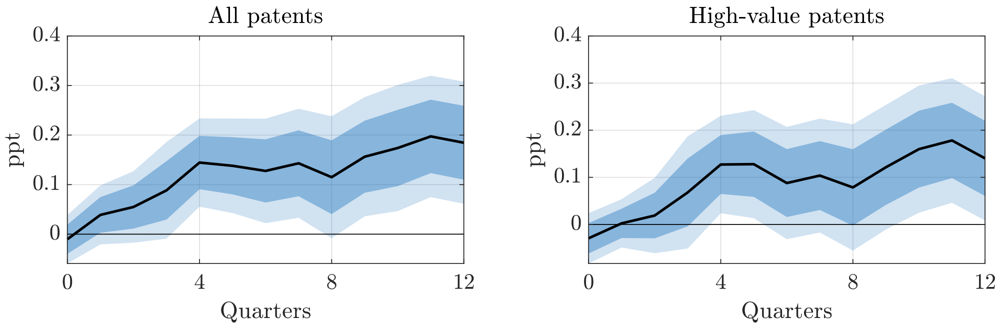


Figure 11: Patenting in Climate Change Mitigation Technologies

Notes: Impulse responses of patenting activity in climate change mitigation technologies, as measured by the number of climate change mitigation patents as a share of all patents filed at the EPO. The left panel displays the share based on all patents while the right panel focuses on high-value patents, i.e. patents filed at multiple patent offices.

The results are shown in Figure 11. We can see that the shock leads to a significant increase in low-carbon patenting, and this is robust to focusing on high-value patents. The effect is also economically significant as the average share of climate change mitigation patents is around 10 percent. Thus, carbon pricing appears to be successful in stimulating green innovation. These results support the findings of Calel and Dechezleprêtre (2016), who employ a quasi-experimental design exploiting inclusion criteria at the installations level to estimate the causal impact of the EU ETS on firms' patenting.

7. Conclusion

Fighting climate change is one of the greatest challenges of our time. While it has proved to be difficult to make progress at the global level, several national carbon pricing policies have been put in place. However, still little is known about the effects of these policies on emissions and the economy. This paper provides new evidence from the largest carbon market in the world, the EU ETS. I show that tightening the carbon pricing regime leads to a significant increase in energy prices, a persistent fall in emissions and an uptick in green innovation. This comes at the cost of temporarily lower economic activity and higher inflation. Importantly, these costs are borne unequally across society. Poorer households lower their consumption significantly and are driving the aggregate response while richer households are less affected. Not only are these households more exposed to carbon pricing because of their higher energy expenditure share, they also experience a larger fall in their income. These indirect effects via income and employment turn out to be quantitatively important. My results suggest that redistributing some of the carbon revenues to the most affected groups can reduce the economic costs of carbon pricing and may help strengthen the public support of the policy. In future work, it would be interesting to better understand how climate, fiscal and monetary policy can be coordinated to organize a successful transition to a low-carbon economy.

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Online Appendix

The Unequal Economic Consequences of Carbon Pricing

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Contents

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A. Data

A.1. Details on regulatory events

In this Appendix, I provide a detailed list of all the regulatory events used in the paper. To collect the events, I relied on a number of different sources. After 2010, most of the relevant news can be found on the European Commission Climate Action news archive: https://ec.europa.eu/clima/news/news_archives_en. Before that, I used information from the official journal of the European Union: https://eur-lex.europa.eu/homepage.html. Finally, the decisions on the NAPs in the first two phases are taken from Mansanet-Bataller and Pardo (2009). Table A.1 lists all the events.

Table A.1: Regulatory Update Events

	Date	Event description	Type
1	25/05/2005	Italian phase I NAP approved	Free alloc.
2	20/06/2005	Greek phase I NAP approved	Free alloc.
3	23/11/2005	Court judgement on proposed amendment to NAP, UK vs Commission	Free alloc.
4	22/12/2005	Further guidance on allocation plans for the 2008–2012 trading period	Cap
5	22/02/2006	Final UK Phase I NAP approved	Free alloc.
6	23/10/2006	Stavros Dimas delivered the signal to tighten the cap of phase II	Cap
7	13/11/2006	Decision avoiding double counting of emission reductions for projects under the Kyoto Protocol	Intl. credits
8	29/11/2006	Commission decision on the NAP of several member states	Free alloc.
9	14/12/2006	Decision determining the respective emission levels of the community and each member state	Cap
10	16/01/2007	Phase II NAPs of Belgium and the Netherlands approved	Free alloc.
11	05/02/2007	Slovenia phase II NAP approved	Free alloc.
12	26/02/2007	Spain phase II NAP approved	Free alloc.
13	26/03/2007	Phase II NAPs of Poland, France and Czech Republic approved	Free alloc.
14	02/04/2007	Austrian phase II NAP approved	Free alloc.
15	16/04/2007	Hungarian phase II NAP approved	Free alloc.
16	30/04/2007	Court order on German NAP, EnBW AG vs Commission	Free alloc.
17	04/05/2007	Estonian phase II NAP approved	Free alloc.
18	15/05/2007	Italian phase II NAP approved	Free alloc.
19	07/11/2007	Court judgement on German NAP, Germany vs Commission	Free alloc.
20	08/04/2008	Court order on German NAP, Saint-Gobain Glass GmbH vs Commission	Free alloc.
21	23/04/2009	Directive 2009/29/EC amending Directive 2003/87/EC to improve and extend the EU ETS	Cap
22	23/09/2009	Court judgement on NAP, Poland vs Commission	Free alloc.
23	24/12/2009	Decision determining sectors and subsectors which have a significant risk of carbon leakage	Free alloc.
24	19/04/2010	Commission accepts Polish NAP for 2008-2012	Free alloc.
25	09/07/2010	Commission takes first step toward determining cap on emission allowances for 2013	Cap
26	14/07/2010	Member states back Commission proposed rules for auctioning of allowances	Auction
27	22/10/2010	Cap on emission allowances for 2013 adopted	Cap
28	12/11/2010	Commission formally adopted the regulation on auctioning	Auction
29	25/11/2010	Commission presents a proposal to restrict the use of credits from industrial gas projects	Intl. credits
30	15/12/2010	Climate Change Committee supported the proposal on how to allocate emissions rights	Free alloc.
31	21/01/2011	Member states voted to support the ban on the use of certain industrial gas credits	Intl. credits
32	15/03/2011	Commission proposed that 120 million allowances to be auctioned in 2012	Auction
33	22/03/2011	Court judgement on NAP, Latvia vs Commission	Free alloc.
34	29/03/2011	Decision on transitional free allocation of allowances to the power sector	Free alloc.
35	27/04/2011	Decision 2011/278/EU on transitional Union-wide rules for harmonized free allocation of allowances	Free alloc.
36	29/04/2011	Commission rejects Estonia's revised NAP for 2008-2012	Free alloc.
37	07/06/2011	Commission adopts ban on the use of industrial gas credits	Intl. credits
38	13/07/2011	Member states agree to auction 120 million phase III allowances in 2012	Auction
39	26/09/2011	Commission sets the rules for allocation of free emissions allowances to airlines	Free alloc.
40	14/11/2011	Clarification on the use of international credits in the third trading phase	Intl. credits
41	23/11/2011	Regulation 1210/2011 determining the volume of allowances to be auctioned prior to 2013	Auction
42	25/11/2011	Update on preparatory steps for auctioning of phase 3 allowances	Auction
43	05/12/2011	Commission decision on revised Estonian NAP for 2008-2012	Free alloc.
44	29/03/2012	Court judgments on NAPs for Estonia and Poland	Free alloc.
45	02/05/2012	Commission publishes guidelines for review of GHG inventories in view of setting national limits for 2013-20	Cap
46	23/05/2012	Commission clears temporary free allowances for power plants in Cyprus, Estonia and Lithuania	Free alloc.
47	05/06/2012	Commission publishes guidelines on State aid measures in the context of the post-2012 trading scheme	Free alloc.

	Date	Event description	Type
48	06/07/2012	Commission clears temporary free allowances for power plants in Bulgaria, Czech Republic and Romania	Free alloc.
49	13/07/2012	Commission rules on temporary free allowances for power plants in Poland	Free alloc.
50	25/07/2012	Commission proposed to backload certain allowances from 2013-2015 to the end of phase III	Auction
51	12/11/2012	Commission submits amendment to back-load 900 million allowances to the years 2019-2020	Auction
52	14/11/2012	Commission presents options to reform the ETS to address growing supply-demand imbalance	Cap
53	16/11/2012	Auctions for 2012 aviation allowances put on hold	Auction
54	30/11/2012	Commission rules on temporary free allowances for power plants in Hungary	Free alloc.
55	25/01/2013	Update on free allocation of allowances in 2013	Free alloc.
56	28/02/2013	Free allocation of 2013 aviation allowances postponed	Free alloc.
57	25/03/2013	Auctions of aviation allowances not to resume before June	Auction
58	16/04/2013	The European Parliament voted against the Commission's back-loading proposal	Auction
59	05/06/2013	Commission submits proposal for international credit entitlements for 2013 to 2020	Intl. credits
60	03/07/2013	The European Parliament voted for the carbon market back-loading proposal	Auction
61	10/07/2013	Member states approve addition of sectors to the carbon leakage list for 2014	Free alloc.
62	30/07/2013	Update on industrial free allocation for phase III	Free alloc.
63	05/09/2013	Commission finalized decision on industrial free allocation for phase three	Free alloc.
64	26/09/2013	Update on number of aviation allowances to be auctioned in 2012	Auction
65	08/11/2013	Member states endorsed negotiations on the back-loading proposal	Auction
66	21/11/2013	Commission submitted non-paper on back-loading to the EU Climate Change Committee	Auction
67	10/12/2013	European Parliament voted for the back-loading proposal	Auction
68	11/12/2013	Climate Change Committee makes progress on implementation of the back-loading propsal	Auction
69	18/12/2013	Commission gives green light for a first set of member states to allocate allowances for calendar year 2013	Free alloc.
70	08/01/2014	Climate Change Committee agrees back-loading	Auction
71	22/01/2014	Commission proposed to establish a market stability reserve for phase V	Cap
72	26/02/2014	Commission gives green light for free allocation by all member states	Free alloc.
73	27/02/2014	Back-loading: 2014 auction volume reduced by 400 million allowances	Auction
74	13/03/2014	Commission approves first batch of international credit entitlement tables	Intl. credits
75	28/03/2014	Commission approves second batch of international credit entitlement tables	Intl. credits
76	04/04/2014	Update on approval of international credit entitlement tables	Intl. credits
77	11/04/2014	Commission approves four more international credit entitlement tables	Intl. credits
78	23/04/2014	Commission approves final international credit entitlement tables	Intl. credits
79	02/05/2014	Commission published the number of international credits exchanged	Intl. credits
80	05/05/2014	Commission submits proposed carbon leakage list for 2015-2019	Free alloc.
81	04/06/2014	Auctioning of aviation allowances to restart in September	Auction
82	04/07/2014	Commission published the first update on the allocation of allowances from the New Entrants' Reserve	Free alloc.
83	09/07/2014	Climate Change Committee agrees proposed carbon leakage list for the period 2015-2019	Free alloc.
84	27/10/2014	Commission adopts the carbon leakage list for the period 2015-2019	Free alloc.
85	04/11/2014	Updated information on exchange and international credit use	Intl. credits
86	04/05/2015	Updated information on exchange and international credit use	Intl. credits
87	15/07/2015	Proposal to revise the EU emissions trading system for the period after 2020	Cap
88	23/07/2015	Commission publishes status update for New Entrants' Reserve and allocation reductions	Free alloc.
89	04/11/2015	Updated information on exchange and international credit use	Intl. credits
90	15/01/2016	Commission publishes status update for New Entrants' Reserve	Free alloc.
91	28/04/2016	Court judgment on free allocation in the EU ETS for the period 2013-2020	Free alloc.
92	02/05/2016	Updated information on exchange and international credit use	Intl. credits
93	23/06/2016	Following court judgement, commission to modify cross-sectoral correction factor for 2018-2020	Free alloc.
94	15/07/2016	Commission published a status update on the allocation of allowances from the New Entrants' Reserve 2013-2020	Free alloc.
95	08/09/2016	Court judgment on free allocation in the EU ETS for the period 2013-2020	Free alloc.
96	04/11/2016	Updated information on exchange and international credit use	Intl. credits
97	16/01/2017	Commission publishes status update for New Entrants' Reserve	Free alloc.
98	24/01/2017	Commission adopts Decision to implement Court ruling on the cross-sectoral correction factor	Free alloc.
99	15/02/2017	European Parliament voted in support of the revision of the ETS Directive for the period after 2021	Cap
100	27/04/2017	Climate Change Committee approves technical changes to auction rules	Auction
101	02/05/2017	Updated information on exchange and international credit use	Intl. credits
102	12/05/2017	Commission publishes first surplus indicator for ETS Market Stability Reserve	Auction
103	17/07/2017	Commission publishes status update for New Entrants' Reserve	Free alloc.
104	26/07/2017	Court judgment again confirms benchmarks for free allocation of ETS allowances for 2013-2020	Free alloc.
105	06/11/2017	Updated information on exchange and international credit use	Intl. credits
106	15/01/2018	Commission publishes status update for New Entrants' Reserve	Free alloc.
107	04/05/2018	Updated information on exchange and international credit use	Intl. credits
108	08/05/2018	Commission Notice on the preliminary carbon leakage list for phase IV (2021-2030)	Free alloc.
109	15/05/2018	ETS Market Stability Reserve will start by reducing auction volume by almost 265 million allowances	Auction
110	16/07/2018	Commission publishes status update for New Entrants' Reserve	Free alloc.
111	30/10/2018	Commission adopts amendment to ETS auctioning regulation	Auction
112	06/11/2018	Updated information on exchange and international credit use	Intl. credits
113	05/12/2018	Poland's 2019 auctions to include some allowances not used for power sector modernization	Auction
114	04/01/2019	Amendment to the ETS auctioning regulation	Auction
115	15/01/2019	Commission publishes status update for New Entrants' Reserve	Free alloc.
116	15/02/2019	Adoption of the Delegated Decision on the carbon leakage list for 2021-2030	Free alloc.
117	23/04/2019	Iceland, Liechtenstein and Norway to start auctions on the common auction platform soon	Auction
118	15/05/2019	ETS Market Stability Reserve to reduce auction volume by almost 400 million allowances	Auction
119	16/05/2019	Revised 2019 auction calendars including EEA EFTA volumes published	Auction
120	12/06/2019	Poland's 2020 auction volume to include allowances not used for power sector modernisation	Auction
121	19/06/2019	Updated information on exchange and international credit use	Intl. credits
122	11/07/2019	2020 and revised 2019 auction calendars of the common auction platform published	Auction
123	15/07/2019	Commission publishes status update for New Entrants' Reserve	Free alloc.

	Date	Event description	Type
124	28/08/2019	Commission amends ETS auctioning regulation for phase 4	Auction
125	31/10/2019	Commission adopts the Regulation on adjustments to free allocation due to activity level changes	Free alloc.
126	08/11/2019	Auctioning regulation amendment for phase 4 of the EU ETS published and to enter into force	Auction

A.2. Macro data

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

Table A.2: Data Description, Sources, and Coverage

Variable	Description	Source	Sample
Instrument			
LEXC.01 (PS)	EUA futures front contract (settlement price)	Datastream	22/04/2005-31/12/2019
ELECWAVG	Wholesale electricity price, constructed as weighted average of EEX, APX, Nordpool, Powernext, OMEL, GME, and the EPX spot price, converted to EUR/tCO2 using GHG emissions intensity of electricity generation	Datastream/European Environment Agency/own calculations	22/04/2005-31/12/2019
Baseline variables			
EKESCPENF	HICP energy (EA-19)	Datastream	1999M1-2019M12
GHGTOTAL	Total GHG emissions excluding LULUCF and including international aviation (EU)	Eurostat/own calculations	1999M1-2019M12
EKCPHARMF	HICP all items (EA-19)	Datastream	1999M1-2019M12
EKIPTOT.G	Industrial production excl. construction (EA-19)	Datastream	1999M1-2019M12
EMECB2Y.	Two-year government bond yield	Datastream	1999M1-2019M12
EKESUNEMO	Unemployment rate (EA-19)	Datastream	1999M1-2019M12
DJSTOXX	Euro STOXX	Datastream	1999M1-2019M12
DCOILBRENTEU	Brent Crude price	FRED	1999M1-2019M12
Additional variables			
Other carbon futures	LEXC.0h (PS), for h in $(2, 3, 4, 5)$	Datastream	22/04/2005-31/12/2019
BAMLHE00EHYIOAS	ICE BofA euro high yield index option-adj. spread	FRED	1999M1-2019M12
VSTOXX	Euro STOXX 50 volatility	stoxx.com	1999M1-2019M12
EKGDP...D	Real GDP (EA-19)	Datastream	1999Q1-2019Q4
EKESENMZD	Final consumption expenditure (EA-19)	Datastream	1999Q1-2019Q4
EKGFCF..D	Gross fixed capital formation (EA-19)	Datastream	1999Q1-2019Q4
EMESJSABB	Wages and salaries: all activities	Datastream	1999Q1-2019Q4
CCPATENTS	Share of climate change mitigation technologies (CCMT) patents filed at EPO	Google Patents Public Data/own calculations	2005Q1-2019Q4

The transformed series used in the baseline VAR are depicted in Figure A.1.

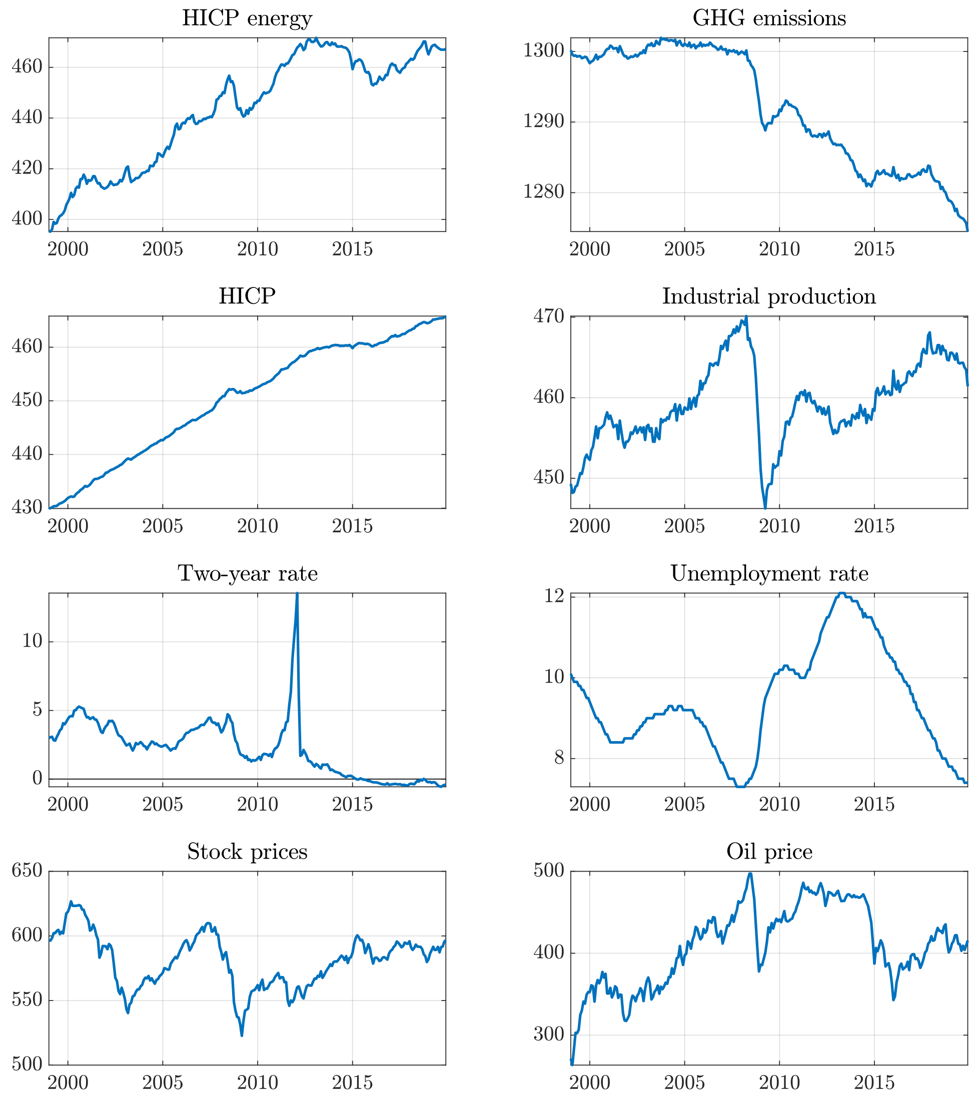


Figure A.1: Transformed Data Series

A.3. Micro data

In this Appendix, I provide detailed information on the micro data used in Sections 5 and 6 of the paper. I use data from a selection of different surveys, which are discussed in detail below.

A.3.1. LCFS

The living costs and food survey (LCFS) data can be obtained from the UK Data Service. I use the waves from 1999-2001 of the Family Expenditure Survey, the 2001-2007 waves from the Expenditure and Food Survey and the 2008-2019 waves from the LCFS, which superseded the previous two surveys. Note that within this sample, the reporting frequency changed two times first from financial year to calendar year and then back again to the financial year format. The waves are adjusted to consistently reflect the calendar year prior to creating the pooled cross-section. Most variables of interest are available in the derived household datasets. The age at which full-time education was completed, as well as current wages, is aggregated from the personal derived datasets.

As the main measure of expenditure, I use total expenditure excluding housing (p550tp-p536tp). For current income, I use current total disposable income, calculated by subtracting income taxes and NI contributions from the gross income (p352p-p392p-p388p-p029hp). I group the households by their normal disposable income (p389p). For earnings, I use wages net of taxes (aggregate p004p to the household level, subtract current taxes and add back taxes on financial income p068h). For financial income, I use p324p, which includes interest income, dividends and rents. For age, I use the age of the household reference person, p396p. Education is proxied by the highest age a person in the household has completed a full-time education (a010 aggregated to the household level). The housing tenure status is recorded in variable a121.

For energy expenditure, I use expenditure on fuel, light and power (p537t). Constructing measures of non-durable, services and durable expenditure is not trivial in the LCFS data, as the broader available expenditure categories do not allow a clean split, e.g. personal goods and services (p544t) is a mix of non-durable goods and services while household goods (p542t) includes both non-durable and durable goods. To construct clean measures of non-durables, services and durables expenditure, I split these broader subcategories into non-durable, services and durable parts by grouping the items in a particular subcategory accordingly, following closely the COICOP guidelines. A further challenge in doing so is that the code names for disaggregated expenditure items changed when the FES became the EFS in 2001. In Table A.3, I detail how the non-durable, services and durable expenditure measures are constructed. At the item level, I provide both, the relevant codes in the FES and the EFS/LCFS. Note that semi-durables are subsumed under non-durables, and services do not include housing.

Table A.3: Expenditure Classification in LCFS

Category	Subcategories	Items
Non-durables	Fuel, light power (p537t)	
	Food, alcoholic drinks, tobacco (p538t, p539t, p540t)	
	Clothing and footwear (p541t)	
	Non-durable household goods (subset of p542t)	*LCFS codes:* c52111t, c52112t, c53311t, c55214t, c56111t, c56112t, c56121t, c56123t, c93114t, c93313t, c93411t, c95311t, c95411t, cc1311t *FES codes:* d070104t, d070105t, d070211t, d070209t, d070401t, d070402t, d070302t, d070601t, d120304t, d070501t

Category	Subcategories	Items
	Non-durable personal goods (subset of p544t)	*LCFS codes:* c61112t, c61211t, c61311t, c61313t, cc1312t, cc1313t, cc1314t, cc1315t, cc1316t, cc1317t, cc3211t, cc3222t, cc3223t, cc3224t *FES codes:* d090402t, d090102t, d090501t, d090101t, d090103t, d090104t, d090105t, d090301t, d090202t, d090302t, d090303t
	Non-durable motoring expenditure (subset of p545t)	*LCFS codes:* c72114t, c72211t, c72212t, c72213t *FES codes:* d100405t, d100301t, d100302t, d100303t
	Non-durable leisure goods (subset of p547t)	*LCFS codes:* c91126t, c91411t, c91412t, c91413t, c91414t, c93111t, c93113t, c93311t, c95111t, c95211t, c95212t *FES codes:* d120114t, d120108t, d120110t, d120109t, d120401t, d120113t, d070703t, d120303t, d120301t, d120302t
	Miscellaneous non-durable goods (subset of p549t)	*LCFS codes:* ck5511c, cc3221t *FES codes:* d070801t, d140601c, d090701t
Services	Household services (p543t)	
	Fares and other travel costs (p546t)	
	Leisure services (p548t)	
	Service part of household goods (subset of p542t)	*LCFS codes:* c53312t, c53313t, c53314t, c93511t, cc5213t *FES codes:* d070212t, d070213t
	Personal services (subset of p544t)	*LCFS codes:* c61111t, c61312t, c62111t, c62112t, c62113t, c62114t, c62211t, c62212t, c62311t, c62321t, c62322t, c62331t, c63111t, cc1111t *FES codes:* d090401t, d090502t, d090403t, d090404t, d090601t
	Service part of motoring expenditure (subset of p545t)	*LCFS codes:* b187-b179, b188, b249, b250, b252, c72313t, c72314t, c72411t, c72412t, c72413t, ck3112t, c72311c, c72312c, cc5411c *FES codes:* b187-b179, b188, b249, b250, b252, d100403t, d100406t, d100407t, d100404t, d100408t, d100201c, d100204c, d100401c
	Leisure services (subset of p547t)	*LCFS codes:* c91511t, c93112t, c94238t, c94239t, c94246t *FES codes:* d120111t, d120112t
	Miscellaneous services (subset of p549t)	*LCFS codes:* b237, b238, ck5315c, ck5213t, ck5214t *FES codes:* b237, b238, d140402, d140406c
Durables	Durable household goods (subset of p542t)	*LCFS codes:* b270, b271, c51111c, c51211c, c51212t, c51113t, c51114t, c53111t, c53121t, c53122t, c53131t, c53132t, c53133t, c53141t, c53151t, c53161t, c53171t, c53211t, c54111t, c54121t, c54131t, c54132t, c55111t, c55112t, c55213t, c56122t, c93212t, c93312t, c93412t, cc1211t *FES codes:* b270, b271, d070101c, d070102c, d070103t, d070304t, d070704t, d070203t, d070202t, d070204t, d070207t, d070208t, d070201t, d070206t, d070303t, d070301t, d070205t, d070701t, d070305t, d070306t, d070702t, d070602t
	Durable personal goods (subset of p544t)	*LCFS codes:* cc3111t *FES codes:* d090201t
	Durable motoring expenditure (subset of p544t)	*LCFS codes:* b244, b2441, b245, b2451, b247, c31315t, c71112t, c71122t, c71212t, c92114t, c92116t, c71111c, c71121c, c71211c, c92113c, c92115c, c72111t, c72112t, c72113t, c91112t *FES codes:* b244, b245, b247, d100105t, d100106t, d100107t, d100101c, d100102c, d100104c, d100203t, d100202t, d100205t

Category	Subcategories	Items
	Durable leisure goods (subset of p547t)	*LCFS codes:* c91124t, c82111t, c82112t, c82113t, c91111t, c91113t, c91121t, c91122t, c91123t, c91125t, c91211t, c91311t, c92211t, c92221t, c93211t *FES codes:* d120104t, d080202t, d080205t, d080207t, d120105t, d120101t, d120102t, d120103t, d120115t, d120402t, d120106t, d120107t, d120201t

Regarding the sample, I apply the following restrictions. I drop households that have a household reference person younger than 18 or older than 90 years. Furthermore, I drop households with a negative normal disposable income. To account for some (unrealistically) high or low values of consumption, for each quarter and income group, I drop the top and bottom 1% of observations for total expenditure.

A.3.2. LFS

To get information on the sector of employment, I use data from the UK Labour Force Survey (LFS). The LFS studies the employment circumstances of the UK population. It is the largest household study in the UK and provides the official measures of employment and unemployment. Apart from detailed information on employment, it also contains a wide range of related topics such as occupation, training, hours of work and personal characteristics of household members aged 16 years and over. The data can be obtained from the UK Data Service. I use the quarterly waves from 1999-2019 to construct a pooled cross-section. For the employment sector, I use the variable indsect, which describes the industry sector in the main job based on the SIC 2003 classification. To proxy income, I use the net pay from the main and second job (netwk and netwk2).

A.3.3. BSA

To proxy public attitudes towards climate policy, I use data from the British social attitudes (BSA) survey. The data can also be obtained from the UK Data Service. I use the waves from 1999-2019 to construct a pooled cross-section. To construct the income groups, I use the income quartiles that are provided from 2010 onwards (hhincq). For the years before, I use the household income variable (hhincome) to construct the quartiles. The survey contains many questions on the attitudes towards climate change, the environment and climate/environmental policy, but unfortunately most variables are not part of the main set of questions that are asked in every year. One exception concerns a question about taxes for car owners (cartaxhi), in particular it asks whether you agree with the following statement:

"For the sake of the environment, car users should pay higher taxes", which was fielded for all years up to 2017. Thus, I use the proportion of households agreeing with this statement as a proxy for the public attitude towards climate policy.

