The economic consequences of putting a price on carbon*

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September, 2021

Abstract

How does carbon pricing affect the economy? Is it successful at reducing emissions and how does it affect economic inequality? Exploiting institutional features of the European carbon market and high-frequency data, I estimate the aggregate and distributional effects of a carbon policy shock. I find that a shock tightening the carbon pricing regime leads to a significant increase in energy prices and a persistent fall in emissions. The drop in emissions 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 barely affected. My results suggest that targeted fiscal policy can reduce the economic costs of carbon pricing – without compromising emission reductions.

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

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

*I am indebted to my advisor Paolo Surico, João Cocco, Elias Papaioannou, Lucrezia Reichlin and Hélène Rey for their invaluable guidance and support. For helpful comments and suggestions, I thank Asger Andersen, Michele Andreolli, Juan Antolin-Diaz, Christiane Baumeister, Jean-Pierre Benoît, Florin Bilbiie, James Cloyne, Martin Ellison, Luis Fonseca, Luca Fornaro, Jordi Galí, Garth Heutel, Yueran Ma, Joseba Martinez, Matthias Meier, Silvia Miranda-Agrippino, Tsvetelina Nenova, Luca Neri, Gert Peersman, Michele Piffer, Richard Portes, Sebastian Rast, Vania Stavrakeva, Nadia Zhuravleva, Nathan Zorzi as well as participants at the EEA-ESEM conference, the Young Economist Symposium, the IAAE conference, the Oxford NuCamp PhD Workshop, the IAEE conference, the Ghent Workshop on Empirical Macro, the QCGBF conference, the QMUL Economics and Finance Workshop and the LBS Brownbag Seminar. I thank Mario Alloza for kindly sharing their fiscal policy shock series. I also thank the IAEE for the best student paper award. Finally, I am very grateful to the London Business School's Wheeler Institute for Business and Development for generously supporting this research.

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1. Introduction

Climate change is one of the greatest challenges of our time, posing significant threats not only to our lives, livelihoods and the environment, but also to the global economy. Fighting climate change, however, has proved very difficult because of its global nature and the pervasive externalities involved. As the threats of a climate crisis are becoming more acute and visible, climate change is now a key priority for policymakers around the world. There is broad agreement that putting a price on carbon emissions is the most effective way to mitigate climate change and several countries have enacted national carbon pricing policies, either via carbon taxes or cap and trade systems. Yet, little is known about the economic effects of such policies. While arguably beneficial in the longer term, there could be short-term economic costs and important distributional consequences.

This paper aims to contribute filling this gap. I propose a novel approach to estimate the dynamic causal effects of a carbon policy shock, exploiting institutional features of the European carbon market and high-frequency data. The European Union Emissions Trading System (EU ETS) is the largest and oldest carbon market in the world, accounting for around 40 percent of the EU's greenhouse gas (GHG) emissions. The market was established in phases and the regulations have been updated continuously. Following an event study approach, I collected 113 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 am able to isolate a series of carbon policy surprises. Reverse causality can be plausibly ruled out as economic conditions are known and priced by the market prior to the regulatory news and unlikely to change within the tight window. Using the surprise series as an instrument, I estimate the aggregate and distributional effects of a structural carbon policy shock.

I find that carbon pricing has significant effects on 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 turns out to be successful in achieving its goal of reducing emissions. However, this does not come without cost. Consumer prices rise significantly and economic activity falls, which is reflected in lower output and higher unemployment. Crucially, the fall in activity appears to be somewhat less persistent than the fall in emissions – improving the emissions intensity in the longer term. The stock market falls for about one and a half years but then rebounds and turns positive after. The euro depreciates in real terms and imports fall significantly. While the shock leads to somewhat heightened financial uncertainty and a short-term deterioration of financial conditions, the main transmission channel appears to work through higher carbon prices, which passing through energy prices leads to lower consumption and investment. At the same time, carbon pricing creates an incentive for green innovation, causing a significant uptick in low-carbon patenting.

Carbon policy shocks have also contributed meaningfully to historical variations in prices, emissions and macroeconomic aggregates. Importantly, however, they did not account for the fall in emissions associated with the global financial crisis – supporting the validity of the identified shock.

My results illustrate that carbon pricing is successful at reducing emissions and mitigating climate change. However, this comes at the cost of lower economic activity today. 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 hardly affected in two ways. First, they spend a larger share of their disposable income on energy and thus the higher energy bill leaves significantly less resources for other expenditures. Second, they also experience the largest fall in income, as they tend to work in sectors that are more exposed to carbon pricing. Crucially, the estimated magnitudes are much larger than what can be accounted for by the direct effect through energy prices alone – pointing to an important role of indirect, general equilibrium effects via income and employment.

These findings suggest that targeted fiscal policies could be an effective way to reduce the economic costs of carbon pricing. To the extent that energy demand is inelastic, which turns out to be the case especially for poorer households, this should not compromise the reductions in emissions. I also show that carbon pricing leads to a significant fall in the support of climate-related policies among low-income households. Thus, such targeted compensations may also help to increase the public support of such policies.

A comprehensive series of sensitivity checks indicate that the results are robust along a number of other dimensions including the selection of event dates, 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. Controlling for such background noise using an heteroskedasticity-based estimator produces very similar results, even though the responses are a bit less precisely estimated.

Related literature and contribution. This paper is related 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 (Lin and Li, 2011; Martin, De Preux, and Wagner, 2014; Andersson, 2019; Pretis, 2019), 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, Kichian, and Islam, 2018). 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 contrast, theoretical studies based on computable general equilibrium models tend to find contractionary output effects (see e.g. McKibbin, Morris, and Wilcoxen, 2014; McKibbin et al., 2017; Goulder and Hafstead, 2018). By way of summary, the existing evidence on the economic effects of carbon pricing is still scarce and inconclusive. I contribute to this literature by providing new estimates for the macroeconomic impact 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 in particular points to large macroeconomic effects of tax changes; a tax increase leads to a significant and persistent decline of output and its components (see also Mertens and Ravn, 2013; Cloyne, 2013). However, it is unclear how much we can learn from these estimates with respect to carbon pricing, which is enacted to correct a clear 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 variation. From a methodological viewpoint, my approach is closely related to the literature on high-frequency identification, which has been developed in the monetary policy setting (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

[1] Contrary to this paper, Metcalf and Stock (2020*a*,*b*) do not study the effects of the EU ETS but national carbon taxes, which are present in many European countries and cover sectors that are not included in the EU ETS.

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 announcements. The idea is to isolate the impact of policy news by measuring the change in asset prices in a tight window around the announcements. I contribute to this literature by extending the high-frequency identification approach to climate policy, exploiting institutional features of the European carbon market.

This paper is not the first to study regulatory news in 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 direct evidence not only on the aggregate but also on the distributional consequences of carbon pricing. There is growing consensus that a sustainable transition to a low-carbon economy has to be fair and equitable (see e.g. European Comission, 2021). Therefore, 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 massively understate the actual distributional impact. Finally, I show that the distributional consequences do not only matter for inequality but also for the transmission of the policy to the macroeconomy.

Roadmap. The paper proceeds as follows. In the next section, I provide some background information on the European carbon market and detail relevant regulatory events in this market. In Section 3, I discuss the high-frequency identification strategy and perform some diagnostic checks on the carbon policy surprise series. Section 4 discusses the econometric approach and introduces the external and internal instrument models. Section 5 presents the results on the aggregate effects of carbon pricing. I start by analyzing the instrument strength before studying the effects on emissions and the macroeconomy, the historical importance and potential propagation channels. Section 6 looks into the heterogeneous effects of carbon pricing, using detailed household-level data on income and expenditure. I analyze the distributional impact, how heterogeneity matters for the transmission and end with some policy implications. In Section 7, I perform a number of robustness checks. Section 8 concludes.

2. 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 covered by 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 enough allowances to cover all their emissions. This is enforced with heavy fines. If a company reduces its emissions, it can keep the spare allowances to cover its future needs or sell them to another company that is short of allowances. A binding limit on the total number of allowances available in the system guarantees a positive price on carbon (see European Comission, 2020*a*, for more information).

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 (Paris), EEX (Leipzig) or Nord Pool (Oslo). Furthermore, there exist also liquid futures markets on EUAs, such as the EEX and ICE (London). In 2018, the cumulative trading volume in the relevant futures and spot markets was about 10 billion EUA (DEHSt, 2019).

A brief history of the EU ETS. The development of the EU ETS has been divided into different phases. The evolution of the carbon price over the phases of the system is depicted in Figure 1. 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 2007, the carbon price fell significantly as it became apparent that the total amount of allowances issued exceeded total emissions significantly, and eventually converged to zero as phase one allowances could not be transferred to phase two.

Figure 1: The carbon price in the EU

Notes: The EUA 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 phase two, based on actual emissions. The proportion of free allocation fell slightly, several countries started to hold auctions, and businesses were allowed to buy a limited amount 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 applies 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 emissions reductions that were greater than expected, which in turn led to a large surplus of allowances and credits weighing down prices.

The subsequent third phase began in 2013 and ran until the end of 2020. Learning from the lessons of the previous phases, the system was changed significantly 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 method for allocating allowances instead of the previous free allocation and harmonized allocation rules apply to 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 allowances to address the surplus of emission allowances that has built up since the Great Recession ('back-loading'). Later, the Commission introduced a market stability reserve, which started operating 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 be auctioned. To this end, the back-loaded allowances were transferred to the reserve rather than auctioned in the last years of phase three and unallocated allowances were transferred to the reserve as well.

The current, fourth phase spans the period from 2021 to 2030. The legislative framework for this trading period was revised in early 2018. In order 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 EU ETS's 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 collected 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 judgement of an European court, for instance. 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 113 such events during the period between 2005 and 2018. The events as well as the sources are detailed in Table A.1 in the Appendix. 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 a court ruling in case of 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. After the pilot phase of the system, there were also a number of important events related to the use and entitlement of international credits. Finally, there are a few events on the setting of the overall cap in the system.

The selection of events is a crucial factor in event studies. As the baseline, I use all of the identified events, however, in Section 7, I study the sensitivity of the results with respect to different event types in detail.

Carbon futures markets. Under the EU ETS, the right to emit a particular amount of greenhouse gases becomes a tradable commodity. The most liquid markets to trade these emission allowances are the futures markets at the EEX and the ICE. 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). The ICE EUA futures are listed on a quarterly expiry cycle and are traded up to 6 quarters out. The contract size is 1,000 EUAs and delivery is physical.

3. 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 implement 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 emission 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 regulatory news, it is possible to isolate the impact of the regulatory decision. 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.

To fix ideas, the carbon policy surprise series is computed by measuring the percentage change in the EUA futures price on the day of the regulatory event to the last trading day before the event:

$$CPSurprise_{t,d} = F_{t,d} - F_{t,d-1}, \tag{1}$$

where d and t indicate the day and the month of the event, respectively, and $F_{t,d}$ is the (log) settlement price of the EUA futures contract in month t on day d. Assuming that risk premia do not change over the narrow event window, we can interpret the resulting surprise as a revision in carbon price expectations caused by the regulatory news.[2]

EUA futures are traded at different maturities. I focus here on the front contract (the contract with the closest expiry date), which is the most liquid. Importantly, near-dated contracts also tend to be less sensitive to risk premia than contracts with longer maturities (Baumeister and Kilian, 2017; Nakamura and Steinsson, 2018). Thus, focusing on the front contract helps to further mitigate concerns about time-varying risk premia.[3]

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.

The resulting carbon policy surprise series is shown in Figure 2. We can see that regulatory news can have a substantial impact on carbon prices, with some news moving prices in excess of 20 percent. In April 2007, for instance, when the Commission approved the NAPs of Austria and Hungary, carbon prices fell by around 30 percent. Later in November, when the general court ruled on ex-post adjustments of Germany's NAP, the carbon price rose by over 30 percent, even though prices were already at very low levels with the end of the pilot phase in sight. Throughout the second phase, the regulatory surprises were a bit smaller, especially at the beginning. Towards the end, there were some larger surprises, for instance in November 2011 when a new regulation determining the volume of allowances to be auctioned prior to 2013 came into force. Some very large

[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). If that is the case, risk premia are differenced out in the computation of the high-frequency surprise series.

[3]As shown in Appendix B.4, using contracts further out produces results that are at least qualitatively similar. However, the first stage gets considerably weaker, further supporting the use of the front contract.

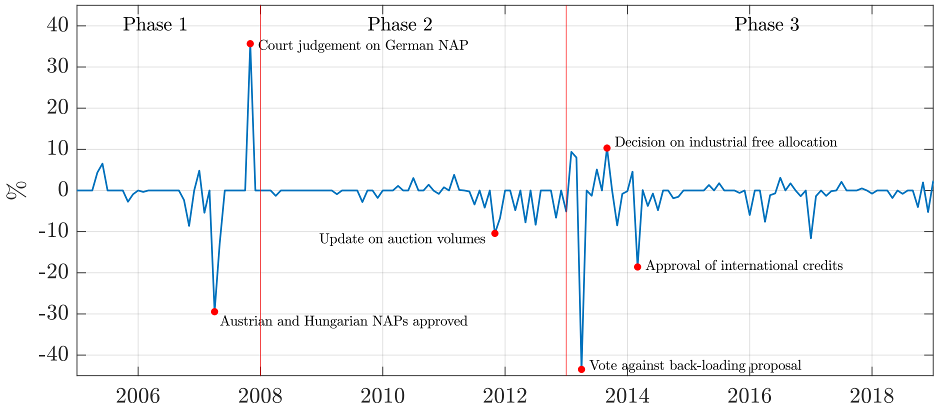

Figure 2: The carbon policy surprise series

Notes: This figure shows the carbon policy surprise series, constructed by measuring the percentage change of the EUA futures price around regulatory policy events concerning the supply of emission allowances in the European carbon market.

surprises occurred at the beginning of the third phase. On April 16, 2013 the European Parliament voted against the Commission's back-loading proposal, which led to a massive price fall of 43 percent. In September 2013, the Commission finalized the free allocation to the industrial sector in phase three, which led to a price increase of 10 percent. And in March 2014, the Commission approved two batches of international credit entitlement tables, sending prices down by almost 20 percent, just to name a few.

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 (cf. Nakamura and Steinsson, 2018). Because the exact release times of the regulatory news detailed in Table A.1 are mostly unavailable, it is practically infeasible to use an intraday window. 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 Section 7).

Finally, to be able to interpret the resulting series as a 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 put great care in selecting regulatory update events that were about very specific 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. Furthermore, I show that excluding the events regarding the overall cap, which are generally broader in scope, leads to very similar results. Likewise, excluding events that overlap with broader news about the carbon market does not change the results materially (see Section 7 for more details). Lastly, the focus on the supply of allowances is also confirmed by looking how some of the major events are received in the press.[4]

Diagnostics. To further assess the validity of the carbon policy surprise series, I perform a number of diagnostic checks. Desirable properties of a surprise series are that it should not be autocorrelated, forecastable nor correlated with other structural shocks (see Ramey, 2016, for a detailed discussion).

Inspecting the autocorrelation function, I find little evidence for serial correlation. The p-value for the Q-statistic that all autocorrelations are zero is 0.92. 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 0.99. I also show that the surprise series is uncorrelated with other structural shock measures from the literature, including oil, uncertainty, financial, fiscal and monetary policy shocks. The corresponding figures and tables can be found in Appendix B.1. Overall, this evidence supports the validity of the carbon policy surprise series.

4. Econometric approach

As illustrated above, the carbon policy surprise series has many desirable properties. Nonetheless, it is only a partial 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 Stock and Watson, 2018, for a detailed discussion of this point).

Thus, 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 use both an external instrument (Stock, 2008; Stock and Watson, 2012; Mertens and Ravn, 2013) and an internal instrument approach (Ramey, 2011; Plagborg-Møller and Wolf, 2019). In the ex-

[4]See e.g. https://www.bbc.com/news/science-environment-22167675 or https://www.argusmedia.com/en/news/2234159-eu-eyes-42pc-lrf-extended-scope-for-ets.

ternal instrument approach, the surprise series is used as an instrument external to the VAR model. While this approach tends to be very efficient, it provides biased estimates if the VAR is not invertible. In contrast, the internal instrument approach, which includes the instrument as the first variable in a recursive VAR, is robust to problems of non-invertibility.

An alternative approach 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.

4.1. 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 $\mathrm{Var}(\mathbf{u}_t) = \boldsymbol{\Sigma}$, $\mathbf{b}$ 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. $\mathrm{Var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Omega}$ is diagonal. From the invertibility assumption (3), we get the standard covariance restrictions $\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$.

We are interested in characterizing the causal impact of a single shock. Without loss of generality, let us denote the 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 $E[z_t \mathrm{u}_{1,t}] \neq 0$.[5] 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), and use Hall's percentile interval to compute the bands.

Internal instrument approach. To assess 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, $\bar{\mathbf{s}}_1 = [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{\cdot,1} / [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{1,1}$. 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.

[5] 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.

To conduct inference, I rely again on a residual-based moving block bootstrap.

4.2. 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 carbon block, I use the energy component of the HICP as well as total GHG emissions.[6] For the macroeconomic block, I include the headline HICP, industrial production, the unemployment rate, the policy rate, a stock market index, as well as the real effective exchange rate (REER).[7] More information on the data and its sources can be found in Appendix A.2.

The sample spans the period from January 1999, when the euro was introduced, to December 2018. 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 theoretical justification of this approach). The motivation for using a longer sample is to increase the precision of the estimates. However, restricting the sample to 2005-2018 produces very similar results.[8]

Following Sims, Stock, and Watson (1990), I estimate the VARs in levels. Apart from the unemployment and the policy 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 Section 7).

5. The aggregate effects of carbon pricing

5.1. First stage

The main identifying assumption 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

[6]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.

[7]A delicate choice concerns the monetary policy indicator. As the baseline, I use the 3-month Euribor. Using the shadow rate or longer-term government bond yields produces similar results.

[8]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).

is the case, I perform the weak instruments test by Montiel Olea and Pflueger (2013).

The heteroskedasticity-robust F-statistic in the first stage of the external instrument VAR is 20.95. Assuming a worst-case bias of 20 percent with a size of 5 percent, the corresponding critical value is 15.06. As the test statistic lies clearly above the critical value, we conclude that the instrument appears to be sufficiently strong to conduct standard inference.

5.2. The impact on emissions and the macroeconomy

Having established that the carbon policy surprise series is a strong instrument, I present now the results from the external and internal instrument models. Figure 3 shows the impulse responses to the identified carbon policy shock, normalized to increase the HICP energy component by one percent on impact. Panel A depicts the responses from the external instrument VAR and Panel B presents the responses from the internal instrument model. I start by discussing the results from the external instrument approach.

A restrictive carbon policy shock leads to a strong, immediate increase in the energy component of the HICP and a significant and persistent fall in GHG emissions. Thus, carbon pricing appears to be successful at reducing emissions and mitigating climate change. Turning to the macroeconomic variables, we can see that the fall in emissions does not come without cost. Consumer prices, as measured by the HICP, increase, industrial production falls, and the unemployment rate rises significantly. The labor market response turns out to be particularly pronounced, consistent with reallocation frictions in the economy. However, the fall in activity and industrial production in particular appears to be less persistent than the fall in emissions – implying an improvement in the emissions intensity in the longer run. While headline consumer prices increase persistently, the response of core HICP turns out to be more short-lived (see Appendix B.2 for more details). Monetary policy seems to largely look through the inflationary pressures caused by the carbon policy shock, as reflected in the insignificant policy rate response. Stock prices fall significantly on impact but recover quite quickly and even turn positive after about two years. Finally, the real exchange rate depreciates significantly.

In terms of magnitudes, a carbon policy shock increasing energy prices by 1 percent causes a decrease in GHG emissions and industrial production by around 0.5 percent, a rise in the unemployment rate of 0.2 percentage points and an increase in consumer prices of slightly more than 0.15 percent – measured at the peak of the responses. Thus, the responses are not only statistically but also eco-

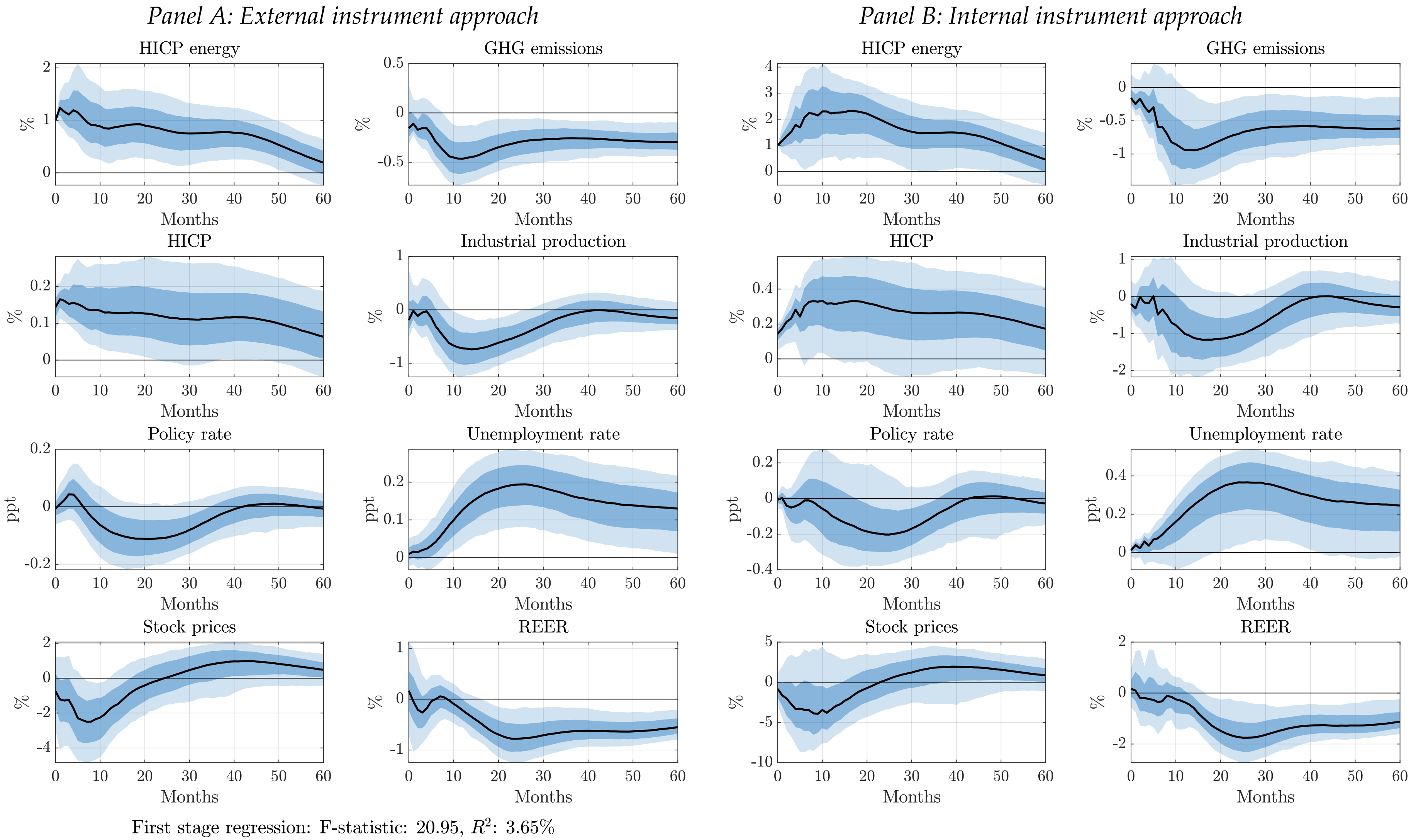

Figure 3: Impulse responses to a carbon policy shock

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.

nomically significant.

The results from the internal instrument model turn out to be very similar. The signs are all consistent and the responses are also similar in shape. The main difference lies in the response of energy prices, which turns out to be stronger and more persistent than in the external instrument model. Consequently, the magnitudes for emissions and the economic variables also turn out to be larger. It should be noted, however, that the responses are also less precisely estimated. Overall, these findings suggest that the results are robust to relaxing the assumption of invertibility. In the remainder of the paper, I thus use the external instruments model as the baseline.

By way of summary, these 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. My results also point to a strong pass-trough of carbon to energy prices, as can be seen from the significant energy price response. Unfortunately, it is not possible to quantify the pass-through directly, as my baseline specification does not include the carbon price, which only became available in 2005 when the carbon market was established. However, estimates from a model including the carbon price, estimated on the shorter sample, point to a pass-through of around 20 percent at its peak (see Appendix B.2).

5.3. 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, however, 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. To get a better idea of the average contribution, I also perform a variance decomposition in Appendix B.2.

Figure 4 shows the historical contribution of carbon policy shocks to energy price inflation and GHG emissions growth. We can see that carbon policy shocks have contributed meaningfully to variations in energy prices and GHG emissions in many episodes. On average, carbon policy shocks account for about a third of the variations in energy prices and a quarter of the variations in emissions at horizons up to one year. Furthermore, carbon policy shocks can also explain a non-negligible share of the variations in other macroeconomic and financial variables (see Appendix B.2). Importantly, we can also see that the significant fall in emissions in the aftermath of the global financial crisis was not driven by carbon policy shocks. This result is reassuring that the high-frequency identification strategy is working 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.

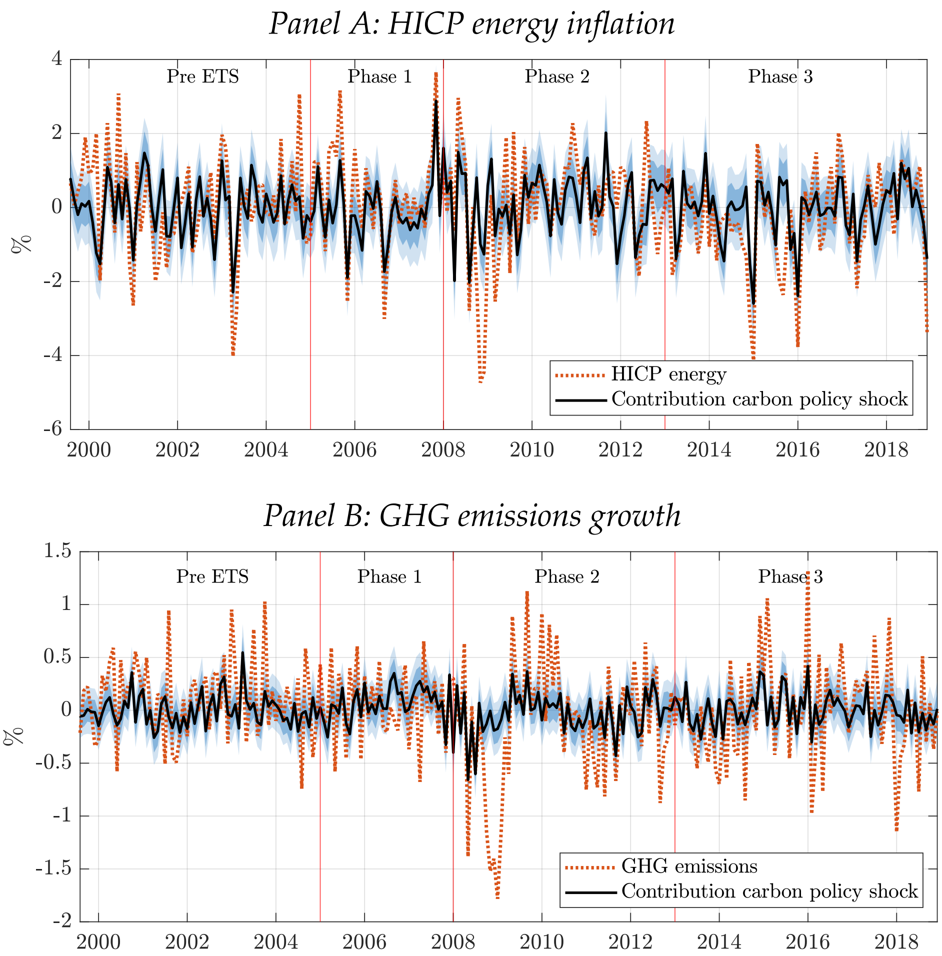

Figure 4: Historical decomposition of energy inflation and emissions growth

Notes: The figure shows the cumulative historical contribution of carbon policy shocks over the estimation sample for a selection of variables against the actual evolution of these variables. Panel A shows the historical contribution to HICP energy inflation, Panel B presents the contribution to GHG emissions growth. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

5.4. Propagation channels

Having established that carbon policy shocks are an important driver of the economy, we now analyze in more detail the underlying transmission channels.

The role of energy prices. The above results suggest that energy prices play a crucial role in the transmission of carbon policy shocks. Power producers seem to pass through the emission costs to energy prices to a significant extent, which is in line with previous empirical evidence (see e.g. Veith, Werner, and Zimmermann, 2009; Bushnell, Chong, and Mansur, 2013). To further corroborate this channel, I perform an event study using daily stock market data. More specifically, I map out the effects of carbon policy surprises on carbon futures and stock prices by running the following set of local projections:

$$q_{i,d+h} - q_{i,d-1} = \beta_0^i + \psi_h^i CPSurprise_d + \beta_{h,1}^i \Delta q_{i,d-1} + \ldots + \beta_{h,p}^i \Delta q_{i,d-p} + \xi_{i,d,h}, \tag{8}$$

where $q_{i,d+h}$ is the (log) price of asset i after h days following the event d, $CPSurprise_d$ is the carbon policy surprise on event day. ψ_h^i measures the effect on asset price i at horizon h. For inference, I follow the lag-augmentation approach proposed by Montiel Olea and Plagborg-Møller (2020). In particular, I augment the controls by an additional lag and use heteroskedasticity-robust standard errors.

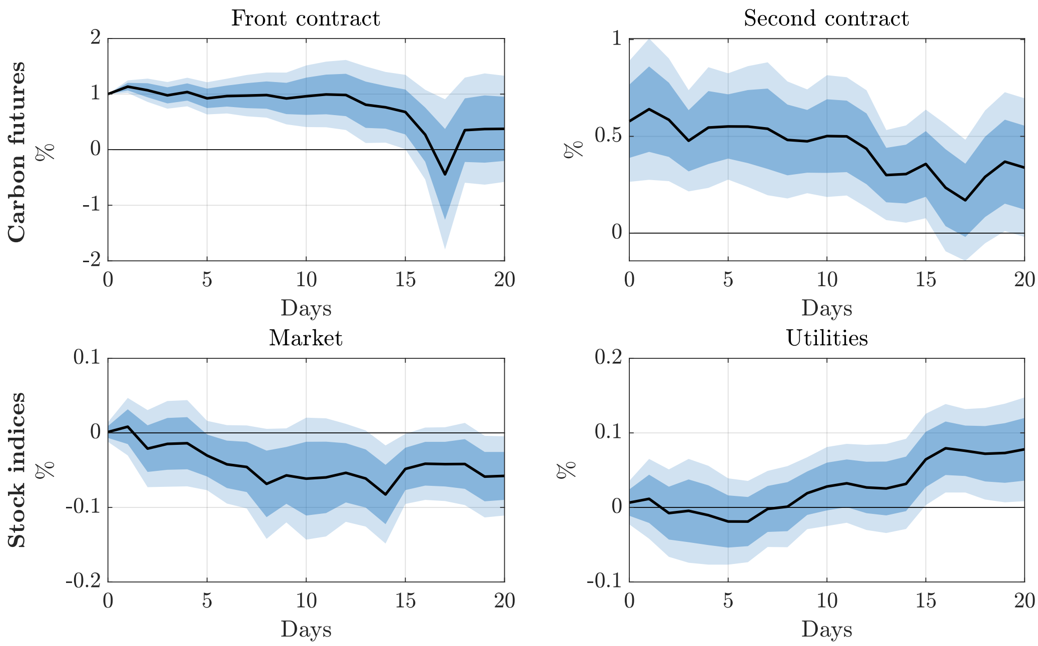

Figure 5: Carbon prices and stock market indices

Notes: Responses of carbon futures prices and stock indices for the market and the utility sector to a carbon policy surprise. The sample spans the period from April 22, 2005 to December 31, 2018. As controls, I use 15 lags of the respective dependent variable.