B. Additional Charts and Tables

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

B.1. Diagnostics of the surprise series

As discussed in the paper, I perform a number of additional validity checks on the surprise series. In particular, I investigate the autocorrelation and forecastability of the surprise series as well as the relation to other shocks from the literature.

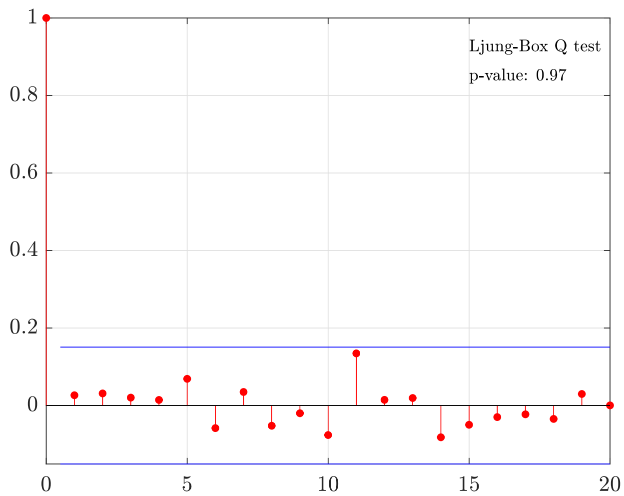


Figure B.1: The Autocorrelation Function of the Carbon Policy Surprise Series

Figure B.1 depicts the autocorrelation function. We can see that there is little evidence that the series is serially correlated. I also perform a series of Granger causality tests. Table B.1 shows that the series is not forecastable by past macroeconomic or financial variables. Finally, I look how the series correlates with other shock series from the literature and find that it is not correlated with other structural shock measures, including oil demand, uncertainty, financial, fiscal and monetary policy shocks, see Table B.2.[2] There is some weak correlation with oil supply shocks, which makes sense against the backdrop that the EU ETS also covers European oil producers in the North Sea.

[2]I thank Mario Alloza for kindly sharing their fiscal policy shock series.

Table B.1: Granger Causality Tests

Variable	p-value
Instrument	0.3279
EUA price	0.7060
HICP energy	0.7961
GHG emissions	0.6615
HICP	0.9949
Industrial production	0.7633
Two-year rate	0.5066
Unemployment rate	0.2473
Stock prices	0.7887
REER	0.1595
Oil price	0.3280
Joint	0.9339

Notes: The table shows the p-values of a series of Granger causality tests of the carbon policy surprise series using a selection of macroeconomic and financial variables.

Table B.2: Correlation with Other Shock Measures

Shock	Source	ρ	p-value	n	Sample
Monthly measures					
Global oil market					
Oil supply	Kilian (2008) (extended)	-0.16	0.10	104	2005M05-2013M12
	Kilian (2009) (updated)	-0.00	0.97	164	2005M05-2018M12
	Caldara, Cavallo, and Iacoviello (2019)	-0.11	0.24	128	2005M05-2015M12
	Baumeister and Hamilton (2019)	-0.15	0.04	176	2005M05-2019M12
	Känzig (2021) (updated)	0.12	0.11	176	2005M05-2019M12
Global demand	Kilian (2009) (updated)	-0.09	0.27	164	2005M05-2018M12
	Baumeister and Hamilton (2019)	-0.07	0.35	176	2005M05-2019M12
Oil-specific demand	Kilian (2009) (updated)	0.10	0.21	164	2005M05-2018M12
Consumption demand	Baumeister and Hamilton (2019)	0.13	0.10	176	2005M05-2019M12
Inventory demand	Baumeister and Hamilton (2019)	0.02	0.78	176	2005M05-2019M12
Monetary policy					
Monetary policy shock	Jarociński and Karadi (2020)	0.08	0.32	140	2005M05-2016M12
Central bank info	Jarociński and Karadi (2020)	0.07	0.40	140	2005M05-2016M12
Financial & uncertainty					
Financial conditions	BBB spread residual	-0.04	0.61	176	2005M05-2019M12
Financial uncertainty	VIX residual (Bloom, 2009)	-0.05	0.48	176	2005M05-2019M12
	VSTOXX residual	-0.06	0.43	176	2005M05-2019M12
Policy uncertainty	Global EPU (Baker, Bloom, and Davis, 2016)	-0.07	0.37	176	2005M05-2019M12
Quarterly measures					
Fiscal policy	Euro area (Alloza, Burriel, and Pérez, 2019)	0.08	0.60	43	2005Q2-2015Q4
	Germany	0.24	0.12	43	2005Q2-2015Q4
	France	-0.03	0.85	43	2005Q2-2015Q4
	Italy	0.05	0.74	43	2005Q2-2015Q4
	Spain	0.14	0.36	43	2005Q2-2015Q4

Notes: The table shows the correlation of the carbon policy surprise series with a wide range of different shock measures from the literature, including global oil market shocks, monetary policy, financial and uncertainty shocks. ρ is the Pearson correlation coefficient, the p-value corresponds to the test whether the correlation is different from zero and n is the sample size.

B.2. More on aggregate effects

In this Appendix, I present some additional results pertaining to the analysis in Section 4 of the paper.

B.2.1. Internal instrument approach

A key advantage of the external instruments approach lies in its efficiency. However, this comes at the cost of assuming (partial) invertibility. If the invertibility assumption is not satisfied, this can lead to biased results (Li, Plagborg-Møller, and Wolf, 2021). To mitigate concerns about invertibility, I also present results from the internal instruments approach (Ramey, 2011; Plagborg-Møller and Wolf, 2019) which is robust to non-invertibility.

The results are shown in Figure B.2. The figure shows the responses from the internal instrument approach together with the external instrument baseline. We can see that the responses turn out to be very similar, both qualitatively and quantitatively. Only the estimated response of the two-year rate is somewhat less stable. We can also see that the internal instrument responses are much less precisely estimated as the confidence bands are significantly more dispersed. Overall, however, these findings suggest that the results are robust to relaxing the assumption of invertibility.

B.2.2. Local projection-instrumental variable approach

As discussed in the main text, I rely on VAR techniques for estimation because the sample is relatively short and VARs provide a parsimonious characterization of the data. However, as a robustness check, I have also tried to estimate the impulse responses using a local projections instrumental variable (LP-IV) approach à la Jordà, Schularick, and Taylor (2015) and Ramey and Zubairy (2018). To fix ideas, the dynamic causal effects, ψ_h^i, can be estimated from the following set of regressions:

$$y_{i,t+h} = \beta_h^i + \psi_h^i y_{1,t} + \boldsymbol{\beta}_h^{i\prime} \mathbf{x}_{t-1} + \xi_{i,t,h}, \tag{1}$$

using z_t as an instrument for $\Delta y_{1,t}$. Here, $y_{i,t+h}$ is the outcome variable of interest, $\Delta y_{1,t}$ is the endogenous regressor, $\mathbf{x}_{t-1}$ is a vector of controls, $\xi_{i,t,h}$ is a potentially serially correlated error term, and h is the impulse response horizon. I use the same controls as in the VAR. For inference, I follow again the lag-augmentation approach proposed by Montiel Olea and Plagborg-Møller (2020).

As the impacts of carbon policy are potentially quite persistent, we want to

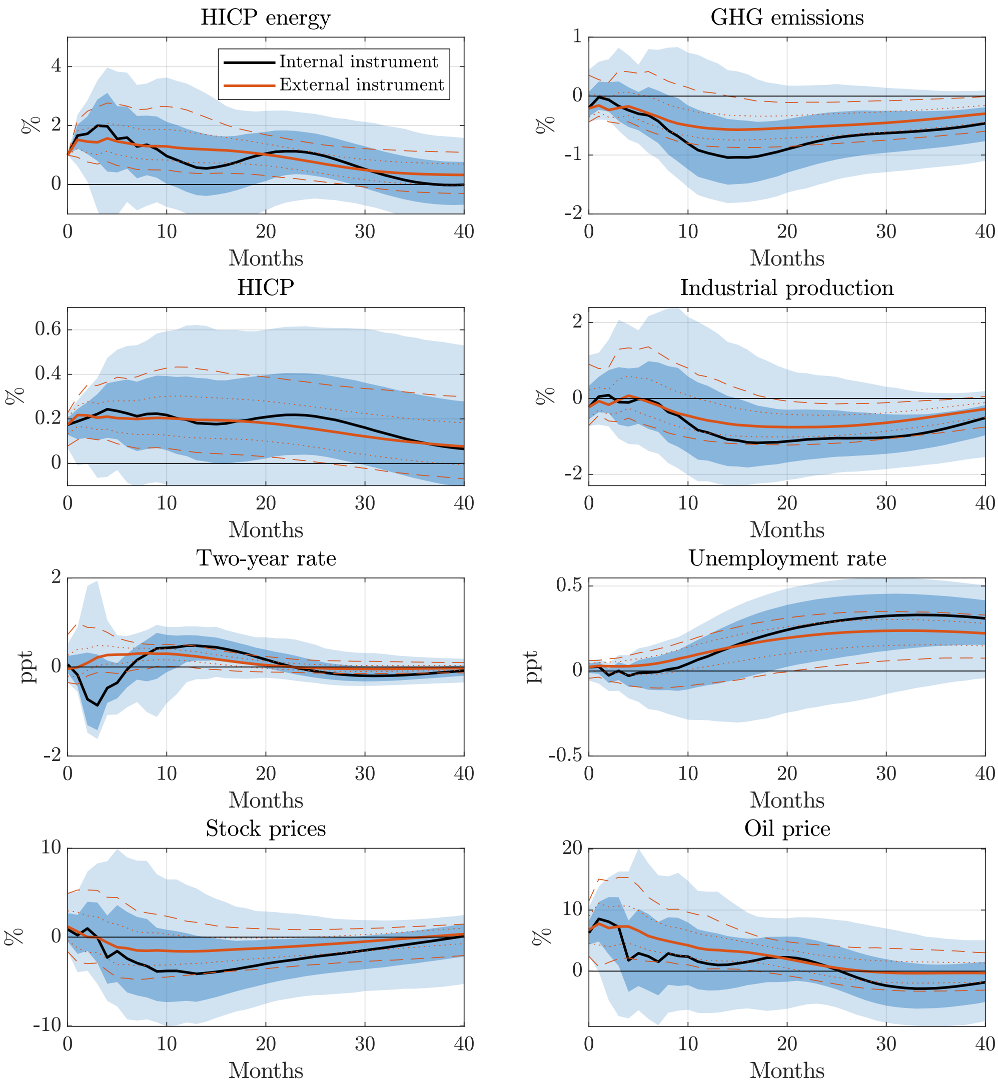


Figure B.2: Internal Versus External Instrument VAR

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid dark and red lines are the point estimates for the internal instrument and the external instrument VAR, respectively, and the shaded areas / dashed lines are 68 and 90 percent confidence bands.

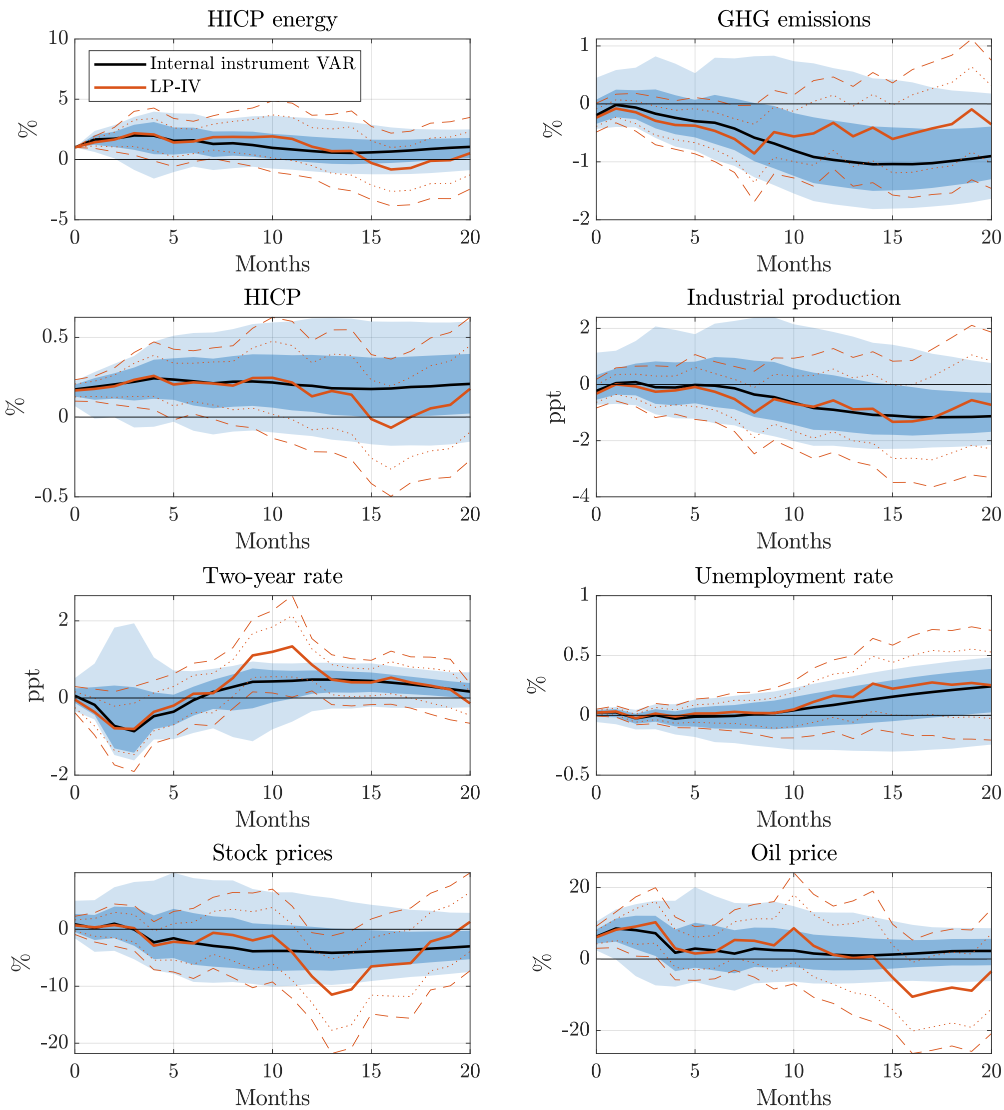


Figure B.3: Internal Instrument VAR Versus LP-IV

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid dark and red lines are the point estimates for the internal instrument VAR and the LP-IV, respectively, and the shaded areas / dashed lines are 68 and 90 percent confidence bands.

look at the dynamic causal effects relatively far out. Given the short sample, this is challenging in the LP-IV framework, which does not use the parametric VAR restriction but estimates the effect by a distinct IV regression at each horizon h. Consequently, the number of observations available for estimation decreases with the impulse horizon. Against this background, I restrict the impulse horizon in the LP-IV regressions to 20 months.

Figure B.3 compares the responses obtained from the LP-IV approach to the ones from the internal instrument VAR. Recall that both approaches rely on the same invertibility-robust identifying restrictions but use different estimation techniques. We can see that the two approaches produce consistent results, especially at horizons up to one year.[3] At longer horizons the differences tend to be larger, however, the responses are also less precisely estimated.

B.2.3. Core versus headline HICP

In the paper, I document a significant and persistent increase in headline HICP. An important question that has also relevant implications for the conduct of monetary policy is how the shock transmits to core consumer prices. To this end, I re-estimate the model substituting headline for core HICP. Figure B.4 presents the response for core HICP together with the HICP headline and energy component from the baseline model. We can see that the response of core consumer prices is more muted and less precisely estimated. This illustrates that this is really a shock to relative prices. Reassuringly, all other responses from the model with core HICP are very similar to the baseline case.

[3]Note that this is despite the fact that we only control for 6 lags in both models.

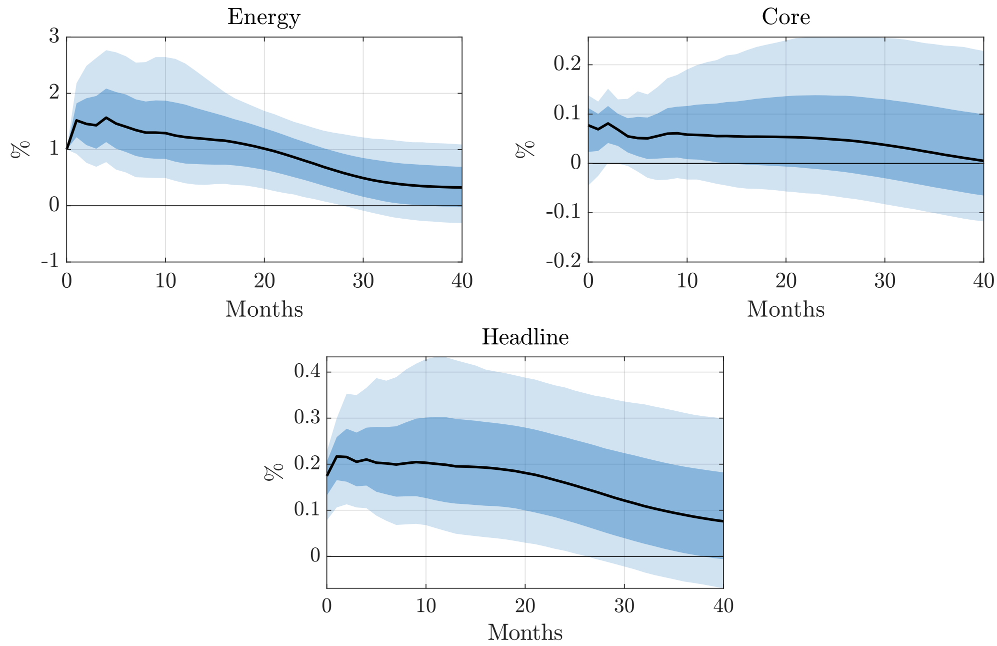


Figure B.4: Headline Versus Core HICP

Notes: Impulse responses of the headline, energy and core HICP to a carbon policy shock. The headline and energy indices are from the baseline model; the core response is from the model featuring core instead of headline HICP. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

B.2.4. Variance Decomposition

To better understand how carbon policy shocks have contributed to variations in macroeconomic and financial variables, I perform a variance decomposition exercise in addition to the historical decomposition presented in the paper. I do so both under the invertibility assumption maintained in the external instrument VAR as well as under weaker assumptions in the context of a general SVMA model, as proposed by Plagborg-Møller and Wolf (2020). In particular, I perform a standard forecast error variance decomposition in the SVAR and compute forecast variance ratios for the SVMA. The forecast variance ratio for variable i at horizon h is given by

$$FVR_{i,h} = 1 - \frac{\text{Var}(y_{i,t+h}|\{y_\tau\}_{-\infty<\tau\leq t}, \{\varepsilon_{1,\tau}\}_{t<\tau<\infty})}{\text{Var}(y_{i,t+h}|\{y_\tau\}_{-\infty<\tau\leq t})}, \tag{2}$$

and measures the reduction in the econometrician's forecast variance that would arise from being told the entire path of future realizations of the shock of interest. Plagborg-Møller and Wolf (2020) show that this statistic is interval-identified under the assumption that a valid instrument is available. Under the assumption of recoverablity, the ratio is point-identified by the upper bound.

The results are shown in Table B.3. We can see that carbon policy shocks have contributed meaningfully to historical variations in the variables of interest. Under the invertibility assumption (Panel A), they account for about 30 percent of the variations in energy prices and around 10 percent of the short-run variations in emissions, which goes up to over 20 percent at the 3 year horizon. Turning to the macroeconomic variables, we can see that they explain a substantial part of variations in the HICP, especially at shorter horizons, and a non-negligible fraction of the variations in industrial production and the unemployment rate at longer horizons. The shocks explain less of the variations in the two-year rate and stock prices but can account for about 20 percent of the variation in oil prices. The forecast variance ratios in Panel B, which dispense from the assumption of invertibility, paint a similar picture.

Table B.3: Variance Decomposition

h	HICP energy	Emissions	HICP	IP	Two-year rate	Unemp. rate	Stock prices	Oil price
Panel A: Forecast variance decomposition (SVAR-IV)								
6	0.38	0.12	0.46	0.02	0.04	0.05	0.02	0.22
	[0.03, 0.49]	[0.02, 0.42]	[0.04, 0.57]	[0.01, 0.30]	[0.01, 0.24]	[0.00, 0.33]	[0.01, 0.31]	[0.01, 0.33]
12	0.31	0.18	0.32	0.05	0.08	0.08	0.03	0.20
	[0.03, 0.41]	[0.02, 0.43]	[0.03, 0.46]	[0.02, 0.33]	[0.01, 0.22]	[0.01, 0.37]	[0.01, 0.33]	[0.02, 0.31]
24	0.30	0.22	0.23	0.13	0.08	0.18	0.04	0.20
	[0.03, 0.38]	[0.02, 0.39]	[0.02, 0.39]	[0.02, 0.34]	[0.02, 0.21]	[0.01, 0.43]	[0.01, 0.31]	[0.02, 0.27]
36	0.28	0.20	0.18	0.16	0.08	0.23	0.04	0.16
	[0.03, 0.35]	[0.02, 0.36]	[0.02, 0.35]	[0.02, 0.33]	[0.02, 0.21]	[0.01, 0.44]	[0.02, 0.31]	[0.02, 0.24]
Forecast variance ratio (SVMA-IV)								
6	0.04, 0.21	0.01, 0.06	0.04, 0.21	0.00, 0.01	0.03, 0.14	0.00, 0.01	0.00, 0.02	0.01, 0.08
	[0.01, 0.39]	[0.00, 0.25]	[0.01, 0.40]	[0.00, 0.17]	[0.01, 0.37]	[0.00, 0.15]	[0.00, 0.19]	[0.01, 0.24]
12	0.03, 0.15	0.03, 0.15	0.03, 0.15	0.01, 0.03	0.03, 0.18	0.00, 0.01	0.01, 0.04	0.01, 0.06
	[0.01, 0.36]	[0.00, 0.45]	[0.01, 0.39]	[0.00, 0.27]	[0.01, 0.41]	[0.00, 0.21]	[0.00, 0.27]	[0.01, 0.26]
24	0.02, 0.13	0.04, 0.23	0.02, 0.11	0.02, 0.10	0.03, 0.19	0.02, 0.09	0.01, 0.06	0.01, 0.06
	[0.01, 0.36]	[0.00, 0.50]	[0.00, 0.39]	[0.00, 0.32]	[0.02, 0.38]	[0.00, 0.33]	[0.00, 0.31]	[0.01, 0.26]
36	0.02, 0.12	0.04, 0.21	0.02, 0.09	0.02, 0.13	0.04, 0.20	0.03, 0.14	0.01, 0.06	0.01, 0.06
	[0.01, 0.33]	[0.00, 0.46]	[0.00, 0.36]	[0.00, 0.32]	[0.02, 0.38]	[0.00, 0.38]	[0.01, 0.31]	[0.01, 0.26]

Notes: The table shows the variance decomposition at horizons ranging from 6 months to 4 years. Panel A includes the forecast error variance decomposition from the external instrument VAR, Panel B shows the identified set for the forecast variance ratio. Bootstrapped 90% confidence intervals are reported in brackets.

B.2.5. Financial conditions and uncertainty

To better understand how the shock transmits to the economy, I have also looked at the responses of indicators for financing conditions and financial uncertainty, see Figure B.5. However, as can be seen from the responses these variables do not appear to play a dominant role in the transmission of the carbon policy shock.

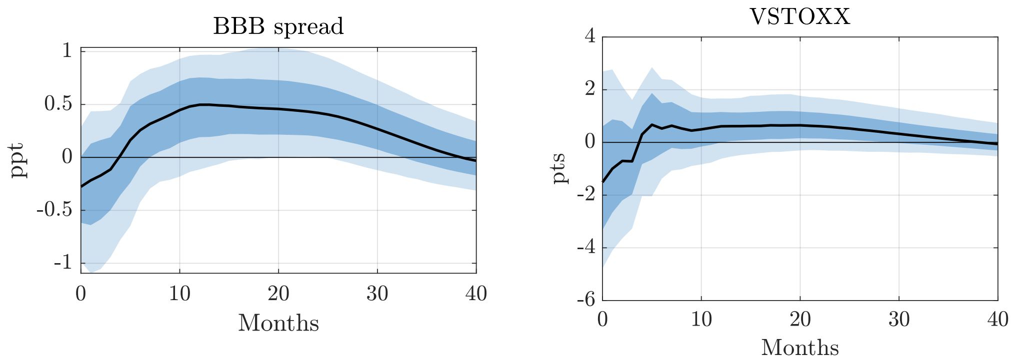


Figure B.5: Financial Conditions and Uncertainty

Notes: Impulse responses of financial conditions, as proxied by the BBB bond spread, and the VSTOXX index as a measure of financial uncertainty.

B.2.6. Aggregate effects for the UK

Because of data availability, the household-level analysis is carried out for the UK. As a validating exercise, I have verified that the aggregate effects on the UK, as measured by real GDP, consumption and investment, are comparable to the EU level responses, see Figure B.6.

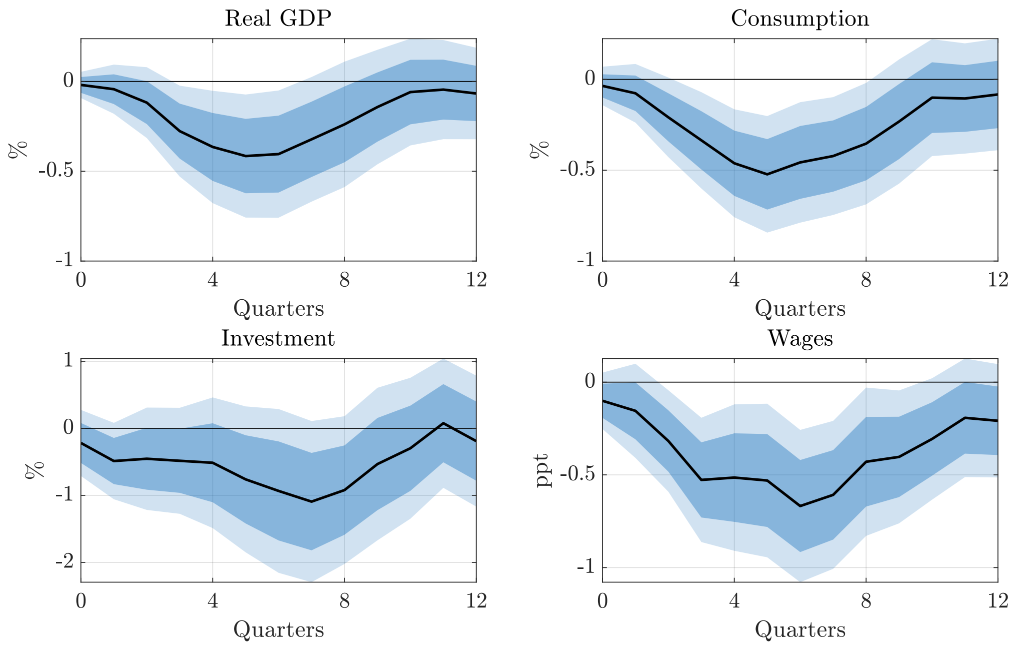


Figure B.6: Effect on GDP, Consumption, Investment and Wages in the UK

Notes: Impulse responses of a selection of quarterly variables estimated using local projections on the carbon policy shock. The responses are normalized to have the same peak effect on HICP energy as in the baseline model.

B.3. More on heterogeneous effects

In this Appendix, I present some additional results pertaining to Section 5 on the heterogeneous effects of carbon pricing in the paper.

B.3.1. Further descriptive statistics

Figure B.7 compares the empirical distribution of age and total expenditure for the three income groups. We can see that the groups are comparable in terms of their age distribution. As expected, higher income groups tend to have higher expenditure but there is also more within group variation.

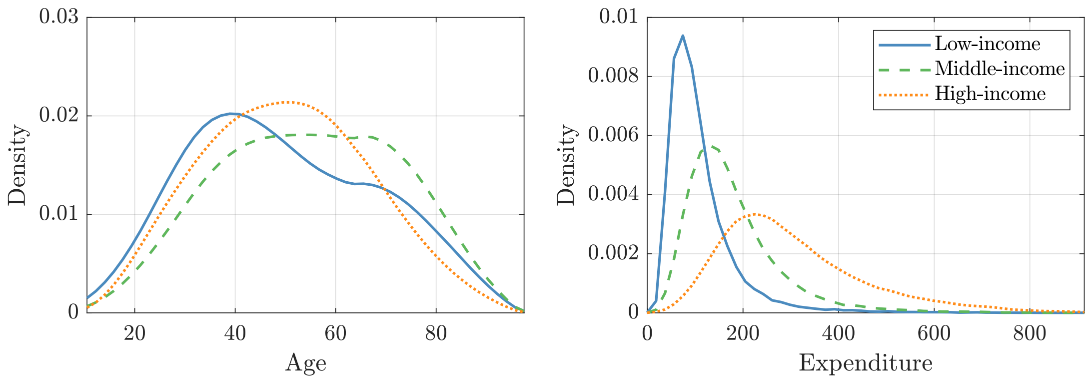


Figure B.7: Empirical Distribution of Age and Total Expenditure in the LCFS

Notes: The figure shows the empirical probability distribution of age and total expenditure (excl. housing) for all three income groups. The distributions are estimated using an Epanechnikov kernel.

Figure B.8 depicts the evolution of different households characteristics, including age, education and housing tenure, over time. We can see that there are some trends in these variables, however, they are rather slow-moving and thus unlikely to confound potential heterogenities in the household responses to carbon policy shocks, which exploit variation at a much higher frequency.

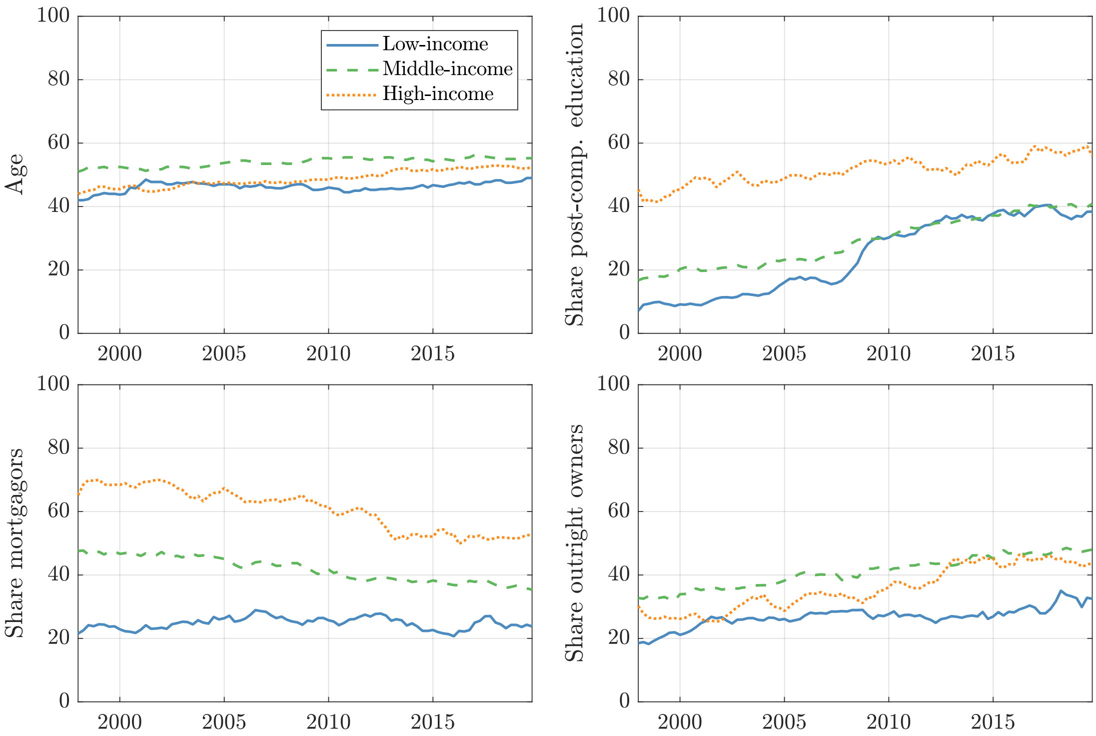


Figure B.8: Evolution of Household Characteristics by Income Group

Notes: The figure shows the evolution of age, education, and housing tenure status over time by income group.

B.3.2. Aggregate expenditure responses

Before studying at the heterogeneous expenditure responses by income group, I look at the aggregate expenditure responses as a validating exercise. The results are shown in Figures B.9. We can see that the response of aggregated expenditure from household micro data is very similar to the consumption response from national statistics – both in terms of shape and magnitude. This supports the notion that the micro data is indeed representative for the macroeconomy. For completeness, I also report the aggregated responses for different expenditure categories.

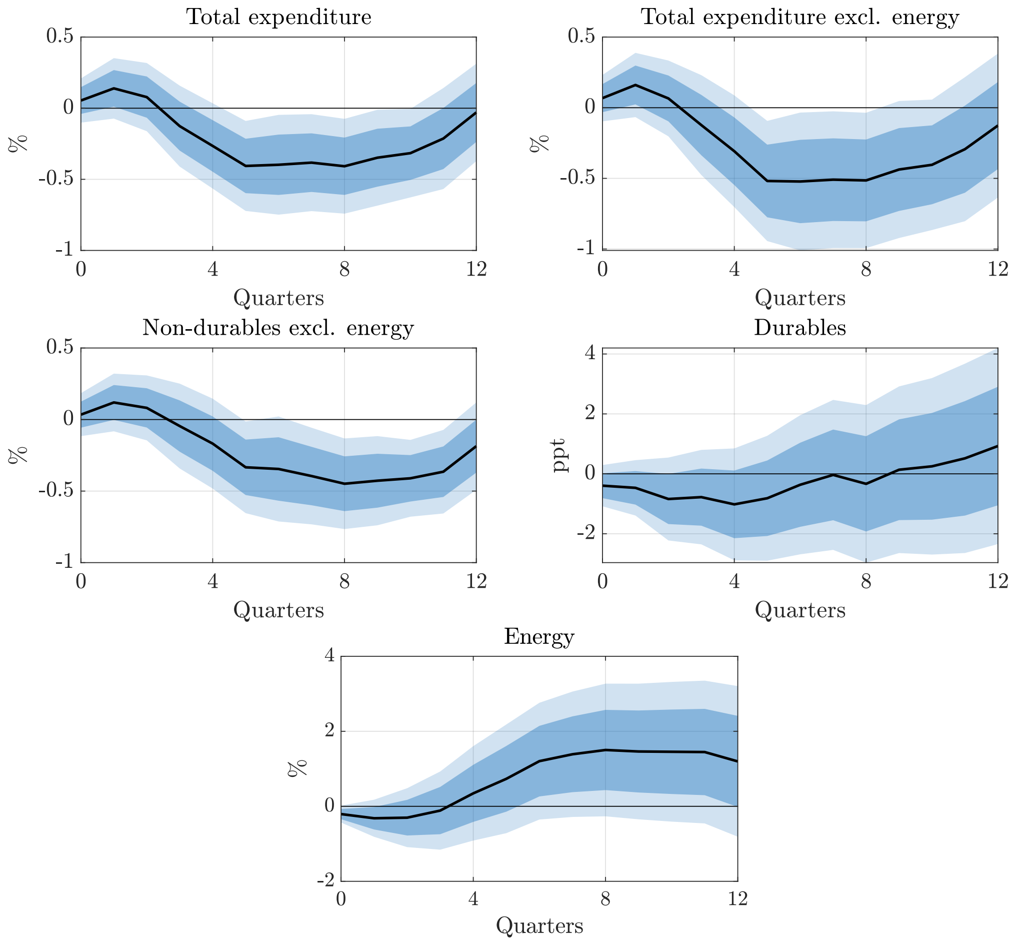


Figure B.9: Aggregate Expenditure Responses

B.3.3. Smoothing impulse responses

In the LCFS, households interviewed at time t are typically asked to report expenditure over the previous three months (with the exception of non-durable consumption which refers to the previous two weeks). To eliminate some of the noise inherent in survey data, I smooth the expenditure and income measures with a backward-looking (current and previous three quarters) moving average, as in Cloyne, Ferreira, and Surico (2020). However, as shown in Figure B.10, the results are very similar when using the raw series instead, even though the responses become more jagged and imprecise, or by using smooth local projections as proposed by Barnichon and Brownlees (2019).

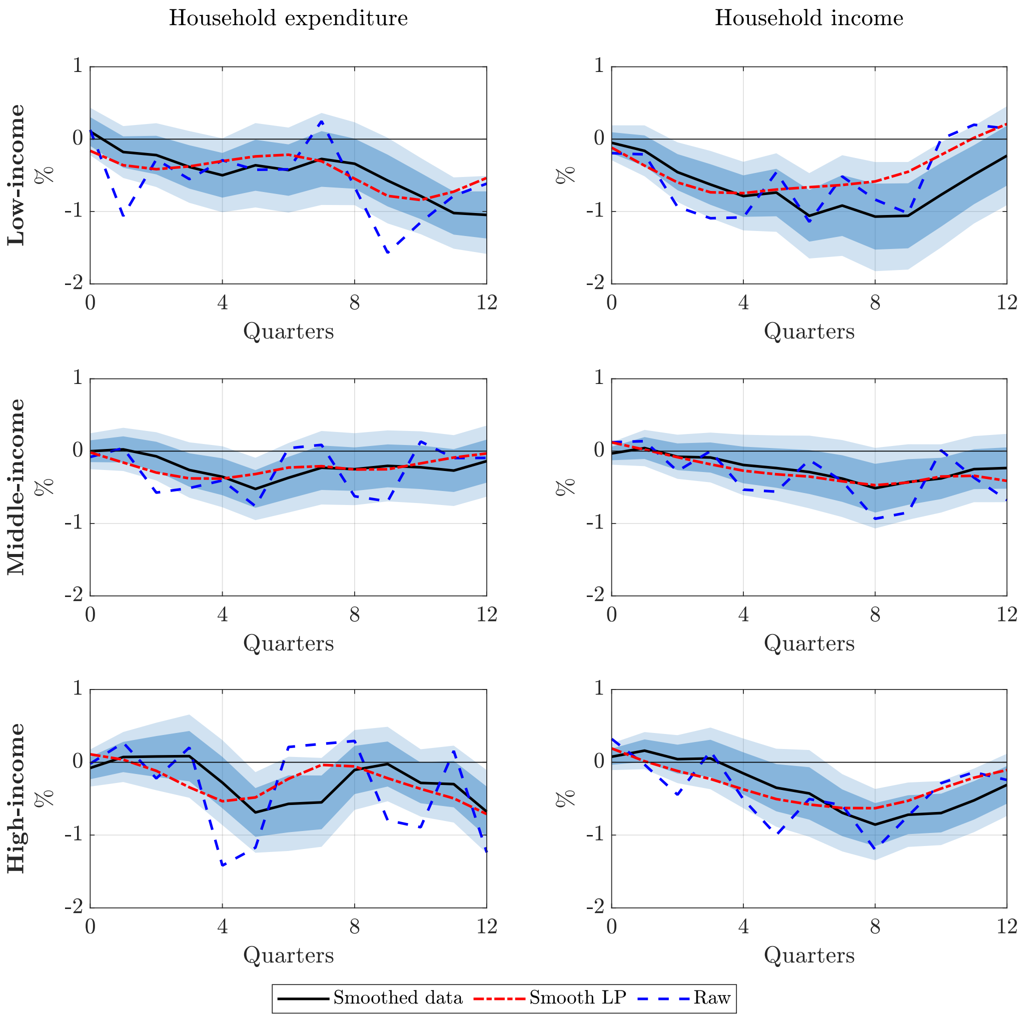


Figure B.10: Sensitivity with Respect to Smoothing of Responses

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income by income group, computed using simple backward-looking moving average (baseline), smooth local projections (red dotted line), and unsmoothed (blue dashed line).

B.3.4. Group differences

In the main text, we document pervasive heterogeneity in the expenditure and income responses by household income group. Another important question is whether these differences are statistically significant. To this end, I estimate the responses of the group differences in expenditure and income, in particular low-income versus middle-income and low-income versus high-income. The responses are shown in Figure B.11. We can see that low-income households display a significantly stronger fall in income and expenditure than higher-income households. Thus, the group differences are not only economically but also statistically significant.

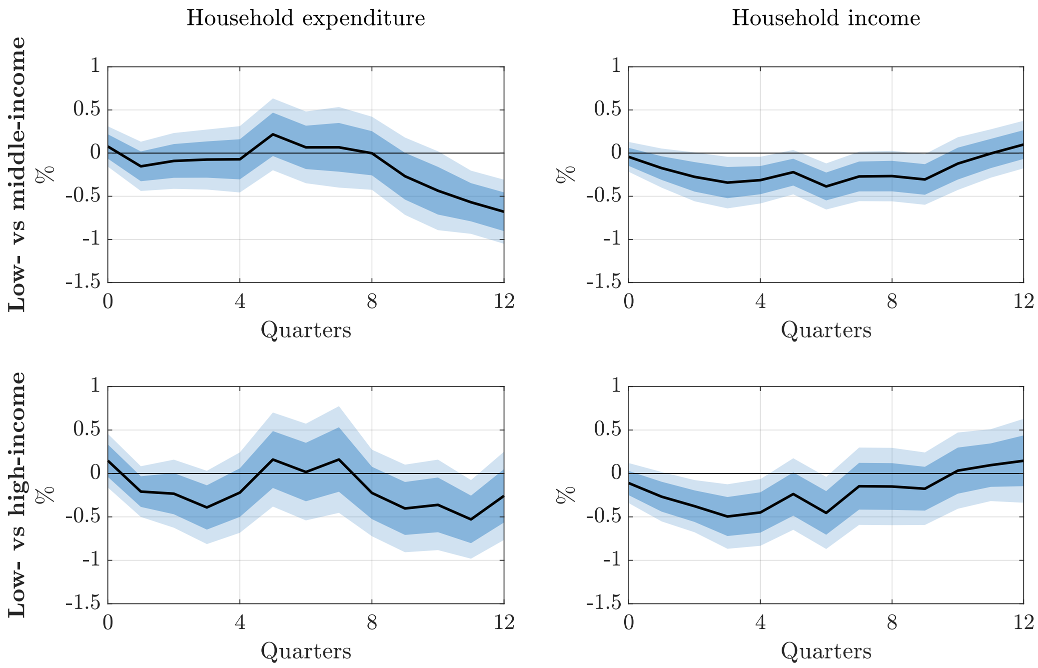


Figure B.11: Group differences in Expenditure and Income Responses

B.3.5. Robustness concerning grouping

To mitigate concerns about endogenous changes in the grouping variable, I look at the responses of current and normal disposable income in Figure B.12. We can see that both variables are rather slow-moving. Current income starts to fall significantly after about a year. In contrast, the response of normal disposable income moves less and is insignificant, supporting its validity as a grouping variable.

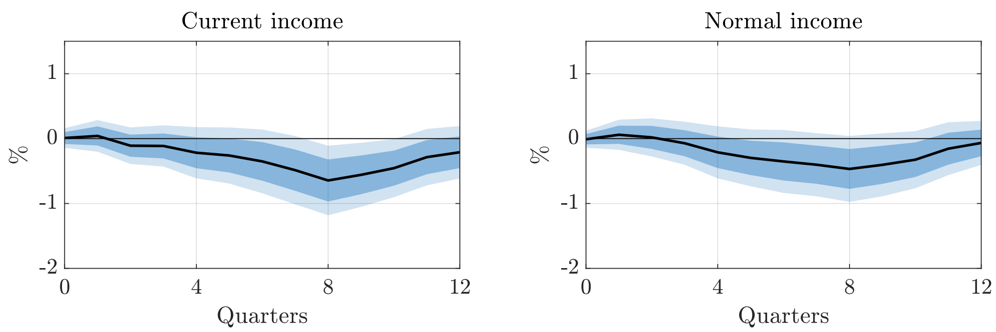


Figure B.12: Responses of Current and Normal Income

As discussed in the main text, the normal income variable can be thought of as a proxy for permanent income. As a robustness check, I compute estimates for permanent income from a Mincerian-type regressions. Specifically, I use age, education, ethnicity, sex, martial status, occupation, the source of the main household income, as well as interactions between age and education, and between age and sex as predictors, as in Alves et al. (2020). Figure B.13 shows the responses by permanent income group. We can see that the results turn out to be robust.

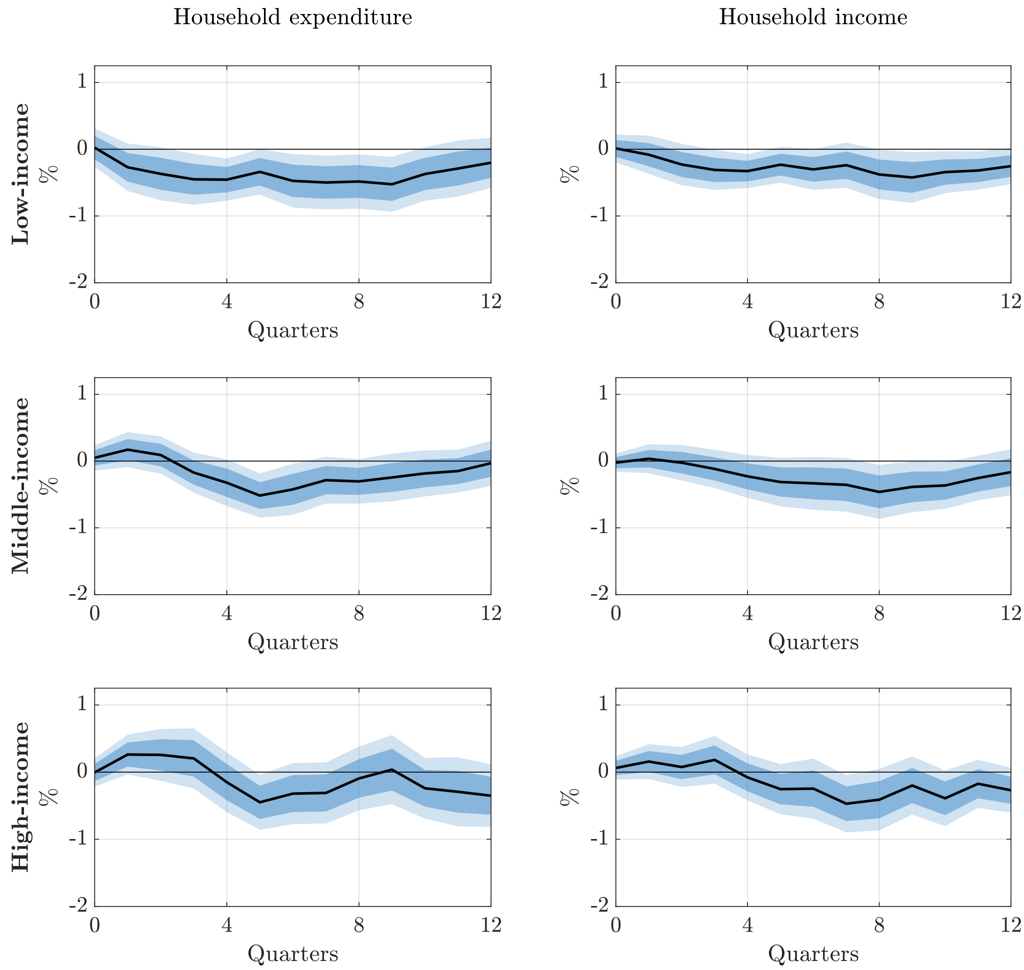


Figure B.13: Expenditure and Income Responses by Permanent Income

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income by permanent income, estimated using a Mincerian-type regression using age, education, ethnicity, sex, martial status, occupation, the source of the main household income, as well as interactions between age and education, and between age and sex (bottom 25 percent, middle 50 percent, top 25 percent).

B.3.6. Selection

To mitigate concerns about selection, I use a number of different grouping variables, including age, education and housing tenure. From Figures B.14-B.16, we can see that none of these alternative grouping variables can account for the patterns uncovered for income, suggesting that we are not spuriously picking up differences in other household characteristics. Similarly, the uncovered heterogeneity can also not be accounted for by occupation, sex and region. These results are available from the author upon request.

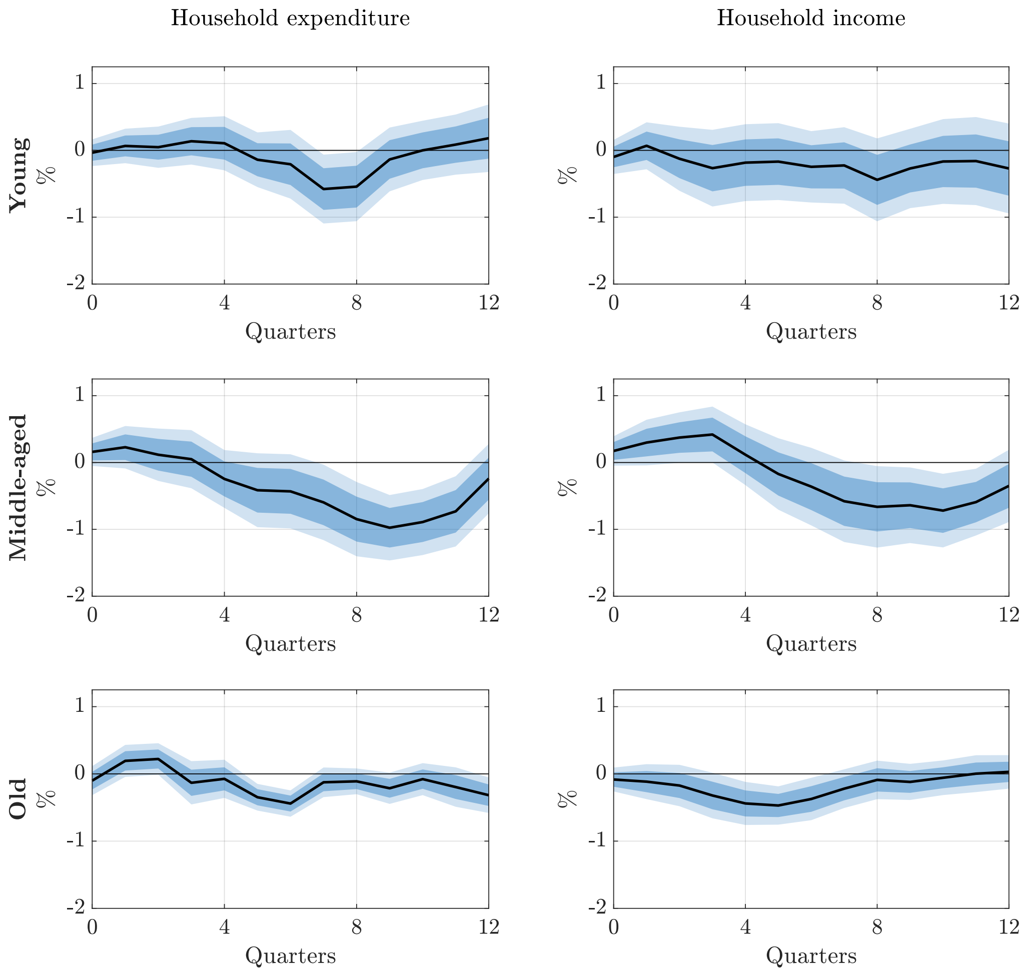


Figure B.14: Household Expenditure and Income Responses by Age Group

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income for young (bottom 33 percent), middle-aged (middle 33 percent) and older households (top 33 percent), based on the age of the household head.

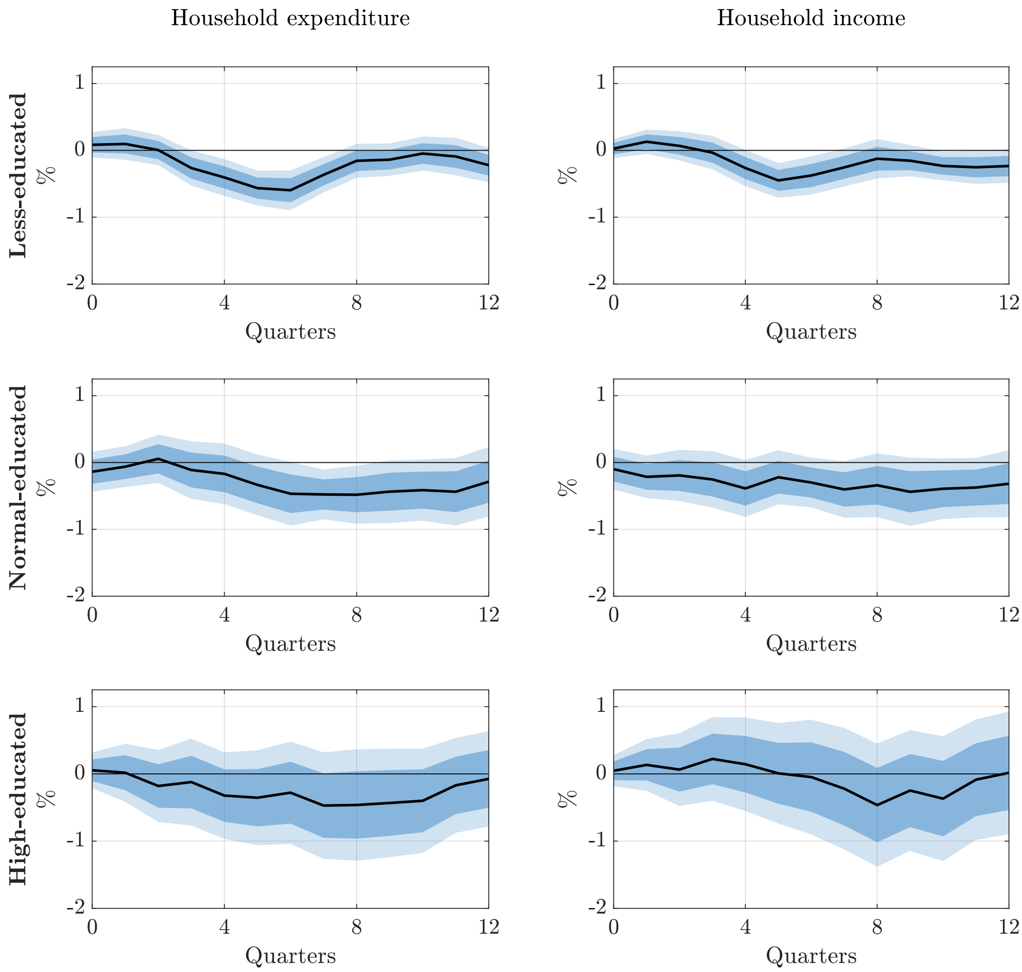


Figure B.15: Household Expenditure and Income Responses by Education Status

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income for less educated, normally educated and well educated households. Education status is proxied by the highest age a household member has completed full-time education and the three groups are below 16 years, between 17 and 18 years (compulsory education), and 19 years or above (post-compulsory).

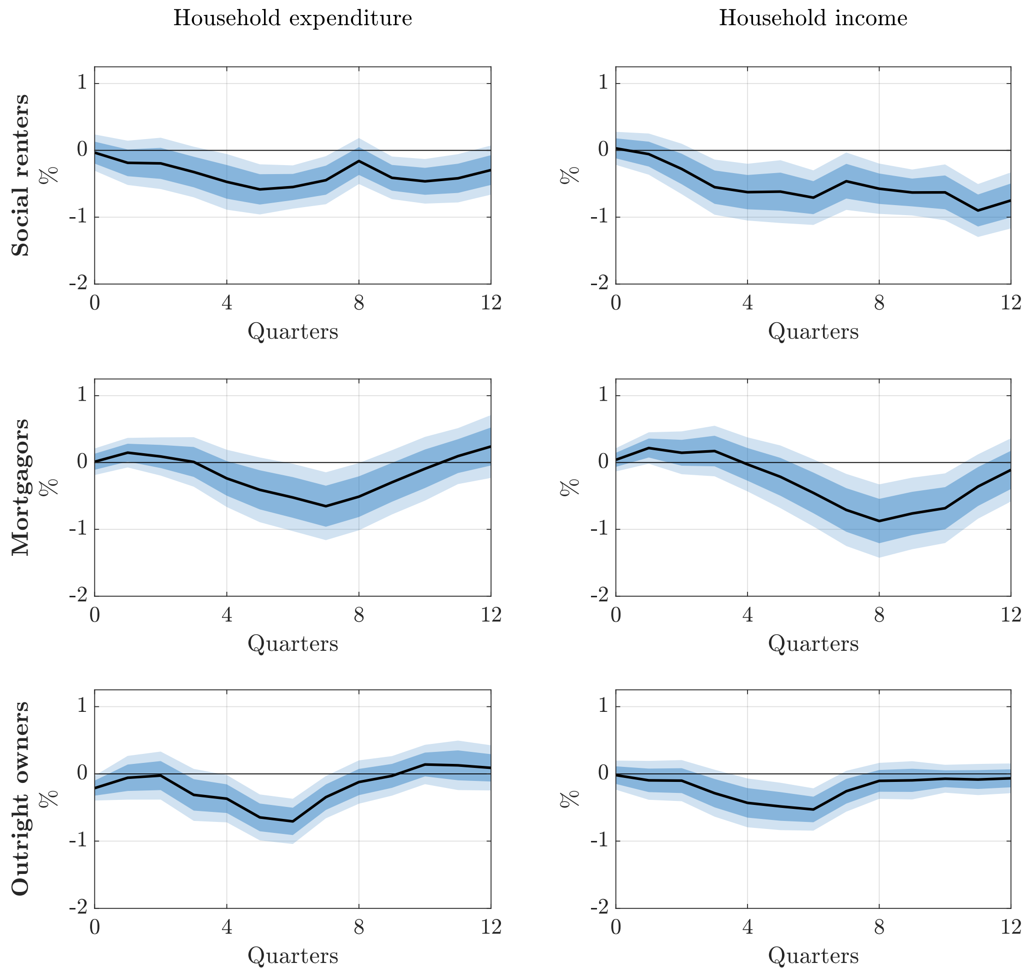


Figure B.16: Household Expenditure and Income Responses by Housing Tenure

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income for social renters, mortgagors and outright owners.