The results are shown in Figure 5. We can see that carbon policy surprises lead to a significant increase in carbon futures prices. The front contract increases significantly for about three weeks. The effect turns out to be quite persistent as the price of the second contract, which expires in the following quarter, also increases significantly. Turning to the stock market, we can see that the market does not seem to move immediately following carbon surprises. Only after about one week, the index starts to fall significantly. This may reflect the fact that the EU ETS is a relatively new market and thus market participants need some time to process the regulatory news. Looking into potential sectoral heterogeneities, I find that most sectors display a similar response to the market. Among the 11 GICS sectors, utilities is the only sector that stands out, displaying a significant increase in stock prices.

These results suggest that the European utility sector is able to profit, at least in the short run, from a more stringent carbon pricing regime. This finding is in line with previous empirical evidence (Veith, Werner, and Zimmermann, 2009; Bushnell, Chong, and Mansur, 2013) and may be explained as follows. The utility sector is segmented due to the structure of existing transmission networks, which substantially limits import penetration from countries without a carbon price. Thus, utility companies are able to increase their product prices without losing market share. At the same time, utilities can decarbonize at relatively low cost, for instance by switching from coal to gas-fired electricity, and sell the excess allowances at a profit. In contrast, for industrial emitters competing in international product markets, passing through the cost of carbon could lead to significant losses in market share, and decarbonizing tends to be more costly.

The transmission to the macroeconomy. To better understand how carbon pricing and the associated increase in energy prices affect the economy, I study the responses of a selection of financial and macroeconomic variables. To be able to estimate the dynamic causal effects on these variables, 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 dynamic causal effects using simple local projections:

$$y_{i,t+h} = \beta_0^i + \psi_h^i CPShock_t + \beta_{h,1}^i y_{i,t-1} + \ldots + \beta_{h,p}^i y_{i,t-p} + \xi_{i,t,h}, \qquad (9)$$

where ψ_h^i 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 as opposed to 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 shock to increase the HICP energy component by one percent on impact. The confidence bands are again computed using the lag-augmentation approach (Montiel Olea and Plagborg-Møller, 2020).[9]

Increases in energy prices can have significant effects on the macroeconomy (see e.g. Hamilton, 2008; Edelstein and Kilian, 2009). They directly affect households and firms by reducing their disposable income. Given that energy demand is considered to be quite inelastic, consumers and firms have less money to spend and invest after paying their energy bills (and financing their emission allowances). Note, however, that the magnitude of this discretionary income effect is bounded by the energy share in expenditure, which is around 7 percent in Europe. In addition, increased uncertainty about future energy prices may lead to a further fall in spending and investment because of precautionary motives.

Energy prices also affect the economy indirectly through the general equilibrium responses of prices and wages and hence of income and employment. After a carbon policy shock increasing energy prices, the direct decrease in households' and firms' consumption and investment expenditure will lead to lower output and exert downward pressure on employment and wages. The additional fall in aggregate demand induced by lower employment and wages lies at the core of the indirect effect.

To shed light on the different transmission channels at work, I study the responses of GDP and its components in Figure 6. We can see that the shock leads to a significant fall in real GDP. The response looks quite similar to the response of industrial production, both in terms of shape and magnitude. Looking at the different components, we can see that the shock leads to a significant and persistent fall in consumption. Investment, as measured by gross fixed capital formation, also falls significantly but the response turns out to be somewhat less persistent. Finally, net exports, expressed as a share of GDP, increase significantly, in line with the real depreciation of the euro. Inspecting the responses of exports and imports separately reveals that both exports and imports fall but imports fall by much more causing the significant increase in net exports.

Importantly, the magnitudes of the effects are by an order of magnitude larger than what can be accounted for by the direct effect through higher energy prices. This suggests that indirect effects play a crucial role in the transmission of carbon policy shocks. In Section 6, I shed more light on the role of different transmission

[9] Reassuringly, the comparison of the internal and external instrument models as well as the robustness checks in Section 7 did not point to any problems of non-invertibilty. As controls in the local projections, I use 7 lags for monthly variables, 3 lags for quarterly variables and 2 lags for annual variables.

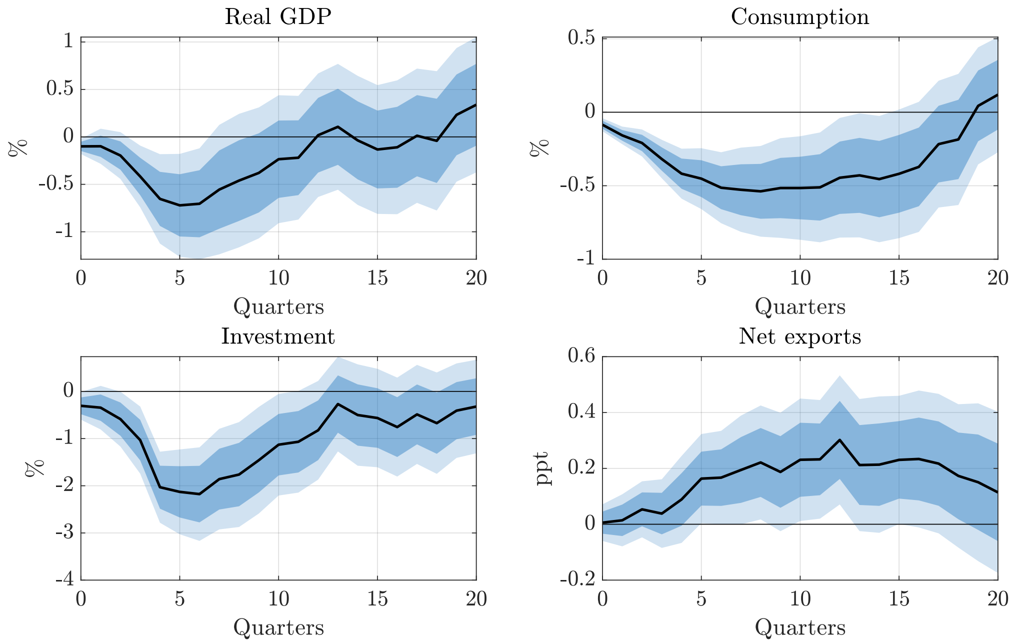

Figure 6: Effect on GDP and components

Notes: Impulse responses of real GDP, consumption, investment and net exports expressed as a share of GDP.

channels using detailed household micro data.

The above results support the notion that higher energy prices and the associated direct and indirect effects are a dominant transmission channel of carbon pricing. However, apart from the effects through energy prices, carbon pricing may also affect the economy through other channels, for instance by affecting financing conditions or increased uncertainty. It turns out, however, that these variables respond to carbon policy shocks only with a lag, similar to stock prices, and the responses do not turn out to be very significant (see Figure B.5 in the Appendix). Thus, these alternative channels are unlikely to play a dominant role in the transmission of carbon policy shocks.

The effect on innovation. We have seen that carbon pricing is successful in reducing emissions but this comes at an economic cost, at least in the short term. However, there could also be positive effects in the longer term, for instance by spurring innovation in low-carbon technologies. In fact, part of the vision for the EU ETS is to promote investment in clean, low-carbon technologies (European Comission, 2020*a*).

To analyze this channel in more detail, I study how the patenting activity in climate change mitigation technologies is affected by the carbon policy shock. The European Patent Office (EPO) has developed specific classification tags for climate change mitigation technologies.

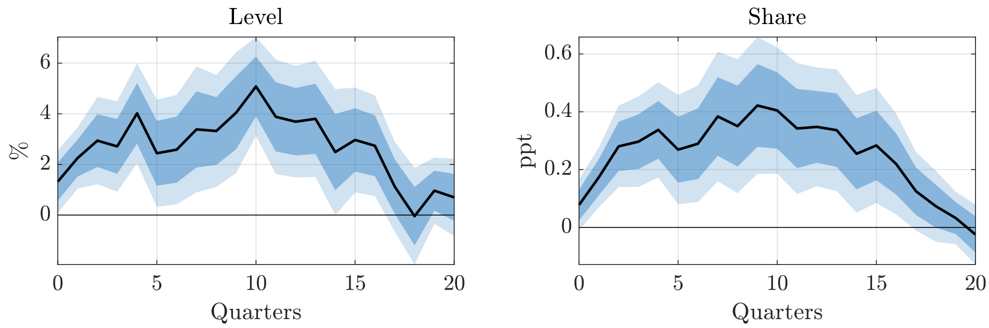

Figure 7: Patenting in climate change mitigation technologies

Notes: Impulse responses of patenting activity in climate change mitigation technologies. Depicted is the response of the number of climate change mitigation patent filings, in absolute terms (left panel) and as a share of all patents filed at the EPO (right panel).

The results are shown in Figure 7. We can see that the shock leads to a significant increase in low-carbon patenting, both in absolute terms and also relative to the overall patenting activity. Thus, carbon pricing appears to be successful in stimulating innovation in climate change mitigation technologies. 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 ETS system's causal impact on firms' patenting, and also chime well with the previously documented stock market response, which rebounds and even turns positive in the longer run.

6. The heterogeneous effects of carbon pricing

Recently, there has been a big debate in Europe on energy poverty and the distributional effects of carbon pricing amid the European Commission's plans of extending the carbon market to buildings and transportation (European Comission, 2021). While the commission did propose a Social Climate Fund to cushion the adverse effects on vulnerable households, several observers have argued that the proposal does not do enough to ensure a fair and equitable transition.[10]

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 can help to better understand the

[10]See e.g. https://righttoenergy.org/2021/07/14/fit-for-55-not-fit-for-europes-energy-poor/.

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, the indirect effects will also be heterogeneous to the extent that individual incomes respond differently to the change in aggregate expenditure, for instance because of differences in the income composition or the sector of employment. 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.

6.1. 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).[11]

The LCFS is the most significant 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 conducted 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 1999 to 2018. 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

[11]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 such as Denmark and Spain are very similar, see Figure B.26.

only collect information about current household income but also about *normal* household income, which should by construction not be affected by temporary shocks.[12] Thus, I use the normal disposable household income to group households into three pseudo-cohorts: low-income, middle-income, and high-income households.[13] 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, unconditional for all households as well as by conditioning on the three income groups. We can see that weekly total expenditure (excl. housing) and housing expenditure are both increasing in income. While low-income households spend a large part of their budget on non-durables, richer households spend more on services and durables. Importantly, poorer households spend a significantly higher share of their expenditure on energy: the (average) energy share stands at close to 9.5 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.

The different income groups turn out to be comparable in terms of their age. This can be seen from the median age which is around 50 for all groups and also from Figure B.8 in the Appendix, which shows that the empirical age distribution is similar across all three income groups. As expected, high-income households tend to be more educated, as can be seen from the larger share of households that have completed post-compulsory education. Finally, higher-income households tend to be homeowners, either by mortgage or outright, while among the low-income there is a large share of social renters. Importantly, all these variables are rather slow-moving and unlikely to confound potential heterogenities in the household responses to carbon policy shocks, which exploit variation at a much higher frequency (see Figure B.9 in the Appendix).

[12]While it may be affected by permanent shocks, this should not be too much of a concern for our grouping strategy as the normal income variable is very slow moving. I have also 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.10 in the Appendix.

[13]In Appendix B.3, I use a selection of other proxies for the income level, including earnings, expenditure, and an estimate for permanent income obtained from a Mincerian-type regression. The results turn out to be robust to using these alternative measures of income for grouping. Alternatively, I tried to group households by their energy share directly. The results turn out again to be very similar, see Figure B.21. This suggests that the energy share is a good proxy for the level of income, with poorer households having higher energy shares (see also Table B.4).

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	236.3	112.6	236.3	466.6
Total expenditure (excl. housing)	157.3	91.6	155.4	269.6
Energy share	7.2	9.4	7.1	5.1
Non-durables (excl. energy) share	49.6	55.0	49.7	44.1
Services share	31.9	26.7	31.9	37.2
Durables share	11.3	8.9	11.3	13.6
Housing	32.0	18.8	31.1	58.0
Household characteristics				
Age	51	46	54	49
Education (share with post-comp.)	33.5	25.0	29.1	51.0
Housing tenure				
Social renters	20.9	47.1	17.4	3.7
Mortgagors	42.6	25.5	41.6	60.4
Outright owners	36.6	27.4	41.0	36.0

Notes: The table shows descriptive statistics on weekly per capita income and expenditure (in 2015 pounds), the breakdown of expenditure into energy, non-durables excl. energy, services 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. Note that the expenditure shares are expressed as a share of total expenditure excl. housing and thus services do not include housing either, 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 member of a household has completed a post-compulsory education.

6.2. Median effect and the response of inequality

We are now in a position to study how households' expenditure and income respond to carbon policy shocks.[14] As a validating exercise, we first look at the median household expenditure response and compare it to the consumption response based on national statistics. As can be seen from the left panel of Figure 8, the median response aligns quite well with the response from national statistics, both in terms of shape and magnitude (see Figure 6).

[14] 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). Similar results are obtained 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), see Figure B.14 in the Appendix. To account for potential seasonal patterns I include a set of quarterly dummies as controls, following again Cloyne, Ferreira, and Surico (2020).

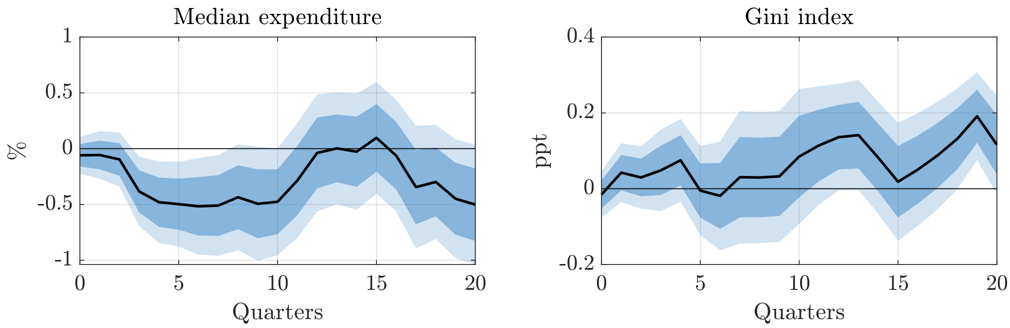

Figure 8: Response of household consumption expenditure

Notes: Impulse responses of total expenditure excluding housing. The left panel shows the median response and the right panel shows the response of consumption inequality, as measured by the Gini coefficient.

To investigate into potential heterogeneities, we also look at the Gini index for household expenditure. The response is shown in the right panel of Figure 8. We can see that the shock leads to a significant increase in inequality, especially at longer horizons. While this result is interesting in itself, it does not tell us which groups are more hardly affected than others.

6.3. Heterogeneity by household income

Having analyzed the aggregate effects as well as the effects on inequality, we now look into the underlying heterogeneity by income group. Figure 9 shows the responses of household expenditure and current income for the three income groups we consider.

We can see that there is pervasive heterogeneity in the expenditure response between 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. Interestingly, the income responses turn out to be somewhat more homogeneous. While low-income households experience the largest drop in income, higher-income households also experience a non-negligible income decline, even though it turns out to be less persistent.[15] The finding that the expenditure of high-income households does nevertheless not respond significantly points to the fact that these households have more savings and liquid assets to smooth the temporary fall in their income. In contrast, the low-income households are hit twofold.

[15]While the income decline of the low- and middle-income households appears to be driven by a fall in earnings, high-income households also experience a fall in their financial income, which then however reverses and turns significantly positive – in line with the stock market response, see Figure B.15 in the Appendix.

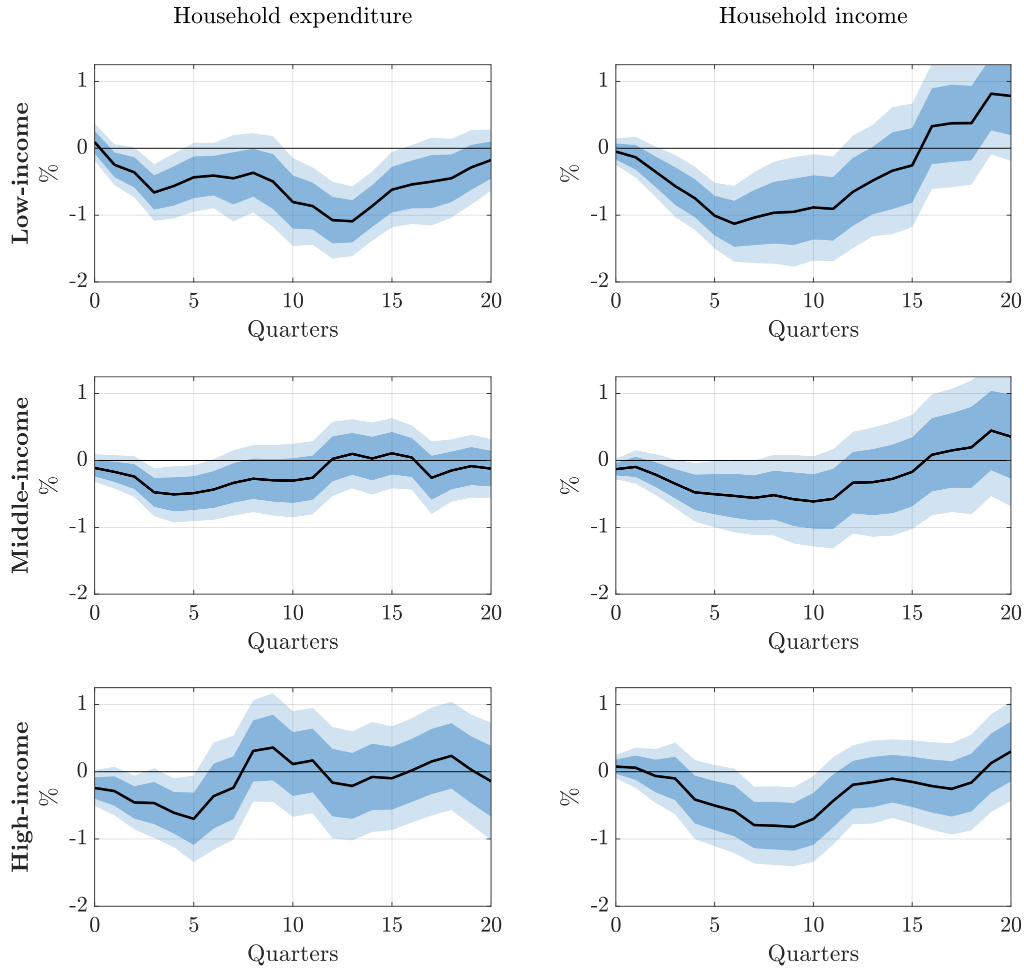

Figure 9: Household expenditure and income responses by income groups

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.

First, they spend a larger share of their budget on energy and are thus, as energy expenditure is highly inelastic, adversely affected by the higher energy bill. Second, they experience a larger fall in income, as they tend to work in sectors that are more hardly affected by the carbon policy shock (see Section 6.4). At the same time, they are more likely to be financially constrained and less able to cope with the adverse effects on their income and budget.

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.16-B.18 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.

6.4. Direct versus indirect effects

While the expenditure responses are, as expected, more pronounced the higher the energy share, the magnitudes are much larger than what can be accounted for by the discretionary income effect alone. Assuming that energy demand is completely inelastic, the direct effect is bounded by the energy share of the respective group.[16] However, the peak response of low-income households is around one – close to ten times the energy share of that group. This suggests that indirect, general equilibrium effects via income and employment account for a large part of the overall effect on household expenditure; a finding that is also supported by the significant effects on unemployment documented in Section 5.2.

To shed more light on these indirect effects, I study how the income response varies by the sector of employment using data from the UK Labour Force Survey (LFS).[17] I consider two dimensions to group sectors. First, I group sectors by

[16]Energy expenditure does indeed turn out to be pretty inelastic, especially for low-income households, see Figures B.19-B.20 in the Appendix. While the energy share of higher-income households does not respond significantly, the energy share of low-income households tends to increase – reflecting the fact that their energy expenditure hardly changes while their total consumption expenditure falls significantly.

[17]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.

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 (see Appendix B.3 for more information).

Table 2: Sectoral distribution of employment

Sectors	Overall	By income group		
		Low-income	Middle-income	High-income
Energy intensity				
High	21.8	9.8	25.8	25.9
Lower	78.2	90.2	74.2	74.1
Demand sensitivity				
High	30.6	49.1	27.3	18.1
Lower	69.4	50.9	72.7	81.9

Notes: The table depicts the sectoral employment distribution of households in the LFS, both overall and by income group (where income is proxied by net pay in the main and second job). I group sectors along two dimensions: their energy intensity and their demand sensitivity. The energy-intensive sectors include agriculture, utilities, transportation, and manufacturing (SIC sections A–E and I). The demand-sensitive sectors include construction, wholesale and retail trade, hospitality, and entertainment and recreation (SIC sections F–H and O–Q).

Table 2 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 manufacturing. 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 demand fluctuations, such as retail or hospitality, while a large majority of higher income households work in less demand-sensitive sectors.

In a next step, I study how the median income across different sectors changes after a carbon policy shock. Figure 10 presents the results. It turns out that the sectors' energy intensity does not appear to play a crucial role for the magnitude of the income response. In fact, the response in sectors with a high energy intensity is relatively comparable to the response in sectors with a lower energy intensity.[18] In contrast, there is significant heterogeneity by the sectors' demand-sensitivity:

[18]Note that I exclude utilities from the energy-intensive group, as there is reason to believe that the utility sector behaves differently from other energy-intensive sectors. In fact, as shown in Figure B.22 in the Appendix, the utility sector does not display a significant fall in incomes, in line with the findings from Section 5.4.

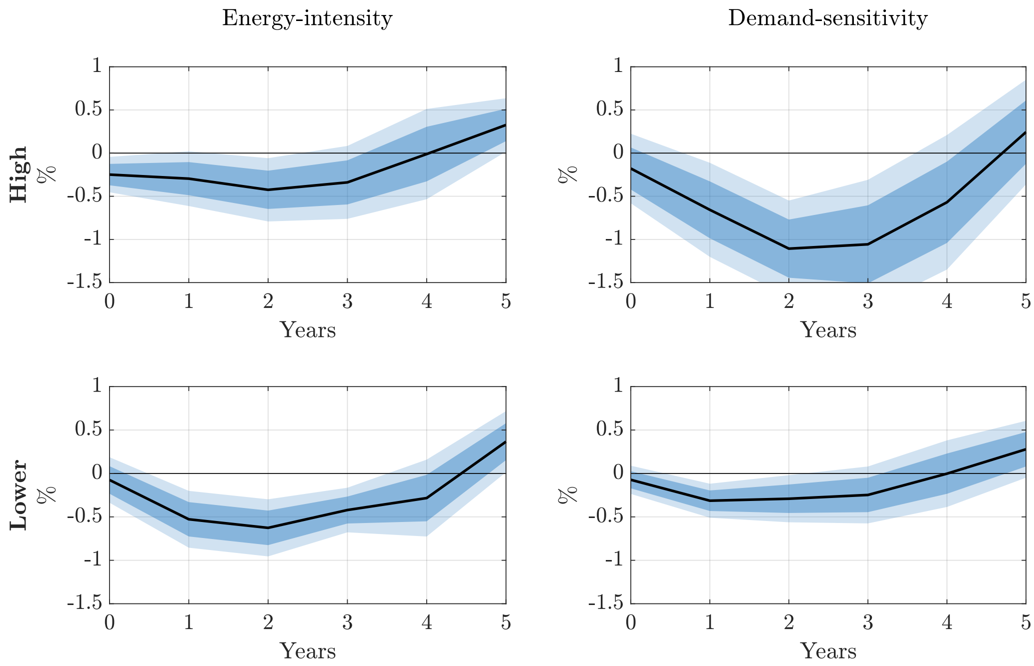

Figure 10: Income response by sector of employment

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 2.

households working in demand-sensitive sectors experience the largest and most significant fall in their income after a carbon policy shock while households in less-demand sensitive sectors face a much more muted income response.

These results support the interpretation that carbon policy shocks mainly transmit to the economy through the demand side, and not by affecting production costs. While this may seem surprising, it is in line with previous evidence by Kilian and Park (2009) on the transmission of energy price shocks. Importantly, the results also help explain why low-income households display a stronger fall in their income, as they disproportionally work in demand-sensitive sectors. In response to a carbon policy shock, these sectors face a stronger decrease in demand than other sectors and thus react by laying off employees and cutting compensation.

To better disentangle these indirect effects from the direct effect via the energy share, I look at the responses of low- and higher-income households conditioning on the most exposed high-energy share households and households with a lower energy share. The responses are shown in Figure B.23 in the Appendix. A few observations emerge from this exercise. First, we can see that low-income households with a high energy share display a much stronger fall in their expenditure than households with a lower energy share in the same income group. This differential response, however, cannot be solely accounted for by the energy share heterogeneity as the income response also turns out to be more pronounced for low-income households with a high energy share. The role of these indirect effects via the decrease in household income can also be appreciated by comparing the responses of low-income and higher-income households conditional on a high energy share. Despite having a comparable energy share, higher-income households lower their expenditure by much less, consistent with the fact that they experience a smaller fall in their incomes. Interestingly, there is less heterogeneity in the expenditure response across income groups conditional on a lower energy share, consistent with the fact that the income responses in this case are also more similar. Overall, these results further illustrate the importance of indirect effects working through income and employment.

Apart from the direct effect on households' discretionary income, there may also be other direct effects at play. For instance, households may postpone purchases of certain durable goods in light of increased uncertainty or there may be a shift in expenditure on durables that are complementary in use with energy (see also Edelstein and Kilian, 2009). However, given the muted response of uncertainty indicators (see Section 5.4) and the relatively small share of durable expenditure, these channels do likely not play a dominant role in the transmission of carbon policy shocks. In fact, as shown in Figures B.24-B.25 in the Appendix, durable expenditures fall but the response turns out to be rather short-lived and can thus not account for the persistent effects observed for total expenditure.

6.5. Policy implications

We have documented substantial heterogeneity in the response of households to carbon policy shocks. The findings illustrate that the economic costs of carbon pricing are not borne equally across society. It is the lower-income income households that are the most hardly affected, having to reduce their expenditures the most, and that are driving the aggregate response. In fact, the overall pound change in expenditure over the five-year period following a carbon policy shock is −£329.9 for low-income, −£183.4 for middle-income, and −£162.2 for high-income households.[19] These heterogeneities are striking against the backdrop that low-income households have much lower levels of expenditure to start with, as shown in Table 1. Put differently, low-income households account for about 40

[19]To compute the overall pound change over the impulse horizon, I compute the present discounted value of the impulse response, using the average real interest rate over the sample of interest, and multiplying this value by the median quarterly expenditure for each group.

percent of the aggregate effect of carbon pricing on consumption, despite the fact that they only represent 25 percent of the population.

The results also highlight the importance of energy prices in the transmission of carbon policy shocks through direct and indirect channels that disproportionally affect lower-income households – the very households that also tend to be financially constrained and have a higher marginal propensity to consume. My findings suggest that fiscal policies targeted to the most affected households can reduce the economic costs of climate change mitigation policies and ameliorate the trade-off between reducing emissions and maintaining economic activity. 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.

Such a policy could be implemented for instance by recycling some of the revenues generated from auctioning allowances. While in the first two phases of the ETS, the majority of allowances was freely allocated, auctioning became the default in the third phase, generating substantial auction revenues. For the period from 2012 to June 2020, the total revenues generated by the member states of the EU ETS exceeded 57 billion euros (European Comission, 2020*b*). In the ETS directive from 2008, the member states agreed that at least half of the auction revenues should be used for climate and energy related purposes, both domestic and internationally. Indeed, over the period 2013-2019, close to 80 percent of auction revenues were used for such purposes, with many countries using all of the revenues for climate action. While this should help to further propel emission reductions, my results indicate that by redistributing part of the auction revenues to the most hardly affected groups in society, it is possible to offset the distributional effects and reduce the economic costs of climate change mitigation policies.[20]

The above intuition is confirmed in a New Keynesian model with a climate block in the spirit of Golosov et al. (2014), featuring heterogeneity in households' energy expenditure shares, income incidence and marginal propensities to consume (MPCs). Calibrated to match key empirical moments from macro and micro data, the model suggests that redistributing carbon revenues to high MPC households can mitigate the effect on aggregate consumption by around 40 percent while reducing inequality at the same time. The model also illustrates that

[20]The current ETS does not feature such a direct redistribution scheme, however, there are certain other, indirect solidarity measures in place, e.g. via the Cohesion Fund, the Just Transition Fund and the European Social Fund Plus. Only in the recent 'Fit for 55' plan, the European Comission takes a step in the direction of redistributing revenues, proposing a new Social Climate Fund. However, the proposed fund will be limited to the new emissions trading system for building and transport fuels, and only includes an amount equivalent to 25 percent of the expected revenues.

household heterogeneity plays a crucial role in the transmission of carbon policy shocks and is key to reconcile the large effects observed in the data (see Appendix D for a detailed description of the model and extended discussion of the results).

These results speak directly to the recent debate on carbon pricing and inequality in Europe. Another 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 demonstration against higher fuel taxes, has shown for instance (see also Knittel, 2014). Indeed, in Appendix B.3 I show that carbon policy shocks lead to a decrease in the public support of climate policy. While the support among low-income households falls significantly and persistently, the response of higher-income households is more short-lived and even turns positive at longer horizons. These results suggest that compensating low-income households that are more exposed to carbon pricing may indeed help to increase the public support of climate change mitigation policies – consistent with recent evidence by Anderson, Marinescu, and Shor (2019).

7. Sensitivity analysis

In this section, I perform a number of robustness checks on the identification strategy and the model specification used to isolate the carbon policy shock. The main results of these checks are summarized below. More information as well as the corresponding figures and tables can be found in Appendix B.4.[21]

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 economic activity. 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 B.29, the results turn out

[21] I focus here on the external instrument VAR for the robustness checks. The results for the internal instrument approach are available upon request.

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 B.30, 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 B.32). Finally, I have verified that the identification strategy does not hinge upon extreme events. Excluding the largest surprises (price change in excess of 30 percent) does not change the results materially, even though the responses are less precisely estimated (see Figure B.33).

Confounding news. Another important choice in high-frequency identification concerns the size of the event window. As discussed in Section 3, 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. An overview of announcement and control dates can be found in Table B.6 in the Appendix. More details on the underlying assumptions and how to implement the heteroskedasticity-based approach are provided in Appendix C.

Figure B.34 shows the carbon policy surprise series together with the control series. We can see that the policy surprise series is over six times more volatile than the control series. It is exactly this shift in variance that can be exploited for identification, assuming that the shift is driven by the carbon policy shock. Figure B.35 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 turn out to be a bit less precisely estimated. These results suggest that the bias induced by background noise is likely negligible in the present application.

Sample and specification choices. An important robustness check concerns the estimation sample. Recall, that 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 2005-2018 period. The responses are shown in Figure B.37. 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.

Another interesting check concerns the sample for the carbon policy surprises. Recall that the EU ETS was established in phases and the first phase was a pilot phase. As a robustness test, I exclude the regulatory news from this first phase. From Figure B.38, we can see that the point estimates turn out to be quite similar. However, as probably had to be expected the responses are much less imprecisely estimated. This illustrates nicely how the identification strategy leverages the fact that establishing the carbon market was a learning-by-doing process where the rules have been continuously updated.

I also perform a number of sensitivity checks on the specification of the model. The baseline VAR includes 8 variables, which is relatively large, especially against the backdrop of the short sample. As a robustness test, I use a 6-variable model, excluding stock prices and the real exchange rate. As can be seen from Figure B.39, 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 (Figures B.41-B.42 show the responses using 3 or 9 lags) and the choice of deterministics (Figure B.40 includes a linear trend). Finally, I also present results from a Bayesian VAR model with 12 lags and using shrinkage priors. The results turn out to be again very similar to the baseline VAR (see Figure B.43).

8. Conclusion

Fighting climate change is one of the greatest challenges of our time. While it has proved to be very 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 on the effects of carbon pricing from the largest carbon market in the world, the EU ETS. I show that tightening the carbon pricing regime leads to a persistent fall in emissions and a significant increase in energy prices. The fall in emissions comes at the cost of temporarily lower economic activity. The results point to a strong transmission mechanism working through energy prices leading to lower consumption and investment. Importantly, these economic costs are not borne equally across society. Lower-income households lower their consumption significantly and are driving the aggregate response while richer households are hardly affected. Thus, re-distributing some of the auction revenues to the most affected groups in society may be an effective way to reduce the economic costs of carbon pricing while at the same time strengthening the public support of the policy.

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Online Appendix

The economic consequences of putting a price on carbon

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September, 2021

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.
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.

	Date	Event description	Type
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

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	22/04/2005-31/12/2018
Baseline variables			
EKESCPENF	HICP energy (EA-19)	Datastream	1999M1-2018M12
GHGTOTAL	Total GHG emissions excluding LULUCF and including international aviation (EU)	Eurostat/own calculations	1999M1-2018M12
EKCPHARMF	HICP all items (EA-19)	Datastream	1999M1-2018M12
EKIPTOT.G	Industrial production excl. construction (EA-19)	Datastream	1999M1-2018M12
EMINTER3	3-month Euribor	Datastream	1999M1-2018M12
EKESUNEMO	Unemployment rate (EA-19)	Datastream	1999M1-2018M12
DJSTO50	Euro STOXX 50	Datastream	1999M1-2018M12
RBXMBIS	Broad REER (EA)	FRED	1999M1-2018M12
Additional variables			
Other carbon futures	LEXC.0h (PS), for h in $(2,3,4,5)$	Datastream	22/04/2005-31/12/2018
Sectoral stock prices	Market [DJSTOXX], Utilities [S1ESU1E]	Datastream	22/04/2005-31/12/2018
BAMLHE00EHYIOAS	ICE BofA euro high yield index option-adj. spread	FRED	1999M1-2018M12
VSTOXX	Euro STOXX 50 volatility	stoxx.com	1999M1-2018M12
EKGDP...D	Real GDP (EA-19)	Datastream	1999M1-2018M12
EKESENMZD	Final consumption expenditure (EA-19)	Datastream	1999M1-2018M12
EKGFCF..D	Gross fixed capital formation (EA-19)	Datastream	1999M1-2018M12
EKNX	Net exports [EKEXNGS.D-EKIMNGS.D] as a share of GDP [EKGDP...D] (EA-19)	Datastream/own calculations	1999M1-2018M12
CCPATENTS	Share of climate change mitigation technologies (CCMT) patents filed at EPO	Google Patents Public Data/own calculations	2005Q1-2018Q4

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

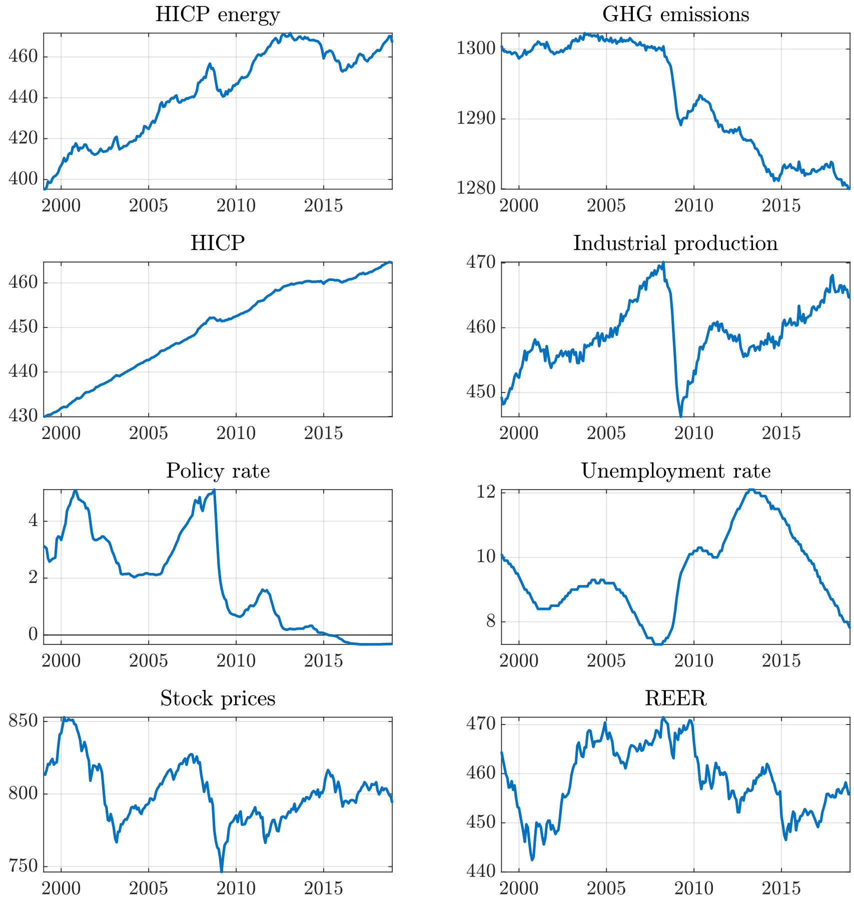


Figure A.1: Transformed data series

A.3. Micro data

In this Appendix, I provide detailed information on the micro data used in Section 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
	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

Category	Subcategories	Items
	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
	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 1999-2018 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 1999-2018 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. Charts, tables and additional sensitivity checks

In this Appendix, I present additional tables and figures, and sensitivity checks that are not featured 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.

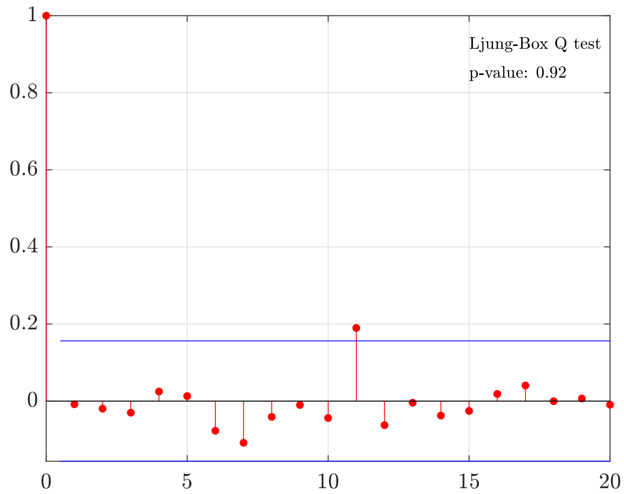


Figure B.1: The autocorrelation function of the carbon policy surprise series

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 number 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, uncertainty, financial, fiscal and monetary policy shocks (see Table B.2).

Table B.1: Granger causality tests

Variable	p-value
Instrument	0.9066
EUA price	0.7575
HICP energy	0.7551
GHG emissions	0.7993
HICP	0.8125
Industrial production	0.7540
Policy rate	0.9414
Unemployment rate	0.9310
Stock prices	0.9718
REER	0.9075
Joint	0.9997

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)	-0.05	0.61	104	2005M05-2013M12
	Kilian (2009) (updated)	-0.02	0.76	164	2005M05-2018M12
	Caldara, Cavallo, and Iacoviello (2019)	-0.05	0.57	128	2005M05-2015M12
	Baumeister and Hamilton (2019)	-0.11	0.17	164	2005M05-2018M12
	Känzig (2021) (updated)	0.02	0.83	164	2005M05-2018M12
Global demand	Kilian (2009) (updated)	0.01	0.93	164	2005M05-2018M12
	Baumeister and Hamilton (2019)	-0.03	0.69	164	2005M05-2018M12
Oil-specific demand	Kilian (2009) (updated)	0.05	0.55	164	2005M05-2018M12
Consumption demand	Baumeister and Hamilton (2019)	0.05	0.51	164	2005M05-2018M12
Inventory demand	Baumeister and Hamilton (2019)	-0.03	0.68	164	2005M05-2018M12
Monetary policy					
Monetary policy shock	Jarociński and Karadi (2020)	0.02	0.80	140	2005M05-2016M12
Central bank info	Jarociński and Karadi (2020)	0.03	0.75	140	2005M05-2016M12
Financial & uncertainty					
Financial conditions	BBB spread residual	0.06	0.43	164	2005M05-2018M12
Financial uncertainty	VIX residual (Bloom, 2009)	0.10	0.22	164	2005M05-2018M12
	VSTOXX residual	0.05	0.50	164	2005M05-2018M12
Policy uncertainty	Global EPU (Baker, Bloom, and Davis, 2016)	0.03	0.71	164	2005M05-2018M12
Quarterly measures					
Fiscal policy	Euro area (Alloza, Burriel, and Pérez, 2019)	0.12	0.44	43	2005Q2-2015Q4
	Germany	0.22	0.15	43	2005Q2-2015Q4
	France	-0.06	0.69	43	2005Q2-2015Q4
	Italy	0.28	0.07	43	2005Q2-2015Q4
	Spain	0.10	0.52	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 5 in the paper.

B.2.1. 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:

$$y_{i,t+h} - y_{i,t-1} = \beta_0^i + \psi_h^i \Delta y_{1,t} + \boldsymbol{\beta}_h^{i\prime} \mathbf{x}_{t-1} + \xi_{i,t,h}, \tag{1}$$

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. 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 very persistent, we want to 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.2 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.[1] At longer horizons the differences tend to be larger, however, the responses are also much less precisely estimated.

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

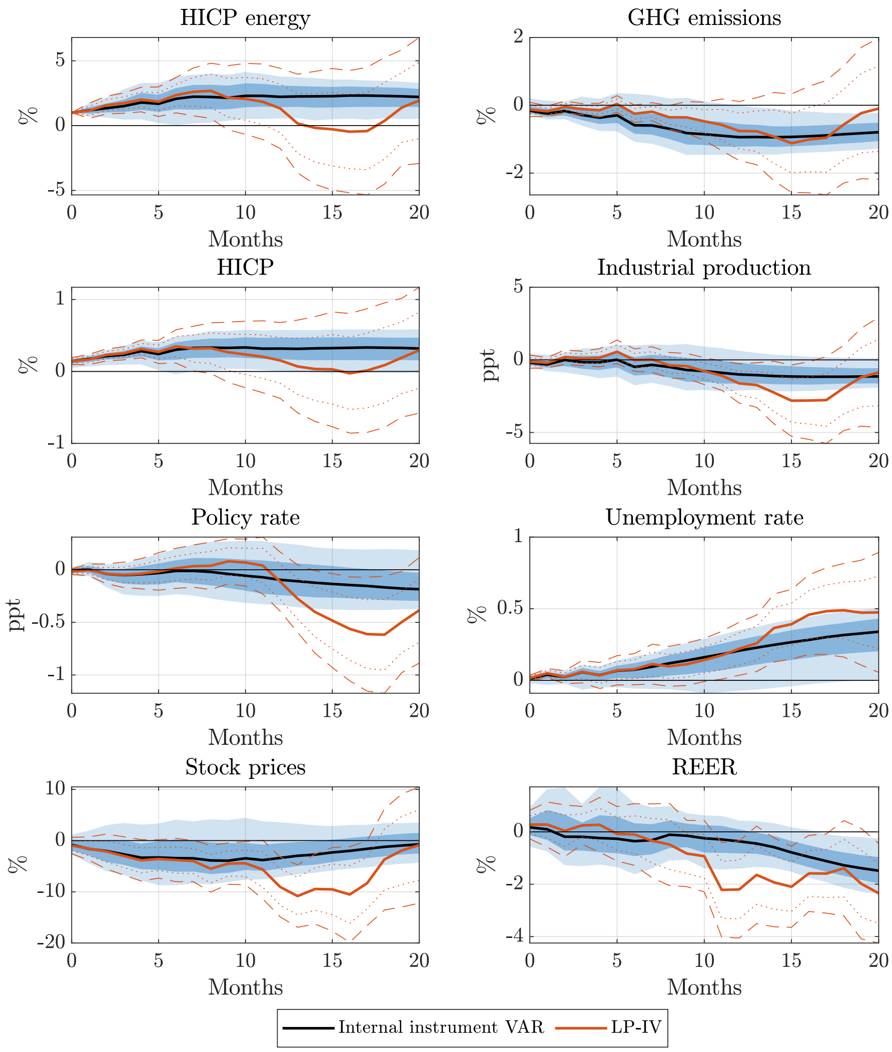


Figure B.2: Robustness with respect to estimation strategy

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.

B.2.2. Core versus headline HICP

In the paper, we have documented 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.3 presents the response for core HICP together with the HICP headline and energy components from the baseline model. We can see that the response of core consumer prices is more muted and much less precisely estimated. Importantly, the response also turns out to be much less persistent, which may reflect the fact that the fall in economic activity exerts downward pressure on prices other than energy, such as services. Reassuringly, all other responses from the model with core HICP are very similar to the baseline case.

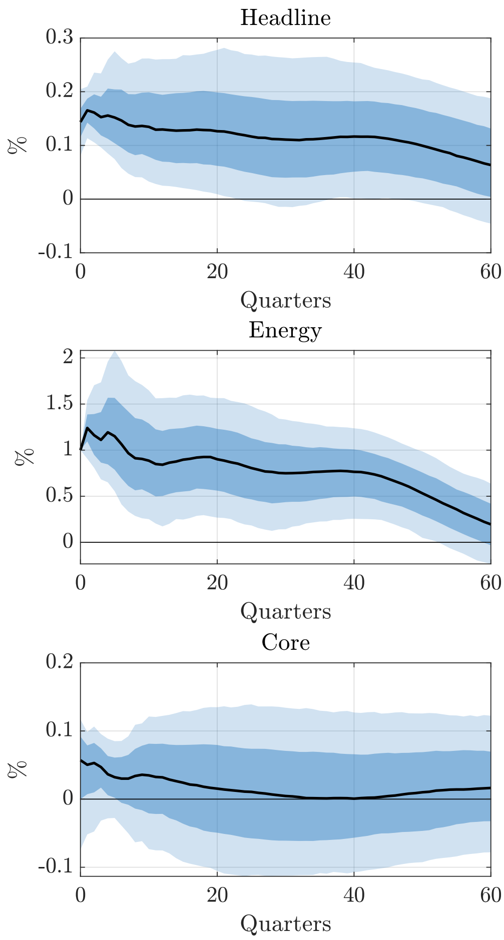


Figure B.3: Robustness with respect to estimation strategy

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.2.3. Model with carbon price

Recall, the baseline model does not include the carbon price as information on prices are only available from 2005 when the carbon market was established. As a robustness check, I estimate a model including the carbon price in lieu of GHG emissions on the shorter sample starting from 2005. The results are depicted in Figure B.4. 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 20 percent at the peak.

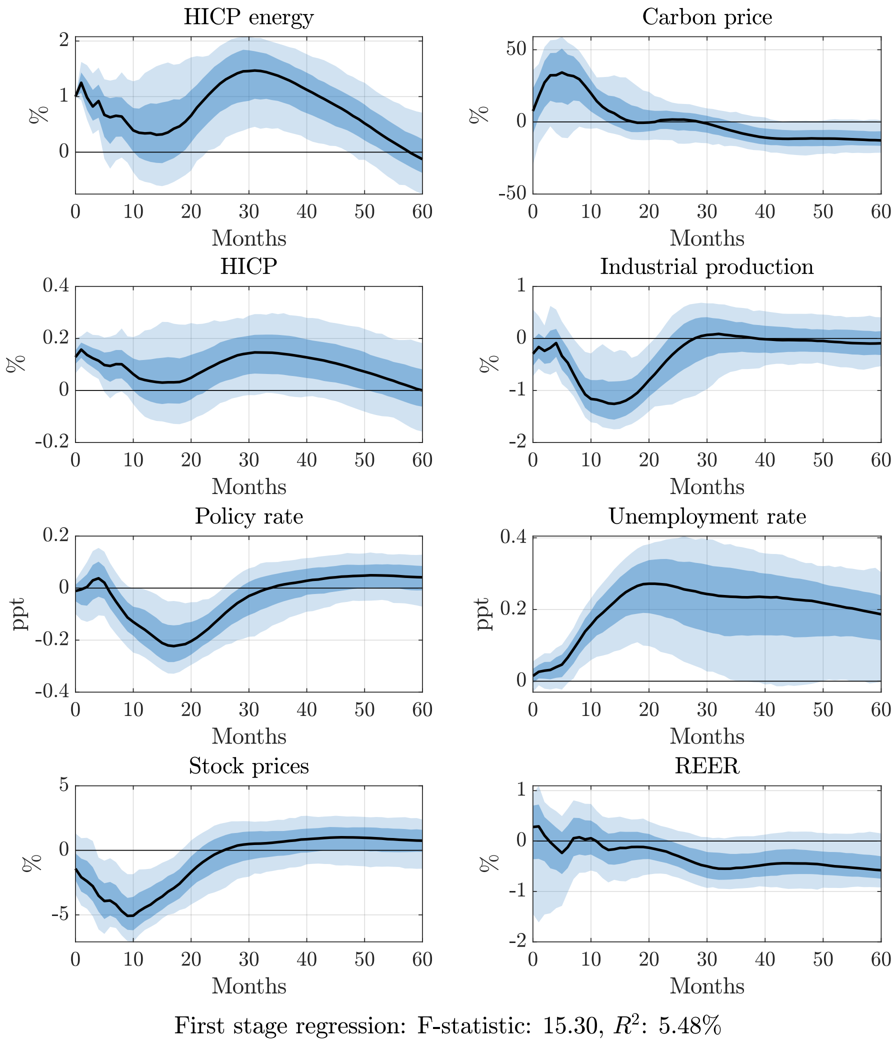


Figure B.4: Model including carbon spot price

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.

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 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

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

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 and given 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 40 percent of the variations in energy prices and around 10 percent of the short-run variations in emissions, which goes up to almost 40 percent at the 5 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 significant fraction of the variations in industrial production and the unemployment rate at longer horizons. The contributions to variations in the policy rate, stock prices and the REER are lower but still non-negligible.

The forecast variance ratios in Panel B, which dispense from the assumption of invertibility, paint a slightly more nuanced picture. In many cases, the point estimates from the external instrument VAR lie within the estimated intervals. The largest differences arise for the contributions to stock prices and the REER which are estimated to be significantly lower when allowing for non-invertibility. However, overall the two approaches produce comparable results.

Table B.3: Variance decomposition

h	HICP energy	Emissions	HICP	IP	Policy rate	Unemp. rate	Stock prices	REER
Panel A: Forecast variance decomposition (assuming invertibility)								
6	0.42	0.12	0.49	0.02	0.00	0.07	0.13	0.00
	[0.20, 0.83]	[0.02, 0.41]	[0.26, 0.87]	[0.00, 0.08]	[0.00, 0.01]	[0.01, 0.56]	[0.03, 0.65]	[0.00, 0.01]
12	0.34	0.25	0.35	0.15	0.03	0.23	0.15	0.00
	[0.14, 0.73]	[0.07, 0.70]	[0.14, 0.69]	[0.04, 0.48]	[0.01, 0.18]	[0.06, 0.84]	[0.04, 0.66]	[0.00, 0.01]
24	0.36	0.32	0.25	0.27	0.13	0.37	0.11	0.09
	[0.15, 0.70]	[0.11, 0.74]	[0.08, 0.56]	[0.09, 0.65]	[0.03, 0.53]	[0.12, 0.90]	[0.03, 0.48]	[0.03, 0.27]
60	0.38	0.39	0.17	0.22	0.11	0.38	0.12	0.25
	[0.18, 0.71]	[0.16, 0.72]	[0.05, 0.45]	[0.08, 0.55]	[0.03, 0.41]	[0.13, 0.82]	[0.03, 0.45]	[0.08, 0.56]
Panel B: Forecast variance ratio (robust to non-invertibility)								
6	0.04, 0.31	0.02, 0.18	0.07, 0.49	0.02, 0.14	0.00, 0.02	0.05, 0.35	0.00, 0.03	0.00, 0.00
	[0.02, 0.54]	[0.01, 0.41]	[0.04, 0.74]	[0.01, 0.34]	[0.00, 0.05]	[0.02, 0.59]	[0.00, 0.08]	[0.00, 0.02]
12	0.05, 0.33	0.03, 0.18	0.07, 0.50	0.02, 0.16	0.00, 0.02	0.05, 0.36	0.01, 0.04	0.00, 0.01
	[0.03, 0.53]	[0.01, 0.36]	[0.04, 0.73]	[0.01, 0.33]	[0.00, 0.05]	[0.03, 0.60]	[0.00, 0.08]	[0.00, 0.02]
24	0.05, 0.32	0.03, 0.19	0.07, 0.50	0.02, 0.18	0.01, 0.08	0.08, 0.55	0.01, 0.04	0.00, 0.01
	[0.02, 0.52]	[0.01, 0.36]	[0.04, 0.72]	[0.01, 0.35]	[0.01, 0.19]	[0.04, 0.78]	[0.00, 0.09]	[0.00, 0.02]
60	0.05, 0.32	0.03, 0.19	0.07, 0.50	0.02, 0.18	0.01, 0.08	0.09, 0.55	0.01, 0.04	0.00, 0.01
	[0.02, 0.52]	[0.01, 0.35]	[0.04, 0.72]	[0.01, 0.35]	[0.00, 0.18]	[0.04, 0.78]	[0.00, 0.09]	[0.00, 0.02]

Notes: The table shows variance decomposition at horizons ranging from 6 months to 5 years. Panel A includes the forecast error variance decomposition from the external instrument VAR with the point estimates and the 90% confidence interval in brackets. Panel B shows the identified set for the forecast variance ratio together with the 90% confidence interval 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.

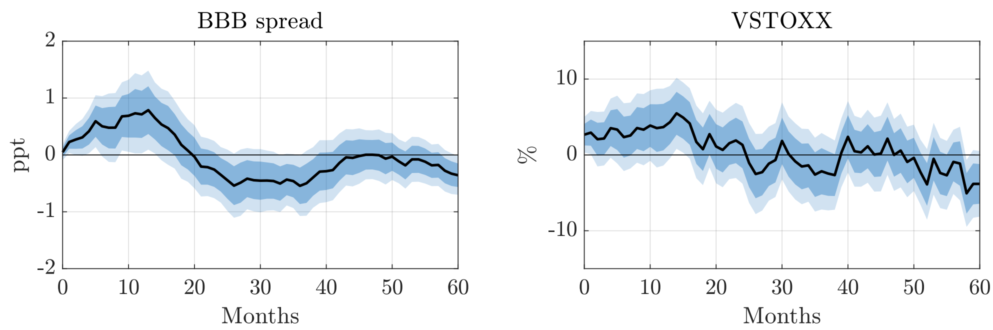


Figure B.5: Financial and uncertainty indicators

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. For better comparison, 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.

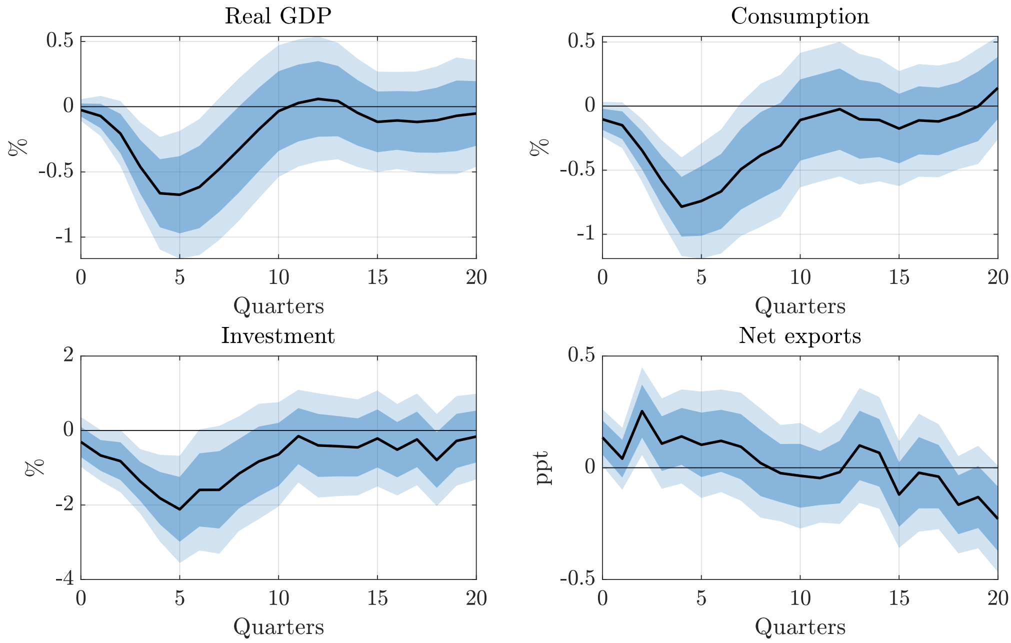


Figure B.6: Effect on UK GDP and components

Notes: Impulse responses of UK real GDP, consumption, investment and net exports expressed as a share of GDP.

Finally, I have also estimated the baseline model using UK data for macroeconomic block. The results are depicted in Figure B.7. We can see that the results are comparable to the model with the EU block, even though the first stage turns out to be weaker and the responses are less precisely estimated.

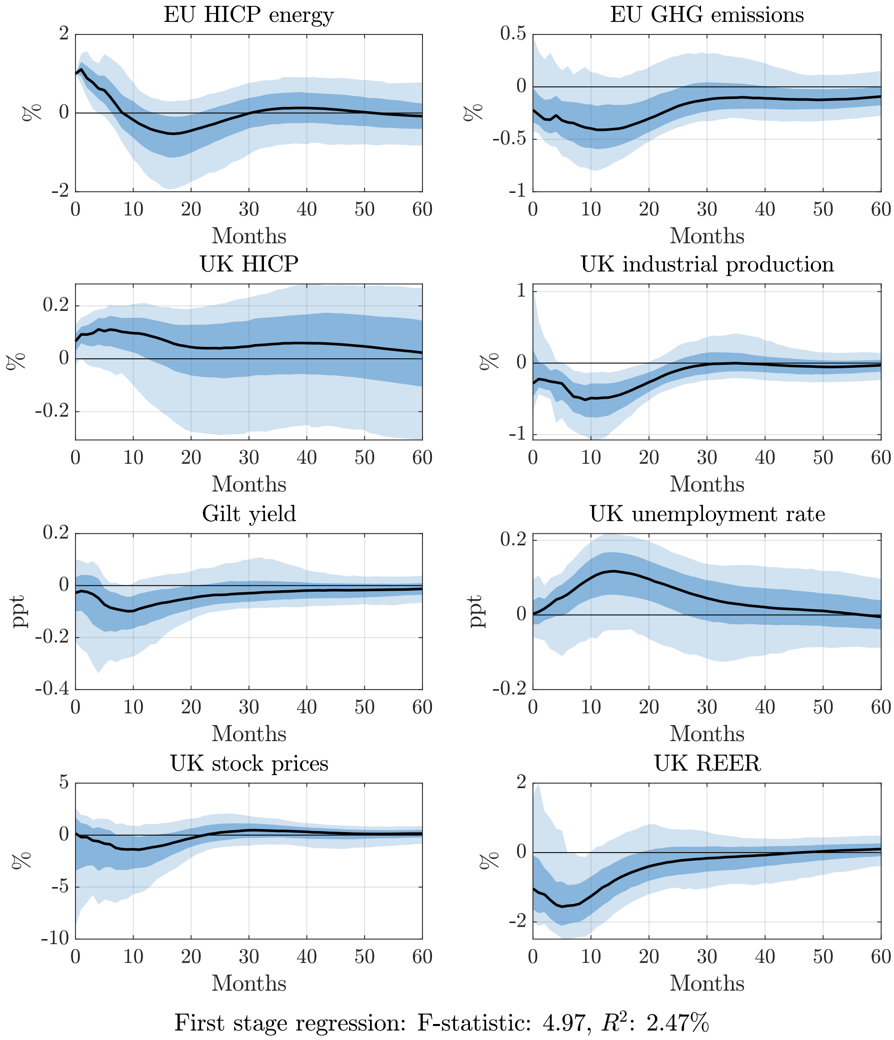


Figure B.7: Model with block for UK economy

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. I keep the carbon block of the model at the EU level and replace the macro block with the corresponding variables for the UK.

B.3. More on heterogeneous effects

In this Appendix, I present some additional results pertaining to Section 6 on the heterogeneous effects of carbon pricing in the paper.

B.3.1. Further descriptive statistics

Figure B.8 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.

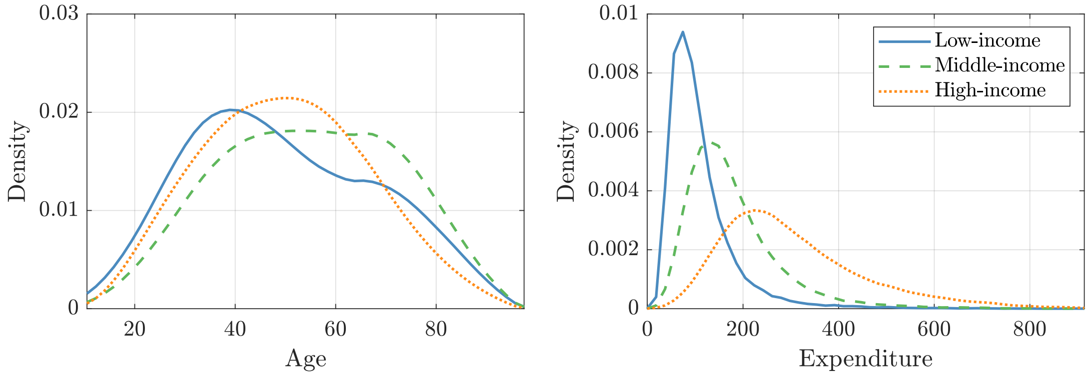


Figure B.8: Empirical distribution of age and total expenditure in the LCFS

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.9 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.

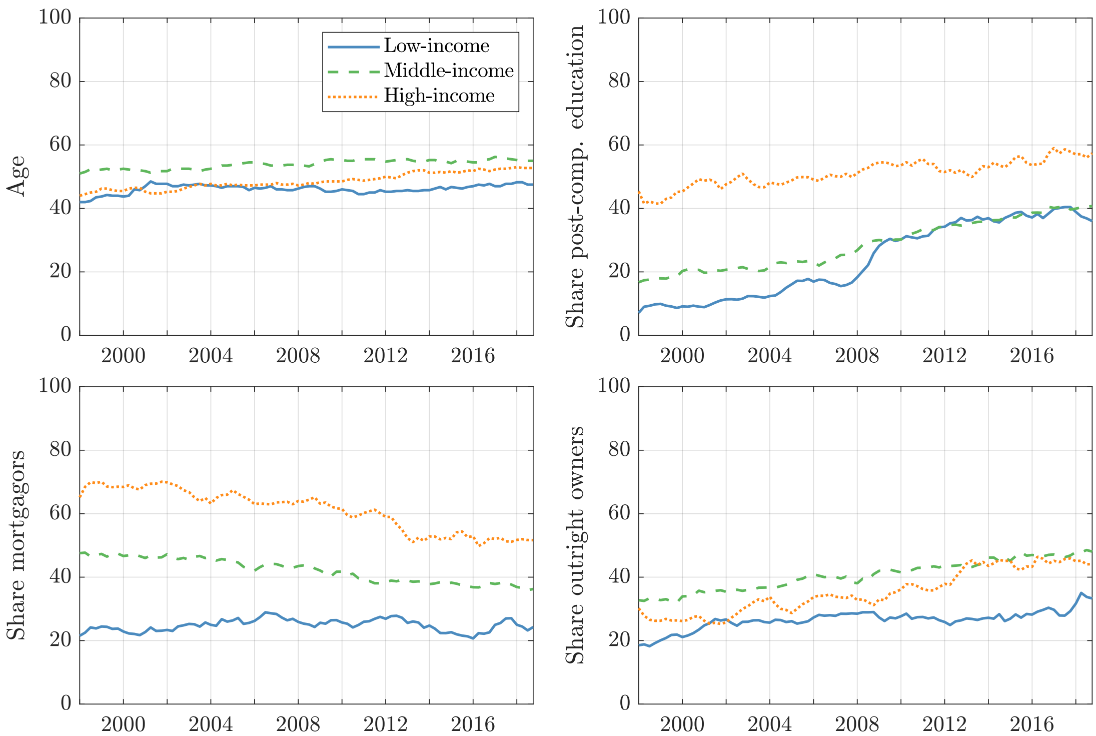


Figure B.9: Evolution of household characteristics by income group

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

B.3.2. 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.10. 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 is insignificant, at least at the 10 percent level, supporting its validity as a grouping variable.