B.3.7. What drives the income response?

To understand what is driving the heterogeneity in the income responses, we study how the labor income responses vary by sector of employment using data from the LFS. To this end, I grouped sectors according to their SIC 2003 sections by their energy intensity and their "demand sensitivity", i.e. how much sectoral labor income changes after changes in aggregate income. The data on energy intensities is from the ONS. The demand sensitivity is proxied by the elasticity of sectoral labor income to aggregate labor income, using sectoral data from the LFS and wage data from national accounts. Similar results are obtained when estimating the elasticity with respect to the unemployment rate. Table B.4 shows the data on sectoral energy intensity and estimated demand sensitivity together with the resulting classification. I define high energy intensive sectors as sectors

Table B.4: Sectors by Energy Intensity and Demand Sensitivity

Panel A: Energy intensity and estimated demand sensitivity

Sectors		Energy intensity (TJ/£m)	Demand sensitivity ($\varepsilon_u y_i$)
A-B:	Agriculture, forestry and fishing	11.4	0.43
C,E:	Mining and quarrying; energy, gas and water	12.8	0.16
D:	Manufacturing	11.6	0.44
F:	Construction	2.6	0.52
G-H:	Wholesale and retail trade; hotels and restaurants	3.0	0.51
I:	Transport, storage and communication	9.4	0.19
J-K:	Banking, finance and insurance	0.7	0.41
L-N:	Public admin, education and health	1.3	0.35
O-Q:	Other services	1.1	0.72

Panel B: Sector classification

Group	Sectors	SIC sections
High energy intensity	Agriculture, forestry, and fishing; mining and quarrying; manufacturing; electricity, gas and water supply (utilities); transport, storage and communications	A-E, I
Lower energy intensity	Construction; Wholesale and retail trade; Hotels and restaurants; Financial intermediation; Real estate, renting and business; Public administration and defense; Education; Health and social work; Other community, social and personal services	F-H, J-Q
High demand sensitivity	Construction; Wholesale and retail trade; Hotels and restaurants; Other community, social and personal services	F-H, O-Q
Lower demand sensitivity	Agriculture, forestry, and fishing; mining and quarrying; manufacturing; electricity, gas and water supply (utilities); transport, storage and communications; Financial intermediation; Real estate, renting and business; Public administration and defense; Education; Health and social work	A-E, J-N

Notes: The sectors are grouped based on SIC 2003 sections. Note that the grouping is not perfect, as the LFS only has information on groups of sections over the entire sample of interest. The data on the energy intensity by sector from 1999-2019 is from the ONS.

with an energy intensity above 5 and high demand sensitive sectors as sectors with a demand sensitivity in excess of 0.5. Choosing the threshold involves some judgment. As a robustness check, I have excluded/included the sectors closest to the two thresholds for both groupings. The results turn out to be not sensitive to the precise level of the threshold.

Finally, another source of heterogeneity in the income response is the income composition. To better understand this, I study the responses of labor earnings and financial income. We can see that the earnings of low-income households fall more promptly and significantly than for higher-income households, consistent with the results on total income. On the other hand, the financial income of low- and middle-income households barely shows a response, reflecting the fact that these households own very little financial assets. In contrast, high-income households experience a temporary fall in their financial income in the short run, which however subsequently reverts (consistent with the stock market response).

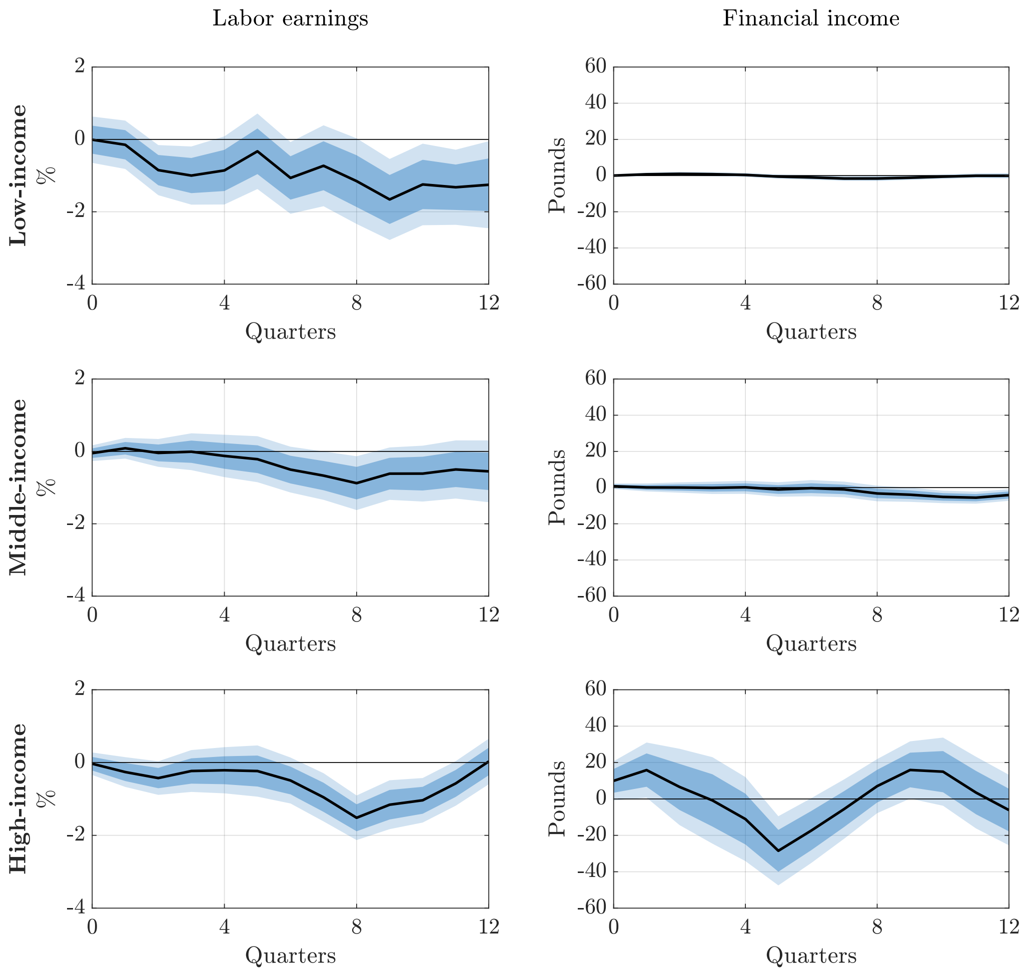


Figure B.17: Responses of Earnings and Financial Income

Notes: Impulse responses of labor earnings (wages from main occupation) and financial income (interest, dividend, rents) by income group (bottom 25 percent, middle 50 percent, top 25 percent).

B.3.8. External validity

To mitigate concerns regarding external validity, I confirm the main results on the heterogeneity in household expenditure by income group using data for Denmark and Spain. As can be seen from Figure B.18, the expenditure response turns out to be significant and persistent for low-income households, while high-income households are much less affected. These findings confirm the results for the UK, supporting the external validity of the results.

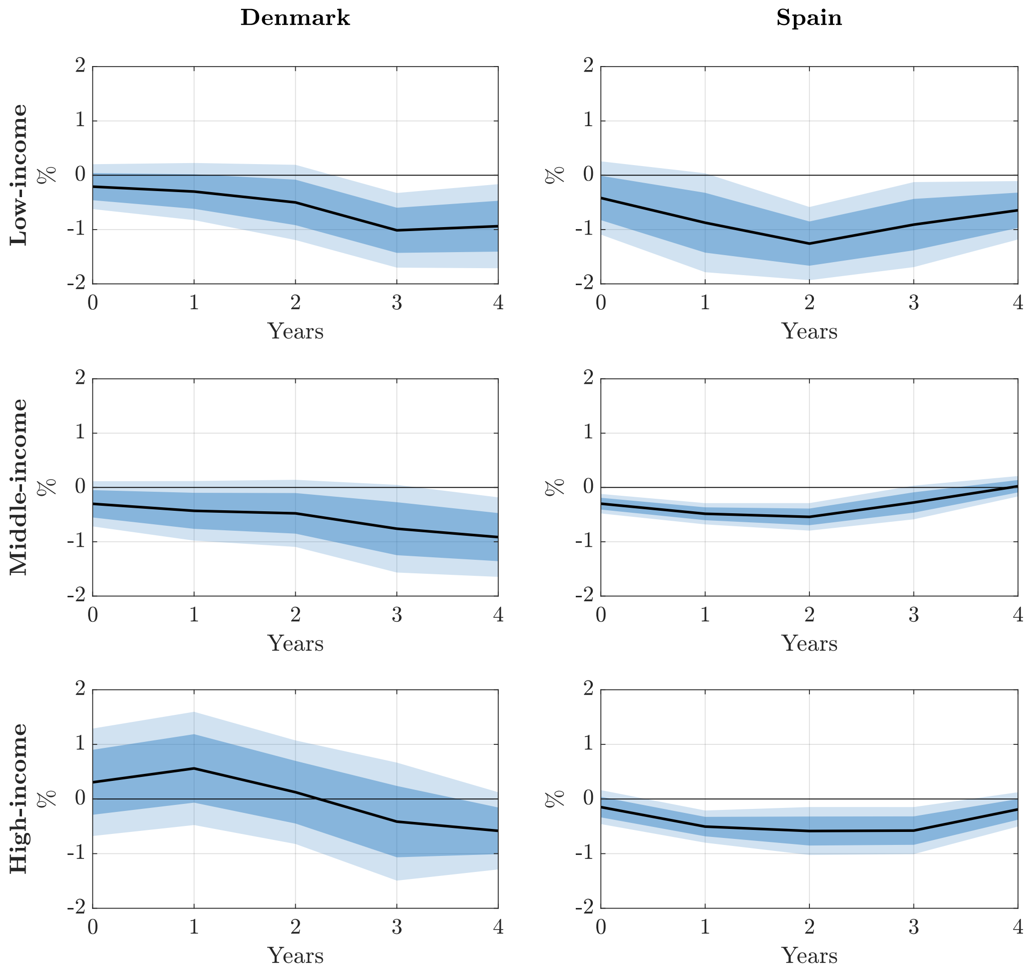


Figure B.18: Expenditure by Income Group for Other European Countries

Notes: Impulse responses of total expenditure for low-income, middle-income and high-income households in Denmark and Spain. The Danish data are from the Danish household budget survey (HBS) available for 1999-2019, accessed via the StatBank Denmark database, and expenditure is grouped by total annual income (under 250K DKK, 250-999K DKK, 1000K DKK or over). The Spanish data are from the Spanish HBS available for 2006-2019, accessed via the INE website, and expenditure is grouped by regular net monthly household income (under 1000 euros, 1000-2499 euros, 2500 euros or over).

B.3.9. Attitudes towards climate policy

As discussed in the paper, public opposition can be an impediment for climate policy. Thus, it is interesting to see how carbon pricing affects the public attitude towards climate policy. To analyze this question, I use data from the British social attitudes (BSA) survey. The BSA is an annual survey that asks about the attitudes of the British population towards a wide selection of topics, ranging from welfare to genomic science. The BSA is used to inform the development of public policy and is an important barometer of public attitudes. Some of the questions in the BSA are repeated over time and thus, it is possible to analyze how certain attitudes have changed over time.

To proxy the public attitude towards climate policy, I rely on a question from the transportation module of the survey, which asks about the attitude towards environmentally-motivated fuel taxes. In particular, the question asks whether the respondent agrees with the following statement: "For the sake of the environment, car users should pay higher taxes". The BSA also includes information about the income of the respondent, thus it is possible to analyze how the attitudes of different income groups have evolved. Figure B.19 shows how the attitude towards climate policy has changed among low- and higher-income households. We can see that the support of climate policy has remained relatively stable at moderate levels for a large part of the sample. In the early to middle 2010s, the support started increasing for higher-income households. In contrast, the support of low-income households has remained stable until the end of the sample.

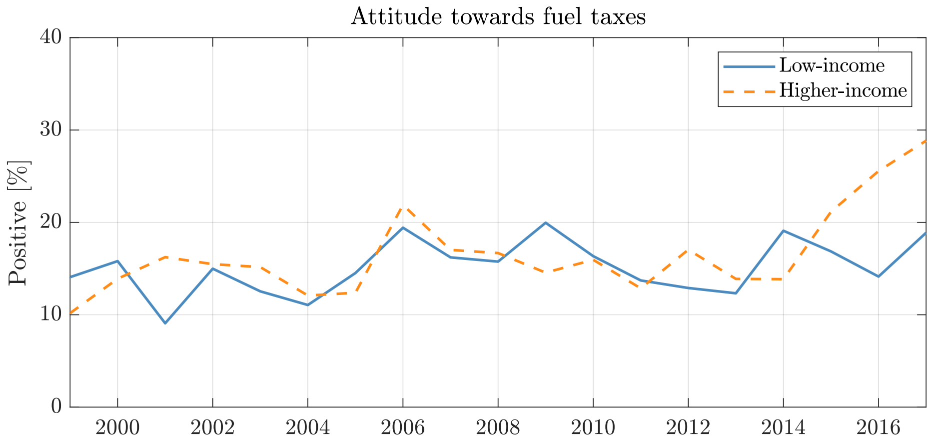


Figure B.19: Public support for climate policy by income group

Notes: The figure shows the evolution of the attitude towards climate policy by income group, as proxied by the share of households in the British social attitudes survey that agree to the following statement: "For the sake of the environment, car users should pay higher taxes".

B.4. Additional results from heterogeneous-agent climate-economy model

In this appendix, we present some additional results from the heterogeneous-agent climate-economy model. Figure B.20 shows the response of emissions under the different carbon revenue redistribution schemes. We can see that emissions fall by somewhat less when redistributing revenues than under the baseline case when all revenues accrue to the savers but importantly, the consumption response is dampened significantly more (by a factor close to 45 percent). This suggests that there may be a trade-off that policy makers could exploit. The intuition behind this result is that low-income households' energy demand is particularly inelastic and they make up only a small share of aggregate emissions to start with.

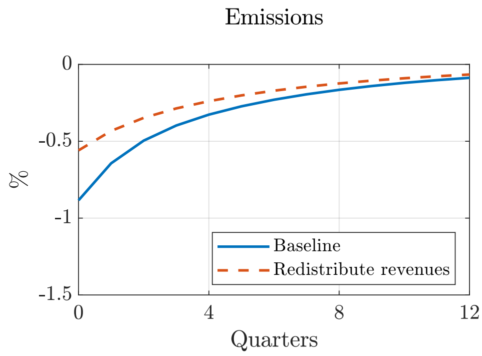


Figure B.20: Emissions Response

As discussed in the main text, monetary policy plays an important role in the transmission of the policy. After a carbon policy shock leading to an increase in energy prices, monetary policy leans against the inflationary pressures by increasing interest rates. This in turn leads to a further fall in consumption and investment. Figure B.21 shows the impulse responses under two different monetary policy rules. As the baseline, we assume that monetary policy targets headline inflation. As an alternative, we consider a rule where monetary policy targets core inflation. We can see that the effects on consumption and income are attenuated significantly when monetary policy targets core instead of headline inflation.

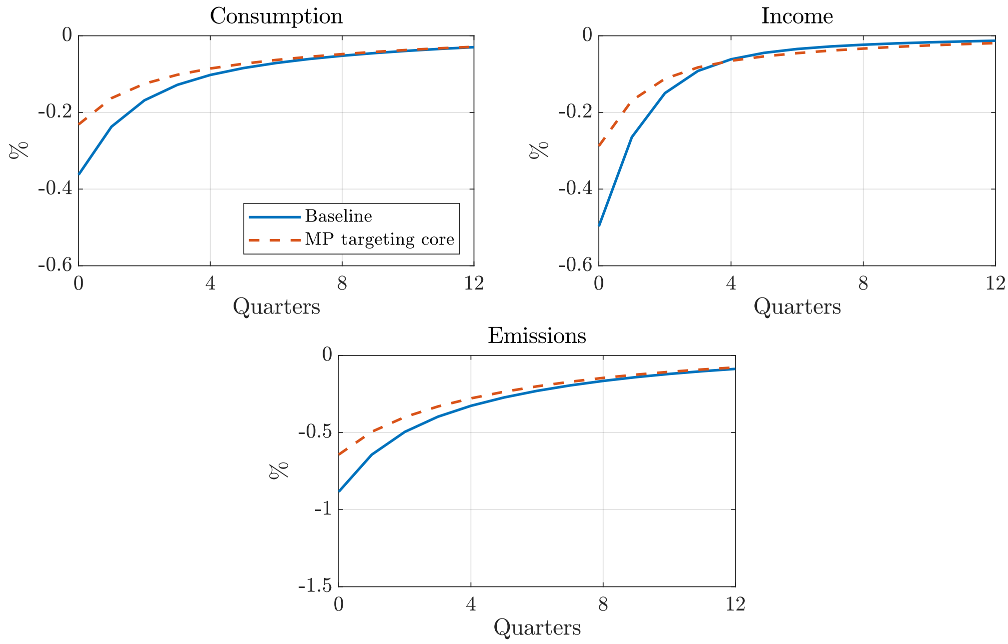


Figure B.21: The Role of Monetary Policy

Household heterogeneity also plays an important role for the magnitudes of the responses. In particular, heterogeneity in MPCs linked to heterogeneity in energy shares and income incidence can amplify the responses further. This is illustrated in Figure B.22, which compares the responses of the heterogeneous agent to the corresponding representative agent version of the model.

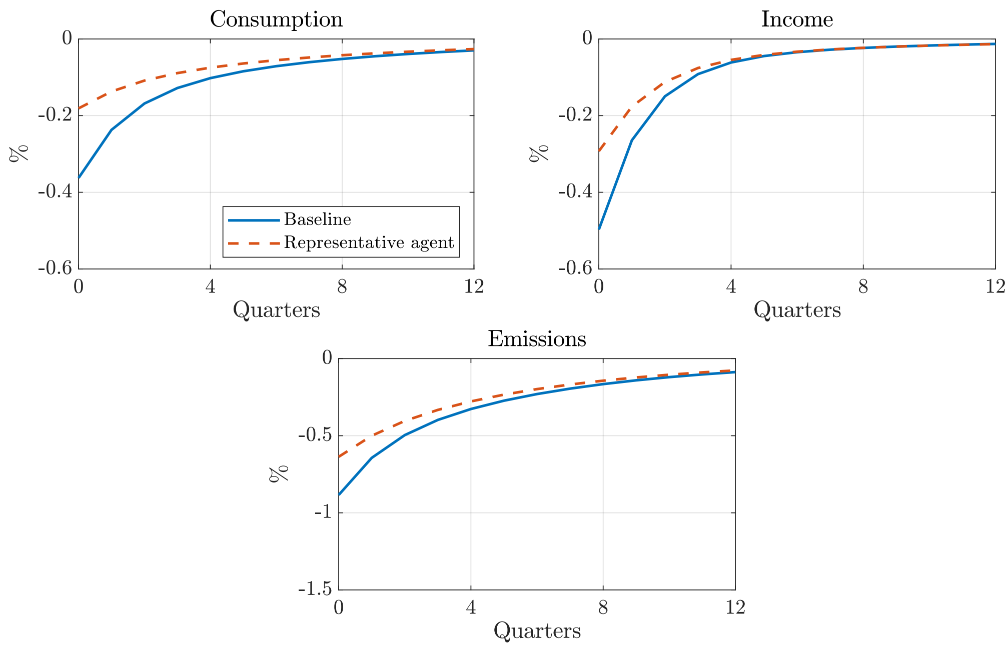


Figure B.22: Heterogeneity Versus Representative Agent

To get a better understanding of how much the heterogeneity matters for the direct and indirect channels we identify, we perform a decomposition. In particular, we compare four different scenarios: (i) a model where there is no heterogeneity in income incidence and energy share (this is achieved by perfectly redistributing income over the cycle and calibrating the energy share for H and S to the same level), (ii) a model with equal incidence but heterogeneity in energy shares, (iii) a model with unequal incidence and no energy share heterogeneity, and (iv) our baseline case with both heterogeneities. From Figure B.23, we can see that the heterogeneity in income incidence turns out to be crucial, accounting for the bulk of the amplification of the aggregate consumption response. This can be seen from the fact that the model with unequal incidence is already very close to the baseline with heterogeneous energy shares and income incidence.

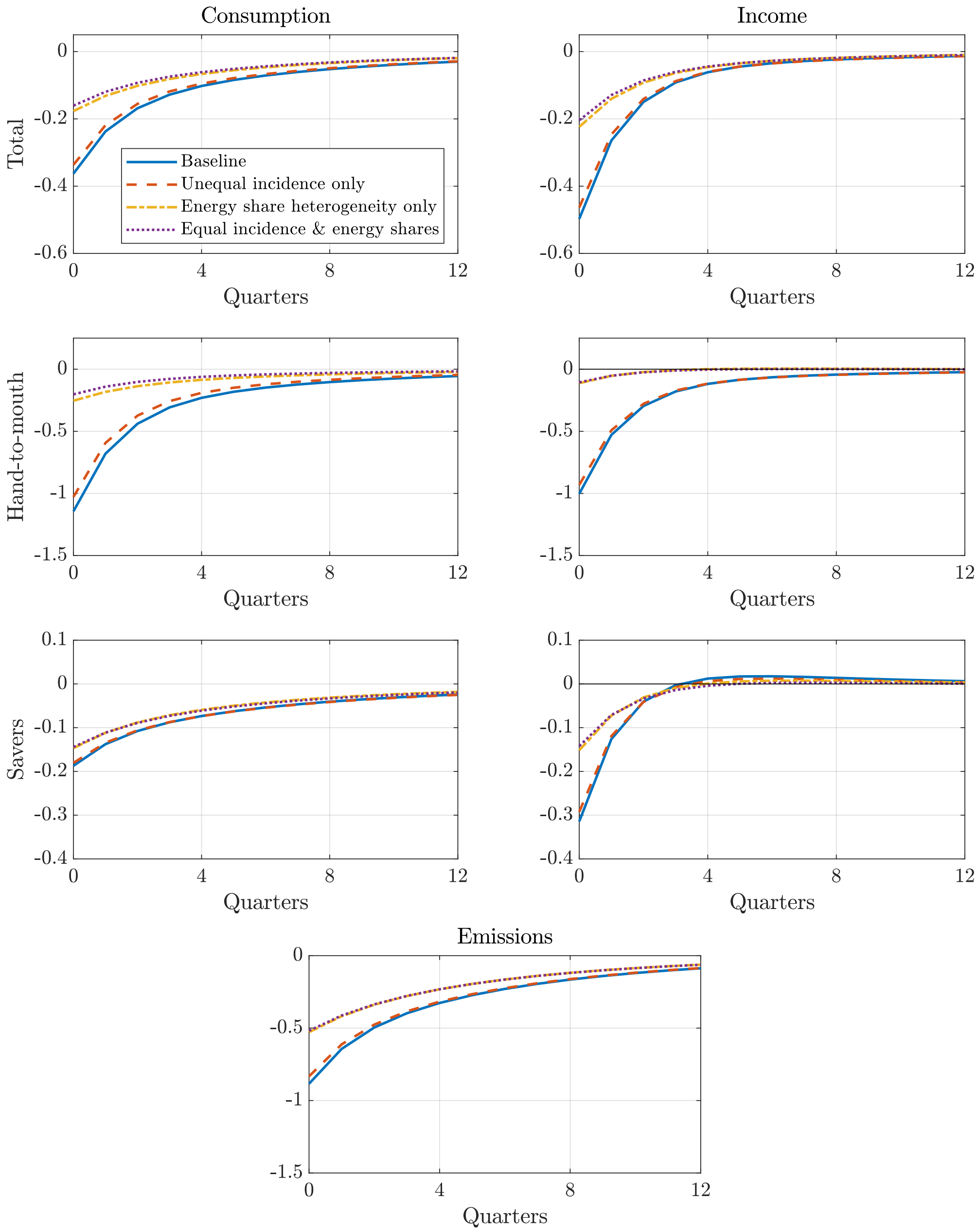


Figure B.23: Role of Unequal Income Incidence and Energy Share Heterogeneity

C. Sensitivity Analysis

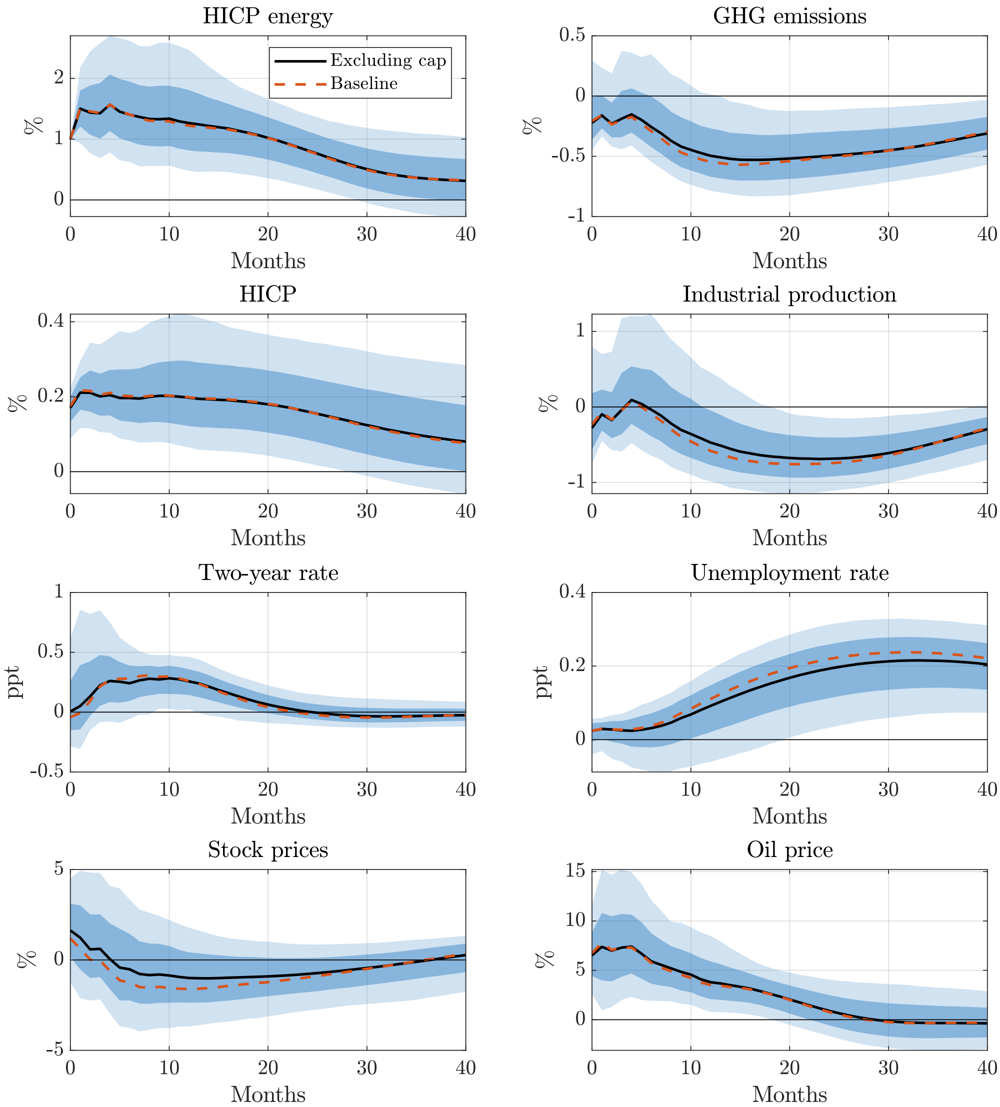
In this Appendix, I perform a number of robustness checks on the identification strategy and the empirical specification used to isolate the carbon policy shock, as discussed in Sections 2-3 of the paper. Throughout, I report the point estimate as the solid black line and 68 and 90 percent confidence bands as dark and light shaded areas, respectively.

C.1. Instrument construction

Selection of relevant events. A crucial choice in the high-frequency event study approach concerns the selection of relevant events. For the exclusion restriction to be satisfied, the events should only release information about the supply of emission allowances and not about other factors such as macroeconomic or geopolitical news. To this end, I have not included broader events such as the Paris agreement or other COP meetings but limited the analysis to specific events in the European carbon market. The most obvious candidates are events about the free allocation and auctioning of emission allowances. I have also included events on the overall cap in the carbon market as well as events about international credits.

Because the events concerning the cap tend to be broader in nature, I exclude these events as a robustness check. As shown in Figure C.1, the results turn out to be robust. I have also tried to exclude the events about international credits, which affect the supply of allowances only indirectly, by changing the number of credits from international projects that can be exchanged for allowances. From Figure C.2, we can see that the results turn out to be very similar. By going through all events in detail, I could also identify some events that are potentially confounded, either because some other event happened on the same day (more on this below) or because they could potentially also contain some information about demand in the carbon market. Reassuringly, however, excluding these events does not change the results materially (see Figure C.3).

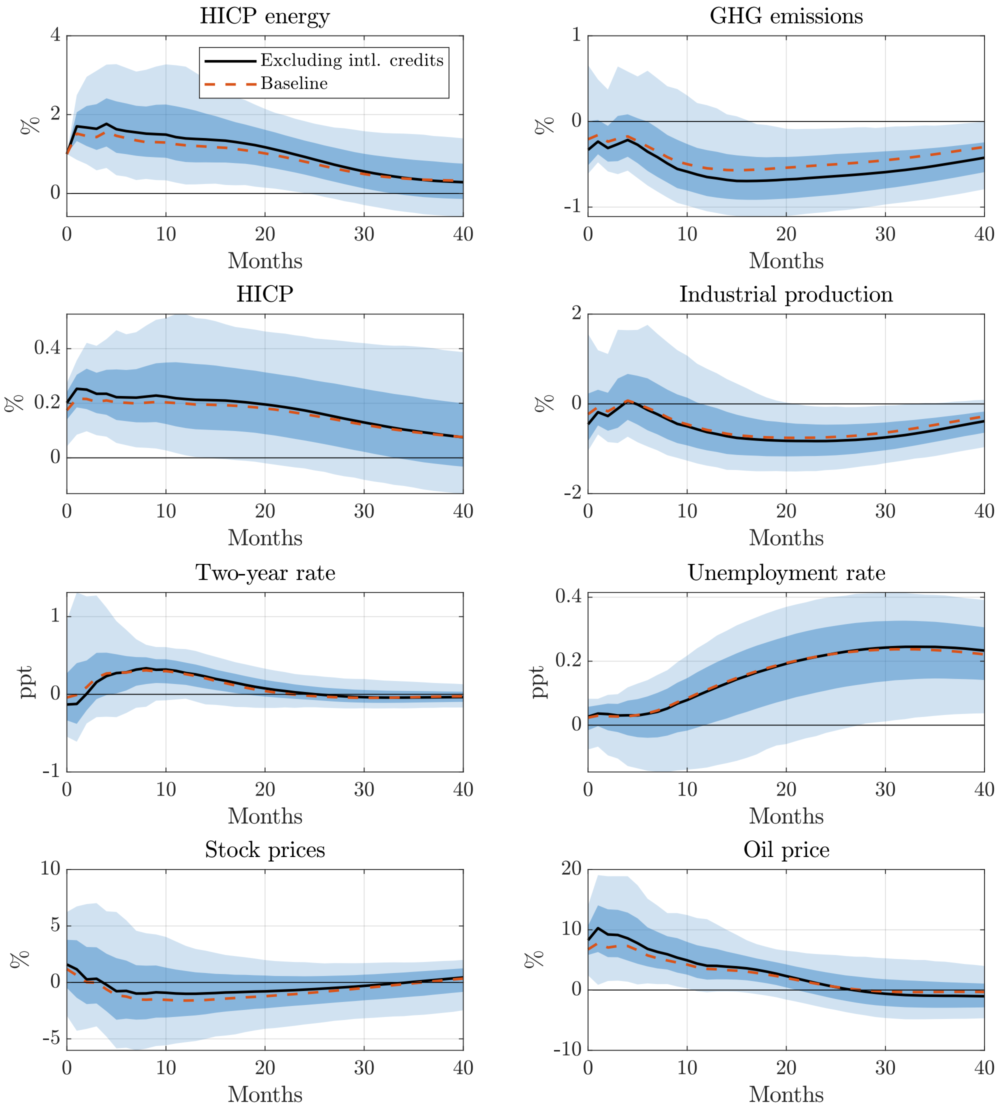
The results are also not driven by events in a given period. Excluding events in phase 1 (2005-2007) or events that occurred during the and European sovereign debt crisis (2009-2012) produces comparable results, see Figures C.4-C.5.



First stage regression: F-statistic: 18.97, R^2: 3.09%

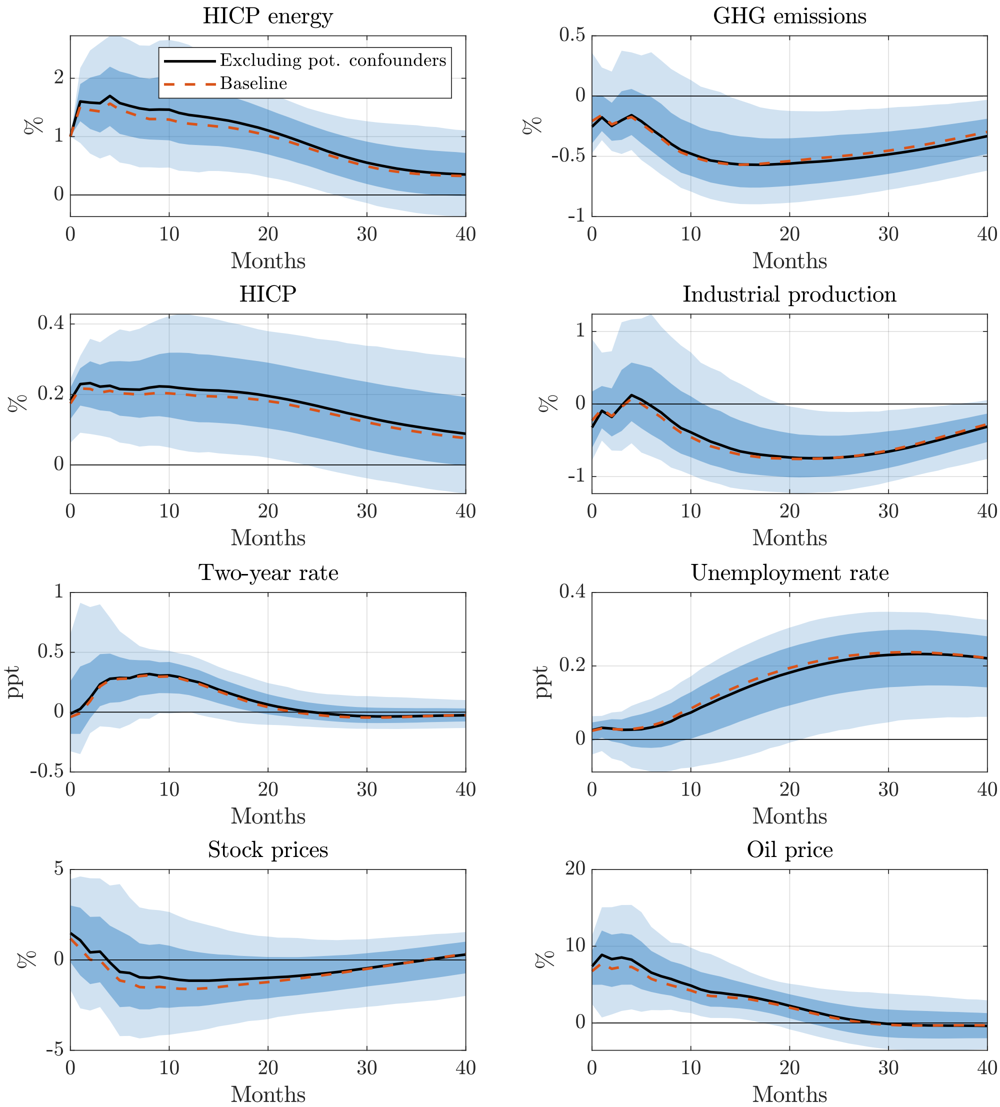
Figure C.1: Excluding Events Regarding Cap

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.



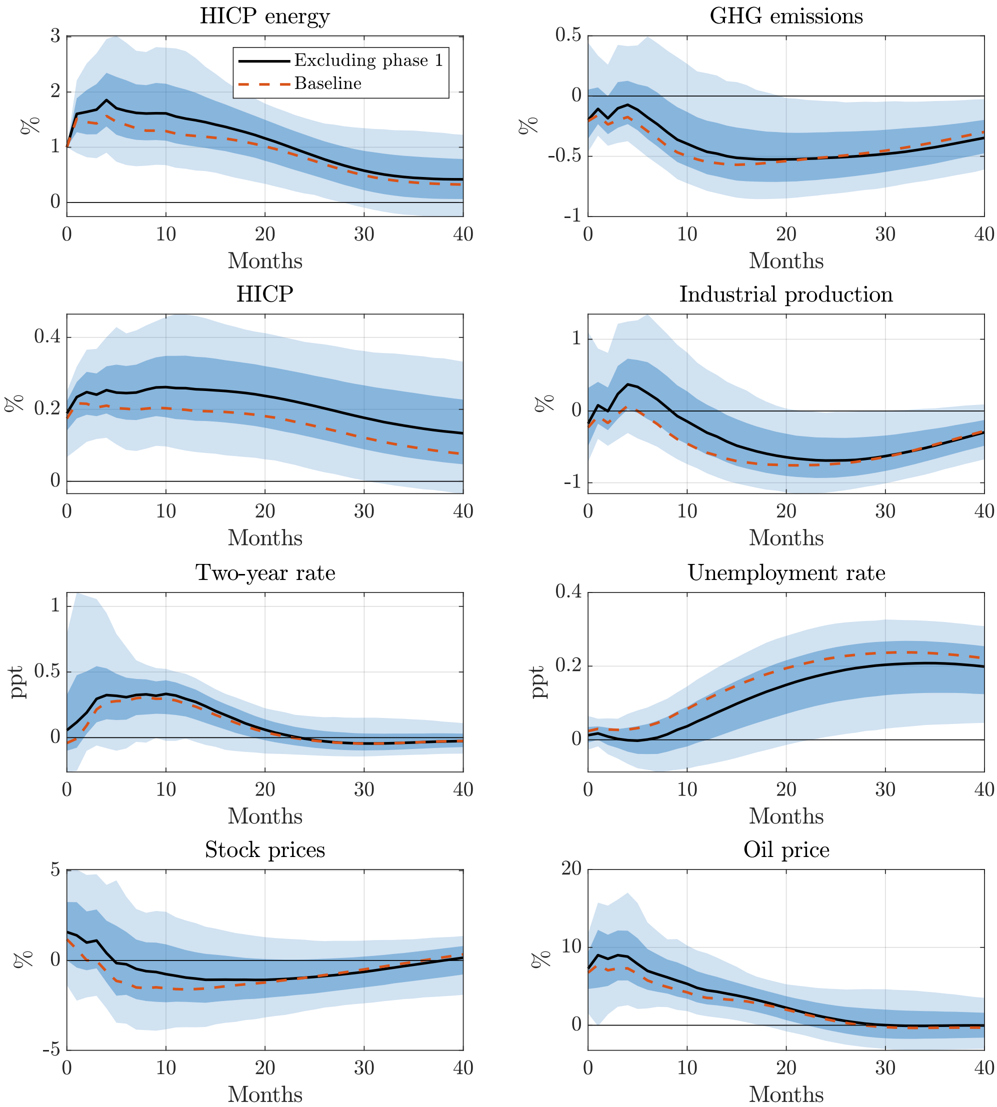
First stage regression: F-statistic: 11.99, R^2: 1.79%

Figure C.2: Excluding Events Regarding International Credits



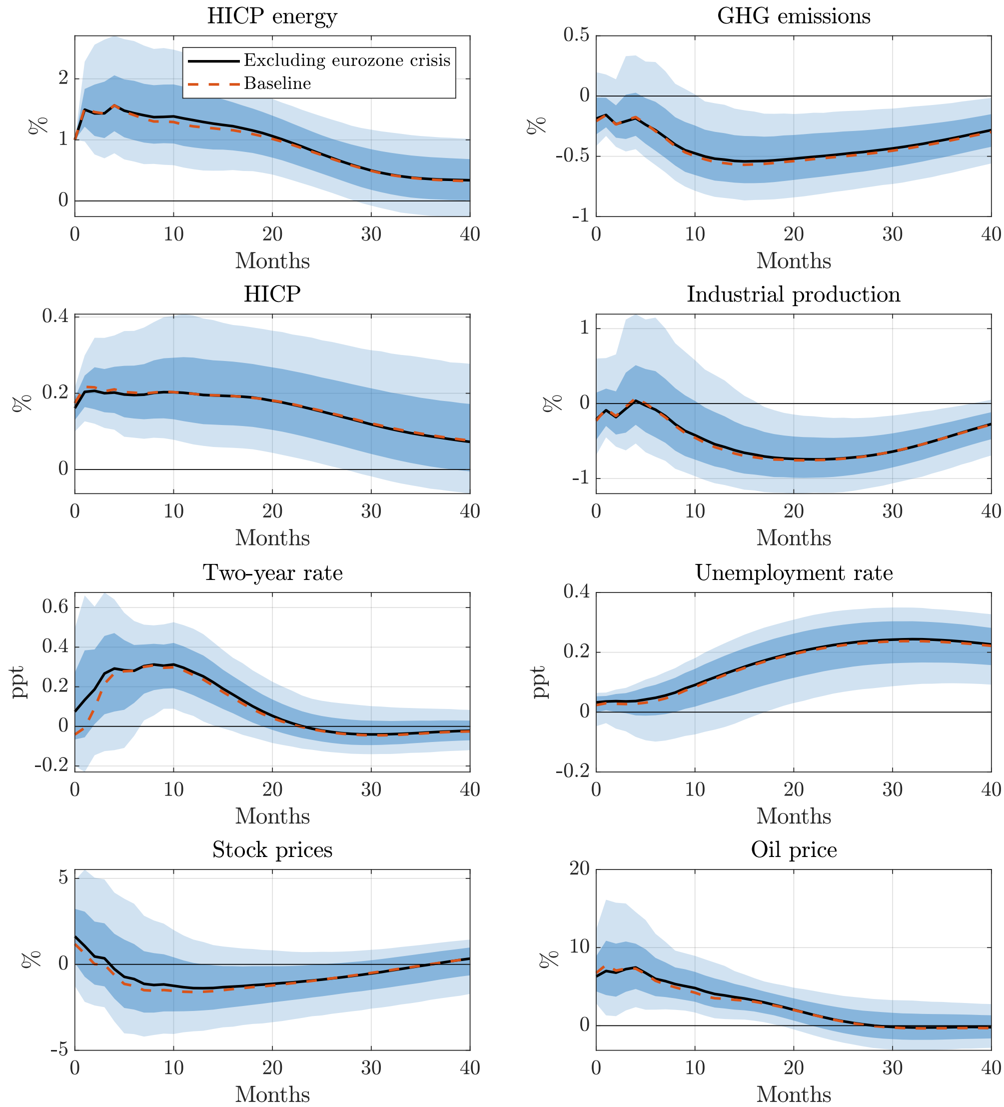
First stage regression: F-statistic: 17.30, R^2: 2.74%

Figure C.3: Excluding Potentially Confounded Events



First stage regression: F-statistic: 16.92, R^2: 2.71%

Figure C.4: Excluding Phase One Events



First stage regression: F-statistic: 21.81, R^2: 3.20%

Figure C.5: Excluding Events During European Sovereign Debt Crisis

Alternative instrument. As discussed in the paper, I measure the carbon policy surprises as the change in the EUA futures price on the day of the regulatory event relative to the prevailing wholesale electricity price on the day before the event. A key advantage of this approach is that it directly gives a notion of how economically relevant a carbon policy surprise is. In particular, it gives less weight to large percentage changes in carbon prices that occurred in an environment where carbon prices were very low. An alternative approach is to simply measure the surprise as the percentage change in the carbon price on event days. To fix ideas, the carbon policy surprise is in this case computed as follows:

$$CPSurprise_{t,d} = \log(F_{t,d}^{carbon}) - \log(F_{t,d-1}^{carbon})$$

where d and t indicate the day and the month of the event, respectively and $F_{t,d}$ is the settlement price of the EUA futures contract. This measure has the advantage that it is less focused on the electricity market but on carbon markets more broadly. However, because this approach generates one relatively large surprise in November 2007 when carbon prices were approaching zero, I exclude this event from the analysis.[4]

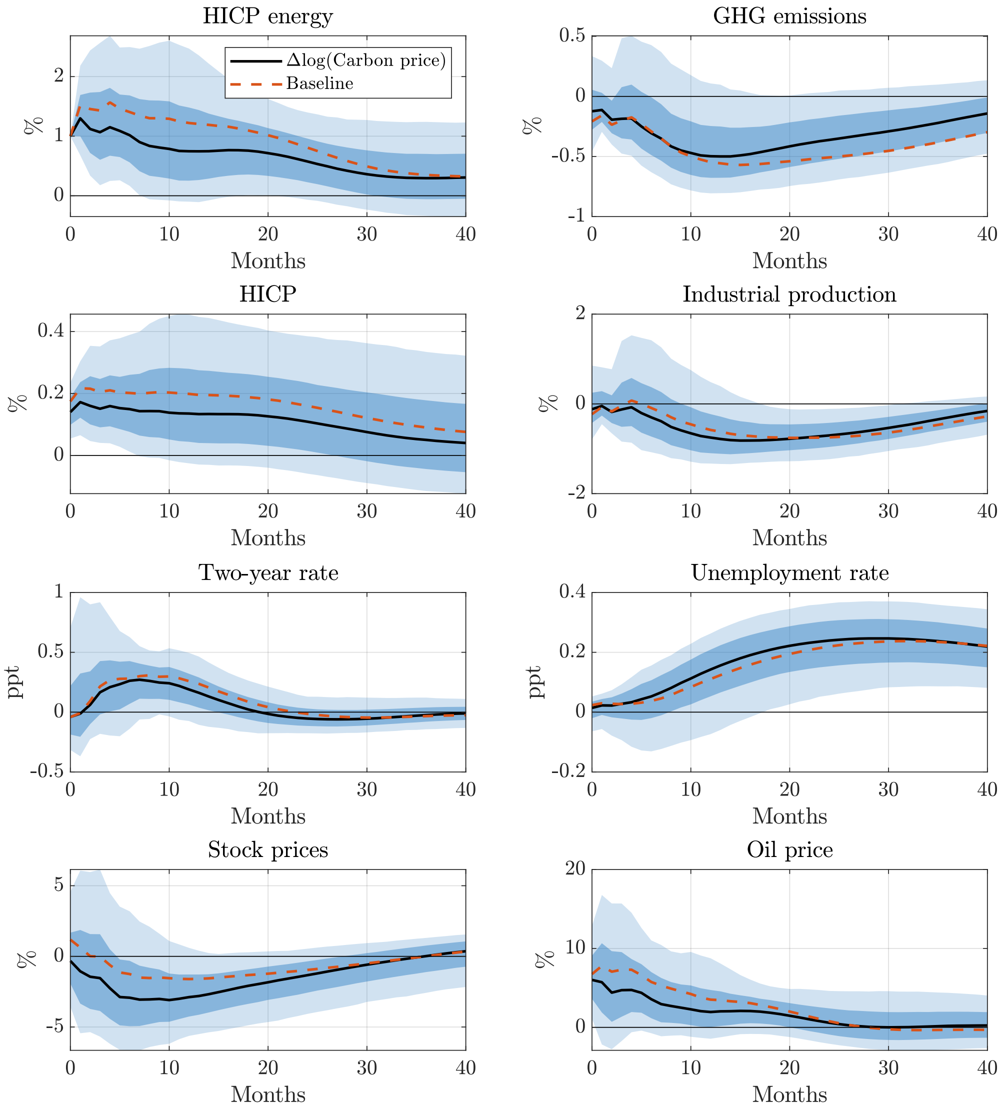
Figure C.6: Alternative Carbon Policy Surprise Series

Notes: The figure shows the carbon policy surprise series, measured as the percentage change in carbon prices around event days, compared to the baseline carbon policy surprise series, which is expressed relative to the prevailing wholesale electricity price before the event.

Figure C.6 shows the carbon policy surprise series, measured as the percentage change in carbon prices, relative to the baseline surprise series. We can see that the series are fairly similar, particularly during phase two and the beginning of the third phase. Overall, the two series are highly correlated, with a correlation coefficient of about 0.7.

Reassuringly, using the alternative instrument produces consistent results. Figure C.7 presents the impulse responses to a carbon policy shock using the alternative instrument, together with the baseline responses. We can see that the responses are very similar, both qualitatively and quantitatively. This illustrates the benefits of using the surprise series as an instrument as opposed to a direct shock measure.

[4]In a previous version of the paper, I used this measure of the carbon policy surprise series as the baseline. Interestingly, this produces very similar results, even when including the November 2007 event.



First stage regression: F-statistic: 16.69, R^2: 2.51%

Figure C.7: Instrument Based on Percentage Change in Carbon Price

Futures contracts. EUA futures are traded at different maturities. I focus on the contracts traded on a quarterly cycle. As a baseline, I use the front contract, which is the contract with the closest expiry date and is the most liquid. Figure C.8 presents the results based on other contracts. Overall, the responses turn out to be robust to using contracts with longer maturities. This supports the notion that the results are not severely affected by changes in risk premia.

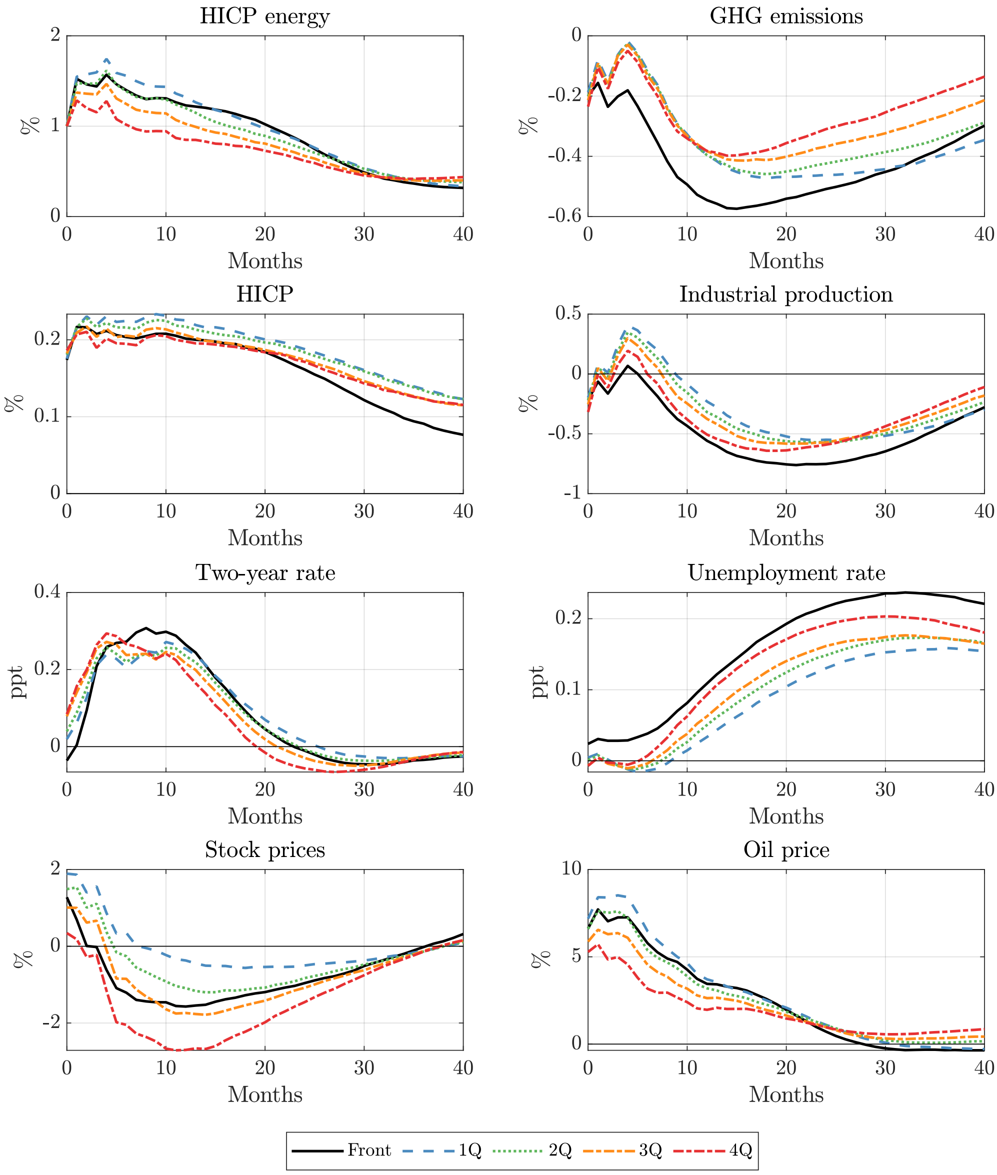


Figure C.8: Using Different Futures Contracts

C.2. Confounding news

Another important choice in high-frequency identification concerns the size of the event window. As discussed in Section 2.2, there is a trade-off between capturing the entire response to the policy news and background noise, i.e. the threat of other news confounding the response. Common window choices range from 30-minutes to multiple days. Unfortunately, the exact release times are unavailable for the majority of the policy events considered, making it infeasible to use an intraday window. Therefore, I use a daily window to compute the policy surprises.

To mitigate concerns about other news confounding the carbon policy surprise series, I employ an alternative identification strategy exploiting the heteroskedasticity in the data (Rigobon, 2003; Nakamura and Steinsson, 2018). The idea is to clean out the background noise in the surprise series by comparing movements in carbon prices during policy event windows to other equally long and otherwise similar event windows that do not contain a regulatory update event. In particular, I use the changes in carbon futures prices on the same weekday and week in the months prior a given regulatory event.

The identification strategy works as follows. Suppose that movements in the EUA futures z_t we observe in the data are governed by both carbon policy and other shocks:

$$z_t = \varepsilon_{1,t} + \sum_{j \neq 1} \varepsilon_{j,t} + v_t,$$

where $\varepsilon_{j,t}$ are other shocks affecting carbon futures and $v_t \sim iidN(0, \sigma_v^2)$ captures measurement error such as microstructure noise. Because z_t is also affected by other shocks, it is no longer a valid external instrument. However, we can still identify the structural impact vector by exploiting the heteroskedasticity in the data.

The identifying assumption is that the variance of carbon policy shocks increases at the time of regulatory update events while the variance of all other shocks is unchanged. Define $R1$ as a sample of regulatory events in the EU ETS and $R2$ as a sample of trading days that do not contain an regulatory event but are comparable on other dimensions. $R1$ can be thought of as the treatment and $R2$ as the control sample. The identifying assumptions can then be written as follows

$$\begin{aligned} \sigma^2_{\varepsilon_1,R1} &> \sigma^2_{\varepsilon_1,R2} \\ \sigma^2_{\varepsilon_j,R1} &= \sigma^2_{\varepsilon_j,R2}, \quad \text{for } j = 2, \ldots, n. \\ \sigma^2_{v,R1} &= \sigma^2_{v,R2}. \end{aligned} \tag{3}$$

Under these assumptions, the structural impact vector is given by

$$\mathbf{s}_1 = \frac{\mathbb{E}_{R1}[z_t \mathbf{u}_t] - \mathbb{E}_{R2}[z_t \mathbf{u}_t]}{\mathbb{E}_{R1}[z_t^2] - \mathbb{E}_{R2}[z_t^2]}. \tag{4}$$

As shown by Rigobon and Sack (2004), we can also obtain this estimator through an IV approach, using $\tilde{\mathbf{z}} = (\mathbf{z}'_{R1}, \ -\mathbf{z}'_{R2})'$ as an instrument in a regression of the reduced-form innovations on $\mathbf{z} = (\mathbf{z}'_{R1}, \ \mathbf{z}'_{R2})'$.

The assumption that the variance of the surprise series is much larger on event days than on a sample of controls days is indeed supported by the data. Figure C.9 shows the carbon policy surprise series together with the control series. We can see that the policy surprise series is much more volatile than the control series, and a Brown–Forsythe test for the equality of group variances confirms that this difference is also statistically significant.

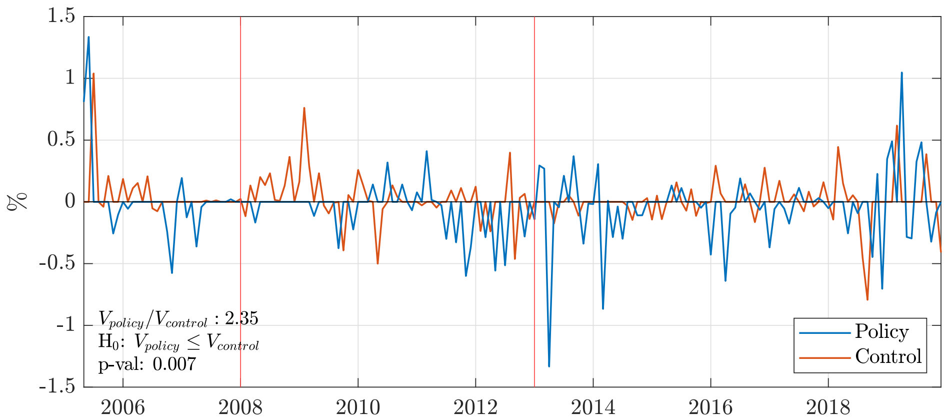


Figure C.9: The Carbon Policy and the Control Series

Notes: This figure shows the carbon policy surprise series together with the surprise series constructed on a selection of control days that do not contain a regulatory announcement but are otherwise similar.

Figure C.10 shows the impulse responses estimated from this alternative approach. The results turn out to be consistent with the baseline results from the external instrument approach, even though the responses are a bit less precisely estimated. These results suggest that the bias induced by background noise is likely negligible in the present application. However, part of the statistical strength under the external/internal instrument approach appears to come from the stronger identifying assumptions.