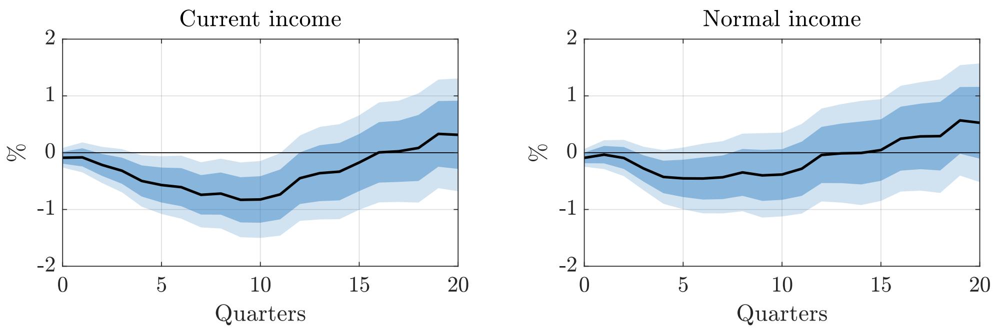


Figure B.10: Responses of current and normal income

Notes: Impulse responses of current disposable income and normal disposable income.

As a robustness check, I use a selection of other proxies for the income level, including earnings, expenditure, and an estimate for permanent income obtained from a Mincerian-type regression. For the latter, 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). From Figures B.11-B.13, we can see that the results turn out to be robust.

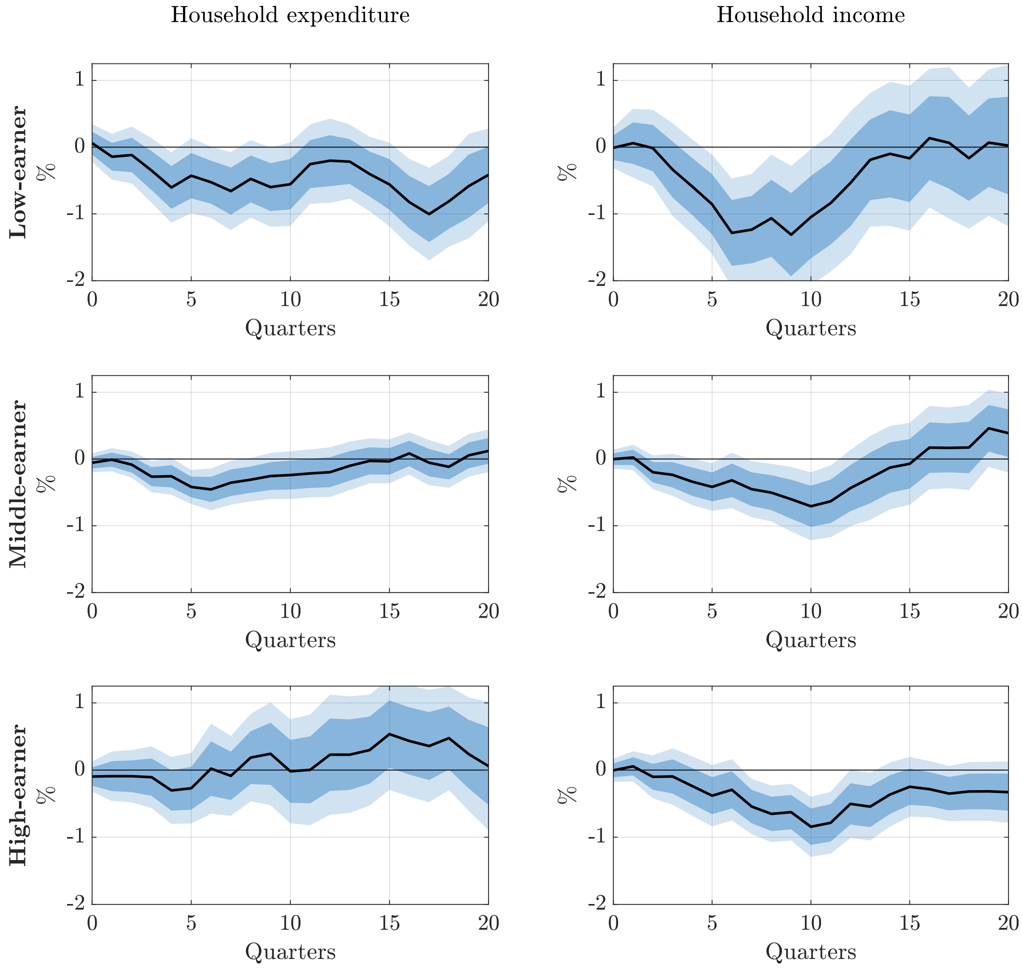


Figure B.11: Expenditure and income responses by earnings groups

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income by earnings (incl. benefits) groups (bottom 25 percent, middle 50 percent, top 25 percent).

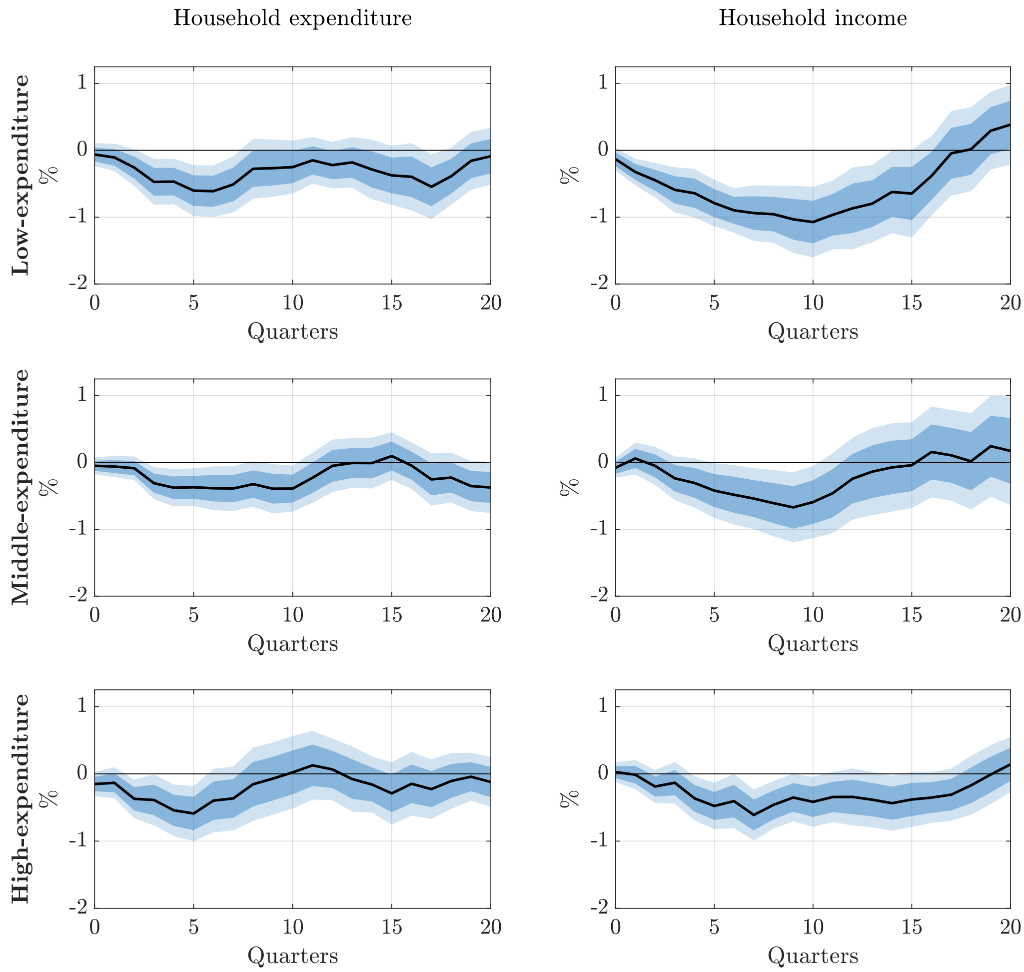


Figure B.12: Expenditure and income responses by expenditure groups

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income by groups of total expenditure as a proxy for permanent income (bottom 25 percent, middle 50 percent, top 25 percent).

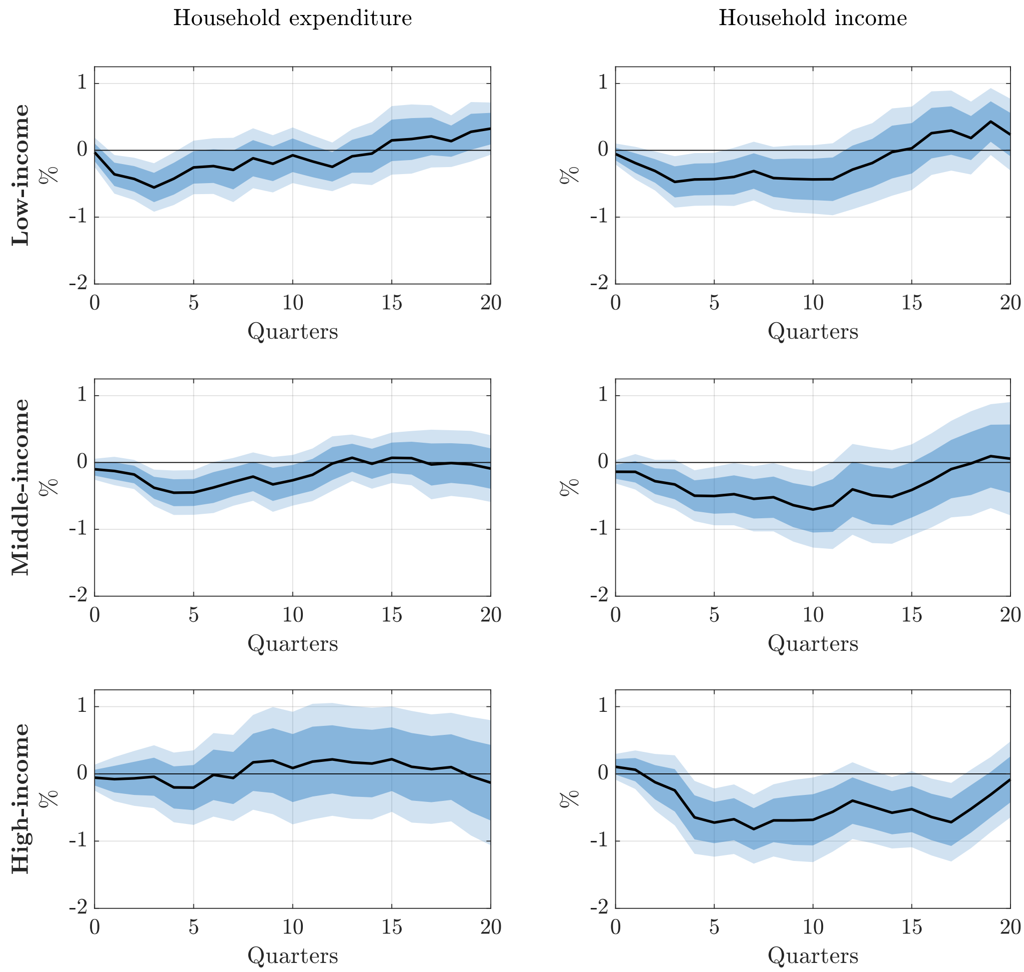


Figure B.13: Expenditure and income responses by permanent income

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.3.3. 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.14, 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).

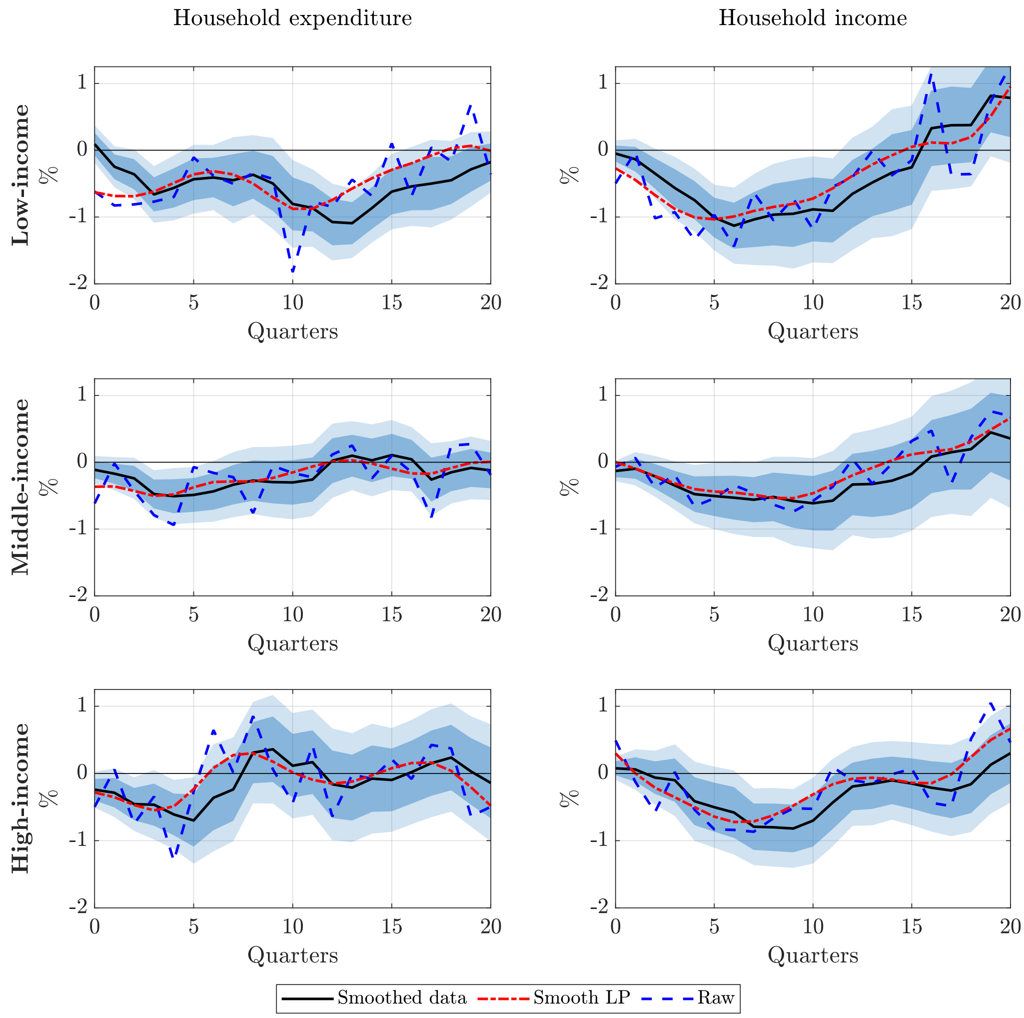


Figure B.14: Sensitivity with respect to smoothing of responses

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. Labor versus financial income

To better understand how the current income of households in different income groups responds, 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. 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 significant fall in their financial income in the short run, which however subsequently reverts (consistent with the stock market response).

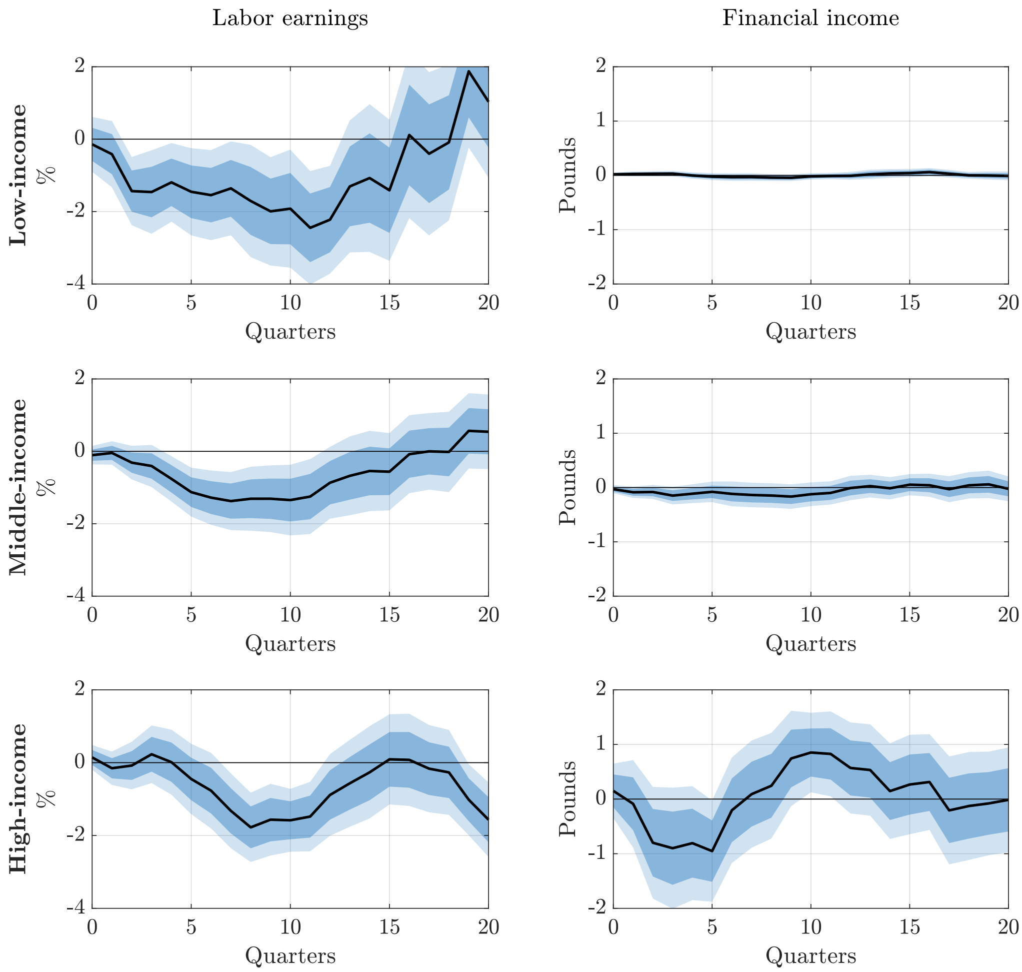


Figure B.15: Responses of earnings and financial income

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.3.5. Selection

To mitigate concerns about selection, I use a number of different grouping variables, including age, education and housing tenure. From Figures B.16-B.18, 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.

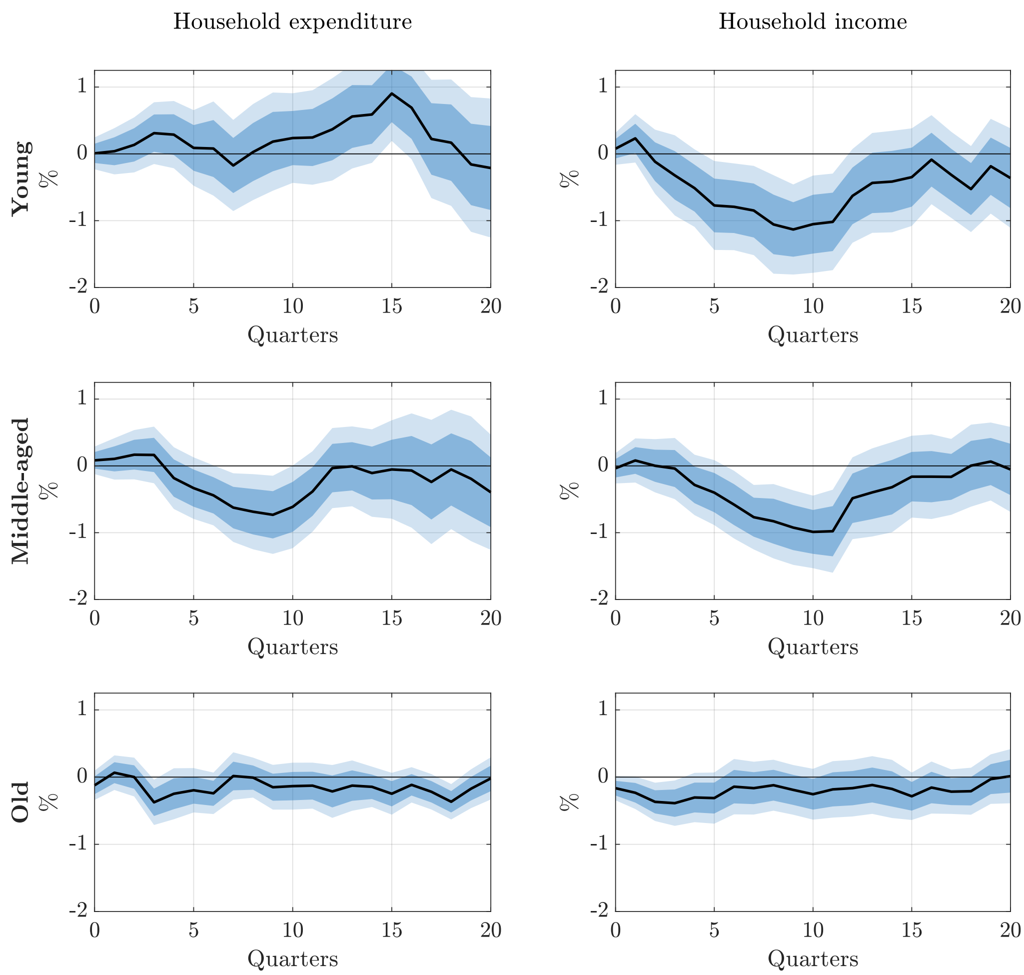


Figure B.16: Household expenditure and income responses by age groups

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

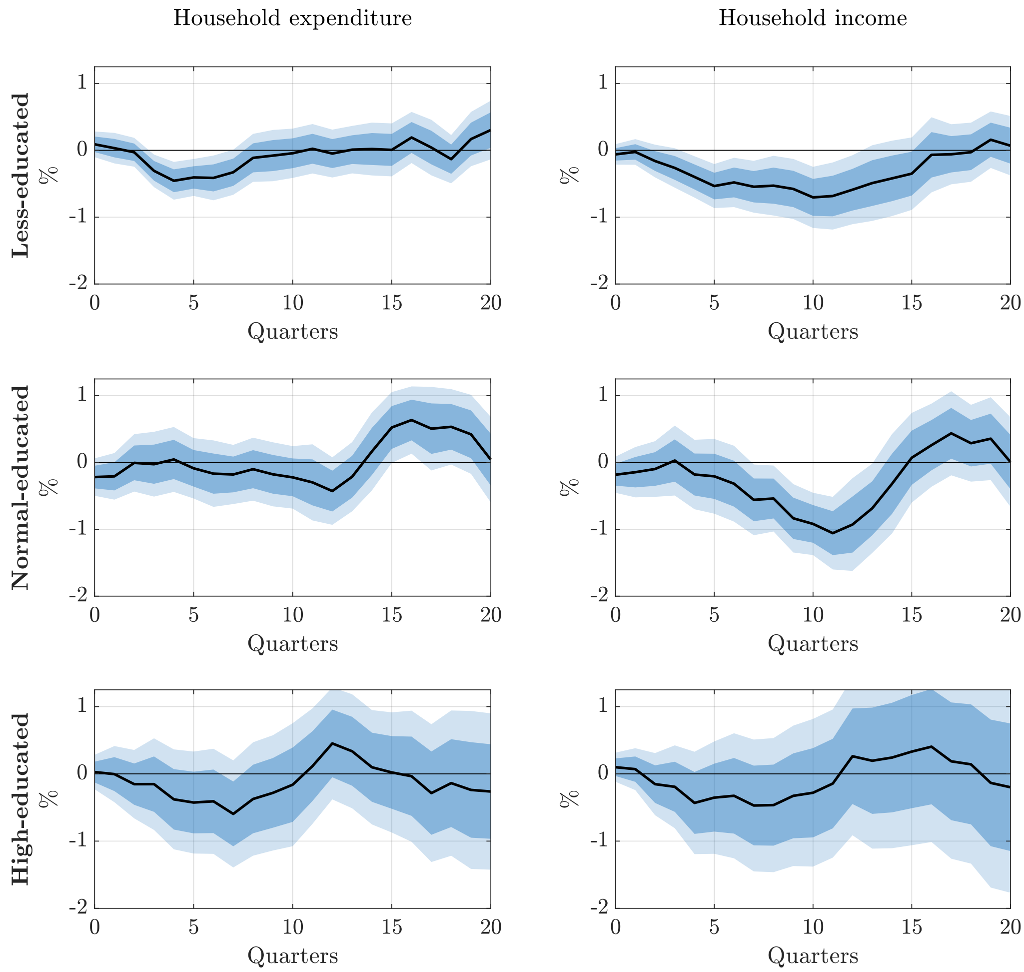


Figure B.17: Household expenditure and income responses by education status

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).

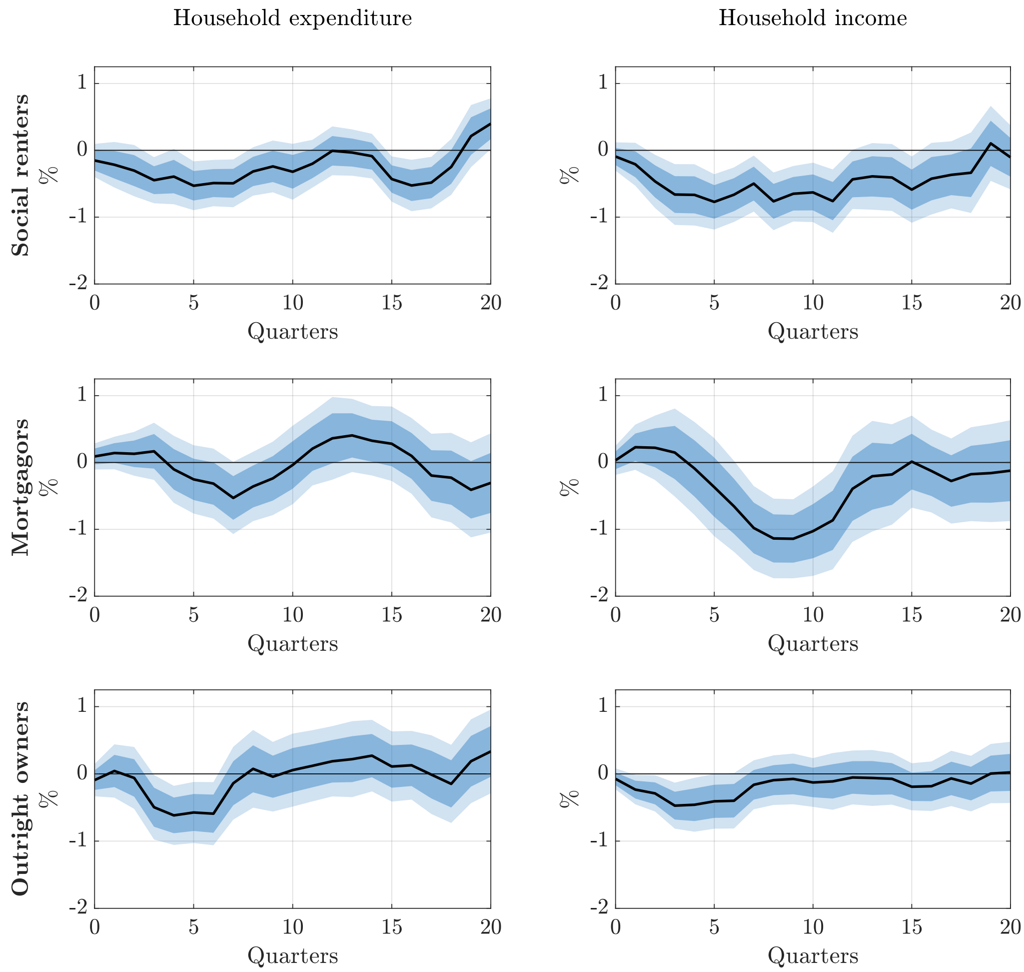


Figure B.18: Household expenditure and income responses by housing tenure

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

B.3.6. The role of the energy share

To further analyze the role of the energy share, I look at the responses of energy expenditure – in absolute terms and as a share of total expenditure.[2] From Figure B.19, we can see that energy expenditure falls slightly on impact but then tends to increase. However, the response is barely significant. This is also reflected in the response of the energy share, which also has a tendency to increase, even though the response is insignificant at the 10 percent level. Figure B.20 further presents the energy expenditure responses by income group. We can see that energy expenditure turns out to be pretty inelastic, especially for low-income households. Higher-income households display a somewhat higher elasticity, however, their energy share does not appear to change significantly after the shock.

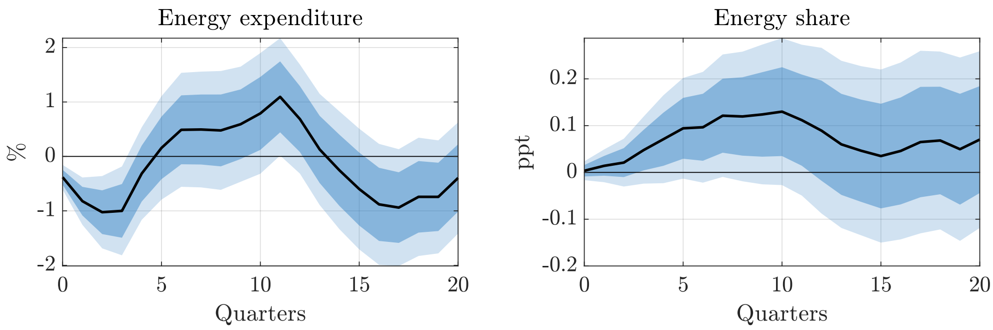


Figure B.19: Responses of energy expenditure and the energy share

Notes: Impulse responses of energy expenditure (expenditure on fuel, light and power) and the budget share of energy (expenditure on fuel, light and power as a share of total expenditure).

[2]To compute real energy expenditure, I deflate nominal energy expenditure by the energy component of the (harmonized) consumer price index.

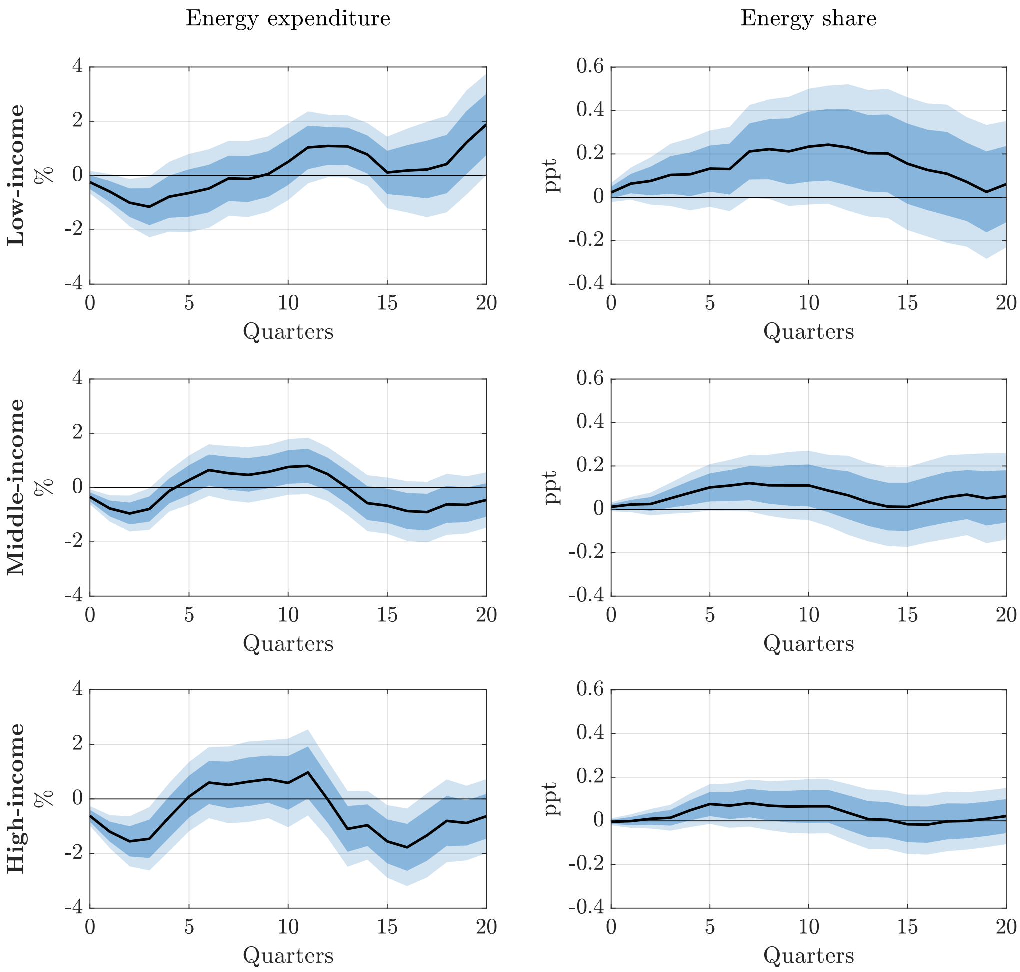


Figure B.20: Energy expenditure and energy share by income group

Notes: Impulse responses of energy expenditure and the budget share of energy by income group (bottom 25 percent, middle 50 percent, top 25 percent).

A key difference between high- and low-income households concerns their energy share. However, as we have argued, heterogeneity in the energy share alone cannot account for the heterogeneous expenditure responses. To make the role of the energy share in the transmission of carbon pricing more explicit, I alternatively group households by their energy share, i.e. households with a high energy share, households with a normal energy share, and households with a low energy share. Table B.4 provides descriptive statistics on income, expenditure and other characteristics by the households' energy share. Note that the heterogeneity in the energy share is now (by construction) much starker: close to 16 percent in the high-share group against only around 2 percent for low-share households. Importantly, the high-, middle- and low-energy share groups turn out to be comparable to the low-, middle- and high-income groups along many other dimensions. In particular, the levels of expenditure and income turn out to be decreasing in the energy share. The largest differences are that high-energy share households tend to be older and more likely to be homeowners than households in the low-income group.

Table B.4: Descriptive statistics on households in the LCFS

	Overall	By energy share		
		High-share	Middle-share	Low-share
Income and expenditure				
Normal disposable income	236.3	180.5	245.2	288.5
Total expenditure (excl. housing)	157.3	95.8	165.4	244.4
Energy share	7.2	15.9	5.5	1.8
Non-durables (excl. energy) share	49.6	51.9	50.7	45.2
Services share	31.9	27.0	32.2	36.2
Durables share	11.3	5.2	11.6	16.8
Housing	32.0	26.3	32.5	38.2
Household characteristics				
Age	51	62	50	45
Education (share with post-comp.)	33.5	17.8	35.3	45.7
Housing tenure				
Social renters	20.9	34.2	15.9	17.7
Mortgagors	42.6	20.6	47.5	55.0
Outright owners	36.6	45.3	36.6	27.3

Notes: The table shows descriptive statistics on weekly per capita income and expenditure (in 2015 pounds), the breakdown of expenditure into energy, non-durables excl. energy, services and durables as well as a selection of household characteristics, both over all households and by energy share 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. Note that the expenditure shares are expressed as a share of total expenditure excl. housing and thus services do not include housing either, 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 member of a household has completed a post-compulsory education.

Figure B.21 shows the corresponding expenditure and income responses. We can see that the magnitude of the expenditure response is clearly increasing in the energy share: while the expenditure of households with a high energy share falls significantly and persistently, households with a low energy share barely alter their expenditure. However, there is also again significant heterogeneity in the income responses, with the high energy share households experiencing the strongest fall in their income. An explanation for this finding is that high energy share households also tend to be poorer and thus have more cyclical income for reasons dicussed in the paper. This makes it difficult to disentangle the direct effects that operate through the energy share from indirect effects. Importantly, the magnitudes of the expenditure responses are again much larger than what can be accounted for by the discretionary income effect alone.

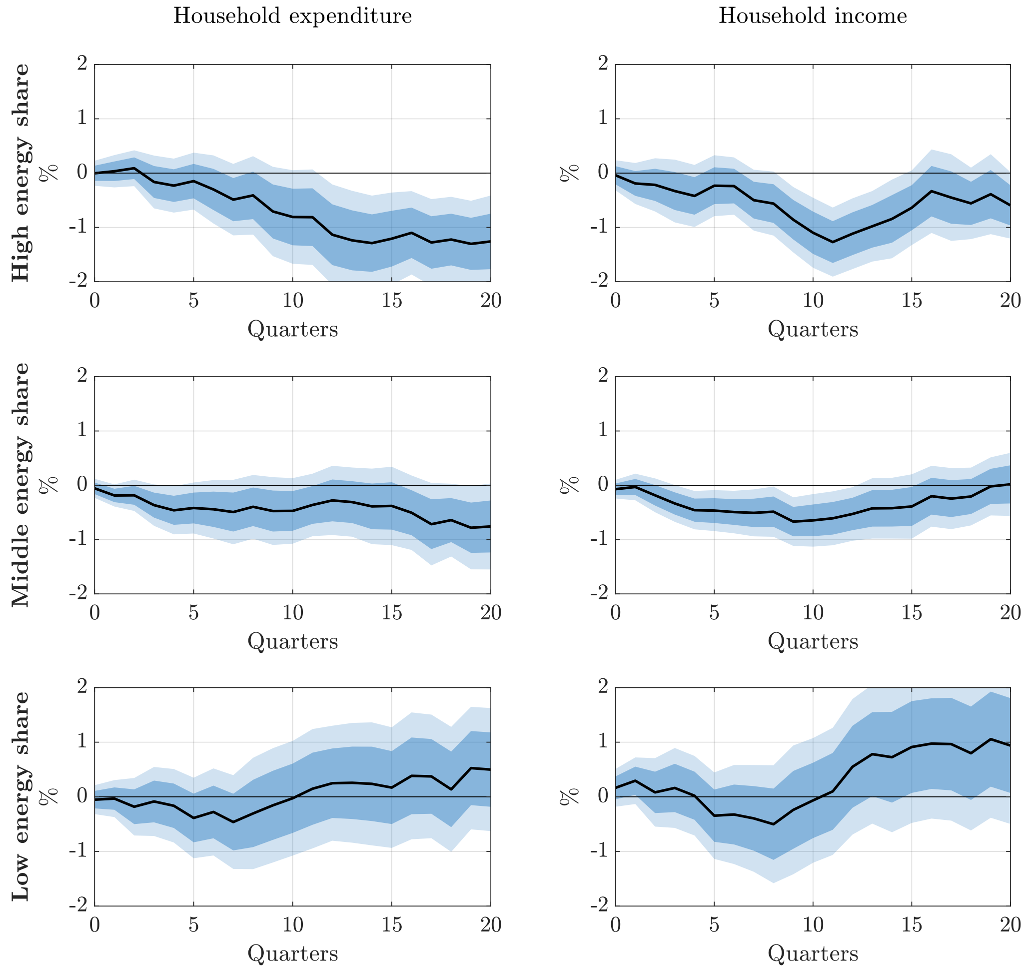


Figure B.21: Household expenditure and income responses by energy share

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income for households with a high energy share (top 25 percent), a typical energy share (middle 50 percent) and low energy share (bottom 25 percent). The energy share is measured as expenditure on fuel, light and power, as a share of total expenditure excluding housing and the responses are computed based on the median of the respective group.

B.3.7. Direct versus indirect effects

To better understand the indirect effects, we have thus looked at the income responses by sector of employment using data from the LFS. In particular, I have grouped sectors by their energy intensity and their demand sensitivity based on information on SIC 2003 sections. A detailed description of all the four groups can be found in Table B.5.

As explained in the main text, I have excluded utilities from the group of energy-intensive sectors when looking at the income response, as the utility sec-

Table B.5: Sectors by energy intensity and demand sensitivity

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 1999-2018 is from the ONS.

tor may respond very differently from other energy-intensive sectors. Indeed, as shown in Figure B.22, the households working in utilities do not experience a significant change in their income, consistent the results from Section 5.4. This further supports the notion that the utility sector can, at least in the short run, profit from a more restrictive carbon pricing regime. In contrast, incomes in other high-energy intensive sectors display a significant fall. However, the response turns out to be more muted compared to demand-sensitive sectors. This may come as a surprise against the backdrop that these sectors are more exposed because of their higher cost share of energy. However, note that these sectors also tend to be less sensitive to changes demand, as they also produce more of essential goods and services. This illustrates again that the shock predominantly transmits through demand and not cost channels.

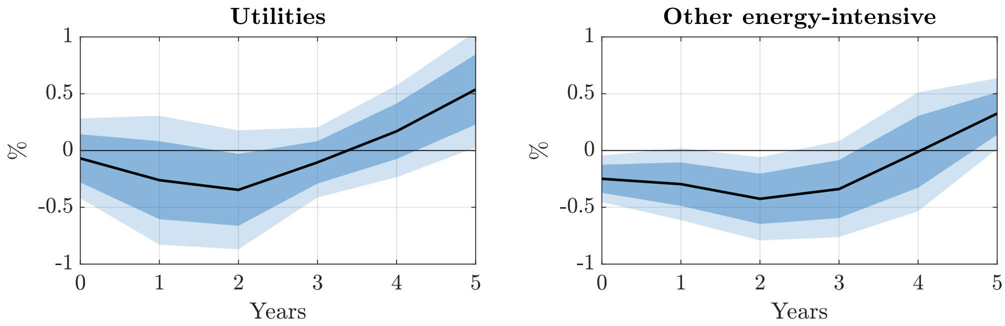


Figure B.22: Income response in energy-intensive sectors

Notes: Impulse responses of median income in utilities and other energy-intensive sectors.

To better understand the role of the energy share across income groups, I look at the responses of low- and higher-income households conditioning on the most exposed high-energy share households and households with a lower energy share, as discussed in the paper. Note that these groups vary in size, as we condition on households in a particular income group that also display a particular energy share. The results are shown in Figure B.23.

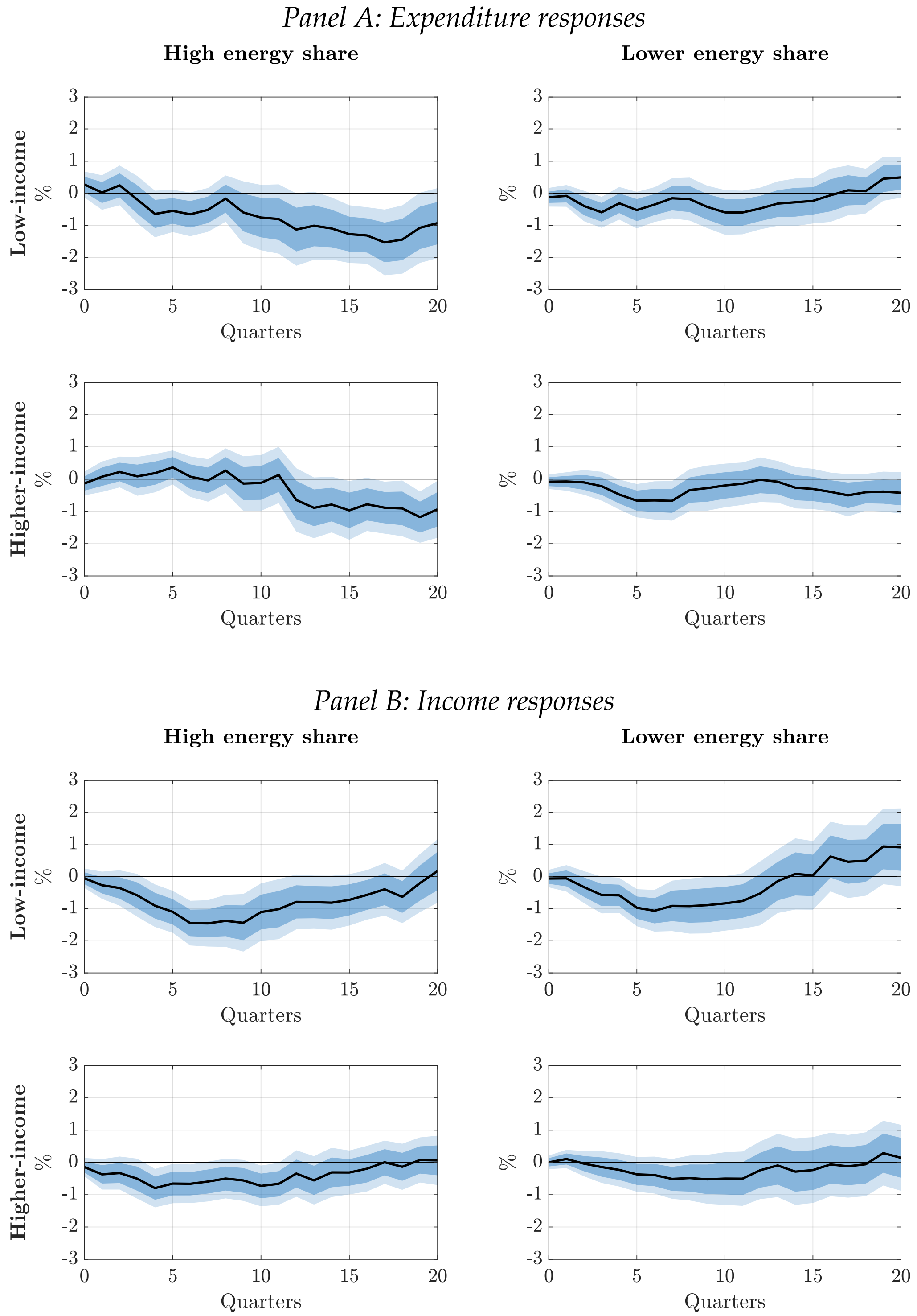


Figure B.23: Responses by income and energy share groups

Notes: Impulse responses of total expenditure excluding housing and current total disposable household income by income group (bottom 25 percent versus other 75 percent), conditioning on households with a high (top 25 percent) or lower energy share (bottom 75 percent).

To investigate into alternative direct channels, I look at the responses of the non-durable, services and durable goods expenditure, first in the aggregate and then by income group. From Figure B.24, we can see that all components fall in response to a carbon policy shock. However, while the fall in services and durable expenditure is more temporary, the response of non-durable expenditure turns out to be very persistent. There is also substantial heterogeneity by income group, in particular for non-durable goods and services. While low-income households experience a significant and persistent fall, the responses of higher income households are much less pronounced and non-durable goods expenditure even tends to increase at shorter horizons. For durables, low-income households also show the strongest response, however, overall the responses tend to be a bit more homogeneous across income groups. Also note that the magnitude of the durable response is larger, in line with the fact that durable expenditure tends to be more volatile.

The results on durable expenditure support the notion that there may be other direct channels at play such as the postponement of durable goods purchases because of increased uncertainty or a shift in expenditure on durables that are complementary in use with energy – channels that tend to be more pronounced for high-income households given their higher share of durables in total expenditure. These channels may help explain the short-lived fall in total expenditure of high-income households, which is absent from non-durable expenditure. However, given the relatively short-lived response, these channels cannot account for the persistent effects observed for total expenditure.

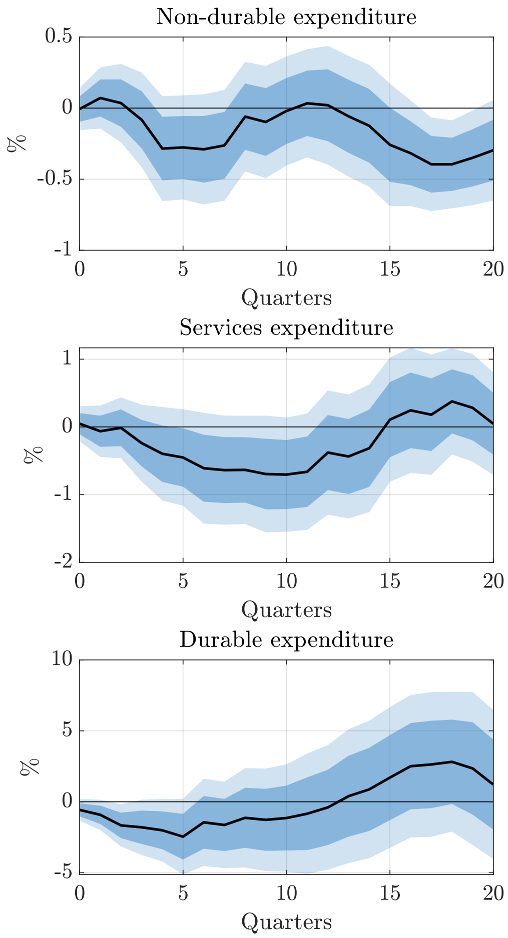


Figure B.24: Responses of non-durable, services, and durable expenditure

Notes: Impulse responses of the non-durable, services and durable components of total expenditure (excluding housing). Non-durable expenditure includes fuel, light and power, food, alcoholic drinks, tobacco, clothing and footwear, and the non-durable parts of household goods, personal goods and services, motoring expenditure, leisure goods and miscellaneous expenditure. Services expenditure includes household services, fares and other travel, leisure services, as well as the services part of personal goods and services and miscellaneous expenditure. Durable expenditure includes the durable part of household goods, personal goods and services, motoring expenditure and leisure goods.

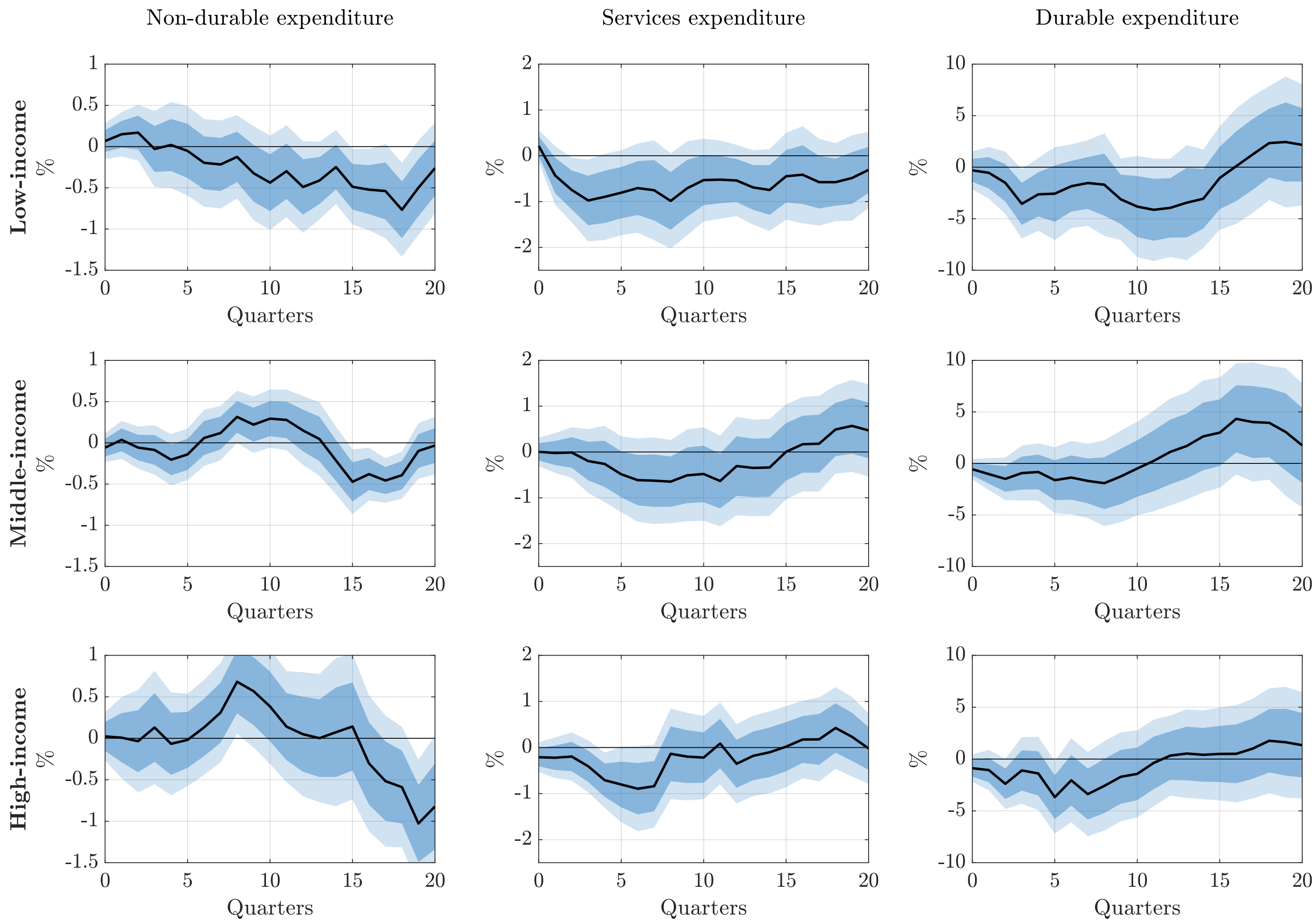


Figure B.25: Responses of non-durable, services, and durable expenditure by income group

Notes: Impulse responses of non-durable, services and durable expenditure 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.26, 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.

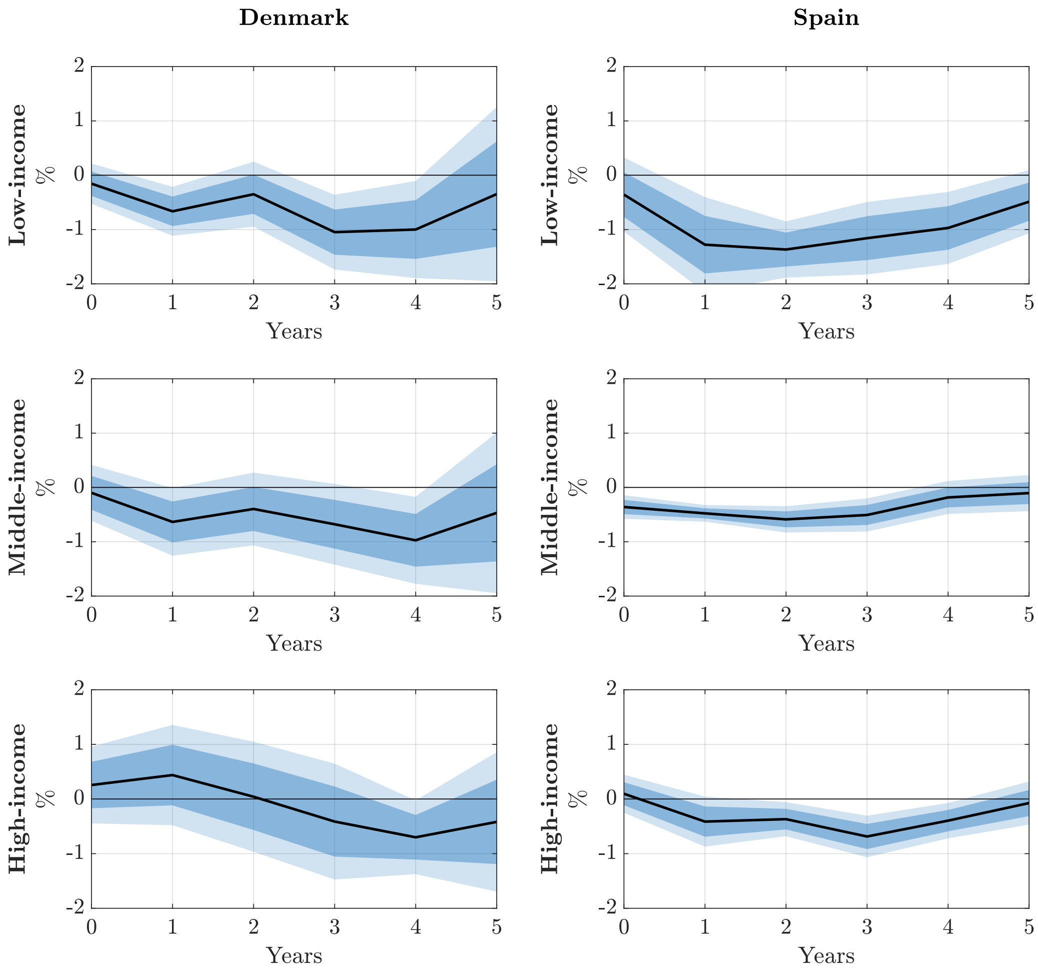


Figure B.26: Expenditure by income groups for other European countries

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 1999-2018, 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 2006-2018, 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 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.27 shows how the attitude towards fuel taxes 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.

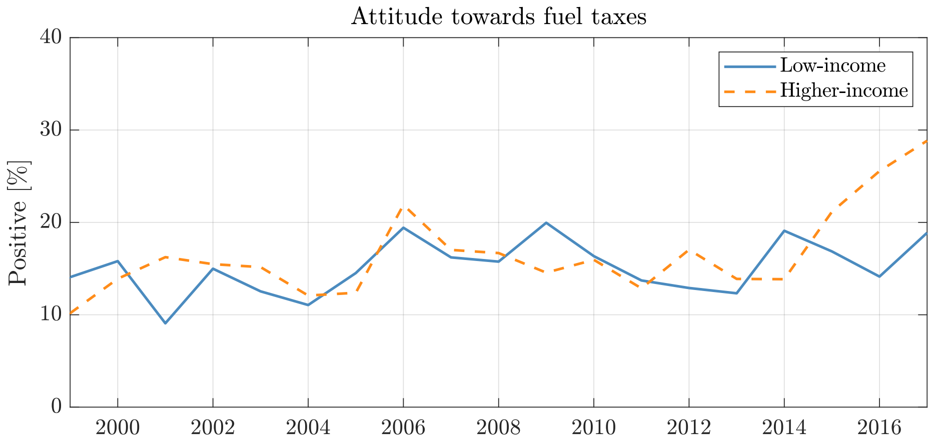


Figure B.27: Public support for climate policy by income group

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".

Figure B.28 shows how the attitude towards fuel taxes among income groups changes after a restrictive carbon policy shock. We can see that carbon pricing leads to a fall in the approval rate of environmentally-motivated tax policies. The effect is very significant and persistent for low-income households, which are also the households that are most hardly affected by carbon pricing in economic terms. In contrast, the response of the high-income group is less precisely estimated and even turns positive in the longer run.

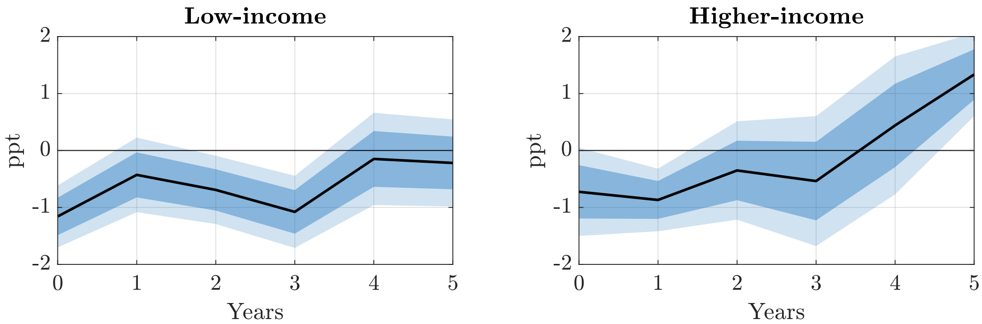


Figure B.28: Effect on attitude towards climate policy by income group

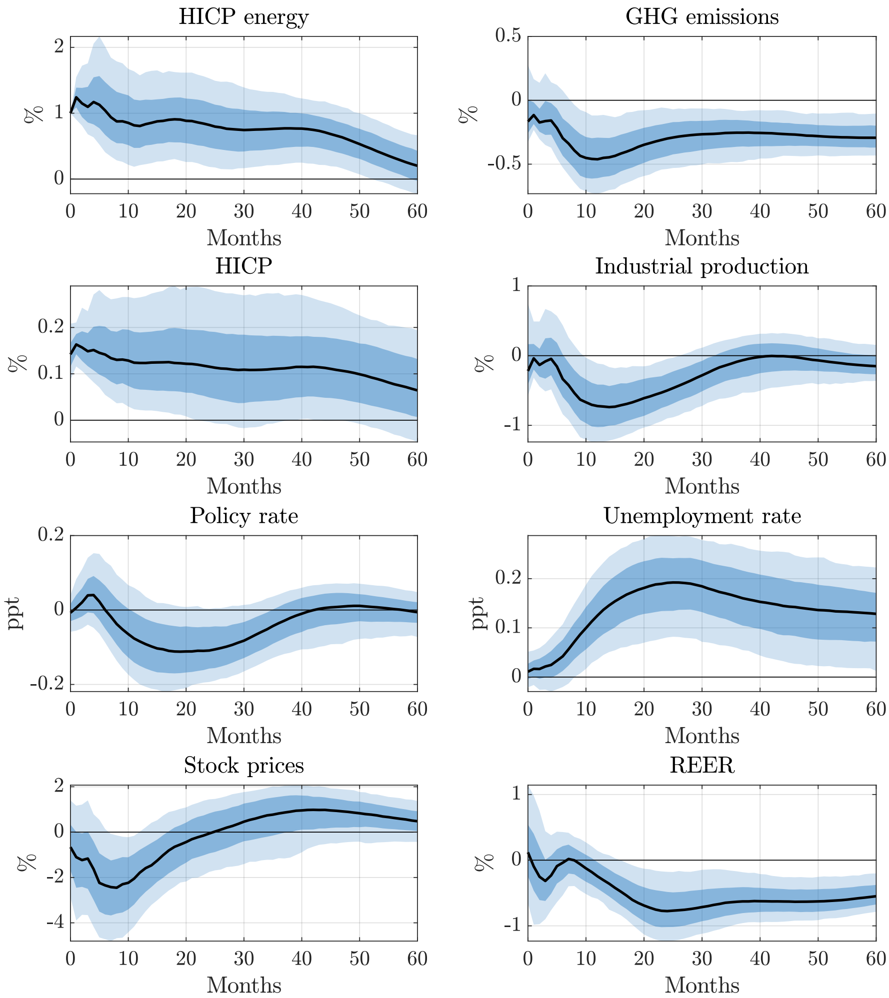
Notes: Impulse responses of public attitude towards climate policy for low- and higher-income groups. The public attitude towards climate policy is proxied by the share of households in the British social attitudes survey that agree to the following statement: "For the sake of the environment, car users should pay higher taxes". Low-income correspond to the bottom 25 percent and higher-income to the other 75 percent of the income distribution.

B.4. Robustness

In this Appendix, I present the Figures and Tables corresponding to the robustness analyses described in Section 7 of the paper.

B.4.1. Selection of events

The first check concerns the selection of the relevant events used for identification. As the baseline, I have included all identified events that concern the supply of emission allowances. Figures B.29-B.32 present the results under varying assumptions and show that the results turn out to be very robust to the selection of events. Figure B.33 also shows that the identification strategy does not depend on very large events, even though these events turn out to be important for the precision of the estimates.



First stage regression: F-statistic: 20.29, R^2: 3.58%

Figure B.29: 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.