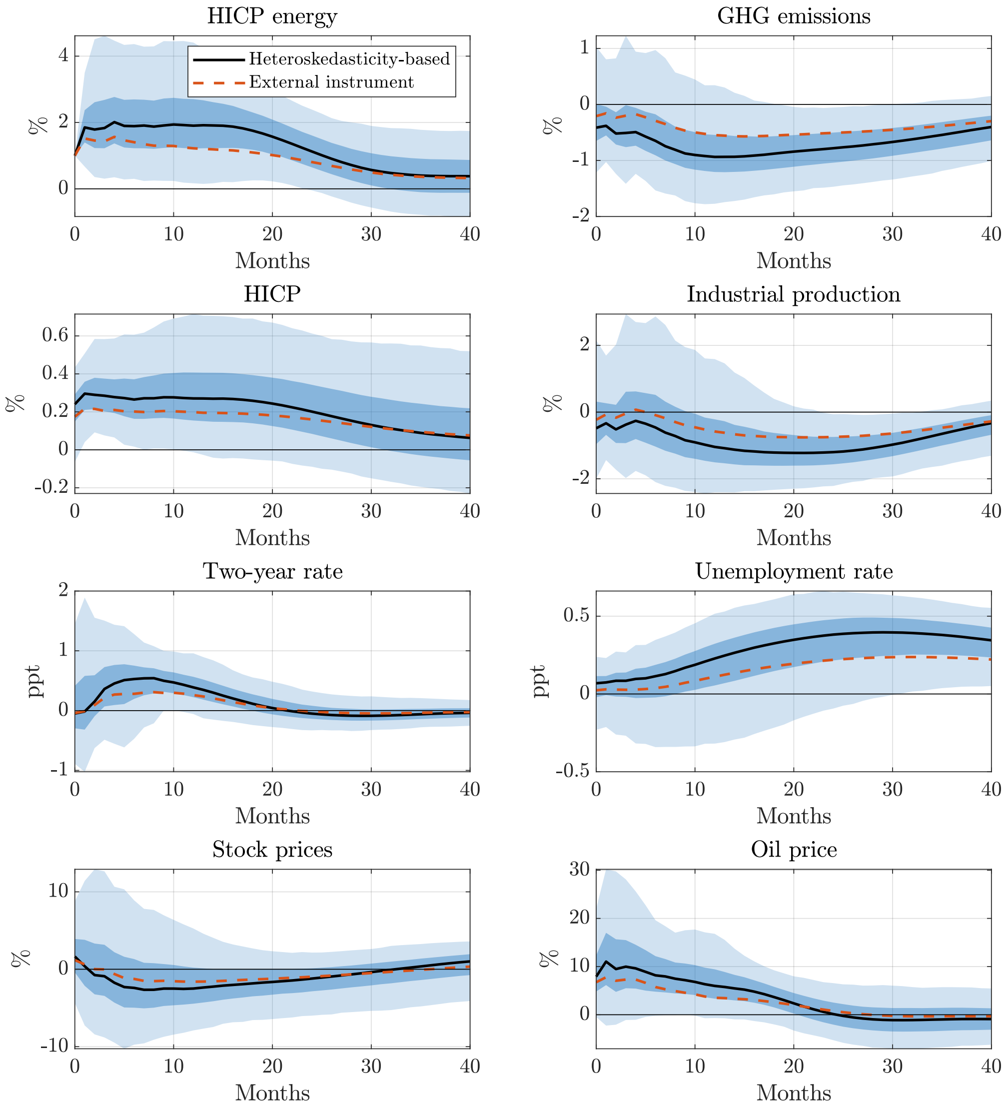


Figure C.10: Heteroskedasticity-based Identification

Interestingly, the heteroskedasticity turns out to be even more stark when using the percentage change in the carbon price as the relevant instrument. As we can see from Figure C.11, in this case, the variance of the surprise series is close to 7 times larger than the variance of the control series. As shown in Figure C.12, this helps to increase the precision of the estimated responses. Reassuringly, the point estimates are again very similar to the baseline external instrument results.

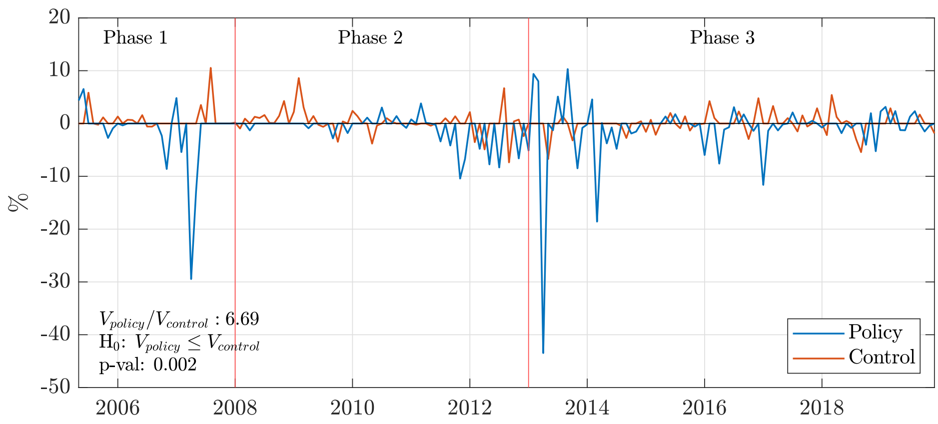


Figure C.11: The Alternative Carbon Policy and the Control Series

Notes: This figure shows the alternative carbon policy surprise series based on the percentage change in carbon prices together with the surprise series constructed on a selection of control days.

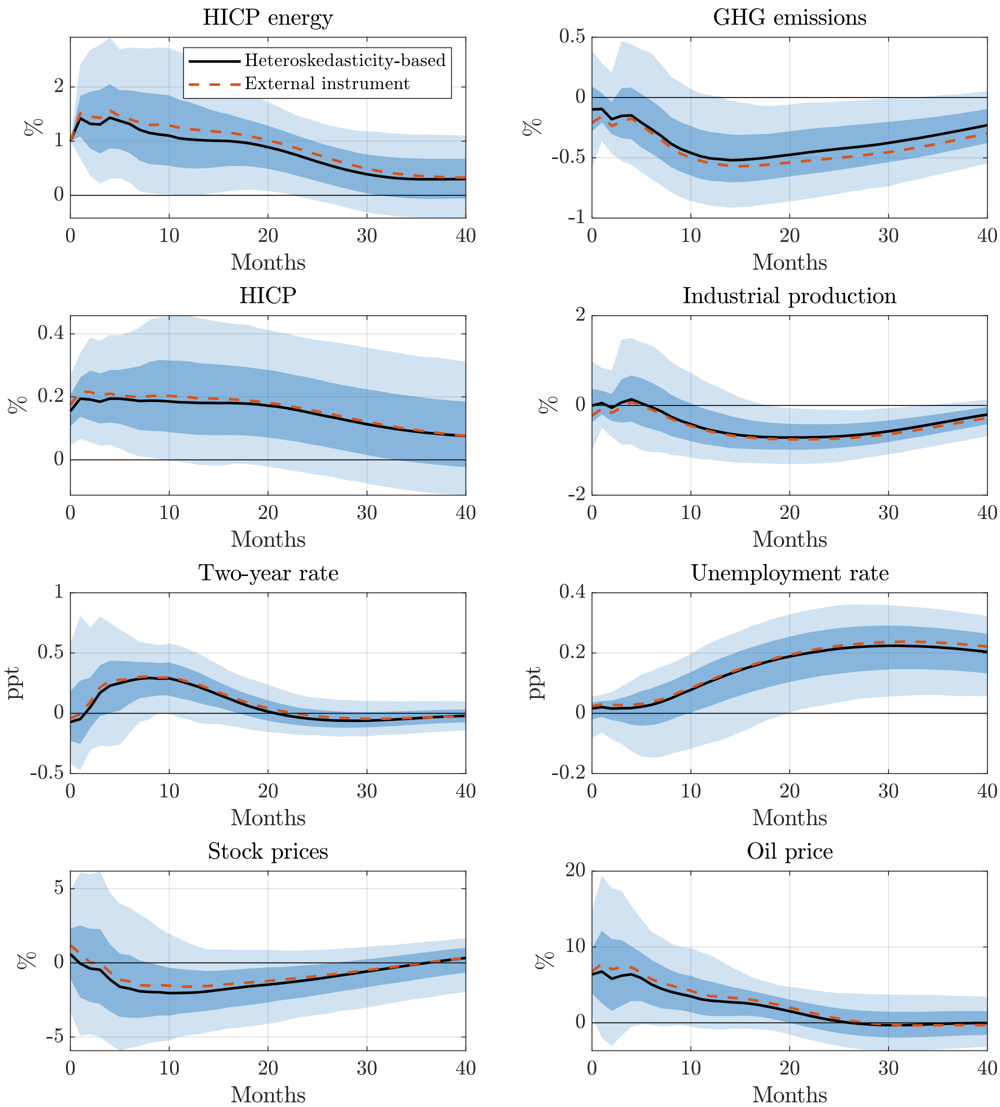


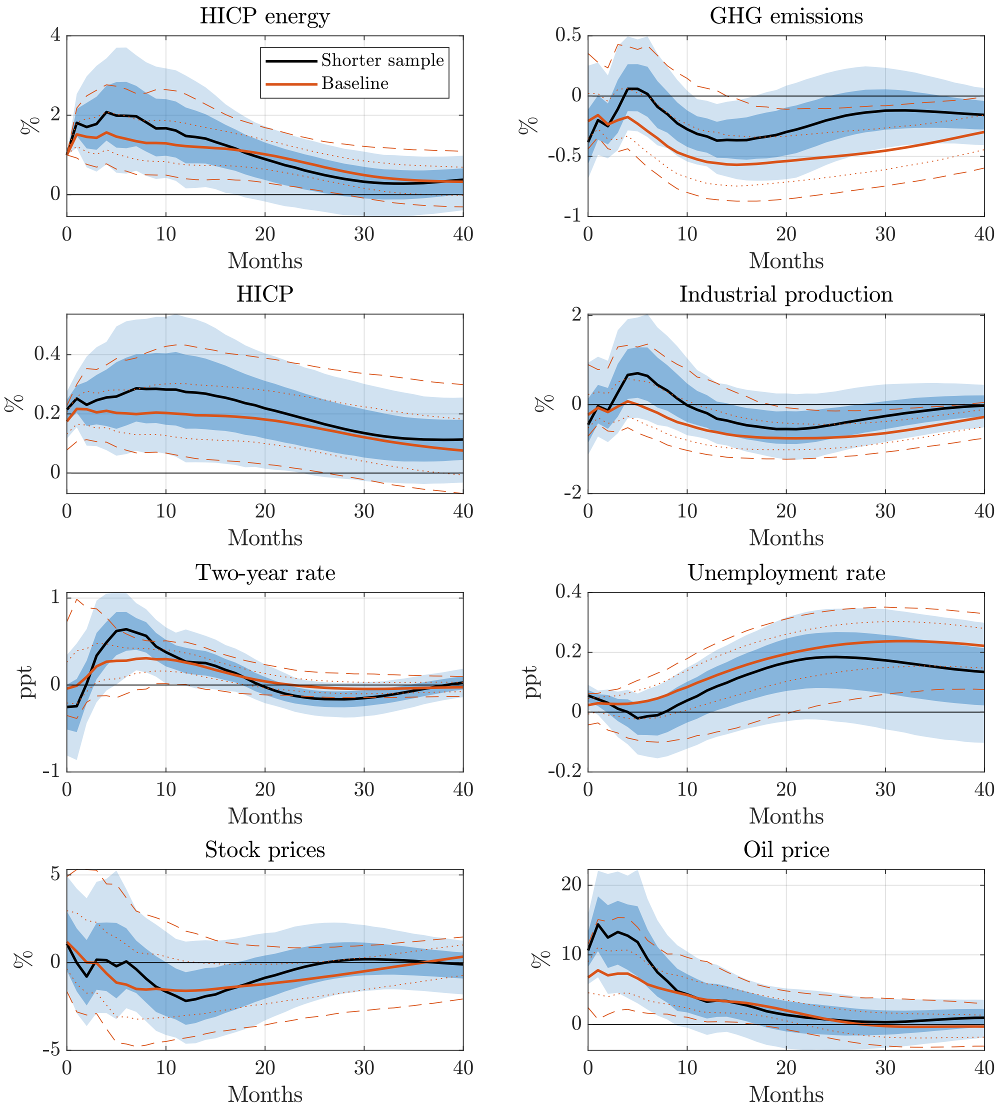
Figure C.12: Heteroskedasticity-based Identification Using Alternative Surprise Series

C.3. Sample and specification choices

An important robustness check concerns the estimation sample. Recall, the baseline sample goes back to 1999, which is longer than the instrument sample which only starts in 2005. The main motivation for using the longer sample is to increase the precision of the estimates. As a robustness check, I restrict the overall sample to the 2005-2019 period. The responses are shown in Figure C.13. Overall, the results are very similar to the ones using the longer sample. However, some responses turn out to be a bit less stable, which could point to difficulties in estimating the model dynamics on the relatively short sample.

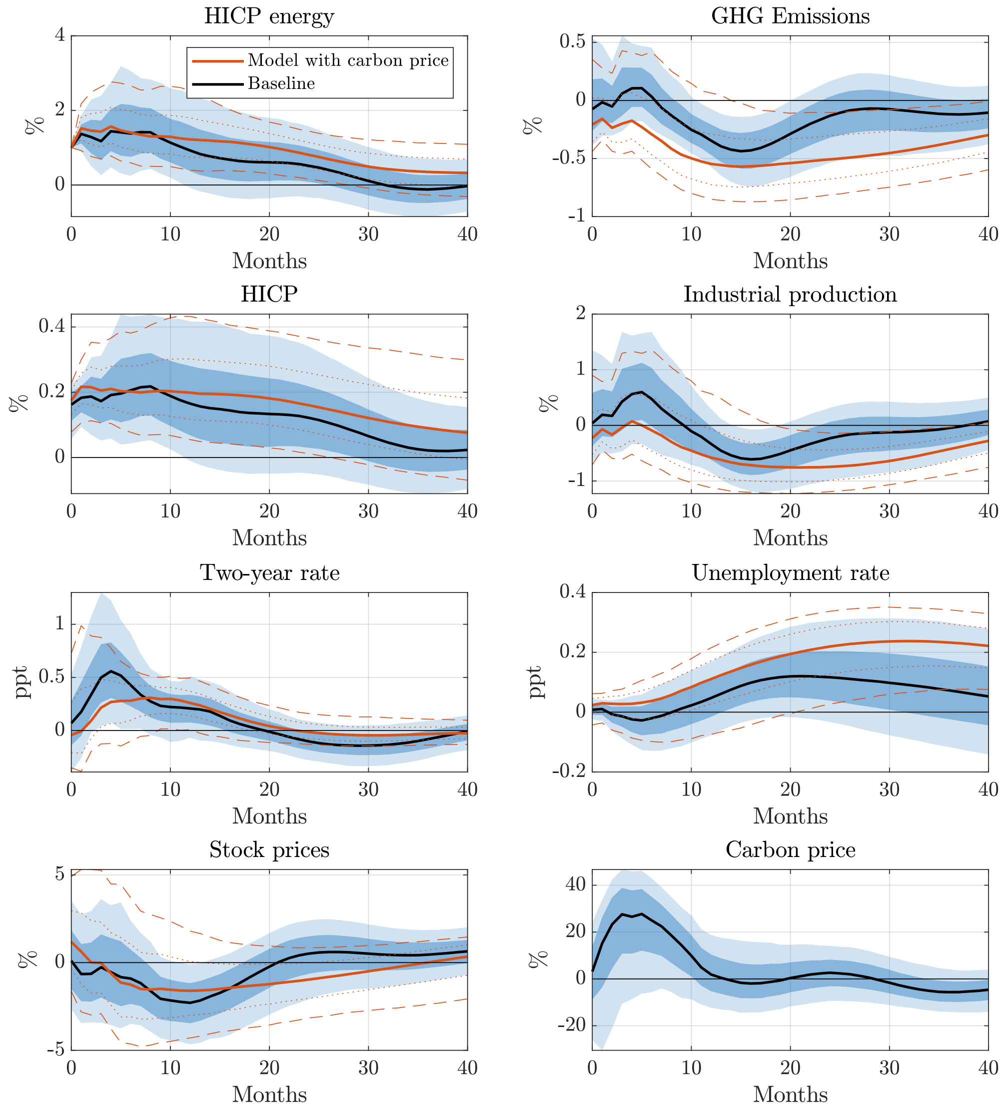
One advantage of the shorter sample is that it is possible to include the carbon price. Figure C.14 shows the response from a model that includes the carbon price in lieu of the oil price. We can see that the shock leads to a significant increase in the carbon price, in line with the interpretation of a shock tightening the carbon pricing regime. Interestingly, however, the carbon price response turns out to be less persistent than the energy price response. We can also back out the elasticity of energy to carbon prices, which turns out to be around 4 percent at the peak. This lies in the ballpark of the average emissions cost share of EU power producers.

I also perform a number of other sensitivity checks on the specification of the model. The baseline VAR includes 8 variables, which is relatively large, especially given the short sample. As a robustness test, I use a 6-variable model, excluding stock prices and the oil price. As can be seen from Figure C.15, the results from this smaller model turn out to be very similar to the larger baseline model. The results also turn out to be robust to the lag order (Figure C.16 shows the responses using 3, 9 or 12 lags) and the choice of deterministics (Figure C.17 includes a linear trend). Only the responses in the model with 3 lags are somewhat different for some variables. This illustrates the importance of controlling for sufficient lags to adequately capture the dynamic relationships in the data. The models with more generously parameterized lag orders produce very similar results to the baseline model with 6 lags.



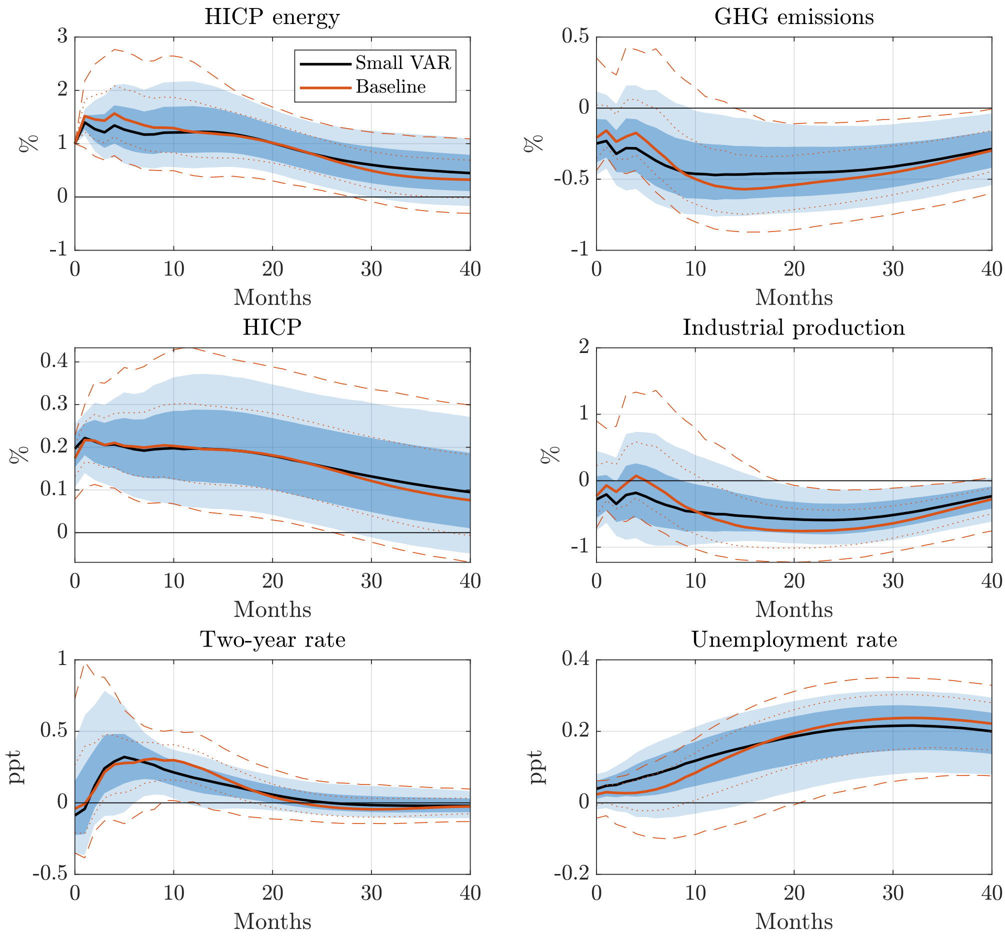
First stage regression: F-statistic: 6.44, R^2: 2.49%

Figure C.13: Results Using 2005-2019 Sample



First stage regression: F-statistic: 9.54, R^2: 4.06%

Figure C.14: Model Including Carbon Spot Price



First stage regression: F-statistic: 6.72, R^2: 1.82%

Figure C.15: Responses from Smaller VAR

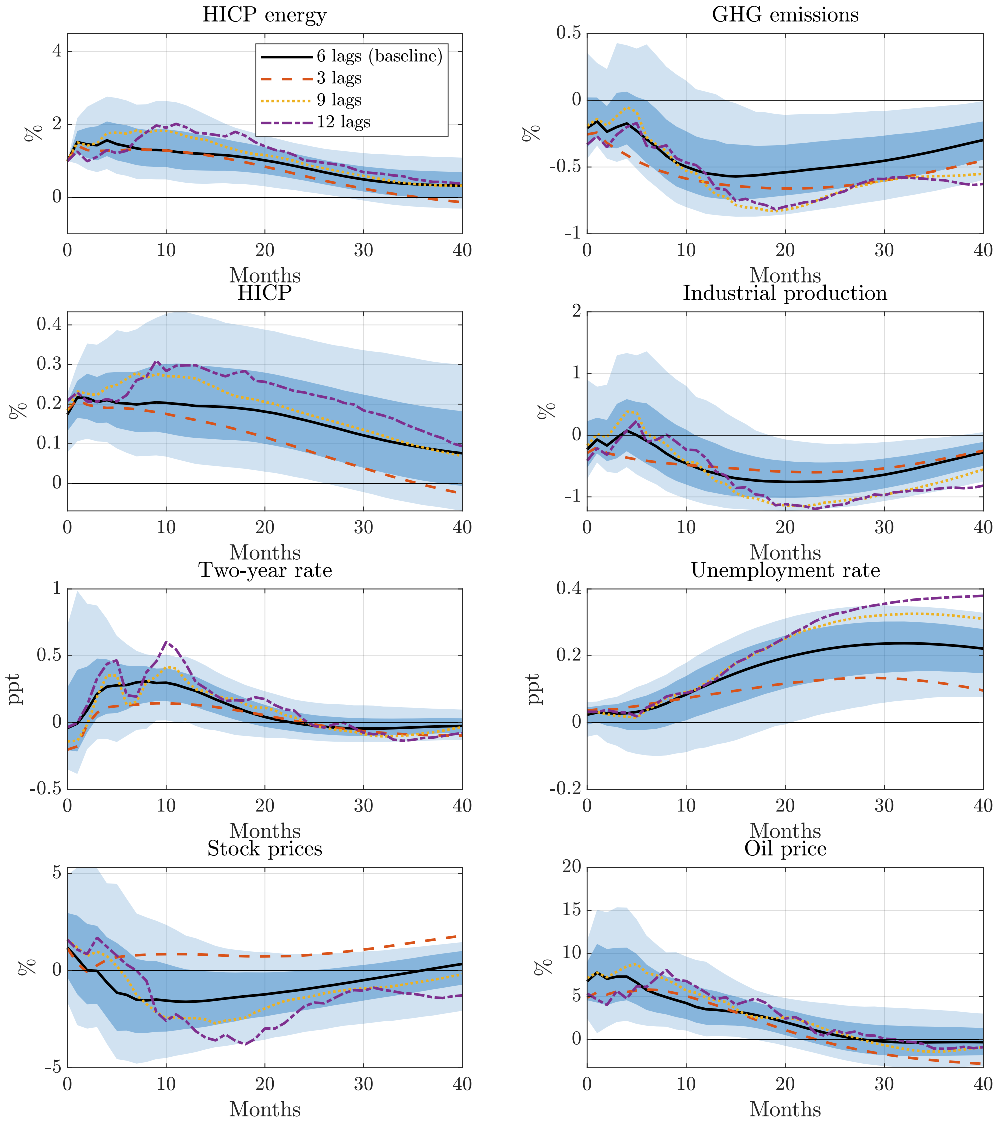
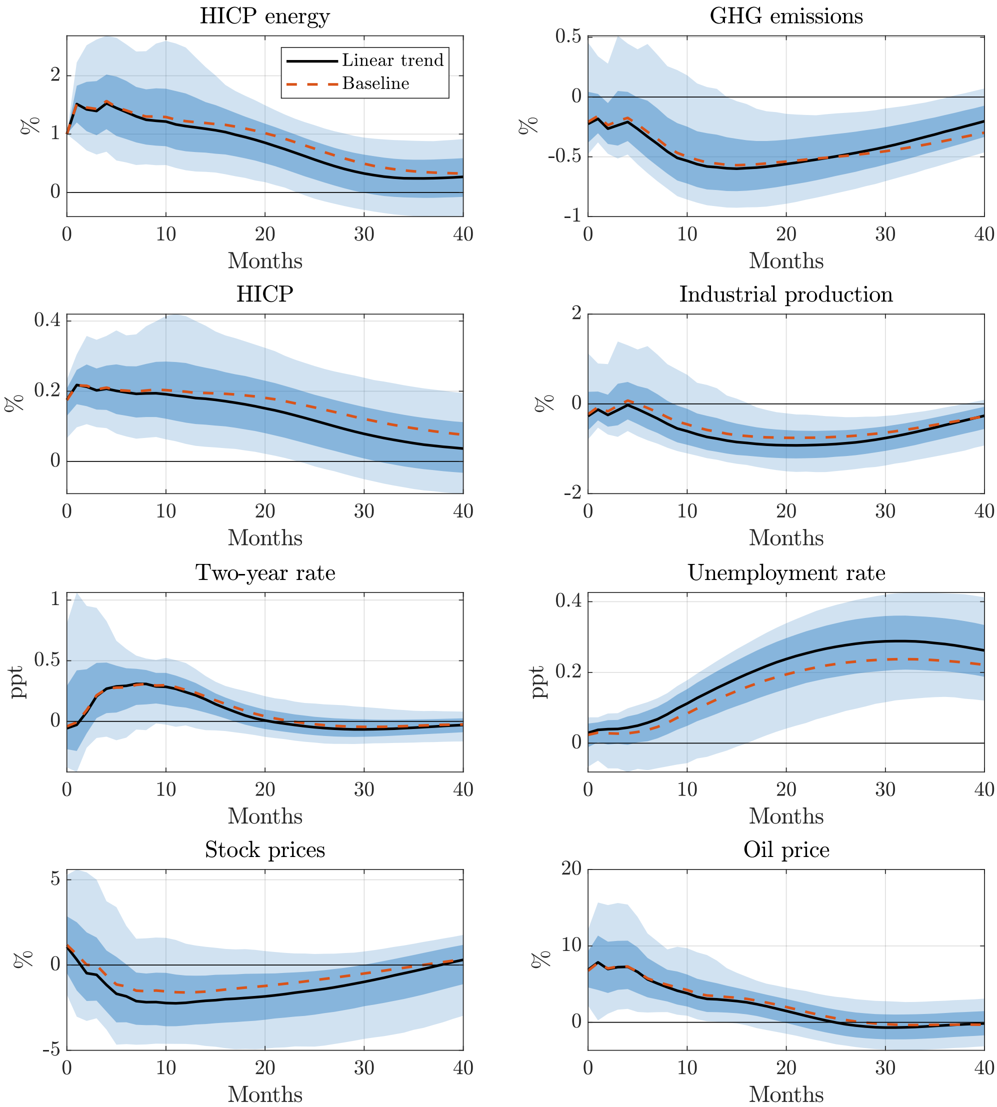


Figure C.16: VARs with Different Lag Orders



First stage regression: F-statistic: 14.60, R^2: 2.68%

Figure C.17: VAR Including Linear Trend

D. A heterogeneous-agent climate-economy model: Derivations

In this appendix, I provide the derivations for the heterogeneous-agent climate-economy model. As discussed in the main text, the aim is to obtain a framework that can account for the empirical findings – both at the aggregate level and along the cross section – and can be used for policy experiments. The model combines a climate-economy structure in the spirit of Golosov et al. (2014) with nominal rigidities, household heterogeneity and risk. The model consists of four building blocks: households, firms, a government and a climate block. The household block consists of two types of households: Households in the *hand-to-mouth* (H) and *savers* (S) state, that differ in their MPCs, income incidence and energy shares. We incorporate idiosyncratic risk by assuming that households switch exogenously between types. The firm block is further divided into consumption good and energy producers. In this appendix, we go over each model block in detail.