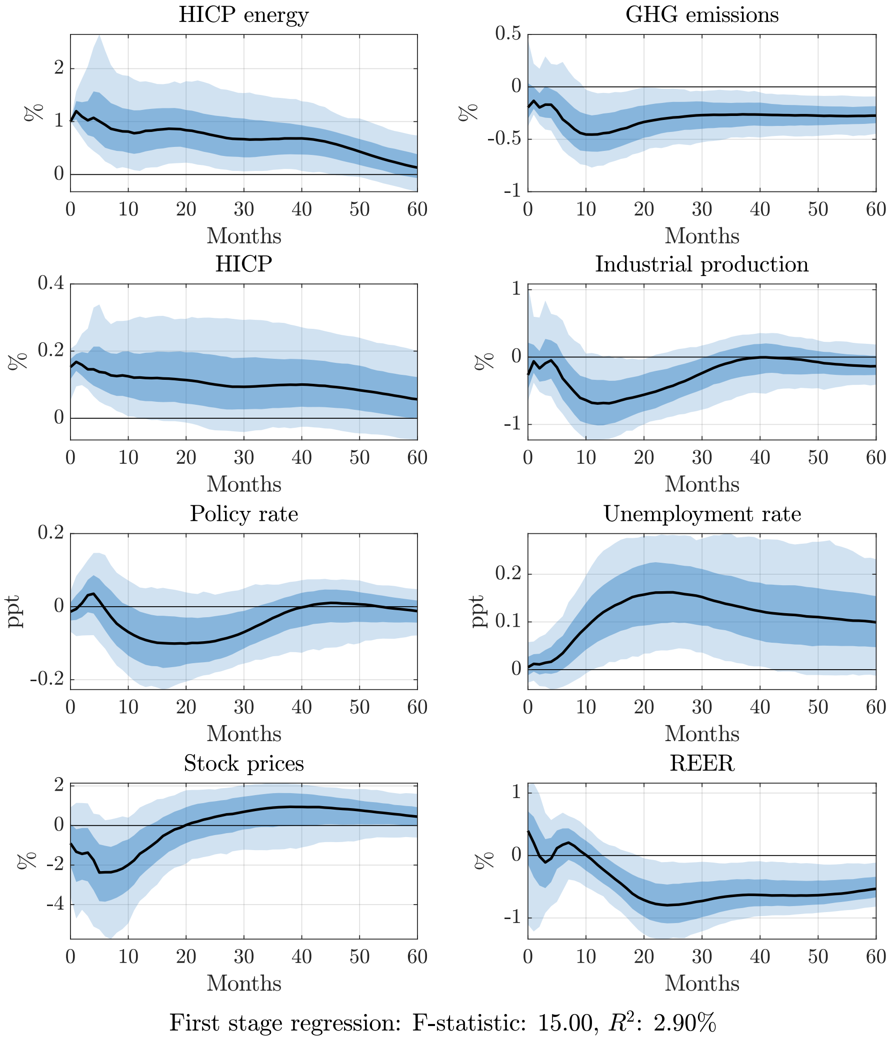


Figure B.30: Excluding events regarding international credits

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.

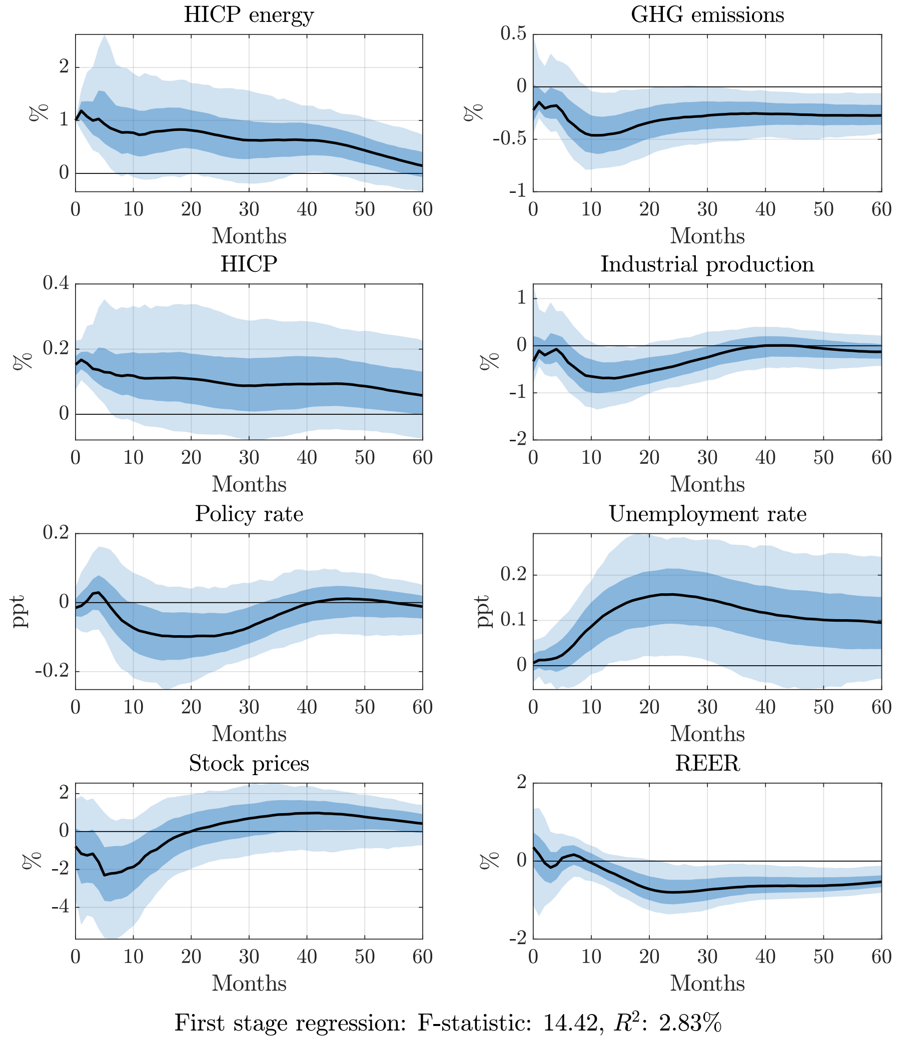
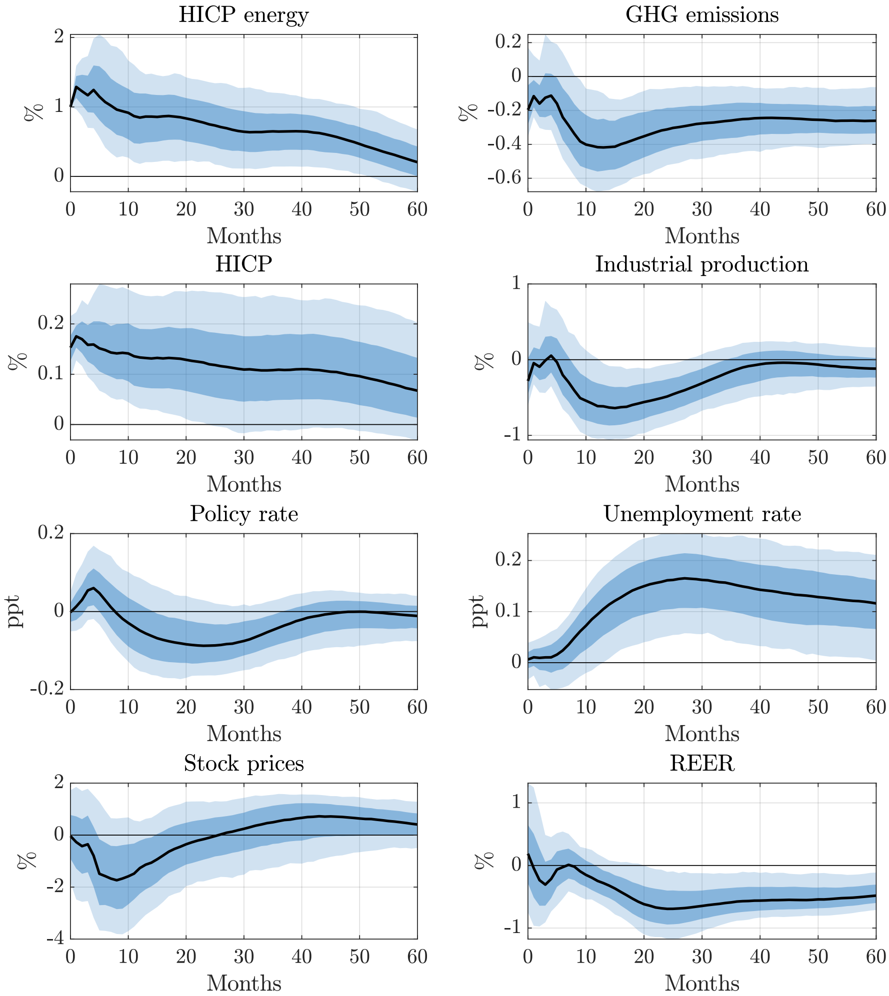


Figure B.31: Only using events on free allocation and auctioning

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: 18.06, R^2: 3.50%

Figure B.32: Excluding potentially confounded events

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.

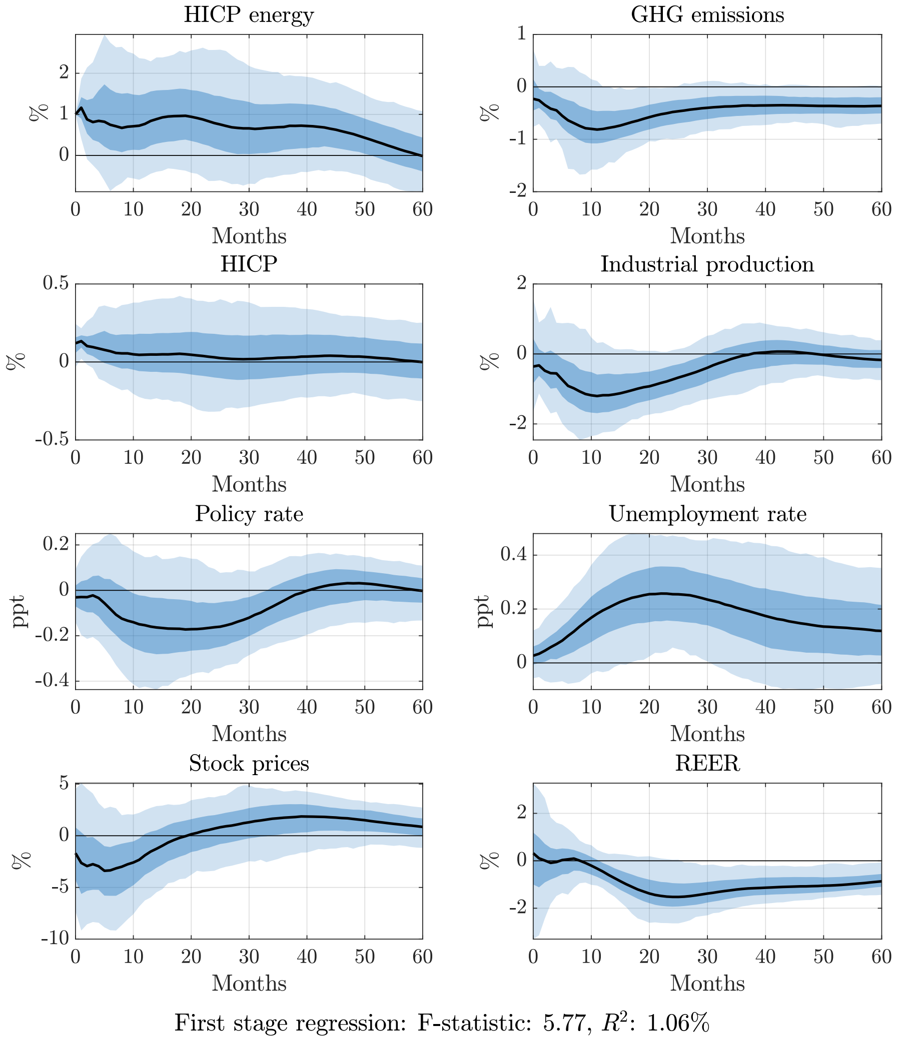


Figure B.33: Excluding extreme events (price change in excess of 30 percent)

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.

B.4.2. Confounding news

An important robustness check concerns the treatment of background noise, i.e. other news occuring on the event day that potentially confound the carbon policy surprise series. Under the external and internal instrument approaches, I assume that this background noise is not large enough to confound my results.

This assumption is supported by the observation that the variance of the surprise series is much larger on event days than on a sample of controls days, which are comparable to event days along many dimensions but do not include a carbon policy event (Table B.6 lists the event and control days used in the analysis. For the controls days, I use days that are on the same weekday and in the same week in months prior a given regulatory event.).

Table B.6: Policy and control events

Month	Policy	Control	Month	Policy	Control
2005M05	25/05/2005		2012M03	29/03/2012	
2005M06	20/06/2005		2012M04		04/04/2012
					25/04/2012
2005M07		27/07/2005	2012M05	02/05/2012	
				23/05/2012	
2005M08		24/08/2005	2012M06	05/06/2012	
2005M09		21/09/2005	2012M07	06/07/2012	
				13/07/2012	
				25/07/2012	
2005M10		26/10/2005	2012M08		13/08/2012
					15/08/2012
					17/08/2012
					31/08/2012
2005M11	23/11/2005		2012M09		10/09/2012
					12/09/2012
					14/09/2012
					28/09/2012
2005M12	22/12/2005		2012M10		08/10/2012
					10/10/2012
					12/10/2012
					26/10/2012
2006M01		25/01/2006	2012M11	12/11/2012	
				14/11/2012	
				16/11/2012	
				30/11/2012	
2006M02	22/02/2006		2012M12		28/12/2012
2006M03		20/03/2006	2013M01	25/01/2013	
2006M04		24/04/2006	2013M02	28/02/2013	
2006M05		22/05/2006	2013M03	25/03/2013	
2006M06		26/06/2006	2013M04	16/04/2013	
2006M07		24/07/2006	2013M05		08/05/2013
2006M08		21/08/2006	2013M06	05/06/2013	
2006M09		25/09/2006	2013M07	03/07/2013	
				10/07/2013	
				30/07/2013	
2006M10	23/10/2006		2013M08		08/08/2013
					29/08/2013
2006M11	13/11/2006		2013M09	05/09/2013	
	29/11/2006			26/09/2013	
2006M12	14/12/2006		2013M10		11/10/2013
2007M01	16/01/2007		2013M11	08/11/2013	
				21/11/2013	
2007M02	05/02/2007		2013M12	10/12/2013	
	26/02/2007			11/12/2013	
				18/12/2013	
2007M03	26/03/2007		2014M01	08/01/2014	
				22/01/2014	
2007M04	02/04/2007		2014M02	26/02/2014	
	16/04/2007			27/02/2014	
	30/04/2007				
2007M05	04/05/2007		2014M03	13/03/2014	
	15/05/2007			28/03/2014	

Month	Policy	Control	Month	Policy	Control
2007M06		06/06/2007	2014M04	04/04/2014	
				11/04/2014	
				23/04/2014	
2007M07		11/07/2007	2014M05	02/05/2014	
				05/05/2014	
2007M08		08/08/2007	2014M06	04/06/2014	
2007M09		05/09/2007	2014M07	04/07/2014	
				09/07/2014	
2007M10		10/10/2007	2014M08		25/08/2014
2007M11	07/11/2007		2014M09		29/09/2014
2007M12		11/12/2007	2014M10	27/10/2014	
2008M01		08/01/2008	2014M11	04/11/2014	
2008M02		05/02/2008	2014M12		01/12/2014
2008M03		11/03/2008	2015M01		05/01/2015
2008M04	08/04/2008		2015M02		02/02/2015
2008M05		22/05/2008	2015M03		02/03/2015
2008M06		26/06/2008	2015M04		06/04/2015
2008M07		24/07/2008	2015M05	04/05/2015	
2008M08		21/08/2008	2015M06		17/06/2015
					25/06/2015
2008M09		25/09/2008	2015M07	15/07/2015	
				23/07/2015	
2008M10		23/10/2008	2015M08		05/08/2015
2008M11		20/11/2008	2015M09		02/09/2015
2008M12		25/12/2008	2015M10		07/10/2015
2009M01		22/01/2009	2015M11	04/11/2015	
2009M02		19/02/2009	2015M12		18/12/2015
2009M03		26/03/2009	2016M01	15/01/2016	
2009M04	23/04/2009		2016M02		25/02/2016
2009M05		20/05/2009	2016M03		31/03/2016
2009M06		24/06/2009	2016M04	28/04/2016	
2009M07		22/07/2009	2016M05	02/05/2016	
2009M08		26/08/2009	2016M06	23/06/2016	
2009M09	23/09/2009		2016M07	15/07/2016	
2009M10		22/10/2009	2016M08		11/08/2016
2009M11		26/11/2009	2016M09	08/09/2016	
2009M12	24/12/2009		2016M10		07/10/2016
2010M01		18/01/2010	2016M11	04/11/2016	
2010M02		15/02/2010	2016M12		19/12/2016
					27/12/2016
2010M03		22/03/2010	2017M01	16/01/2017	
				24/01/2017	
2010M04	19/04/2010		2017M02	15/02/2017	
2010M05		14/05/2010	2017M03		30/03/2017
		19/05/2010			
2010M06		11/06/2010	2017M04	27/04/2017	
		16/06/2010			
2010M07	09/07/2010		2017M05	02/05/2017	
	14/07/2010			12/05/2017	
2010M08		20/08/2010	2017M06		19/06/2017
					28/06/2017
2010M09		24/09/2010	2017M07	17/07/2017	
				26/07/2017	
2010M10	22/10/2010		2017M08		07/08/2017
2010M11	12/11/2010		2017M09		04/09/2017
	25/11/2010				

Month	Policy	Control	Month	Policy	Control
2010M12	15/12/2010		2017M10		09/10/2017
2011M01	21/01/2011		2017M11	06/11/2017	
2011M02		15/02/2011	2017M12		18/12/2017
		22/02/2011			
		28/02/2011			
2011M03	15/03/2011		2018M01	15/01/2018	
	22/03/2011				
	29/03/2011				
2011M04	27/04/2011		2018M02		02/02/2018
	29/04/2011				06/02/2018
					13/02/2018
2011M05		10/05/2011	2018M03		02/03/2018
					06/03/2018
					13/03/2018
2011M06	07/06/2011		2018M04		06/04/2018
					10/04/2018
					17/04/2018
2011M07	13/07/2011		2018M05	04/05/2018	
				08/05/2018	
				15/05/2018	
2011M08		29/08/2011	2018M06		18/06/2018
2011M09	26/09/2011		2018M07	16/07/2018	
2011M10		17/10/2011	2018M08		28/08/2018
		26/10/2011			
		28/10/2011			
2011M11	14/11/2011		2018M09		25/09/2018
	23/11/2011				
	25/11/2011				
2011M12	05/12/2011		2018M10	30/10/2018	
2012M01		26/01/2012	2018M11	06/11/2018	
2012M02		23/02/2012	2018M12	05/12/2018	

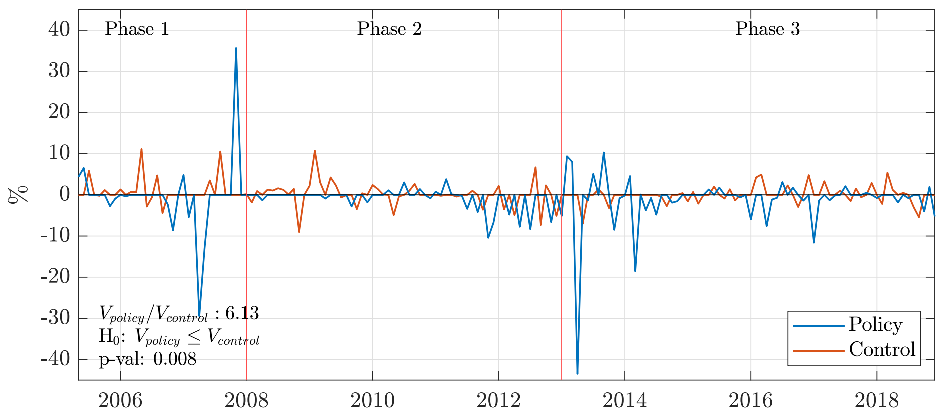
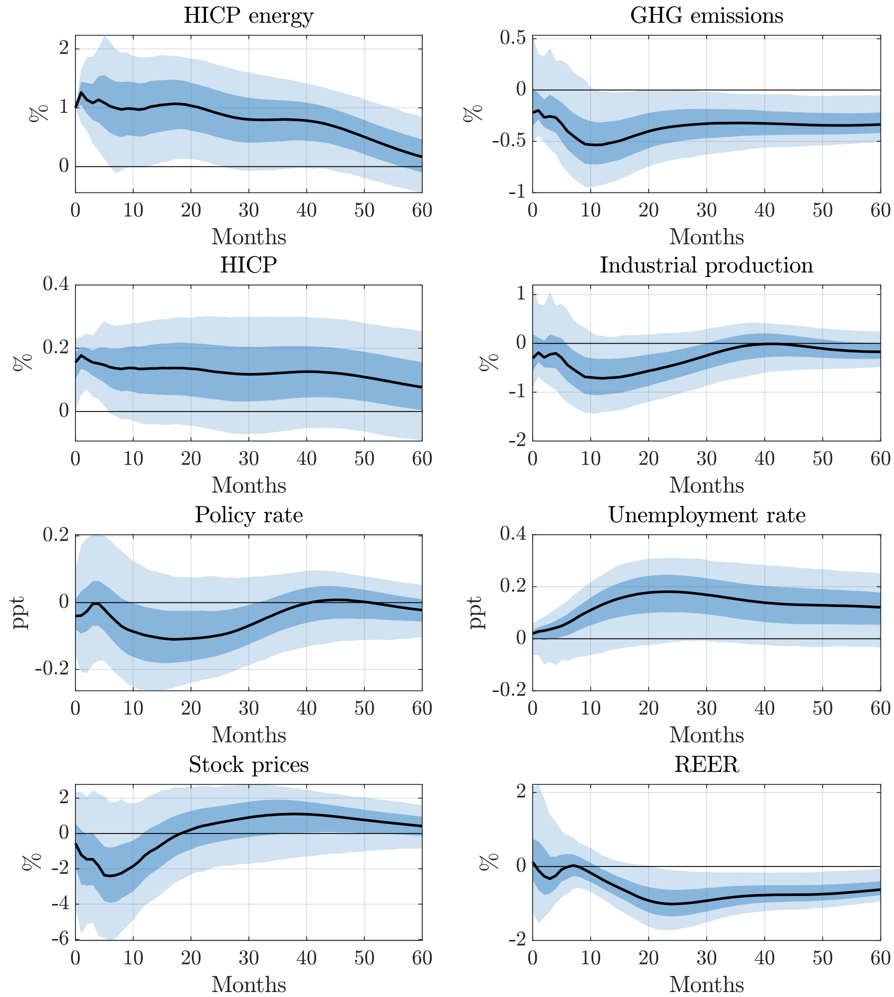


Figure B.34: The carbon policy and the control series

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 B.34 displays the carbon policy surprise series together with the control series over the sample of interest. We can see that the carbon policy surprise series is significantly more volatile than the control series and a Brown-Forsythe test for the equality of group variances confirms that this difference is statistically significant.



First stage regression: F-statistic: 37.55, R^2: 51.68%

Figure B.35: Heteroskedasticity-based identification

Notes: Impulse responses to a carbon policy shock identified using the heteroskedasticity-based approach, 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.

It is exactly this shift in variance that can be exploited for identification using a heteroskedasticity-based approach in the spirit of Rigobon (2003), assuming that the shift is driven by the carbon policy shock. Figure B.35 shows the results from this alternative approach. The responses turn out to be very similar, both in terms of shape and magnitudes, but turn out to be 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.

B.4.3. Futures contracts

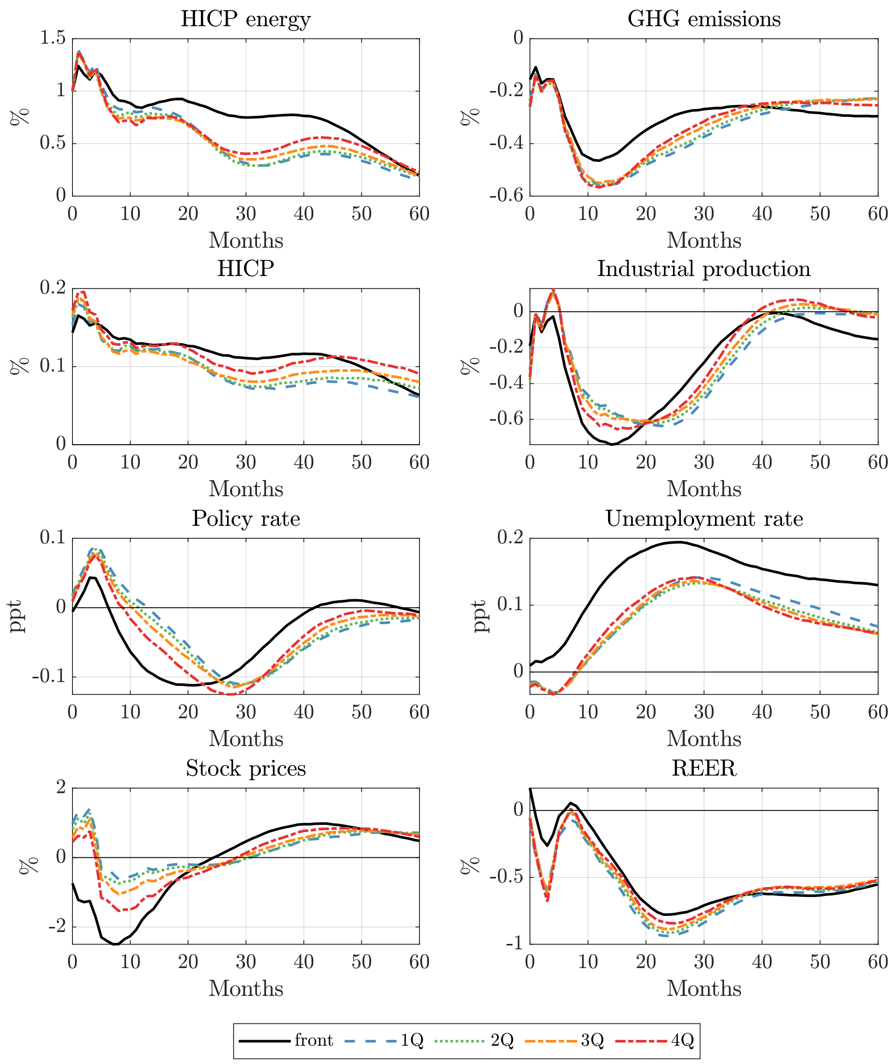


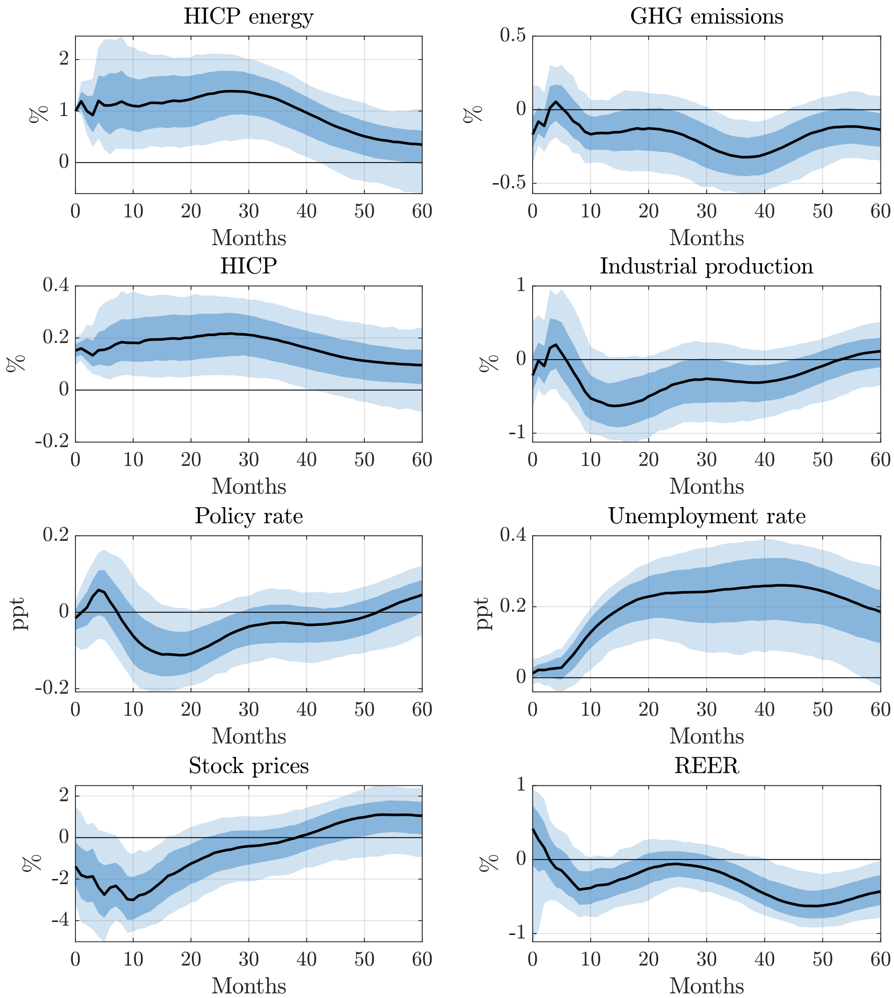
Figure B.36: Using different futures contracts for the instrument

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. Depicted are the point estimates using different futures contracts to construct the instrument.

EUA futures are traded at different maturities. I focus on the quarterly contracts, with expiry date in March, June, September and December. As a baseline, I use the front contract, which is the contract with the closest expiry date and is usually the most liquid. Figure B.36 presents the results based on contracts with longer maturities. The responses based on the second to the fourth contract are all very similar. The largest difference emerge compared to the front contract, however, most responses are qualitatively very similar. However, it should be noted that using contracts further out weakens the first stage considerably. Overall, these results support the focus on the front contract, to mitigate concerns about risk premia.

B.4.4. Sample and specification choices

Finally, I perform a number of sensitivity checks concerning the sample and model specification. Figure B.37 shows the results based on the shorter sample running from 2005, when the ETS was established, to 2018. The results turn out to be very similar to the baseline case.

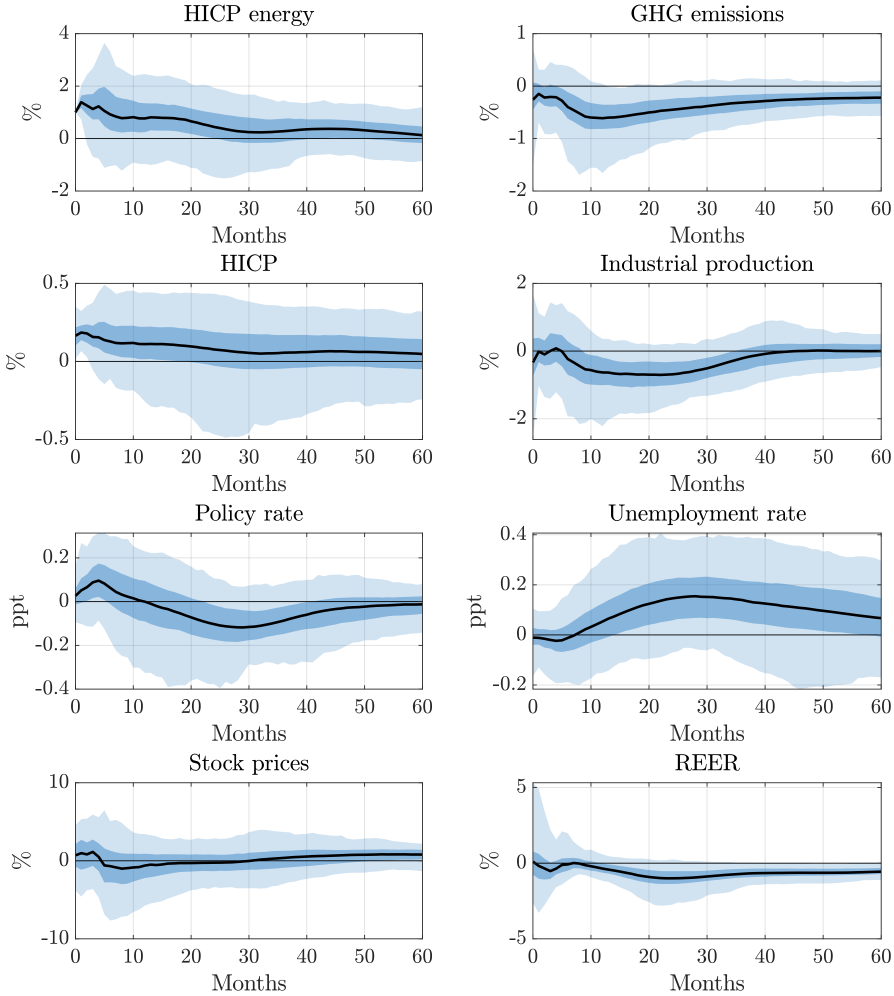


First stage regression: F-statistic: 14.11, R^2: 4.49%

Figure B.37: Results using 2005-2018 sample

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.