D.1. Households

The household sector consists of a continuum of infinitely lived households, indexed by $i \in [0,1]$. Households are assumed to have identical preferences with felicity function $U(x,h)$, deriving utility from consumption x and disutility from labor h. We assume that the felicity function is of the constant elasticity class and separable in consumption and labor:

$$U(x_{i,t}, h_{i,t}) = \frac{x_{i,t}^{1-\sigma} - 1}{1-\sigma} - \psi_i \frac{h_{i,t}^{1+\theta}}{1+\theta},$$

where $1/\sigma$ is the intertemporal elasticity of substitution and $1/\theta$ is the labor supply elasticity.

Households have access to three assets: a risk-free bond, shares in imperfectly competitive firms, and physical capital. They participate infrequently in financial markets. When they do, they can freely adjust their portfolio and receive dividends from dividends and capital income. We call this the savers' state (S). When agents do not participate in financial markets, they can use only bonds to smooth consumption. We call this the hand-to-mouth state (H). We denote by s the probability to keep participating capital markets in period $t+1$, conditional upon participating at t, i.e. $s = p(s_{t+1}^j = S | s_t^j = S)$, where s_t^j is the current state of household j. Similarly, we call h the probability to keep being excluded from financial markets, i.e. $h = p(s^j_{t+1} = H | s^j_t = H)$. Hence, the probability to become a financial market participant is $(1 - h)$. The share of hand-to-mouth households thus evolves as $\lambda_{t+1} = h\lambda_t + (1 - s)(1 - \lambda_t)$. We focus on the stationary equilibrium with $\lambda = (1 - s)/(2 - s - h)$, which is the *unconditional* probability of being hand-to-mouth.

The requirement $s \geq 1 - h$ ensures stationary and has a straightforward interpretation: the probability to remain in state S is larger than the probability to move to state S (the conditional probability is larger than the unconditional one). In the limit case of $s = 1 - h = 1 - \lambda$, idiosyncratic shocks are iid: being S or H tomorrow is independent on whether one is S or H today. At the other extreme stands TANK: idiosyncratic shocks are permanent ($s = h = 1$) and λ stays at its initial value (a free parameter).

We make two key assumptions to obtain a tractable representation. First, there is perfect insurance among the households in a particular state but not between households in different states. Accordingly, we can think of households as living on two different islands and that within each island all resources are pooled. Households on the same island will thus make the same consumption and saving choices. Second, however, we assume that stocks and capital are *illiquid*. When savers can no longer participate in financial markets, they cannot take their stock and capital holdings with them. Only bonds are liquid and can be transferred when switching between islands.

The timing is as follows. At the beginning of every period, resources within types are pooled. The aggregate shocks are revealed and households make their consumption and saving choices. Next, households learn their state in the next period and have to move to the corresponding island accordingly, taking an (equally-split) fraction of the bonds on the current island with them.

The flows across islands are as follows. The total measure of households leaving the H island each period is the number of households who participate next period: $\lambda(1 - h)$. The measure of households staying on the island is thus λh. In addition, a measure $(1 - \lambda)(1 - s)$ leaves the S island for the H island at the end of each period. Recall that our assumptions regarding insurance imply symmetric consumption/saving choices for all households in a given island. Denote by $b_{S,t+1}$ the per-capita beginning-of-period $t + 1$ bonds of S (after the consumption-saving choice, and *also after* changing state and pooling). The end-of-period t per capita real values (after the consumption/saving choice but *before* agents move across islands) are $z_{S,t+1}$. Likewise, $b_{H,t+1}$ is the per capita beginning-of-period $t + 1$ bonds in the H island (where the only asset is bonds). The end-of-period t values (before agents move across islands) are $z_{H,t+1}$. We have the following relations:

$$\begin{aligned}
\mathbf{b}_{S,t+1} &= (1-\lambda)b_{S,t+1} = (1-\lambda)sz_{S,t+1} + \lambda(1-h)z_{H,t+1}\\
\mathbf{b}_{H,t+1} &= \lambda b_{H,t+1} = (1-\lambda)(1-s)z_{S,t+1} + \lambda h z_{H,t+1},
\end{aligned}$$

where $\mathbf{b}_{i,t+1}$, $i \in \{S, H\}$ denote the bond holdings of the entire island. As stocks and capital do not leave the S island, we do not have to keep track of them.

Capital accumulation is simply characterized by:

$$k_{t+1} = i_t - \frac{\varphi_k}{2}\left(\frac{i_t}{k_t} - \delta\right)^2 k_t + (1-\delta)k_t,$$

where δ is the depreciation rate and φ_k is a parameter that governs the costs of adjusting the capital stock.

The program of savers reads

$$\begin{aligned}
V^S(\mathbf{b}_{S,t}, \omega_t, k_t) = \max_{x_{S,t}, z_{S,t+1}, \omega_{t+1}, k_{t+1}, i_t, h_{S,t}} \quad & \frac{(x_{S,t})^{1-\sigma}}{1-\sigma} - \psi_S \frac{h_{S,t}^{1+\theta}}{1+\theta} + \beta E_t V^S(\mathbf{b}_{S,t+1}, \omega_{t+1}, k_{t+1})\\
& + \beta \frac{\lambda}{1-\lambda} E_t V^H(\mathbf{b}_{H,t+1})
\end{aligned}$$

subject to

$$\begin{aligned}
& p_{S,t}x_{S,t} + z_{S,t+1} + \nu_t \frac{\omega_{t+1}}{1-\lambda} + \frac{i_t}{1-\lambda} = w_t h_{S,t} + \frac{R^b_{t-1}}{\Pi_t}\frac{\mathbf{b}_{S,t}}{1-\lambda} + \left(\nu_t + (1-\tau^d)d_t\right)\frac{\omega_t}{1-\lambda} + (1-\tau^k)r_t \frac{k_t}{1-\lambda} + \omega_{S,t}\\
& k_{t+1} = i_t - \frac{\varphi_k}{2}\left(\frac{i_t}{k_t} - \delta\right)^2 k_t + (1-\delta)k_t\\
& \mathbf{b}_{S,t+1} = (1-\lambda)sz_{S,t+1} + \lambda(1-h)z_{H,t+1}\\
& \mathbf{b}_{H,t+1} = (1-\lambda)(1-s)z_{S,t+1} + \lambda h z_{H,t+1}\\
& z_{S,t+1} \geq 0.
\end{aligned}$$

The household internalizes how aggregate bond holdings evolve according to households switching between types. Furthermore, the bond holdings a household takes from an island cannot be negative, i.e. borrowing is not possible.

The first-order conditions read

$$
\begin{aligned}
\frac{x_{S,t}^{-\sigma}}{p_{S,t}} &= \lambda_{S,t} \\
\lambda_{S,t} &= \beta(1-\lambda)sE_t[V_b^S(\mathbf{b}_{S,t+1},\omega_{t+1},k_{t+1})] + \beta\lambda(1-s)E_t[V_b^H(\mathbf{b}_{H,t+1})] + \xi_{S,t} \\
\frac{\lambda_{S,t}\nu_t}{1-\lambda} &= \beta E_t[V_\omega^S(\mathbf{b}_{S,t+1},\omega_{t+1},k_{t+1})] \\
\zeta_t &= \beta E_t[V_k^S(\mathbf{b}_{S,t+1},\omega_{t+1},k_{t+1})] \\
\frac{\lambda_{S,t}}{1-\lambda} &= \zeta_t\left(1-\varphi_k\left(\frac{i_t}{k_t}-\delta\right)\right) \\
\lambda_{S,t}w_t &= \psi_S h_{S,t}^\theta
\end{aligned}
$$

together with the complementary slackness condition:

$$
z_{S,t+1}\xi_{S,t} = 0,
$$

with $\xi_{S,t} \geq 0$. $\lambda_{S,t}$, ζ_t and $\xi_{S,t}$ are Lagrange multipliers associated with the budget constraint, capital accumulation, and the inequality constraint, respectively.

From the Envelope theorem, we have

$$
\begin{aligned}
V_b^S(\mathbf{b}_{S,t},\omega_t,k_t) &= \frac{\lambda_{S,t}}{1-\lambda}\frac{R_{t-1}^b}{\Pi_t} \\
V_\omega^S(\mathbf{b}_{S,t},\omega_t,k_t) &= \frac{\lambda_{S,t}}{1-\lambda}\left(\nu_t+(1-\tau^d)d_t\right) \\
V_k^S(\mathbf{b}_{S,t},\omega_t,k_t) &= \frac{\lambda_{S,t}}{1-\lambda}(1-\tau^k)r_t + \zeta_t\left(1-\delta-\frac{\varphi_k}{2}\left(\frac{i_t}{k_t}-\delta\right)^2+\varphi_k\left(\frac{i_t}{k_t}-\delta\right)\frac{i_t}{k_t}\right).
\end{aligned}
$$

Using this in the FOCs gives

$$
\begin{aligned}
\frac{x_{S,t}^{-\sigma}}{p_{S,t}} &= \lambda_{S,t} \\
\lambda_{S,t} &= \beta sE_t\left[\lambda_{S,t+1}\frac{R_t^b}{\Pi_{t+1}}\right] + \beta\lambda(1-s)E_t[V_b^H(\mathbf{b}_{H,t+1})] + \xi_{S,t} \\
\lambda_{S,t} &= \beta E_t\left[\lambda_{S,t+1}\frac{\nu_{t+1}+(1-\tau^d)d_{t+1}}{\nu_t}\right] \\
\zeta_t &= \beta E_t\left[\frac{\lambda_{S,t+1}}{1-\lambda}(1-\tau^k)r_{t+1} + \zeta_{t+1}\left(1-\delta-\frac{\varphi_k}{2}\left(\frac{i_{t+1}}{k_{t+1}}-\delta\right)^2+\varphi_k\left(\frac{i_{t+1}}{k_{t+1}}-\delta\right)\frac{i_{t+1}}{k_{t+1}}\right)\right] \\
\frac{\lambda_{S,t}}{1-\lambda} &= \zeta_t\left(1-\varphi_k\left(\frac{i_t}{k_t}-\delta\right)\right) \\
\lambda_{S,t}w_t &= \psi_S h_{S,t}^\theta.
\end{aligned}
$$

Tobin's marginal q is defined as $q_t = \frac{\zeta_t}{\lambda_{S,t}/(1-\lambda)}$. Using this, we can rewrite the optimal capital and investment decision as

$$q_t = \beta E_t \left[\frac{\lambda_{S,t+1}}{\lambda_{S,t}} \left((1-\tau^k) r_{t+1} + q_{t+1} \left(1 - \delta - \frac{\varphi_k}{2} \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right)^2 + \varphi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right) \frac{i_{t+1}}{k_{t+1}} \right) \right) \right]$$
$$1 = q_t \left(1 - \varphi_k \left(\frac{i_t}{k_t} - \delta \right) \right).$$

The only thing that remains to be determined is $V_b^H(\mathbf{b}_{H,t+1})$. We can obtain this from the problem of the hand-to-mouth. Their program reads

$$V^H(\mathbf{b}_{H,t}) = \max_{x_{H,t}, z_{H,t+1}, h_{H,t}} \quad \frac{x_{H,t}^{1-\sigma}}{1-\sigma} - \psi_H \frac{h_{H,t}^{1+\theta}}{1+\theta} + \beta E_t V^H(\mathbf{b}_{H,t+1}) + \beta \frac{1-\lambda}{\lambda} E_t V^S(\mathbf{b}_{S,t+1}, \omega_{t+1}, k_{t+1})$$

subject to

$$\begin{aligned}
p_{S,t} x_{H,t} + z_{H,t+1} &= w_t h_{H,t} + \frac{R_{t-1}^b}{\Pi_t} \frac{\mathbf{b}_{H,t}}{\lambda} + \omega_{H,t} \\
\mathbf{b}_{S,t+1} &= (1-\lambda) s z_{S,t+1} + \lambda (1-h) z_{H,t+1} \\
\mathbf{b}_{H,t+1} &= (1-\lambda)(1-s) z_{S,t+1} + \lambda h z_{H,t+1} \\
z_{H,t+1} &\geq 0.
\end{aligned}$$

The first-order conditions read

$$\begin{aligned}
x_{H,t}^{-\sigma} &= \lambda_{H,t} \\
\lambda_{H,t} &= \beta \lambda h E_t [V_b^H(\mathbf{b}_{H,t+1})] + \beta (1-\lambda)(1-h) E_t [V_b^S(\mathbf{b}_{S,t+1}, \omega_{t+1}, k_{t+1})] + \xi_{H,t} \\
\lambda_{H,t} w_t &= \psi_H h_{H,t}^{\theta}
\end{aligned}$$

together with the complementary slackness condition:

$$z_{H,t+1} \xi_{H,t} = 0,$$

with $\xi_{H,t} \geq 0$.

From the Envelope theorem, we have

$$V_b^H(\mathbf{b}_{H,t}) = \frac{\lambda_{H,t}}{\lambda} \frac{R_{t-1}^b}{\Pi_t}.$$

Thus, we can rewrite the Euler equations for bonds accordingly

$$\lambda_{H,t} = \beta E_t \left[\frac{R_t^b}{\Pi_{t+1}} \left(h\lambda_{H,t+1} + (1-h)\lambda_{S,t+1} \right) \right] + \xi_{H,t}$$

and similarly for the savers:

$$\lambda_{S,t} = \beta E_t \left[\frac{R_t^b}{\Pi_{t+1}} \left(s\lambda_{S,t+1} + (1-s)\lambda_{H,t+1} \right) \right] + \xi_{S,t}.$$

Note that the Euler equation for stocks and capital are isomorphic to the conditions in a representative-agent setting. There is no self-insurance motive, for they cannot be carried to the H state.[5]

In contrast, the bond Euler equations are of the same form as in fully-fledged incomplete-markets models of the Bewely-Huggett-Aiyagari type. In particular, the probability $(1-s)$ measures the uninsurable risk to switch to a bad state next period, risk for which only bonds can be used to self-insure, thus generating a demand for bonds for "precautionary" purposes.

Two additional assumptions are required to deliver our simple equilibrium representation. First, we focus on equilibria where (whatever the reason) the constraint of H agents always binds (i.e. $\xi_H > 0$) and their Euler equation is in fact a strict inequality (for instance, because the shock is a "liquidity" or impatience shock making them want to consume more today, or because their average income in that state is lower enough than in the S state, as would be the case if average profits were high enough; or simply because of a technological constraint preventing them from accessing any asset markets) and the constraint of S never binds ($\xi_S = 0$) so that their Euler equation always holds with equality. Second, we focus on the zero-liquidity limit, that is we assume that even though the demand for bonds from S is well-defined (the constraint is not binding), the net supply of bonds is zero, so there are no bonds traded in equilibrium.

Under these assumptions, the H households are indeed hand-to-mouth as their budget constraint reads

$$p_{S,t}x_{H,t} = w_t h_t + \omega_{H,t}. \tag{5}$$

[5] As households pool resources when participating (which would be optimal with t=0 symmetric agents and $t = 0$ trading), they perceive a return conditional on participating next period. This exactly compensates for the probability of not participating next period, thus generating the same Euler equation as with a representative agent.

The intertemporal consumption/saving behavior by savers is characterized by

$$\lambda_{S,t} = \frac{x_{S,t}^{-\sigma}}{p_{S,t}} \tag{6}$$

$$\lambda_{S,t} = \beta E_t \left[\frac{R_t^b}{\Pi_{t+1}} \left(s\lambda_{S,t+1} + (1-s)\lambda_{H,t+1} \right) \right] \tag{7}$$

$$\lambda_{S,t} = \beta E_t \left[\lambda_{S,t+1} \frac{v_{t+1} + (1-\tau^d) d_{t+1}}{v_t} \right] \tag{8}$$

$$q_t = \beta E_t \left[\frac{\lambda_{S,t+1}}{\lambda_{S,t}} \left((1-\tau^k) r_{t+1} + q_{t+1} \left(1 - \delta - \frac{\varphi_k}{2} \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right)^2 + \varphi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta \right) \frac{i_{t+1}}{k_{t+1}} \right) \right) \right] \tag{9}$$

$$1 = q_t \left(1 - \varphi_k \left(\frac{i_t}{k_t} - \delta \right) \right) \tag{10}$$

$$p_{S,t} x_{S,t} + i_{S,t} + b_{S,t+1} = w_t h_t + \frac{R_{t-1}^b}{\Pi_t} b_{S,t} + (1-\tau^k) r_t k_{S,t} + \frac{(1-\tau^d) d_t}{1-\lambda} + \omega_{S,t} \tag{11}$$

$$k_{t+1} = i_t - \frac{\varphi_k}{2} \left(\frac{i_t}{k_t} - \delta \right)^2 k_t + (1-\delta) k_t, \tag{12}$$

as market clearing implies that $\omega_t = \omega_{t+1} = 1$.

As to the intratemporal choice between energy and non-energy consumption, recall that the final consumption bundle $x_{S,t}$ is a CES aggregate of consumption and energy goods

$$x_{S,t} = \left(a_{S,c}^{\frac{1}{\epsilon_x}} c_{S,t}^{\frac{\epsilon_x - 1}{\epsilon_x}} + a_{S,e}^{\frac{1}{\epsilon_x}} e_{S,t}^{\frac{\epsilon_x - 1}{\epsilon_x}} \right)^{\frac{\epsilon_x}{\epsilon_x - 1}},$$

where $a_{S,c}$ and $a_{S,e}$ are distribution parameters with $a_{S,c} + a_{S,e} = 1$[6] , and ϵ_x is the

[6]Note that the distribution parameters $a_{S,c}$ and $a_{S,e}$, sometimes also referred to as shares, are in fact not shares but depend on underlying dimensions unless $\epsilon_x = 1$. In other words, these parameters are not deep parameters but depend on a mixture of parameters that depends on the choice of units. To circumvent this issue, we follow the re-parameterization approach proposed by Cantore and Levine (2012). In particular, we calibrate the steady-state energy share and to back out the implied distribution parameters. We have:

$$a_{S,e} = \frac{p_e e_S}{p_S x_S} \left(\frac{p_e}{p_S} \right)^{\epsilon_x - 1} = \omega_{S,e} \left(\frac{p_e}{p_S} \right)^{\epsilon_x - 1},$$

where $\omega_{S,e}$ is the energy expenditure share. From this, we then have $a_{S,c} = 1 - a_{S,e}$. Note that this share is dimensionless. Thus, we can calibrate or estimate it. By using this strategy, we can also perform comparative statics, varying the elasticity ϵ_x.

elasticity of substitution between non-energy and energy goods: $\frac{\partial(c_t/e_{c,t})/(c_t/e_{c,t})}{\partial(p_{e,t}/1)/(p_{e,t}/1)}$.[7] Making the distribution parameters household-specific allows for heterogeneity in the households' energy share.

The demands for the consumption and energy good the are given by

$$c_{S,t} = a_{S,c}\left(\frac{1}{p_{S,t}}\right)^{-\epsilon_x} x_{S,t} \tag{13}$$

$$e_{S,t} = a_{S,e}\left(\frac{p_{e,t}}{p_{S,t}}\right)^{-\epsilon_x} x_{S,t}, \tag{14}$$

respectively. Note that the consumption good is chosen to be the numeraire, i.e. it's price is one in real terms.

The corresponding price index is

$$p_{S,t} = \left(a_{S,c} + a_{S,e}p_{e,t}^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}}. \tag{15}$$

Similarly, for the hand-to-mouth, we have

$$c_{H,t} = a_{H,c}\left(\frac{1}{p_{S,t}}\right)^{-\epsilon_x} x_{H,t} \tag{16}$$

$$e_{H,t} = a_{H,e}\left(\frac{p_{e,t}}{p_{S,t}}\right)^{-\epsilon_x} x_{H,t} \tag{17}$$

and the price of their bundle is

$$p_{H,t} = \left(a_{H,c} + a_{H,e}p_{e,t}^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}}. \tag{18}$$

Finally, the optimal labor supply decisions are characterized as

$$\lambda_{S,t}w_t = \psi_S h_{S,t}^{\theta} \tag{19}$$

$$\lambda_{H,t}w_t = \psi_H h_{H,t}^{\theta}. \tag{20}$$

D.2. Firms

The firm block of the model consists of two sectors: energy and non-energy producers. Importantly, non-energy firms also use energy as an intermediate input to produce the non-energy good. Further, we assume that non-energy firms face some restrictions in adjusting their prices while the energy sector does not face

[7] If ϵ_x approaches ∞, the goods are perfect substitutes; if ϵ_x approaches 0, the goods are perfect complements; and if ϵ_x approaches 1, the goods are one-for-one substitutable, which corresponds to the Cobb-Douglas case.

any price rigidity.

Energy producers. The energy firm produces energy using labor only according to the following production function:

$$e_t = a_{e,t} h_{e,t}. \tag{21}$$

We assume that there is only a single source of energy (e.g. coal) that is available in (approx.) infinite supply. Note that we measure energy in terms of carbon content (carbon amount emitted). Energy firms are subject to a carbon tax τ_t.

Their maximization problem reads

$$\begin{aligned} \max_{h_{e,t}} \quad & (1-\tau_t) p_{e,t} e_t - w_t h_{e,t} \\ \text{s.t.} \quad & e_t = a_{e,t} h_{e,t} \end{aligned}$$

The FOC gives the optimal energy supply:

$$\frac{w_t}{(1-\tau_t) p_{e,t}} = \frac{e_t}{h_{e,t}}. \tag{22}$$

Non-energy firms. To simplify matters, we split the non-energy goods sectors into two subsectors: a representative competitive final goods firm which aggregates intermediate goods according to a CES technology and a continuum of intermediate goods producers that produce different varieties using capital, energy and labor as an input. To the extent to which the intermediate goods are imperfect substitutes, there is a downward-sloping demand for each intermediate variety, giving the intermediate producers some pricing power. Importantly, however, intermediate goods producers cannot freely adjust prices. Nominal price rigidities are modeled according to Calvo (1983) mechanism. In each period, a firm faces a constant probability $1-\theta_p$ of being able to reoptimize the nominal wage.

Final goods producer. Final goods firms maximize profits subject to the production function by taking prices as given. Since final goods firms are all identical, we can focus on one representative firm. These firms bundle the differentiated goods into a final good using a CES technology. Taking prices as given, the final goods producer chooses intermediate good quantities $y_t(i)$ to maximize profits:

$$\max_{y_t(i)} P_t y_{d,t} - \int_0^1 P_t(i) y_t(i) di \qquad \text{s.t.} \quad y_{d,t} = \left(\int_0^1 y_t(i)^{\frac{\epsilon_p - 1}{\epsilon_p}} di \right)^{\frac{\epsilon_p}{\epsilon_p - 1}},$$

where $y_{d,t}$ is aggregate demand and $\epsilon_p > 1$ is the elasticity of substitution. When goods are perfectly substitutable $\epsilon_p \to \infty$, we approach the perfect competition benchmark.

From the first order condition, we get the usual demand schedule

$$y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon_p} y_{d,t}.$$

From the zero profit condition we obtain the aggregate price level $P_t = \left(\int_0^1 P_t(i)^{1-\epsilon_p} dj\right)^{\frac{1}{1-\epsilon_p}}$.

Intermediate goods producers. Intermediate inputs are produced by a continuum of monopolistic firms indexed by $i \in [0,1]$ according to the following CES production technology, using capital $k_t(i)$, energy $e_{y,t}(i)$, and labor $h_{y,t}(i)$ as inputs

$$y_t(i) = e^{-\gamma s_t} \left[(1-\nu)^{1/\epsilon_y} \left(a_t k_t(i)^\alpha h_{y,t}(i)^{1-\alpha}\right)^{(\epsilon_y-1)/\epsilon_y} + \nu^{1/\epsilon_y} \left(e_{y,t}(i)\right)^{(\epsilon_y-1)/\epsilon_y}\right]^{\epsilon_y/(\epsilon_y-1)}, \tag{23}$$

where a_t is a technology shifter, and $e^{-\gamma s_t}$ captures climate damages, modeled as a function of the atmospheric carbon concentration s_t. We assume that capital/labor and energy are complements, i.e. $\epsilon_y < 1$.

As intermediate goods producers are monopolists, they maximize profits by taking the demand function of final goods firms into account. We consider now the problem of an intermediate goods firm i. For the sake of simplicity the program is split into two sub-problems: the cost minimization and the price setting problem. To find the real cost function, factor costs are minimized subject to the production function. The program of firm i reads

$$\min_{k_t(i),h_{y,t}(i),e_{y,t}(i)} r_t k_t(i) + w_t h_{y,t}(i) + p_{e,t} e_{y,t}(i)$$

$$\text{s.t.} \quad y_t(i) \le e^{-\gamma s_t} \left[(1-\nu)^{1/\epsilon_y} \left(a_t k_t(i)^\alpha h_{y,t}(i)^{1-\alpha}\right)^{(\epsilon_y-1)/\epsilon_y} + \nu^{1/\epsilon_y} \left(e_{y,t}(i)\right)^{(\epsilon_y-1)/\epsilon_y}\right]^{\epsilon_y/(\epsilon_y-1)}$$

The FOCs read

$$\frac{r_t k_t(i)}{y_t(i)} = \alpha(1-\nu)^{\frac{1}{\epsilon_y}} \lambda_t(i) \left(\frac{e^{-\gamma s_t} a_t k_t(i)^\alpha h_{y,t}(i)^{1-\alpha}}{y_t(i)}\right)^{\frac{\epsilon_y-1}{\epsilon_y}}$$

$$\frac{w_t h_{y,t}(i)}{y_t(i)} = (1-\alpha)(1-\nu)^{\frac{1}{\epsilon_y}} \lambda_t(i) \left(\frac{e^{-\gamma s_t} a_t k_t(i)^{\alpha} h_{y,t}(i)^{1-\alpha}}{y_t(i)} \right)^{\frac{\epsilon_y - 1}{\epsilon_y}}$$

$$\frac{p_{e,t} e_{y,t}(i)}{y_t(i)} = \nu^{\frac{1}{\epsilon_y}} \lambda_t(i) \left(\frac{e^{-\gamma s_t} e_{y,t}(i)}{y_t(i)} \right)^{\frac{\epsilon_y - 1}{\epsilon_y}}$$

where $\lambda_t(i)$ is the corresponding Lagrange multiplier. This multiplier has the interpretation as real marginal cost – how much will costs change if you are forced to produce an extra unit of output, i.e. $\lambda_t(i) = mc_t(i)$, and it is equal across firms, i.e. $mc_t(i) = mc_t$. This in turn implies that the output-capital, output-labor, and output-energy ratios are the same across firms.

Now that we have found the real cost function, we can move to the intermediate goods firms' price setting problem. Intermediate goods producers set prices to maximize the expected discounted stream of (real) profits. However, as outlined above, firms are not able to freely adjust price each period. In particular, in each period there is a fixed probability of $1 - \theta_p$ that a firm can adjust its price. Since there is a chance that the firm will get stuck with its price for multiple periods, the pricing problem becomes dynamic. Firms will discount profits k periods into the future by $M_{t,t+k}\theta_p^k$, where $M_{t,t+k} = \beta^k \frac{\lambda_{S,t+k}}{\lambda_{S,t}}$ is the stochastic discount factor, which follows from the fact that the firm is owned by the savers. The price setting problem reads

$$\begin{aligned} \max_{P_t(i)} \quad & E_t \sum_{k=0}^{\infty} (\beta\theta_p)^k \frac{\lambda_{S,t+k}}{\lambda_{S,t}} \left(\frac{P_t(i)}{P_{t+k}} y_{t+k}(i) - mc_{t+k} y_{t+k}(i) \right) \\ \text{s.t.} \quad & \left\{ y_{t+k}(i) = \left(\frac{P_t(i)}{P_{t+k}} \right)^{-\epsilon_p} y_{d,t+k} \right\}_{k=0}^{\infty} . \end{aligned}$$

The FOC reads

$$E_t \sum_{k=0}^{\infty} (\beta\theta_p)^k \lambda_{S,t+k} \left((1-\epsilon_p) P_{t+k}^{\epsilon_p - 1} y_{d,t+k} + \epsilon_p \, mc_{t+k} P_t(i)^{-1} P_{t+k}^{\epsilon_p} y_{d,t+k} \right) = 0.$$

By rearranging, we obtain

$$P_t(i) = \frac{\epsilon_p}{\epsilon_p - 1} \frac{E_t \sum_{k=0}^{\infty} (\beta\theta_p)^k \lambda_{S,t+k} mc_{t+k} P_{t+k}^{\epsilon_p} y_{d,t+k}}{E_t \sum_{k=0}^{\infty} (\beta\theta_p)^k \lambda_{S,t+k} P_{t+k}^{\epsilon_p - 1} y_{d,t+k}}.$$

Note that nothing on the RHS depends on i. Thus, all firms will choose the same reset price $P_t^* = P_t(i)$.

We can write the optimal price more compactly as

$$P_t^* = \frac{\epsilon_p}{\epsilon_p - 1}\frac{X_{1,t}}{X_{2,t}}$$

with

$$\begin{aligned} X_{1,t} &= E_t \sum_{k=0}^{\infty} (\beta\theta_p)^k \lambda_{S,t+k} mc_{t+k} P_{t+k}^{\epsilon_p} y_{d,t+k} \\ X_{2,t} &= E_t \sum_{k=0}^{\infty} (\beta\theta_p)^k \lambda_{S,t+k} P_{t+k}^{\epsilon_p - 1} y_{d,t+k}. \end{aligned}$$

We can also write the X's recursively

$$\begin{aligned} X_{1,t} &= \lambda_{S,t} mc_t P_t^{\epsilon_p} y_{d,t} + \beta\theta_p E_t X_{1,t+1} \\ X_{2,t} &= \lambda_{S,t} P_t^{\epsilon_p - 1} y_{d,t} + \beta\theta_p E_t X_{2,t+1}.\text{[8]} \end{aligned}$$

Let us now rewrite these expressions in terms of inflation (as the price level may be non-stationary). Define $x_{1,t} = \frac{X_{1,t}}{P_t^{\epsilon_p}}$ and $x_{2,t} = \frac{X_{2,t}}{P_t^{\epsilon_p - 1}}$. Thus, we have

$$\begin{aligned} x_{1,t} &= \lambda_{S,t} mc_t y_{d,t} + \beta\theta_p E_t x_{1,t+1} \Pi_{t+1}^{\epsilon_p} \\ x_{2,t} &= \lambda_{S,t} y_{d,t} + \beta\theta_p E_t x_{2,t+1} \Pi_{t+1}^{\epsilon_p - 1}. \end{aligned}$$

The reset price equation then writes

$$\begin{aligned} P_t^* &= \frac{\epsilon_p}{\epsilon_p - 1} P_t \frac{x_{1,t}}{x_{2,t}} \\ \Rightarrow \Pi_t^* &= \frac{\epsilon_p}{\epsilon_p - 1} \Pi_t \frac{x_{1,t}}{x_{2,t}}, \end{aligned}$$

where we define reset price inflation as $\Pi_t^* = \frac{P_t^*}{P_{t-1}}$.

Exploiting the Calvo assumption, we can write the aggregate price index as

$$\Pi_t^{1-\epsilon_p} = (1 - \theta_p)(\Pi_t^*)^{1-\epsilon_p} + \theta_p.$$

[8] If $\theta_p = 0$, then this would reduce to

$$P_t^* = \underbrace{\frac{\epsilon_p}{\epsilon_p - 1}}_{\mathcal{M}} P_t \, mc_t,$$

i.e. the optimal price would be a fixed markup over nominal marginal cost.

By way of summary, optimal behavior of firm i is characterized by

$$\frac{r_t k_t}{y_t} = \alpha(1-\nu)^{\frac{1}{\epsilon_y}} mc_t \left(\frac{e^{-\gamma s_t} a_t k_t^{\alpha} h_{y,t}^{1-\alpha}}{y_t}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}} \tag{24}$$

$$\frac{w_t h_{y,t}}{y_t} = (1-\alpha)(1-\nu)^{\frac{1}{\epsilon_y}} mc_t \left(\frac{e^{-\gamma s_t} a_t k_t^{\alpha} h_{y,t}^{1-\alpha}}{y_t}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}} \tag{25}$$

$$\frac{p_{e,t} e_{y,t}}{y_t} = \nu^{\frac{1}{\epsilon_y}} mc_t \left(\frac{e^{-\gamma s_t} e_{y,t}}{y_t}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}} \tag{26}$$

$$\Pi_t^* = \frac{\epsilon_p}{\epsilon_p - 1} \Pi_t \frac{x_{1,t}}{x_{2,t}} \tag{27}$$

$$x_{1,t} = \lambda_{S,t} mc_t y_{d,t} + \beta \theta_p E_t x_{1,t+1} \Pi_{t+1}^{\epsilon_p} \tag{28}$$

$$x_{2,t} = \lambda_{S,t} y_{d,t} + \beta \theta_p E_t x_{2,t+1} \Pi_{t+1}^{\epsilon_p - 1} \tag{29}$$

$$\Pi_t^{1-\epsilon_p} = (1-\theta_p)(\Pi_t^*)^{1-\epsilon_p} + \theta_p \tag{30}$$

$$y_t(i) = e^{-\gamma s_t} \left[(1-\nu)^{1/\epsilon_y} \left(a_t k_t(i)^{\alpha} h_{y,t}(i)^{1-\alpha}\right)^{(\epsilon_y - 1)/\epsilon_y} + \nu^{1/\epsilon_y} \left(e_{y,t}(i)\right)^{(\epsilon_y - 1)/\epsilon_y}\right]^{\epsilon_y/(\epsilon_y - 1)}$$

The aggregate production is given by

$$\begin{aligned}
y_t &= \int_0^1 y_t(i) di \\
&= \int_0^1 e^{-\gamma s_t} \left[(1-\nu)^{1/\epsilon_y} \left(a_t k_t(i)^{\alpha} h_{y,t}(i)^{1-\alpha}\right)^{(\epsilon_y - 1)/\epsilon_y} + \nu^{1/\epsilon_y} \left(e_{y,t}(i)\right)^{(\epsilon_y - 1)/\epsilon_y}\right]^{\epsilon_y/(\epsilon_y - 1)} di \\
\Rightarrow y_t &= e^{-\gamma s_t} \left[(1-\nu)^{1/\epsilon_y} \left(a_t k_t^{\alpha} h_{y,t}^{1-\alpha}\right)^{(\epsilon_y - 1)/\epsilon_y} + \nu^{1/\epsilon_y} \left(e_{y,t}\right)^{(\epsilon_y - 1)/\epsilon_y}\right]^{\epsilon_y/(\epsilon_y - 1)} \qquad (31) \\
&= \int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon_p} di y_{d,t} = \Delta_t y_{d,t},
\end{aligned}$$

where we have exploited the fact that factors are hired in the same proportion and plugged in for the demand function. Note that there is a wedge between aggregate output and aggregate demand. The intuition is that with Calvo pricing, firms charging prices in different periods will generally have different prices, which implies that the model features price dispersion.

We can rewrite the dispersion term in terms of inflation making use of the Calvo assumption. We have

$$\Delta_t = (1-\theta_p)(\Pi_t^*)^{-\epsilon_p} \Pi_t^{\epsilon_p} + \theta_p \Pi_t^{\epsilon_p} \Delta_{t-1}. \tag{32}$$

Firms profits are

$$d_t = \int_0^1 \frac{P_t(i)}{P_t} y_t(i) di - mc_t \int_0^1 y_t(i) di.$$

Plugging in the demand function gives

$$d_t = y_{d,t} P_t^{\epsilon_p - 1} \int_0^1 P_t(i)^{1-\epsilon_p} di - mc_t y_{d,t} \int_0^1 \left(\frac{P_t(i)}{P_t} \right)^{-\epsilon_p} di.$$

Now since $P_t^{1-\epsilon_p} = \int_0^1 P_t(i)^{1-\epsilon_p} di$, this reduces to

$$d_t = y_{d,t} - mc_t y_{d,t} \int_0^1 \left(\frac{P_t(i)}{P_t} \right)^{-\epsilon_p} di$$

Thus, we can write profits as

$$d_t = (1 - mc_t \Delta_t) y_{d,t}. \tag{33}$$

Further, note that

$$mc_t y_t = r_t k_t + p_{e,t} e_{y,t} + w_t h_{y,t}.$$

Thus, we can also write profits as

$$d_t = y_{d,t} - r_t k_t - p_{e,t} e_{y,t} - w_t h_{y,t}.$$

D.3. Climate block

Following Golosov et al. (2014), I model the current level of atmospheric carbon concentration as a function of current and past emissions:

$$s_t = \sum_{s=0}^{\infty} (1 - d_s) e_{t-s},$$

where $1 - d_s = (1 - \varphi_L) \varphi_0 (1 - \varphi)^s$. Here, $1 - \varphi_0$ is the share of remaining emissions exiting the atmosphere immediately while φ_0 is the remaining share of emissions that decay over time at a geometric rate $1 - \varphi$. We can write this in recursive form as

$$s_t = (1 - \varphi) s_{t-1} + \varphi_0 e_t. \tag{34}$$

D.4. Fiscal and monetary policy

The government runs a balanced budget in every period, i.e. all transfers are financed by tax revenues. We consider the following transfer policy

$$\lambda \omega_{H,t} = \tau^d d_t + \tau^k r_t^K k_t + \mu \tau_t p_{e,t} e_t \tag{35}$$

$$(1-\lambda)\omega_{S,t} = (1-\mu)\tau_t p_{e,t} e_t. \tag{36}$$

The distribution of carbon tax revenues are governed by parameter μ. As the baseline, we assume that all carbon revenues are obtained by the savers, i.e. $\mu = 0$. Later, we will experiment with alternative transfer policies.[9]

Carbon taxes τ_t are set according to the following rule:

$$\tau_t = (1-\rho_\tau)\tau + \rho_\tau \tau_{t-1} + \epsilon_{\tau,t}. \tag{37}$$

Finally, we assume that there is a monetary authority that conducts monetary policy according to the following Taylor rule (in log-linear form):

$$\hat{r}_t^b = \rho_r \hat{r}_{t-1}^b + (1-\rho_r)\phi_\pi \hat{\pi}_{T,t} + \epsilon_{mp,t}, \tag{38}$$

where $\hat{\pi}_{T,t}$ is headline consumer price inflation: $\hat{\pi}_{T,t} = \lambda \hat{\pi}_{H,t} + (1-\lambda)\hat{\pi}_{S,t}$ with $\Pi_{H,t} = \frac{p_{H,t}}{p_{H,t-1}}\Pi_t$ and $\Pi_{S,t} = \frac{p_{S,t}}{p_{S,t-1}}\Pi_t$.

D.5. Aggregation and market clearing

Because capital is only held by S, we have that $(1-\lambda)k_{S,t} = k_t$ and $(1-\lambda)i_{S,t} = i_t$. Because bonds are in zero net supply, we have $z_{S,t} = z_{H,t} = b_{S,t} = b_{H,t} = 0$.

Aggregate total, non-energy, and energy consumption are given by $x_t = \lambda x_{H,t} + (1-\lambda)x_{S,t}$, $c_t = \lambda c_{H,t} + (1-\lambda)c_{S,t}$, and $e_{c,t} = \lambda e_{H,t} + (1-\lambda)e_{S,t}$, respectively. Labor market clearing requires $\lambda h_{H,t} + (1-\lambda)h_{S,t} = h_{y,t} + h_{e,t}$. The energy market clears if $e_t = e_{c,t} + e_{y,t}$. Finally, goods market clearing requires that

$$c_t + i_t = y_{d,t}. \tag{39}$$

To derive this, we multiply the households budget constraints by their shares and sum over them:

[9] Furthermore, we assume that $\tau^d = \tau^k = 0$. However, the tax scheme can be used to equalize incomes if $\tau^d = \tau^k = \mu = \lambda$.

$$
\begin{aligned}
\lambda p_{H,t}x_{H,t} + (1-\lambda)(p_{S,t}x_{S,t} + i_{S,t} + b_{S,t+1}) = \lambda(w_t h_{H,t} + \omega_{H,t}) + (1-\lambda)\left(w_t h_{S,t} + \frac{R^b_{t-1}}{\Pi_t} b_{S,t} + (1-\tau^k) r_t k_{S,t} + \frac{(1-\tau^d)d_t}{1-\lambda} + \omega_{S,t}\right) \\
c_t + i_t + p_{e,t}e_{c,t} = w_t h_t + r_t k_t + \tau_t p_{e,t} e_t + d_t \\
c_t + i_t + p_{e,t}e_{c,t} = w_t h_t + r_t k_t + \tau_t p_{e,t} e_t + y_{d,t} - r_t k_t - w_t h_{y,t} - p_{e,t} e_{y,t} \\
c_t + i_t = w_t h_{y,t} + w_t h_{e,t} + \tau_t p_{e,t} e_t + y_{d,t} - w_t h_{y,t} - p_{e,t} e_t \\
c_t + i_t = (1-\tau_t) p_{e,t} e_t + \tau_t p_{e,t} e_t + y_{d,t} - p_{e,t} e_t \\
c_t + i_t = y_{d,t}.
\end{aligned}
$$

D.6. Equilibrium

A general equilibrium of this economy is defined as a sequence of quantities $\mathcal{Q} = \{x_t, x_{S,t}, x_{H,t}, c_t, c_{S,t}, c_{H,t}, e_{c,t}, e_{S,t}, e_{H,t}, i_t, k_{t+1}, y_t, y_{d,t}, h_{H,t}, h_{S,t}, h_{y,t}, h_{e,t}, e_{y,t}, mc_t, e_t, s_t, \tau_t, \omega_{H,t}, d_t, \Delta_t, x_{1,t}, x_{2,t}\}_{t=0}^{\infty}$, a sequence of prices $\mathcal{P} = \{\lambda_{S,t}, w_t, r_t, p_{e,t}, p_{S,t}, p_{H,t}, R^b_t, \Pi_t, \Pi^*_t, \Pi_{e,t}, \Pi_{T,t}\}_{t=0}^{\infty}$, and a sequence of forcing variables $\mathcal{F} = \{a_t, a_{e,t}, \epsilon_{\tau,t}, \epsilon_{mp,t}\}_{t=0}^{\infty}$ such that

1. Given a sequence of prices $\mathcal{P}$, and a forcing sequence $\mathcal{F}$, the sequence of quantities $\mathcal{Q}$ solves the households' and the firms' problems.

2. Given a sequence of quantities $\mathcal{Q}$ and a sequence of forcing variables $\mathcal{F}$, the sequence of prices $\mathcal{P}$ clears all markets.

The equilibrium is characterized by the following set of equations:

Table D.1: Summary of Equilibrium Conditions

1:	Labor supply, S	$\frac{x_{S,t}^{-\sigma}}{p_{S,t}} w_t = \psi_S h_{S,t}^{\theta}$
2:	Non-energy demand, S	$c_{S,t} = a_{S,c} \left(\frac{1}{p_{S,t}}\right)^{-\epsilon_x} x_{S,t}$
3:	Energy demand, S	$e_{S,t} = a_{S,e} \left(\frac{p_{e,t}}{p_{S,t}}\right)^{-\epsilon_x} x_{S,t}$
4:	Shadow value of wealth	$p_{S,t}\lambda_{S,t} = x_{S,t}^{-\sigma}$
5:	Bonds Euler equation, S	$\frac{x_{S,t}^{-\sigma}}{p_{S,t}} = \beta E_t \left[\frac{R_t^b}{\Pi_{t+1}} \left(s\frac{x_{S,t+1}^{-\sigma}}{p_{S,t+1}} + (1-s)\frac{x_{H,t+1}^{-\sigma}}{p_{H,t+1}}\right)\right]$
6:	Investment Euler equation, S	$q_t = \beta E_t \left[\frac{\lambda_{S,t+1}}{\lambda_{S,t}} \left((1-\tau^k)r_{t+1} + q_{t+1}\left(1 - \delta - \frac{\varphi_k}{2}\left(\frac{i_{t+1}}{k_{t+1}} - \delta\right)^2 + \varphi_k \left(\frac{i_{t+1}}{k_{t+1}} - \delta\right)\frac{i_{t+1}}{k_{t+1}}\right)\right)\right]$
7:	Tobin's q	$1 = q_t \left(1 - \varphi_k \left(\frac{i_t}{k_t} - \delta\right)\right)$
8:	Capital accumulation	$k_{t+1} = i_t - \frac{\varphi_k}{2}\left(\frac{i_t}{k_t} - \delta\right)^2 k_t + (1-\delta)k_t$
9:	Final good price index, S	$p_{S,t} = \left(a_{S,c} + a_{S,e}p_{e,t}^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}}$
10:	Labor supply, H	$\frac{x_{H,t}^{-\sigma}}{p_{H,t}} w_t = \psi_H h_{H,t}^{\theta}$
11:	Non-energy demand, H	$c_{H,t} = a_{H,c} \left(\frac{1}{p_{H,t}}\right)^{-\epsilon_x} x_{H,t}$
12:	Energy demand, H	$e_{H,t} = a_{H,e} \left(\frac{p_{e,t}}{p_{H,t}}\right)^{-\epsilon_x} x_{H,t}$
13:	Consumption, H	$p_{H,t}x_{H,t} = w_t h_t + \omega_{H,t}$
14:	Final good price index, H	$p_{H,t} = \left(a_{H,c} + a_{H,e}p_{e,t}^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}}$
15:	Capital demand non-energy firm	$\frac{r_t k_t}{y_t} = \alpha(1-\nu)^{\frac{1}{\epsilon_y}} mc_t \left(\frac{e^{-\gamma s_t}a_t k_t^{\alpha} h_{y,t}^{1-\alpha}}{y_t}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}}$
16:	Labor demand non-energy firm	$\frac{w_t h_{y,t}}{y_t} = (1-\alpha)(1-\nu)^{\frac{1}{\epsilon_y}} mc_t \left(\frac{e^{-\gamma s_t}a_t k_t^{\alpha} h_{y,t}^{1-\alpha}}{y_t}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}}$
17:	Energy demand non-energy firm	$\frac{p_{e,t}e_{y,t}}{y_t} = \nu^{\frac{1}{\epsilon_y}} mc_t \left(\frac{e^{-\gamma s_t}e_{y,t}}{y_t}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}}$
18:	Reset price	$\Pi_t^* = \frac{\epsilon_p}{\epsilon_p - 1}\Pi_t \frac{x_{1,t}}{x_{2,t}}$
19-20:	Auxiliary terms	$x_{1,t} = \lambda_t mc_t y_{d,t} + \beta\theta_p E_t x_{1,t+1}\Pi_{t+1}^{\epsilon_p}$
		$x_{2,t} = \lambda_t y_{d,t} + \beta\theta_p E_t x_{2,t+1}\Pi_{t+1}^{\epsilon_p - 1}$
21:	Aggregate inflation	$\Pi_t^{1-\epsilon_p} = (1-\theta_p)(\Pi_t^*)^{1-\epsilon_p} + \theta_p$
22:	Price dispersion	$\Delta_t = (1-\theta_p)(\Pi_t^*)^{-\epsilon_p}\Pi_t^{\epsilon_p} + \theta_p \Pi_t^{\epsilon_p}\Delta_{t-1}$
23:	Aggregate demand non-energy	$y_{d,t}\Delta_t = y_t$
24:	Prod. function non-energy firm	$y_t = e^{-\gamma s_t}\left[(1-\nu)^{\frac{1}{\epsilon_y}}\left(a_t k_t^{\alpha} h_{y,t}^{1-\alpha}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}} + \nu^{\frac{1}{\epsilon_y}}\left(e_{y,t}\right)^{\frac{\epsilon_y - 1}{\epsilon_y}}\right]^{\frac{\epsilon_y}{\epsilon_y - 1}}$
25:	Energy supply	$(1-\tau_t)p_{e,t}e_t = w_t h_{e,t}$
26:	Production function energy firm	$e_t = a_{e,t}h_{e,t}$
27:	Carbon emissions	$s_t = (1-\varphi)s_{t-1} + \varphi_0 e_t$
28:	Aggregate total consumption	$x_t = \lambda x_{H,t} + (1-\lambda)x_{S,t}$
29:	Aggregate non-energy consumption	$c_t = \lambda c_{H,t} + (1-\lambda)c_{S,t}$
30.	Aggregate energy consumption	$e_{c,t} = \lambda e_{H,t} + (1-\lambda)e_{S,t}$
31:	Labor market clearing	$\lambda h_{H,t} + (1-\lambda)h_{S,t} = h_{y,t} + h_{e,t}$

32:	Energy market clearing	$e_t = e_{c,t} + e_{y,t}$
33:	Goods market clearing	$c_t + i_t = y_{d,t}$
34:	Tax schedule	$\tau_t = (1-\rho_\tau)\tau + \rho_\tau \tau_{t-1} + \epsilon_{\tau,t}$
35:	Transfers, H	$\lambda \omega_{H,t} = \tau^d d_t + \tau^k r_t^K k_t + \mu \tau_t p_{e,t} e_t$
36:	Dividends	$d_t = (1 - mc_t \Delta_t) y_{d,t}$
37:	Taylor rule	$\hat{r}_t^b = \rho_r \hat{r}_{t-1}^b + (1-\rho_r)(\phi_\pi \hat{\pi}_{T,t}) + \epsilon_{mp,t}$
38:	Headline inflation	$\hat{\pi}_{T,t} = \lambda \hat{\pi}_{H,t} + (1-\lambda)\hat{\pi}_{S,t}$
39:	Inflation, p_H	$\Pi_{H,t} = \frac{p_{H,t}}{p_{H,t-1}} \Pi_t$
40:	Inflation, p_S	$\Pi_{S,t} = \frac{p_{S,t}}{p_{S,t-1}} \Pi_t$

D.7. Calibration

We parameterize the model as follows. The time period is a quarter. The discount factor β takes the standard value 0.99, which implies an annualized steady-state interest rate of 4 percent. The intertemporal elasticity of substitution $1/\sigma$ and the labor supply elasticity $1/\theta$ are set to 1. These are standard values in the literature.

The labor weight in the utility function, φ_i is set such that steady-state hours worked h_i are normalized to one. I calibrate the share of hand-to-mouth λ to 25 percent, corresponding to the low-income threshold used in the LCFS. Such a share is also in line with the estimates of hand-to-mouth households in Kaplan, Violante, and Weidner (2014). Idiosyncratic risk is calibrated to $1 - s = 0.04$, as in Bilbiie (2020). The distribution parameters $a_{H,e}$ and $a_{S,e}$ are set to match the energy expenditure shares of 9.5 percent for the hand-to-mouth and 6.5 percent for the savers as observed in the LCFS. Note that the elasticity of substitution ϵ_x is the same as the own price elasticity in this model. I calibrate ϵ_x to 0.05 for hand-to-mouth and 0.275 for savers, as my empirical evidence points to a lower elasticity for constrained households. The implied average elasticity is consistent with Labandeira, Labeaga, and López-Otero (2017) who perform a meta analysis on the price elasticity of energy demand and find an average short-run elasticity of around 0.21.

Turning to the production side, I set the depreciation rate δ to 0.025, implying an annual depreciation on capital of 10 percent. The capital adjustment cost parameter is set to $\varphi_k = 4$, which implies an elasticity of investment to Tobin's marginal q of 10. I set α to 0.3, implying a steady-state capital share of around 70 percent (see e.g. Smets and Wouters, 2003). Using data on non-household energy consumption and energy prices in the EU, I estimate a energy share of around 7 percent. To approximate that share, I thus set $\nu = 0.07$. The elasticity of substitution between energy and capital/labor is set to 0.21, drawing again on the evidence in Labandeira, Labeaga, and López-Otero (2017). The elasticity of substitution between non-energy varieties is assumed to be 6, which is a standard value and implies a steady-state markup of 20 percent, consistent with the evidence in Christopoulou and Vermeulen (2012). The Calvo parameter θ_p is set to 0.825, which implies an average price duration of 5-6 quarters, in line with the empirical estimates in Alvarez et al. (2006). These parameter choices imply a relatively flat Phillips curve with a slope of 0.04.

For the climate block, I rely on the values in Golosov et al. (2014). I abstract from uncertainty about the damage parameter and use the deterministic, long-run value from Golosov et al. (2014). Note, however, that carbon emissions in my model are in arbitrary units. Thus, following Heutel (2012) I scale the damage parameter to make the increase in output damages from doubling the steady-state carbon stock consistent with the projected increase in damages from doubling CO2 levels in 2005. Turning to the carbon cycle, note that the excess carbon has a half-life of about 300 years (Archer, 2005). This implies a value of $1 - \varphi = 0.9994$.[10] Furthermore, according to the 2007 IPCC reports, about half of the CO2 pulse to the atmosphere is removed after a time scale of 30 years. This implies that $\varphi_0 = \frac{0.5}{(1-\varphi)^{120}} = 0.5359$.

Turning to fiscal and monetary policy, I compute the steady-state carbon tax as the implied tax rate implied by the average EUA price which is around 3.9 percent (the average real EUA price as a share of gross electricity prices in emission units). The persistence of the tax shock is set to 0.85, which is broadly consistent with the shock persistence estimated in the external instruments VAR. Finally, the Taylor rule coefficient on inflation is set to 1.5, and interest smoothing is assumed to be 0.8. These values are standard in the literature.

All other taxes are assumed to be zero in the baseline case, later we will use them to equalize the income incidence. Furthermore, we assume that all carbon tax revenues accrue to the savers, $\mu = 0$, motivated by the fact that there is no redistribution scheme in the current EU ETS in place. The calibration is summarized in Table D.2.

[10]From the carbon cycle, we have $E_t s_{t+h} = (1-\varphi)^h s_t = 0.5 s_t$. Thus, we impose $(1-\varphi)^{1200} = 0.5$ to get φ.

Table D.2: Calibration

Parameter	Description	Value	Target/Source/Comments
β	Discount factor	0.99	Standard value
$1/\sigma$	Intertemporal elasticity of substitution	1	Standard value
$1/\theta$	Labor supply elasticity	1	Standard value
λ	Share of hand-to-mouth	0.25	Share of low-income households, LCFS
$1-s$	Probability of becoming H	0.04	Bilbiie (2020)
$a_{H,e}$	Distribution parameter H	0.078	Energy share of 9.5%, LCFS
$a_{S,e}$	Distribution parameter S	0.056	Energy share of 6.5%, LCFS
ϵ_{xH}	Elasticity of substitution energy/non-energy H	0.05	LCFS, Labandeira, Labeaga, and López-Otero (2017)
ϵ_{xS}	Elasticity of substitution energy/non-energy S	0.275	LCFS, Labandeira, Labeaga, and López-Otero (2017)
ϵ_y	Elasticity of substitution energy/non-energy firms	0.21	Labandeira, Labeaga, and López-Otero (2017)
δ	Depreciation rate	0.025	Standard value
φ_k	Capital adjustment costs	4	Standard value
α	Capital returns-to-scale	0.3	Standard value
ν	Energy returns-to-scale	0.07	Steady-state energy share of $\approx$ 7%; Eurostat
ϵ_p	Price elasticity	6	Steady-state markup of 20%
θ_p	Calvo parameter	0.825	Average price duration of 5-6 quarters
γ	Climate damage parameter	$5.3 * 10^{-5}$	Golosov et al. (2014)
φ_0	Emissions staying in atmosphere	0.5359	Golosov et al. (2014)
$1-\varphi$	Emissions decay parameter	0.9994	Golosov et al. (2014)
ϕ_π	Taylor rule coefficient inflation	1.5	Standard value
ρ_r	Interest smoothing	0.8	Standard value
τ	Steady-state carbon tax	0.039	Implied tax rate from average EUA price
ρ_τ	Persistence carbon tax shock	0.85	Persistence in the data

D.8. Steady state and model solution

We assume that $a = a_e = 1$ in steady state and we normalize ψ_i such that $h_i = 1$. Furthermore, τ is calibrated. Finally, we assume that there is zero inflation in steady state, i.e. $\Pi = \Pi_T = 1$. From the definition of aggregate inflation and the price dispersion, this implies $\Pi^* = 1$, $\Delta = 1$ and $y_d = y$.

From the investment Euler equation, we have

$$r = \frac{\frac{1}{\beta} - 1 + \delta}{1 - \tau^k}.$$

From the bonds Euler, we get

$$R^b = \frac{1}{\beta}.$$

From the reset price, we get

$$mc = \frac{\epsilon_p - 1}{\epsilon_p}.$$

From Tobin's q, we have $q = 1$.

To solve for the steady state, we guess k and e. From [27], we get s.[11] From [26], we get h_e. From [31], we get h_y. From [15] we get y. From [24], we get e_y. From [32], we get e_c. From [17], we get p_e. From [16], we get w. From [8], we get i. From [33], we get c. From [9], we get p_S:

$$\begin{aligned}
p_S &= \left(a_{S,c} + a_{S,e} p_e^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}} \\
&= \left(1 - \omega_{S,e} p_e^{\epsilon_x - 1} p_S^{1-\epsilon_x} + \omega_{S,e} p_S^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}} \\
&= p_S \left(p_S^{\epsilon_x - 1} - \omega_{S,e} p_e^{\epsilon_x - 1} + \omega_{S,e}\right)^{\frac{1}{1-\epsilon_x}} \\
\Rightarrow 1 &= p_S^{\epsilon_x - 1} - \omega_{S,e} p_e^{\epsilon_x - 1} + \omega_{S,e} \\
p_S &= \left(1 + \omega_{S,e} p_e^{\epsilon_x - 1} - \omega_{S,e}\right)^{\frac{1}{\epsilon_x - 1}}.
\end{aligned}$$

From this we then have $a_{S,e} = \omega_{S,e} \left(\frac{p_e}{p_S}\right)^{\epsilon_x - 1}$ and $a_{S,c} = 1 - a_{S,e}$. Similarly we get from [14] p_H and $a_{H,e}$ and $a_{H,c}$. From [36], we get d. From [35], we get ω_H. From [13], we get x_H. From [11], we get c_H. From [12], we get e_H. From [29], we get c_S. From [30], we get e_S. From [3], we get x_S. From [4], we get λ. From [1], we get ψ_S and from [10], we get ψ_H. From [19]-[20], we get the values of the auxiliary terms x_1 and x_2.
Then we optimize such that [2] and [25] hold.

To solve the model, we log-linearize the equilibrium equations around the deterministic steady state and solve for a set of linearized policy functions using Dynare.

[11] The equation numbers here refer to the equations in Table D.1.

References Appendix

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