Figure B.38 excludes events in phase one (2005-2007) in the construction of the instruments. While the point estimates are similar, the responses are much less precisely estimated, illustrating how the identification strategy leverages the fact that establishing the carbon market was a learning-by-doing process where the rules have been continuously updated.



First stage regression: F-statistic: 8.23, R^2: 1.11%

Figure B.38: Excluding phase one events

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.

The baseline model includes 8 variables and 6 lags, which is relatively large for a comparably short sample. Therefore, Figures B.39-B.43 analyze the robustness with respect to the variables included and number of lags used. Alternatively, I estimate the model using shrinkage priors.[3] The results turn out to be robust along all these dimensions.

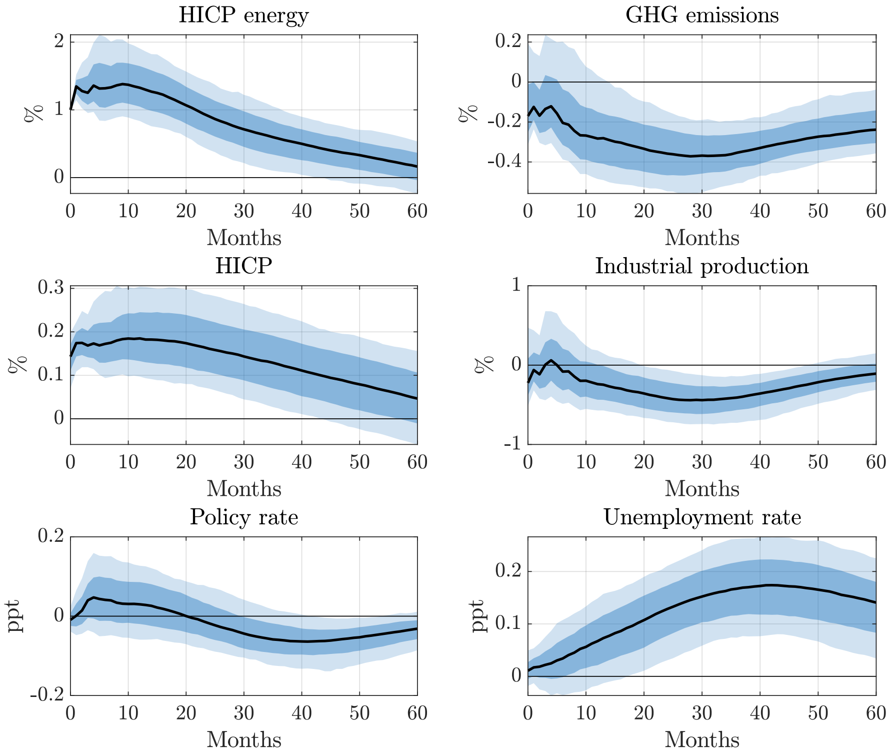
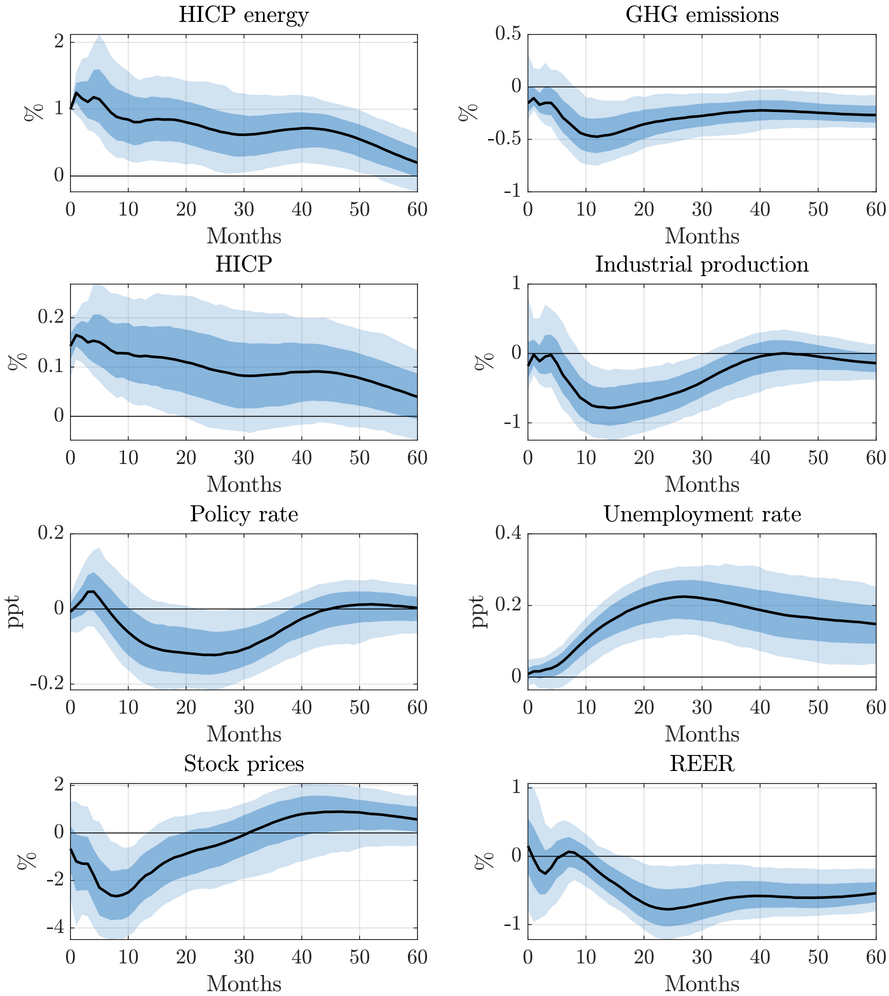


Figure B.39: Responses from smaller VAR

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.

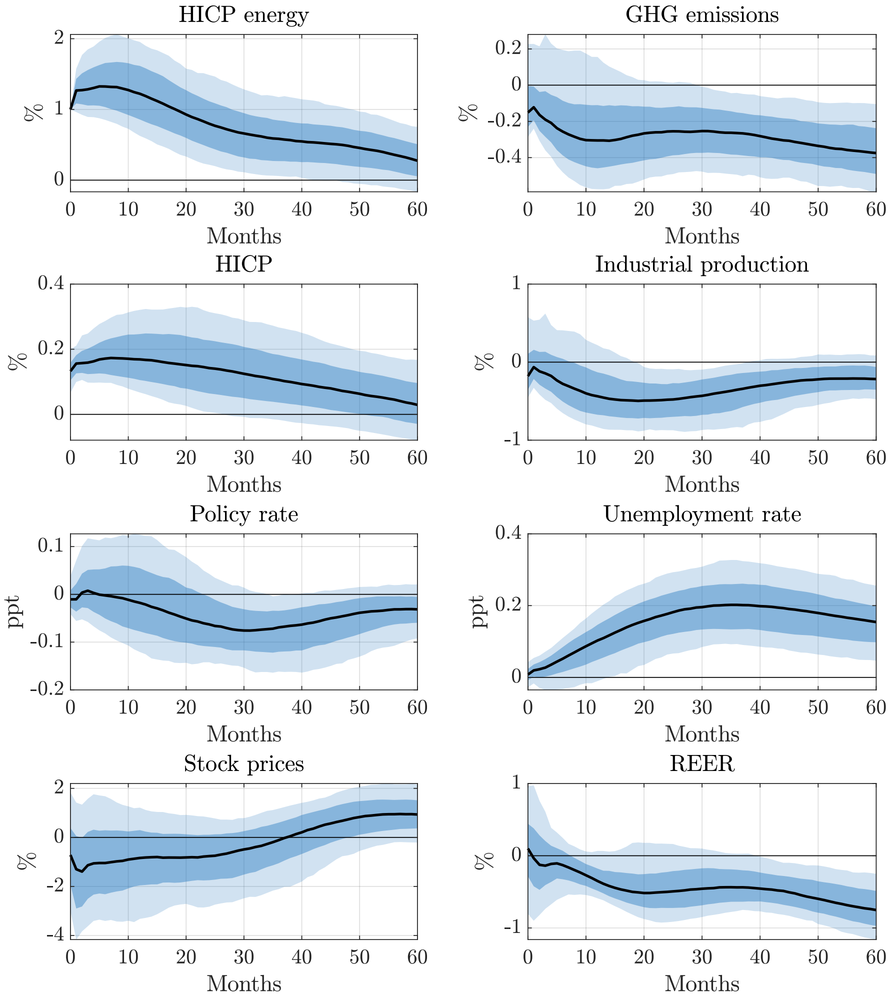
[3]In particular, I use a Minnesota prior with a tightness of 0.1 and a decay of 1.



First stage regression: F-statistic: 20.70, R^2: 3.70%

Figure B.40: VAR including linear trend

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: 9.73, R^2: 2.86%

Figure B.41: VAR with 3 lags

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.

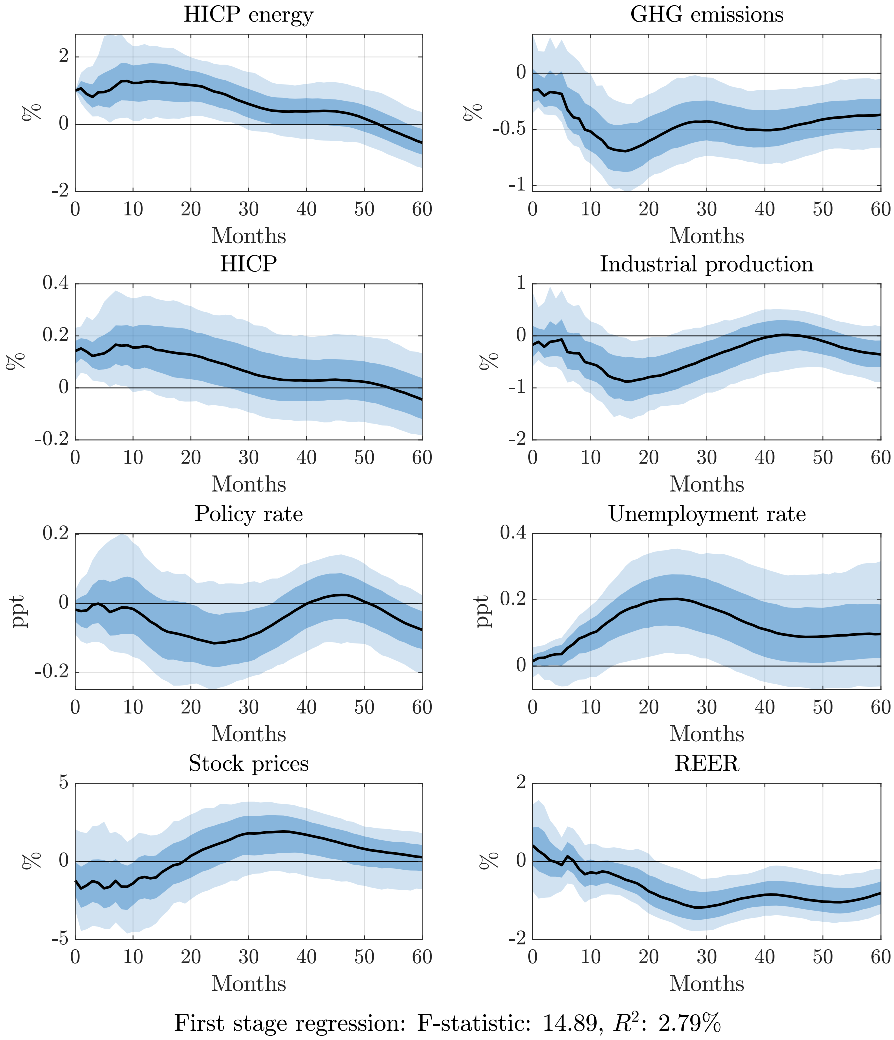


Figure B.42: VAR with 9 lags

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.

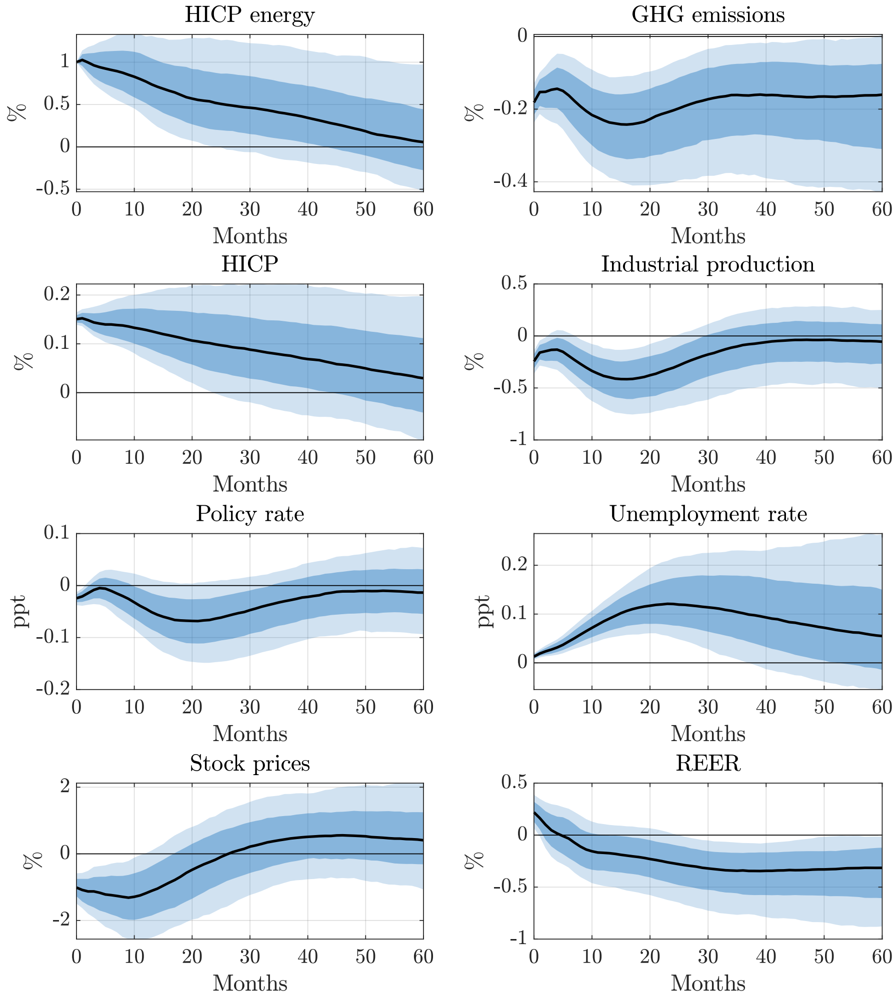


Figure B.43: Bayesian VAR with shrinkage priors

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

C. Heteroskedasticity-based identification

As discussed in Section 7, we can also identify the structural impact vector under weaker assumptions, allowing for the presence of other shocks contaminating the instrument over the daily event window. 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 (see Appendix B.4 for more information and some descriptive statistics of the instrument in the treatment and the control sample). The identifying assumptions can then be written as follows

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

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 $\mathbf{z} = (\mathbf{z}'_{R1}, \mathbf{z}'_{R2})'$.

D. A climate DSGE model with heterogeneous agents and sticky prices

D.1. Overview and results

In this appendix, I develop the theoretical model. The aim is to derive 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 belongs to the dynamic stochastic general equilibrium (DSGE) class and augments the climate-economy structure by Golosov et al. (2014) with nominal rigidities. The model consists of four building blocks: households, firms, a government and a climate block. The firm block is further divided into consumption good and energy producers. Importantly, there is heterogeneity in the household block with respect to households' energy shares, income incidence and marginal propensities to consume. A detailed derivation of the model can be found in Appendix D.2.

D.1.1. 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. 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 who live paycheck by paycheck and consume all of their income and a share $1-\lambda$ **savers** S who choose their consumption intertemporally. Apart from the difference in their marginal propensities to consume (MPC), households differ along two key dimensions: (i) the expenditure energy share and (ii) the income incidence. In line with the data, we assume that hand-to-mouth households have a higher energy share than savers and that their income is more elastic to changes in aggregate income than savers'.

Labor supply decisions are relegated to a labor union, which sets wages according to the following schedule:

$$w_t = \varphi h_t^{\theta} \left(\lambda \frac{1}{p_{H,t}} U_x(x_{H,t}, h_t) + (1-\lambda) \frac{1}{p_{S,t}} U_x(x_{S,t}, h_t) \right)^{-1}, \tag{5}$$

where w_t is the real wage charged by the union, $p_{H,t}$ and $p_{S,t}$ are the relative prices of the hand-to-mouth and the savers' consumption baskets, respectively, and $U_x(\cdot)$ is the marginal utility of consumption. The labor market structure equalizes labor income across households; thus all income heterogeneity in the model will come from heterogeneity in financial income.[4]

Savers. Savers maximize their lifetime utility

$$E_t \left[\sum_{s=0}^{\infty} \beta^s U(x_{S,t+s}, h_{t+s}) \right],$$

choosing how much to consume $x_{S,t}$, save $b_{S,t+1}$ and invest $i_{S,t}$. Their consumption bundle $x_{S,t}$ is a composite of a non-energy good $c_{S,t}$ and energy $e_{S,t}$:

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

where $a_{S,c}$ and $a_{S,e}$ are distribution parameters satisfying $a_{S,c} + a_{S,e} = 1$, and ϵ_x is the elasticity of substitution between non-energy and energy goods.

The demand functions for the consumption and energy good the are

$$c_{S,t} = a_{S,c} \left(\frac{1}{p_{S,t}} \right)^{-\epsilon_x} x_{S,t} \tag{6}$$

$$e_{S,t} = a_{S,e} \left(\frac{p_{e,t}}{p_{S,t}} \right)^{-\epsilon_x} x_{S,t}, \tag{7}$$

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

Each period, savers face the following flow budget constraint

$$p_{S,t} x_{S,t} + i_{S,t} + b_{S,t+1} = y_{S,t}. \tag{8}$$

The savers' income is given by $y_{S,t} = w_t h_t + \frac{R^b_{t-1}}{\Pi_t} b_{S,t} + (1 - \tau^k) r_t k_{S,t} + \frac{(1-\tau^d) d_t}{1-\lambda} + \omega_{S,t}$, where $p_{S,t}$ is the price of the savers' final consumption bundle, $\frac{R^b_{t-1}}{\Pi_t}$ is the risk-free rate deflated by inflation, r_t is the rental rate of capital, d_t are dividends, and $\omega_{S,t}$ are transfers from the government.

Capital accumulation is given by

$$k_{S,t+1} = i_{S,t} + (1 - \delta) k_{S,t}. \tag{9}$$

[4]This is a reduced-form way of capturing the income responses observed in the data. In the model, this labor market structure helps to mitigate varying labor supply responses offsetting income heterogeneity. Furthermore, it allows to introduce sticky wages relatively straightforwardly.

Savers' optimizing behavior is characterized by the following equations

$$\lambda_t = \beta E_t[(1 + (1 - \tau^k) r_{t+1} - \delta)\lambda_{t+1}] \tag{10}$$

$$\lambda_t = \beta E_t \left[\frac{R_t^b}{\Pi_{t+1}} \lambda_{t+1} \right], \tag{11}$$

where $\lambda_t = U_x(x_{S,t}, h_t)/p_{S,t}$ is the shadow value of wealth.

Hand-to-mouth. Hand-to-mouth households have no assets and thus consume all of their income in every period:

$$p_{H,t} x_{H,t} = y_{H,t}. \tag{12}$$

The income of the hand-to-mouth is given by $y_{H,t} = w_t h_t^d + \omega_{H,t}$, where $\omega_{H,t}$ are government transfers. The demand functions for non-energy goods and energy are

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

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

with the associated price $p_{H,t} = \left(a_{H,c} + a_{H,e} p_{e,t}^{1-\epsilon_x} \right)^{\frac{1}{1-\epsilon_x}}$.

D.1.2. 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 costs in adjusting their prices while the energy sector does not face any price rigidity while energy producers do not, in line with the empirical evidence (Dhyne et al., 2006; Alvarez et al., 2006).

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 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. However, importantly, 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.

Non-energy firms. The final non-energy good is produced by a perfectly competitive firm, combining a continuum of intermediate inputs $y_t(i)$ according to the following standard CES production function: $y_{d,t} = \left(\int_0^1 y_t(i)^{\frac{\epsilon_p-1}{\epsilon_p}} di\right)^{\frac{\epsilon_p}{\epsilon_p-1}}$, with $\epsilon_p > 1$. Taking prices as given, the final good producer chooses intermediate good quantities $y_t(i)$ to maximize profits, resulting in the usual demand schedule $y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} y_{d,t}$. 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 inputs are produced by a continuum of monopolistic firms indexed by $i \in [0,1]$ according to the following constant returns to scale technology, using capital $k_t(i)$, energy $e_{y,t}(i)$, and labor $h_{y,t}(i)$ as inputs

$$y_t(i) = e^{-\gamma s_t} a_t k_t(i)^\alpha e_{y,t}(i)^\nu h_{y,t}(i)^{1-\alpha-\nu}, \tag{15}$$

where a_t is TFP, and s_t is the atmospheric carbon concentration. Note that there is a feedback loop between climate and the economy. Higher economic activity increases carbon emissions via higher energy use, which in turn increases the carbon concentration (or equivalently the total stock of emissions). A higher carbon concentration will have economic damages in turn (e.g. via weather events etc.), which reduce output. We model this by a damage function term in the firms' production function. The damage function is given by an exponential function (as in Golosov et al., 2014). The parameter γ can be used to scale the damage function.

Intermediate goods producers maximize profits, taking the demand of their variety into account. Importantly, intermediate goods producers cannot freely adjust prices. As in Calvo (1983), in each period they face a constant probability of $1-\theta_p$ of being able to reoptimize their price.

The cost-minimization problem gives rise to the standard factor demands

$$\begin{aligned} r_t &= \alpha mc_t \frac{y_t}{k_t} \\ p_{e,t} &= \nu mc_t \frac{y_t}{e_{y,t}} \\ w_t &= (1-\alpha-\nu) mc_t \frac{y_t}{h_{y,t}}, \end{aligned} \tag{16}$$

which are common across firms. Here, mc_t are real marginal costs.

When setting prices, intermediate goods producers take into account that the choice today might affect not only current but also future profits. The optimality condition is given by

$$E_t \sum_{k=0}^{\infty} (\beta\theta_p)^k \lambda_{t+k} y_{d,t+k} P_{t+k}^{\epsilon_p - 1} \left(P_t(i) - \mathcal{M}_p \, P_{t+k} mc_{t+k} \right) = 0, \tag{17}$$

where $\mathcal{M}_p = \frac{\epsilon_p}{\epsilon_p - 1}$ is the steady-state markup and λ_t is the shadow value of wealth for a saver. In log-linear terms, this gives rise to the standard Phillips curve $\hat{\pi}_t = \kappa \hat{mc}_t + \beta E_t \hat{\pi}_{t+1}$, where $\kappa = \frac{(1-\theta_p)(1-\theta_p\beta)}{\theta_p}$ is the slope of the curve.

Finally, monopoly profits are given by $d_t = \int_0^1 [\frac{P_t(i)}{P_t} y_t(i) - mc_t y_t(i)] di$.

Energy producers. As in Golosov et al. (2014), the energy firm produces energy using labor according to the following technology

$$e_t = a_{e,t} h_{e,t}. \tag{18}$$

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. For convenience we model it as a sales tax τ_t, however, we can equally model it as a unit tax (see also the discussion in Golosov et al., 2014).

Optimizing behavior is characterized by the following equation

$$w_t = (1 - \tau_t) p_{e,t} \frac{e_t}{h_{e,t}}. \tag{19}$$

D.1.3. 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

$$s_t = (1 - \varphi)s_{t-1} + \varphi_0 e_t. \tag{20}$$

D.1.4. 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

$$\lambda \omega_{H,t} = \tau^d d_t + \tau^k r_t^K k_t + \mu \tau_t p_{e,t} e_t \tag{21}$$

$$(1-\lambda)\omega_{S,t} = (1-\mu)\tau_t p_{e,t} e_t \tag{22}$$

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.[5]

Carbon taxes τ_t are set according to the following rule:

$$\tau_t = (1-\rho_\tau)\tau + \rho_\tau \tau_{t-1} + \epsilon_{\tau,t}. \tag{23}$$

Finally, we assume that there is a monetary authority that conducts monetary policy according to the following simple Taylor rule

$$\frac{R_t^b}{R^b} = \left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} e^{\epsilon_{mp,t}}. \tag{24}$$

D.1.5. 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 $b_t = (1-\lambda)b_{S,t} = 0$.

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 $h_t = h_{y,t} + h_{e,t}$. The energy market clears if $e_t = e_{c,t} + e_{y,t}$.

Aggregate production is given by

$$y_t = \int_0^1 y_t(i)di = e^{-\gamma s_t} a_t k_t^\alpha e_{y,t}^\nu h_{y,t}^{1-\alpha-\nu} = \Delta_t y_{d,t}, \tag{25}$$

where $\Delta_t = \int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon_p} di$ is a price dispersion term, generating a wedge between aggregate output and aggregate demand.

Finally, goods market clearing requires that

$$c_t + i_t = y_{d,t}. \tag{26}$$

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

D.1.6. Calibration and functional forms

The felicity function is assumed to be

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

for $i \in \{H, S\}$. This function belongs to the commonly used constant elasticity class, where $1/\sigma$ is the intertemporal elasticity of substitution and $1/\theta$ is the labor supply elasticity.

We calibrate 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 $1/\sigma$ is set to 2.[6] I set 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, Weidner, and Violante (2014). The distribution parameters $a_{H,e}$ and $a_{S,e}$ are calibrated 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. The elasticity of substitution between energy and non-energy goods ϵ_x is set to a relatively low value of 0.3. This corresponds approximately to the impact elasticity estimated in the LCFS and is in line with the insignificant energy share response. The labor supply elasticity $1/\theta$ is set to 4. While this value is at the upper range of the values commonly used in the literature, a relatively high labor supply elasticity helps to generate income responses that are consistent in magnitude with the responses observed in the data. The labor weight in the utility function, φ is calibrated such that steady-state hours worked h are normalized to one.

Turning to the production side, I set the depreciation rate δ to 0.025, implying an annual depreciation on capital of 10 percent. I set α to 0.275, which implies a standard steady-state capital share (rk/y) of 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 $(p_e e_y/y)$ of around 7 percent. This is slightly higher than the energy share in the US, as estimated for instance by Hassler, Krusell, and Olovsson (2012), and implies a value of $\nu = 0.085$. 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

[6] This is value is at the upper range of the values commonly used in the literature, however, the results are robust to using the more standard unitary elasticity.

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 $1 - \varphi = 0.9994$.[7] 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 3.2 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 implies that the shock is close to being fully reabsorbed after about 20 quarters, which is consistent with the shock dynamics observed in the external instruments VAR. Finally, the Taylor rule coefficient on inflation is set to 1.05. This value is motivated by the absent reaction of monetary policy to carbon policy shocks observed in the data, and also confirms well with the anecdotal evidence in Konradt and di Mauro (2021).[8]

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.1.

[7] 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.

[8] A lower Taylor rule coefficient also ensures the model to have a determinate solution. Conditional on the other parameter values used, a Taylor rule coefficient above 1.1 will cause the model to be indeterminate.

Table D.1: Calibration

Parameter	Description	Value	Target/Source
β	Discount factor	0.99	Smets and Wouters (2003)
$1/\sigma$	Intertemporal elasticity of substitution	2	Gruber (2013)
λ	Share of hand-to-mouth	0.25	Share of low-income households, LCFS
$a_{H,e}$	Distribution parameter H	0.103	Energy share of 9.5%, LCFS
$a_{S,e}$	Distribution parameter S	0.071	Energy share of 6.5%, LCFS
ϵ_x	Elasticity of substitution energy/non-energy	0.3	Empirical estimate, LCFS
$1/\theta$	Labor supply elasticity	4	Empirical income responses, LCFS
φ	Labor utility weight	0.799	Steady-state hours normalized to 1
δ	Depreciation rate	0.025	Smets and Wouters (2003)
α	Capital returns-to-scale	0.275	Steady-state capital share of 30%; Smets and Wouters (2003)
ν	Energy returns-to-scale	0.085	Steady-state energy share of 7%; Eurostat
ϵ_p	Price elasticity	6	Steady-state markup of 20%; Christopoulou and Vermeulen (2012)
θ_p	Calvo parameter	0.825	Average price duration of 5-6 quarters; Alvarez et al. (2006)
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	1.05	VAR evidence/determinacy
τ	Steady-state carbon tax	0.039	Implied tax rate from average EUA price
ρ_τ	Persistence carbon tax shock	0.85	Mean-reversion of approx. 20 quarters

D.1.7. Main results

We will now study how a carbon policy shock affects the economy. As in the empirics, I will normalize the shock such that it increases the energy price $p_{e,t}$ by one percent on impact. As mentioned above, I assume that all carbon revenues go to the savers as the baseline. Alternatively, I will consider the case in which all revenues are redistributed to the hand-to-mouth.

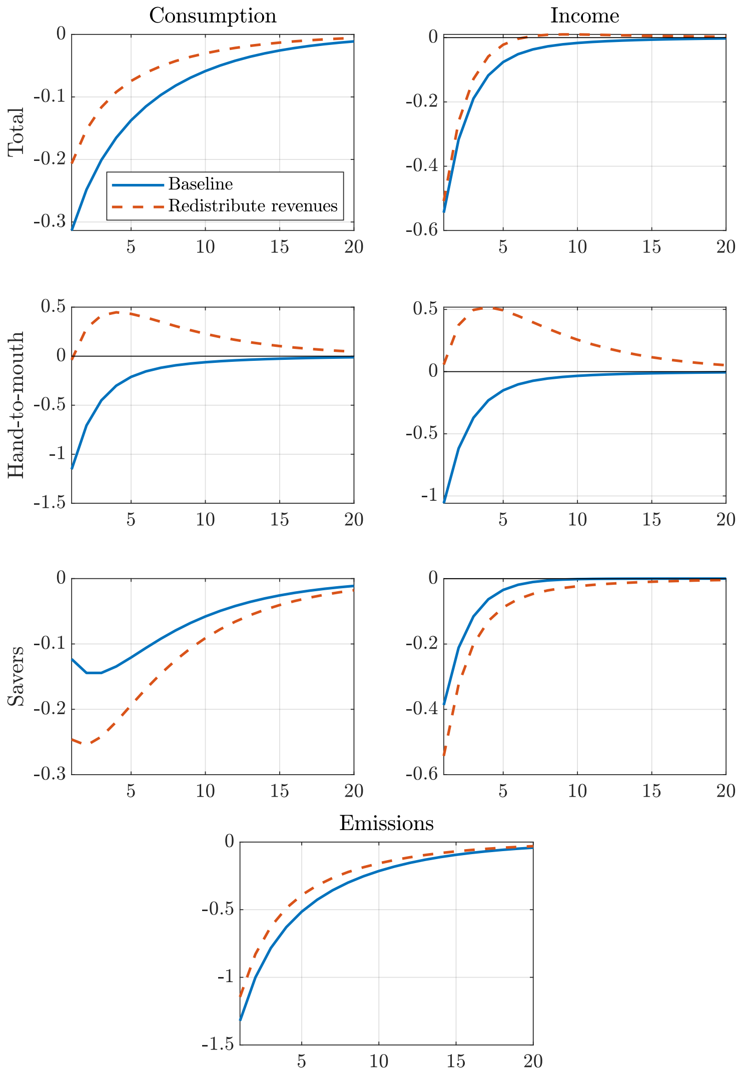


Figure D.1: Baseline responses

Figure D.1 displays the consumption and income responses, both in the aggregate and by household group. We can see that a carbon policy shock leads to a significant fall in consumption and income and the magnitudes of the peak responses are in the same ballpark as in the empirical evidence.[9] Importantly, we can see that the hand-to-mouth play a crucial role in the transmission of carbon policy. They experience a much stronger income response, which in combination with the higher energy share leads to a pronounced fall in their expenditure, with a peak response of around -1 percent. In contrast, the savers' response is much more muted. Finally, the shock also leads to a significant fall in energy use/emissions.

Redistributing carbon tax revenues alters the transmission of the shock sub-

[9]The model is, however, by construction not able to match the hump shape of the responses. To this end, additional model features would be needed such as habit persistence, adjustment costs or rational inattention. To retain tractability, I have deliberately abstracted from these features.

stantially. Both aggregate consumption and income fall by substantially less. The income response of hand-to-mouth turns positive and allows the hand-to-mouth to increase their expenditure. The saver's income and expenditure responses are slightly more pronounced but the positive response of hand-to-mouth outweighs these effects such that aggregate consumption response drops from -0.3 to -0.2 on impact. Importantly, the response of emissions changes by much less, supporting the interpretation that the effects of carbon pricing can be mitigated by targeted fiscal policies without compromising emission reductions.[10]

As illustrated in Figure D.2, the heterogeneity is crucial in getting the empirical magnitudes of the consumption responses. Without the heterogeneity in MPCs, energy shares and income incidence, it is not possible to get the sizeable responses observed in the data without implausibly high firm and household energy shares.

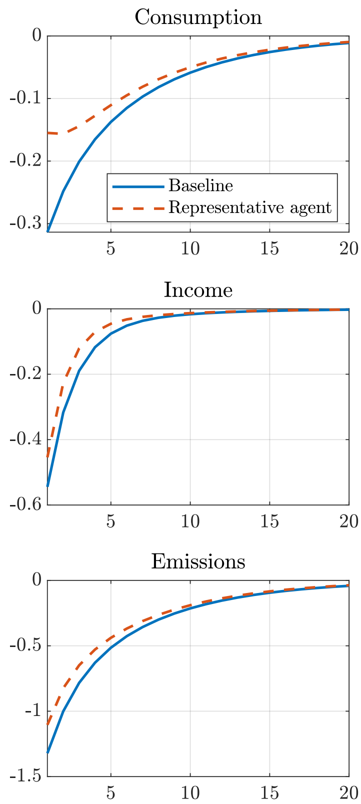


Figure D.2: Heterogeneous versus representative agent

Finally, Figure D.3 illustrates the importance of the direct effects via energy

[10]Note that it is theoretically possible for the negative effects on the savers, which decrease investment and thus the capital stock and future consumption, to outweigh the positive effect on the hand-to-mouth. In this case, redistributing the tax revenues to the hand-to-mouth would make the aggregate consumption response more pronounced. However, in the parameter region that can deliver empirically plausible income and expenditure responses, redistribution turns out to be robustly beneficial.

shares and the indirect effects through the income incidence. We can see that the heterogeneity in energy share can only account for a limited part of the aggregate consumption response, as the model with unequal incidence is already very close to the baseline with heterogeneous energy shares and income incidence.

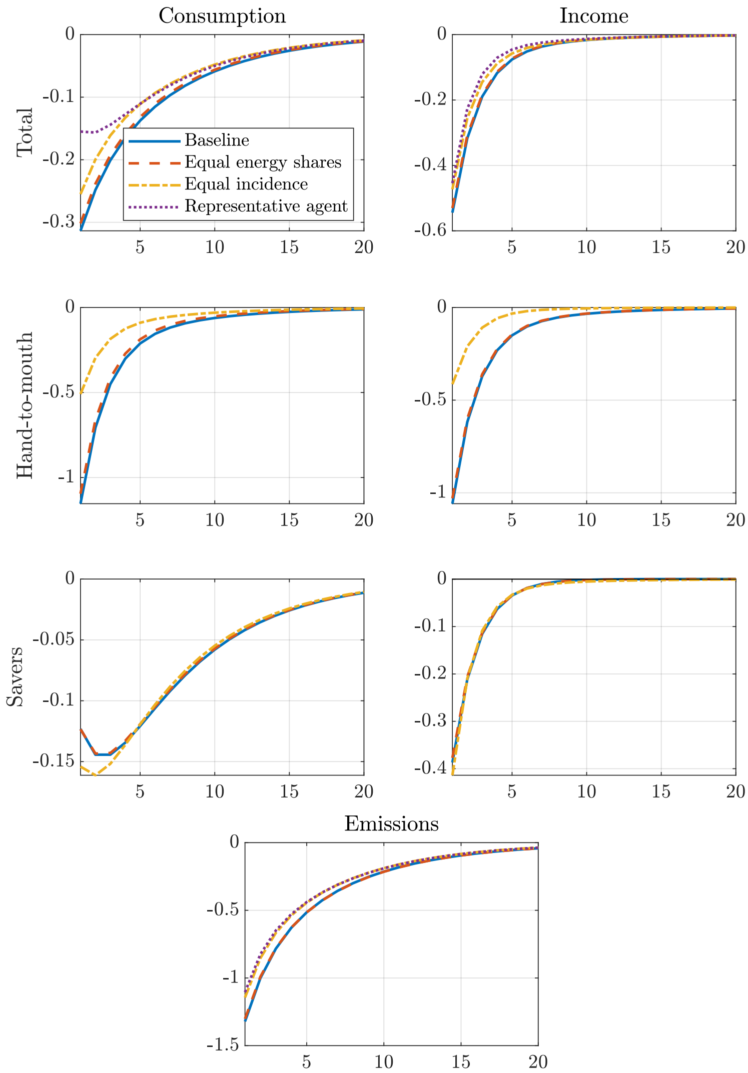


Figure D.3: Decomposition of direct and indirect effects

D.2. Model derivations

D.2.1. Labor market structure

We assume that there is a continuum of differentiated labor inputs indexed by $j \in [0, 1]$.

Labor packer. There is a labor packer that bundles differentiated labor inputs into aggregate labor demand according to a CES technology:

$$\max_{h_t(j)} w_t h_{d,t} - \int_0^1 w_t(j) h_t(j) dj \qquad \text{s.t.} \quad h_{d,t} = \left(\int_0^1 h_t(j)^{\frac{\epsilon_w - 1}{\epsilon_w}} dj \right)^{\frac{\epsilon_w}{\epsilon_w - 1}}$$

The labor demand is

$$h_t(j) = \left(\frac{w_t(j)}{w_t} \right)^{-\epsilon_w} h_{d,t}.$$

and the aggregate wage w_t is

$$w_t = \left(\int_0^1 w_t(j)^{1-\epsilon_w} dj \right)^{\frac{1}{1-\epsilon_w}}.$$

Unions. As in Schmitt-Grohé and Uribe (2005), each household supplies each possible type of labor. Wage-setting decisions are made by labor-type specific unions $j \in [0, 1]$.[11] Given the wage $w_t(j)$ fixed by union j, households stand ready to supply as many hours to the labor market j, $h_t(j)$, as demanded by firms

$$h_t(j) = \left(\frac{w_t(j)}{w_t} \right)^{-\epsilon_w} h_{d,t},$$

where $\epsilon_w > 1$ is the elasticity of substitution between labor inputs. Here, w_t is an index of the real wages prevailing in the economy at time t and $h_{d,t}$ is the aggregate labor demand.

Households are distributed uniformly across unions and hence aggregate demand for labor type j is spread uniformly across households. It follows that the

[11]This is different from the standard way of introducing sticky wages (see Christopher J. Erceg, Dale W Henderson and Andrew T. Levin, 2000), which assumes that each household supplies a differentiated type of labor input. This assumption introduces equilibrium heterogeneity across households in the number of hours worked. To avoid this heterogeneity from spilling over into consumption heterogeneity, it is typically assumed that preferences are separable in consumption and labor and that financial markets exists that allow agents to fully insure against unemployment risk. With the Schmitt-Grohé and Uribe formulation, one does not have to make these restrictive assumptions.

individual quantity of hours worked, $h_t(i)$, is common across households and we denote it as h_t. This must satisfy the time resource constraint $h_t = \int_0^1 h_t(j)dj$. Plugging in for the labor demand from above, we get

$$h_t = h_{d,t} \int_0^1 \left(\frac{w_t(j)}{w_t}\right)^{-\epsilon_w} dj.$$

The labor market structure rules out differences in labor income between households without the need to resort to contingent markets for hours. The common labor income is given by

$$w_t h_{d,t} = \int_0^1 w_t(j)h_t(j)dj = h_{d,t}\int_0^1 w_t(j)\left(\frac{w_t(j)}{w_t}\right)^{-\epsilon_w} dj.$$

Wage setting. Unions set their charged wages w^j by maximizing a social welfare function, given by the weighted average of hand-to-mouth and savers' utility, with the weights are equal to the shares of the households.[12] The union problem reads

$$\begin{aligned}
\max_{w_t(j)} \quad & \left(\lambda\frac{(x_{H,t})^{1-\sigma}-1}{1-\sigma} + (1-\lambda)\frac{(x_{S,t})^{1-\sigma}-1}{1-\sigma}\right) - \varphi\frac{h_t^{1+\theta}}{1+\theta} \\
\text{s.t.} \quad & h_t = h_{d,t}\int_0^1 \left(\frac{w_t(j)}{w_t}\right)^{-\epsilon_w} dj. \\
& p_{S,t}x_{S,t} + i_{S,t} + b_{S,t+1} = h_{d,t}\int_0^1 w_t(j)\left(\frac{w_t(j)}{w_t}\right)^{-\epsilon_w} dj + \frac{R^b_{t-1}}{\Pi_t}b_{S,t} + (1-\tau^k)r_t k_{S,t} + \frac{(1-\tau^d)d_t}{1-\lambda} + \omega_{S,t} \\
& p_{H,t}x_{H,t} = h_{d,t}\int_0^1 w_t(j)\left(\frac{w_t(j)}{w_t}\right)^{-\epsilon_w} dj + \omega_{H,t}
\end{aligned}$$

The FOC is given by

$$\begin{aligned}
\lambda x_{H,t}^{-\sigma}\frac{1}{p_{H,t}}h_{d,t}w_t^{\epsilon_w}(1-\epsilon_w)w_t(j)^{-\epsilon_w} + (1-\lambda)x_{S,t}^{-\sigma}\frac{1}{p_{S,t}}h_{d,t}w_t^{\epsilon_w}(1-\epsilon_w)w_t(j)^{-\epsilon_w} = \\
\varphi h_t^{\theta}h_{d,t}w_t^{\epsilon_w}(-\epsilon_w)w_t(j)^{-\epsilon_w-1}
\end{aligned}$$

This rewrites

$$w_t(j) = \frac{\epsilon_w}{\epsilon_w - 1}\varphi h_t^{\theta}\left(\lambda\frac{1}{p_{H,t}}x_{H,t}^{-\sigma} + (1-\lambda)\frac{1}{p_{S,t}}x_{S,t}^{-\sigma}\right)^{-1},$$

[12] This welfare function follows from the assumption that each household i supplies each possible type of labor input j and there are a share of λ hand-to-mouth and a share of $1-\lambda$ savers.

where $\frac{\epsilon_w}{\epsilon_w - 1} = \mathcal{M}_w$ is the constant wage markup. By putting an optimal subsidy in place, we can neutralize the markup and arrive at

$$w_t(j) = \varphi h_t^{\theta} \left(\lambda \frac{1}{p_{H,t}} x_{H,t}^{-\sigma} + (1-\lambda) \frac{1}{p_{S,t}} x_{S,t}^{-\sigma} \right)^{-1}.$$

Note that because everything on the right-hand-side is independent of j, it follows that all unions charge the same wage $w_t(j) = w_t$. From the definition of aggregate labor supply, we further have $h_{d,t} = h_t$.

Thus, wage setting is characterized by the following equation:

$$w_t = \varphi h_t^{\theta} \left(\lambda \frac{1}{p_{H,t}} x_{H,t}^{-\sigma} + (1-\lambda) \frac{1}{p_{S,t}} x_{S,t}^{-\sigma} \right)^{-1}.$$

Using this in the households' budget constraints:

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

D.2.2. Households

Savers. Savers maximize their lifetime utility subject to their budget constraint, taking prices and wages as given, choosing how much to consume $x_{S,t}$, to invest in capital $i_{S,t}$, and how much to save in risk-free bonds $b_{S,t+1}$ (in real terms, $B_{S,t+1}/P_t$). Their program reads

$$\begin{aligned} \max_{x_{S,t}, i_{S,t}, b_{S,t+1}} \quad & E_t \left[\sum_{s=0}^{\infty} \beta^s \left(\frac{x_{S,t+s}^{1-\sigma} - 1}{1-\sigma} - \psi \frac{h_{t+s}^{1+\theta}}{1+\theta} \right) \right] \\ \text{s.t.} \quad & p_{S,t} x_{S,t} + i_{S,t} + b_{S,t+1} = w_t h_{d,t} + \frac{R_{t-1}^b}{\Pi_t} b_{S,t} + (1-\tau^k) r_t k_{S,t} + \frac{(1-\tau^d) d_t}{1-\lambda} + \omega_{S,t} \\ & k_{S,t+1} = i_{S,t} + (1-\delta) k_{S,t}, \end{aligned}$$

where we have expressed everything in real terms: $p_{S,t}$ is the price of the savers' final consumption bundle, w_t is the real wage, $w_t h_{d,t}$ is real labor income, $\frac{R_{t-1}^b}{\Pi_t}$ is the risk-free rate deflated by inflation, r_t is the rental rate of capital, d_t are dividends, and $\omega_{S,t}$ are lump-sum transfers from the government. σ is the relative risk aversion ($1/\sigma$ is the intertemporal elasticity of substitution) and ψ is a parameter governing the disutility of labor.

The first-order conditions read

$$p_{S,t}\lambda_t = x_{S,t}^{-\sigma}$$
$$\lambda_t = \beta E_t[(1+(1-\tau^k)r_{t+1}-\delta)\lambda_{t+1}]$$
$$\lambda_t = \beta E_t\left[\frac{R_t^b}{\Pi_{t+1}}\lambda_{t+1}\right]$$

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 $a_{S,c}+a_{S,e}=1$[13] , and ϵ_x is the elasticity of substitution between non-energy and energy goods: $\frac{\partial(c_t/e_{c,t})/(c_t/e_{c,t})}{\partial(p_{e,t}/1)/(p_{e,t}/1)}$.[14] 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

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

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

[13]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.

[14]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.

The corresponding price index is

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

Hand-to-mouth. Hand-to-mouth households have no assets and thus consume their labor income as well as the transfer they get from the government. Their problem is thus static and reads

$$\max_{x_{H,t}} \quad \frac{x_{H,t}^{1-\sigma} - 1}{1-\sigma} - \psi \frac{h_t^{1+\theta}}{1+\theta}$$
$$\text{s.t.} \quad p_{H,t} x_{H,t} \leq w_t h_{d,t} + \omega_{H,t}$$

Because of monotonicity, hand-to-mouth households will consume as much as their budget constraint allows

$$p_{H,t} x_{H,t} = w_t h_t^d + \omega_{H,t}.$$

Similarly, consumption and energy demands are

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

and the price of their bundle is

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

D.2.3. 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 costs in adjusting their prices while the energy sector does not face any price rigidity.

[15] Finally, their distribution parameters are given by $a_{H,e} = \omega_{H,e} \left(\frac{p_e}{p_H}\right)^{\epsilon_x - 1}$ and $va_{H,c} = 1 - a_{H,e}$.

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 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. However, importantly, 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. The program of such a representative final goods firm (set up in nominal terms) reads

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

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

From the first order condition, we get the factor demand

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

From the zero profit condition one can deduce the aggregate price level $P_t = \left(\int_0^1 P_t(i)^{1-\epsilon} dj \right)^{\frac{1}{1-\epsilon}}$.

Intermediate goods producers. We asume that non-energy intermediate goods producers have the following production technology

$$y_t(i) = e^{-\gamma s_t} a_t k_t(i)^{\alpha} e_{y,t}(i)^{\nu} h_{y,t}(i)^{1-\alpha-\nu},$$

where a_t is TFP, and s_t is the atmospheric carbon concentration.

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

$$\min_{n_t(i)} r_t k_t(i) + w_t h_{y,t}(i) + p_{e,t} e_{y,t}(i) \qquad \text{s.t.} \quad y_t(i) \leq e^{-\gamma s_t} a_t k_t(i)^{\alpha} e_{y,t}(i)^{\nu} h_{y,t}(i)^{1-\alpha-\nu}$$

The FOCs read

$$\begin{aligned} r_t &= \alpha \lambda_t(i) \frac{y_t(i)}{k_t(i)} \\ p_{e,t} &= \nu \lambda_t(i) \frac{y_t(i)}{e_{y,t}(i)} \\ w_t &= (1-\alpha-\nu) \lambda_t(i) \frac{y_t(i)}{h_{y,t}(i)} \end{aligned}$$

where $\lambda_t(i)$ is the corresponding Lagrange multiplier. This multiplier will again have the interpretation as real marginal cost – how much will costs change if you are forced to produce an extra unit of output, i.e. $mc_t(i) = \lambda_t(i)$. To prove this, let us solve for the Lagrange multiplier as a function of output. We have

$$\lambda_t(i) = \frac{1}{\alpha} r_t \frac{k_t(i)}{y_t(i)} = \frac{1}{\nu} p_{e,t} \frac{e_{y,t}(i)}{y_t(i)} = \frac{1}{1-\alpha-\nu} w_t \frac{h_{y,t}(i)}{y_t(i)}.$$

Thus,

$$\begin{aligned} k_t(i) &= \frac{\alpha}{1-\alpha-\nu} \frac{w_t}{r_t} h_{y,t}(i) \\ e_{y,t}(i) &= \frac{\nu}{1-\alpha-\nu} \frac{w_t}{p_{e,t}} h_{y,t}(i) \end{aligned}$$

Plugging this in the constraint

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

From this we get the factor demand for labor, capital and energy

$$\begin{aligned} h_{y,t}(i) &= e^{\gamma s_t} \left(\frac{\alpha}{1-\alpha-\nu} \frac{w_t}{r_t} \right)^{-\alpha} \left(\frac{\nu}{1-\alpha-\nu} \frac{w_t}{p_{e,t}} \right)^{-\nu} \frac{y_t(i)}{a_t} \\ k_t(i) &= e^{\gamma s_t} \left(\frac{\alpha}{1-\alpha-\nu} \frac{w_t}{r_t} \right)^{1-\alpha} \left(\frac{\nu}{1-\alpha-\nu} \frac{w_t}{p_{e,t}} \right)^{-\nu} \frac{y_t(i)}{a_t} \\ e_{y,t}(i) &= e^{\gamma s_t} \left(\frac{\alpha}{1-\alpha-\nu} \frac{w_t}{r_t} \right)^{-\alpha} \left(\frac{\nu}{1-\alpha-\nu} \frac{w_t}{p_{e,t}} \right)^{1-\nu} \frac{y_t(i)}{a_t}, \end{aligned}$$

which in turn can be used to get the Lagrange multiplier

$$\lambda_t(i) = e^{\gamma s_t}\alpha^{-\alpha}\nu^{-\nu}(1-\alpha-\nu)^{-(1-\alpha-\nu)}r_t^{\alpha}p_{e,t}^{\nu}w_t^{1-\alpha-\nu}\frac{1}{a_t}.$$

Using the factor demands, we can solve for the cost function:

$$C(r_t, p_{e,t}, w_t, y_t(i)) = e^{\gamma s_t}\alpha^{-\alpha}\nu^{-\nu}(1-\alpha-\nu)^{-(1-\alpha-\nu)}r_t^{\alpha}p_{e,t}^{\nu}w_t^{1-\alpha-\nu}\frac{y_t(i)}{a_t}$$

Thus, one can see that the multiplier is equal to the marginal cost function: $\lambda_t(i) = C_y(r_t, p_{e,t}, w_t, y_t(i)) = mc_t(i)$. Note that in the definition of the marginal cost (Lagrange multiplier) above, there is nothing that depends on i. Thus, it follows that marginal costs are the same across firms, i.e $mc_t(i) = mc_t$.

Another important result can be obtained by dividing the two factor demands:

$$\frac{k_t(i)}{h_{y,t}(i)} = \frac{\alpha}{1-\alpha-\nu}\frac{w_t}{r_t}$$
$$\frac{k_t(i)}{e_{y,t}(i)} = \frac{\alpha}{\nu}\frac{p_{e,t}}{r_t}$$

From this one can see that all firms hire capital and energy in the same ratio, i.e. $\frac{k_t(i)}{h_{y,t}(i)} = \frac{k_t}{h_{y,t}}$ and $\frac{e_{y,t}(i)}{h_{y,t}(i)} = \frac{e_{y,t}}{h_{y,t}}$. This also 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 (that is real revenue minus real labor input). However, as outlined above, firms are not able to freely adjust price each period. In particular, each period there is a fixed probability of $1-\theta_p$ that a firm can adjust its price. This means that the probability a firm will be stuck with a price one period is θ_p, for two periods is θ_p^2, and so on (thus we assume independence from time since last price adjustment). Consider the pricing problem of a firm given the opportunity to adjust its price in a given period. 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 s periods into the future by $M_{t,t+s}\theta_p^s$, where $M_{t,t+s} = \beta^s\frac{\lambda_{t+s}^S}{\lambda_t^S}$ is the stochastic discount factor, which follows from the fact that the firm is owned by the savers. The price setting problem reads

$$\max_{P_t(i)} \qquad E_t\sum_{k=0}^{\infty}(\beta\theta_p)^k\frac{\lambda_{t+k}}{\lambda_t}\left(\frac{P_t(i)}{P_{t+k}}y_{t+k}(i) - mc_{t+k}y_{t+k}(i)\right)$$

$$\text{s.t.} \qquad \left\{ y_{t+k}(i) = \left(\frac{P_t(i)}{P_{t+k}} \right)^{-\epsilon_p} y_{d,t+k} \right\}_{k=0}^{\infty}.$$

The FOC reads

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

Simplifying gives

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

By rearranging, we obtain

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

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

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

[16] 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. The distortion coming from this fixed markup over marginal cost can be easily eliminated using a constant subsidy. In this case we have that $\mathcal{M} = 1$ and

$$P_t = MC_t$$

in the limiting case when prices are flexible. However, with sticky prices this markup will be time varying, which introduces another distortion. In steady state, however, there will be no markup, i.e. real marginal costs will be one.

We can also write the X's recursively

$$X_{1,t} = \lambda_t mc_t P_t^{\epsilon_p} y_{d,t} + \beta\theta_p E_t X_{1,t+1}$$
$$X_{2,t} = \lambda_t P_t^{\epsilon_p - 1} y_{d,t} + \beta\theta_p E_t X_{2,t+1}.$$ [16]

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

$$x_{1,t} = \lambda_t mc_t y_{d,t} + \beta\theta_p E_t x_{1,t+1} \Pi_{t+1}^{\epsilon_p}$$
$$x_{2,t} = \lambda_t y_{d,t} + \beta\theta_p E_t x_{2,t+1} \Pi_{t+1}^{\epsilon_p - 1}.$$

The reset price equation then writes

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

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

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

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

$$r_t = \alpha mc_t \frac{y_t}{k_t}$$
$$p_{e,t} = \nu mc_t \frac{y_t}{e_{y,t}}$$
$$w_t = (1 - \alpha - \nu) mc_t \frac{y_t}{h_{y,t}}$$
$$\Pi_t^* = \frac{\epsilon_p}{\epsilon_p - 1} \Pi_t \frac{x_{1,t}}{x_{2,t}}$$
$$x_{1,t} = \lambda_t mc_t y_{d,t} + \beta\theta_p E_t x_{1,t+1} \Pi_{t+1}^{\epsilon_p}$$
$$x_{2,t} = \lambda_t y_{d,t} + \beta\theta_p E_t x_{2,t+1} \Pi_{t+1}^{\epsilon_p - 1}$$
$$\Pi_t^{1-\epsilon_p} = (1 - \theta_p)(\Pi_t^*)^{1-\epsilon_p} + \theta_p$$
$$y_t(i) = e^{-\gamma s_t} a_t k_t(i)^{\alpha} e_{y,t}(i)^{\nu} h_{y,t}(i)^{1-\alpha-\nu}$$

The aggregate production is given by

$$y_t = \int_0^1 y_t(i)di = \int_0^1 e^{-\gamma s_t} a_t k_t(i)^{\alpha} e_{y,t}(i)^{\nu} h_{y,t}(i)^{1-\alpha-\nu} di$$
$$\Rightarrow y_t = e^{-\gamma s_t} a_t k_t^{\alpha} e_{y,t}^{\nu} h_{y,t}^{1-\alpha-\nu} = \Delta_t y_{d,t},$$

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. When firms have different relative prices, there are distortions that create a wedge between between aggregate output measured in terms of production factor inputs and aggregate demand measured in terms of the composite good. The higher the price dispersion, the more labor and capital are needed to produce a given level of output.

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

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

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

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

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

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

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

$$e_t = a_{e,t} h_{e,t}.$$

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. For each unit of emitted CO2, they have to pay 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:

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

D.2.4. Market clearing

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

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

D.2.5. Equilibrium

A general equilibrium of this economy is defined as a sequence of quantities $\mathcal{Q} = \{x_t, x_{S,t}, x_{H,t}, c_t, c_{S,t}, c_{H,t}, e_{c,t}, e_{S,t}, e_{H,t}, i_t, k_{t+1}, y_t, y_{d,t}, h_t, h_{y,t}, h_{e,t}, e_{y,t}, mc_t, e_t, s_t, \tau_t, \omega_{H,t}, d_t, \Delta_t, x_{1,t}, x_{2,t}\}_{t=0}^{\infty}$, a sequence of prices $\mathcal{P} = \{\lambda_t, w_t, r_t, p_{e,t}, p_{S,t}, p_{H,t}, R_t^b, \Pi_t, \Pi_t^*\}_{t=0}^{\infty}$, 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.2: Summary of equilibrium conditions

1:	Wage setting	$w_t = \varphi h_t^{\theta}\left(\lambda \frac{1}{p_{H,t}} x_{H,t}^{-\sigma} + (1-\lambda)\frac{1}{p_{S,t}} x_{S,t}^{-\sigma}\right)^{-1}$
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	$p_{S,t}\lambda_t = x_{S,t}^{-\sigma}$
5:	Investment Euler equation, S	$\lambda_t = \beta E_t[(1+(1-\tau^k)r_{t+1}-\delta)\lambda_{t+1}]$
6:	Bonds Euler equation, S	$\lambda_t = \beta E_t\left[\frac{R_t^b}{\Pi_{t+1}}\lambda_{t+1}\right]$
7:	Capital accumulation	$k_{t+1} = i_t + (1-\delta)k_t$
8:	Final good price index, S	$p_{S,t} = \left(a_{S,c} + a_{S,e} p_{e,t}^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}}$
9:	Non-energy demand, H	$c_{H,t} = a_{H,c}\left(\frac{1}{p_{H,t}}\right)^{-\epsilon_x} x_{H,t}$
10:	Energy demand, H	$e_{H,t} = a_{H,e}\left(\frac{p_{e,t}}{p_{H,t}}\right)^{-\epsilon_x} x_{H,t}$
11:	Consumption, H	$p_{H,t}x_{H,t} = w_t h_t + \omega_{H,t}$
12:	Final good price index, H	$p_{H,t} = \left(a_{H,c} + a_{H,e} p_{e,t}^{1-\epsilon_x}\right)^{\frac{1}{1-\epsilon_x}}$
13:	Capital demand non-energy firm	$r_t = \alpha mc_t \frac{y_t}{k_t}$
14:	Labor demand non-energy firm	$w_t = (1-\alpha-\nu) mc_t \frac{y_t}{h_{y,t}}$
15:	Energy demand non-energy firm	$p_{e,t} = \nu mc_t \frac{y_t}{e_{y,t}}$
16:	Reset price	$\Pi_t^* = \frac{\epsilon_p}{\epsilon_p - 1}\Pi_t \frac{x_{1,t}}{x_{2,t}}$
17-18:	Auxiliary terms	$x_{1,t} = \lambda_t mc_t y_{d,t} + \beta\theta_p E_t x_{1,t+1}\Pi_{t+1}^{\epsilon_p}$
		$x_{2,t} = \lambda_t y_{d,t} + \beta\theta_p E_t x_{2,t+1}\Pi_{t+1}^{\epsilon_p - 1}$
19:	Aggregate inflation	$\Pi_t^{1-\epsilon_p} = (1-\theta_p)(\Pi_t^*)^{1-\epsilon_p} + \theta_p$
20:	Price dispersion	$\Delta_t = (1-\theta_p)(\Pi_t^*)^{-\epsilon_p}\Pi_t^{\epsilon_p} + \theta_p \Pi_t^{\epsilon_p}\Delta_{t-1}$
21:	Aggregate demand non-energy	$y_{d,t}\Delta_t = y_t$
22:	Production function non-energy firm	$y_t = e^{-\gamma s_t} a_t k_t^{\alpha} e_{y,t}^{\nu} h_{y,t}^{1-\alpha-\nu}$
23:	Energy supply	$(1-\tau_t)p_{e,t}e_t = w_t h_{e,t}$
24:	Production function energy firm	$e_t = a_{e,t}h_{e,t}$
25:	Carbon emissions	$s_t = (1-\varphi)s_{t-1} + \varphi_0 e_t$
26:	Aggregate total consumption	$x_t = \lambda x_{H,t} + (1-\lambda)x_{S,t}$
27:	Aggregate non-energy consumption	$c_t = \lambda c_{H,t} + (1-\lambda)c_{S,t}$
28.	Aggregate energy consumption	$e_{c,t} = \lambda e_{H,t} + (1-\lambda)e_{S,t}$
29:	Labor market clearing	$h_t = h_{y,t} + h_{e,t}$
30:	Energy market clearing	$e_t = e_{c,t} + e_{y,t}$
31:	Goods market clearing	$c_t + i_t = y_{d,t}$
32:	Tax schedule	$\tau_t = (1-\rho_\tau)\tau + \rho_\tau\tau_{t-1} + \epsilon_{\tau,t}$
33:	Transfers, H	$\lambda\omega_{H,t} = \tau^d d_t + \tau^k r_t^K k_t + \mu\tau_t p_{e,t}e_t$
34:	Dividends	$d_t = (1 - mc_t\Delta_t)y_{d,t}$
35:	Taylor rule	$\frac{R_t^b}{R^b} = \left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} e^{\epsilon_{mp,t}}$

D.2.6. Steady state and model solution

We assume that $a = a_e = 1$ in steady state. Furthermore, we normalize ψ such that $h = 1$. Furthermore, τ is calibrated. Finally, we assume that there is zero inflation in steady state, i.e. $\Pi = 1$. 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

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

To solve for the steady state, we guess k and e. From (13) with the above equation we get y.[17] From (24), we get h_e. From (29), we get h_y. From (25), we get s. From (22), we get e_y. From (28), we get e_c. From (15), we get p_e. From (14), we get w. From (7), we get i. From (31), we get c. From (8), 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 (12) p_H and $a_{H,e}$ and $a_{H,c}$. From (34), we get d. From (33), we get ω_H. From (11), we get x_H. From (9), we get c_H. From (10), we get e_H. From (27), we get c_S. From (28), we get e_S. From (3), we get x_S. From (26), we get x. From (4),

[17] The equation numbers here refer to the equations in Table D.2.

we get λ. From (1), we get ψ. From (17)-(18), we get the values of the auxiliary terms x_1 and x_2.
Then we minimize such that (2) and (23) 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.

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