# The economic consequences of putting a price on carbon*

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**Abstract**

How does carbon pricing affect the economy? Answering this question is crucial for governments to calibrate policies to fight climate change. Exploiting institutional features of the European carbon market and high-frequency data, I estimate the dynamic causal 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 and increase the public support of such policies – without compromising emission reductions.

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

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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 – information that is crucial for policy design and calibration.

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 allows me to estimate the dynamic causal 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 appears 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. Interestingly, the fall in activity appears to be somewhat less persistent than the fall in emissions. This is also reflected in the stock market response, which displays a significant fall in stock prices for about one and a half years but then rebounds and turns even positive after. The shock also causes a real depreciation of the euro, which in turn causes a significant decline in imports. 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 lead to lower consumption and investment. At the same time, carbon pricing creates an incentive for green innovation, which is reflected in a significant uptick in low-carbon patenting.

Carbon policy shocks have also contributed meaningfully to historical variations in energy prices and emissions. At the one year horizon, they account for over a third of the variations in energy prices and for a quarter of the variations in emissions. They also explain a non-negligible share of the variations in macroeconomic and financial variables. Looking at the historical decomposition, we can see that carbon policy shocks played an important role in many historical episodes but importantly, 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 in 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. In contrast, the fall in earnings for high-income households gets partially offset by an increase in their financial income.

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 lower income households. Thus, such targeted compensations may also help to increase the public support of climate policy.

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 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] Finally, some studies investigated the impact of the EU ETS on economic performance at the firm level, finding no significant negative impact on regulated firms (Dechezleprêtre, Nachtigall, and Venmans, 2018; Marin, Marino, and Pellegrin, 2018; Martin, Muûls, and Wagner, 2016). By way of summary, the empirical 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 methodologi-

[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.

cal 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 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 policy 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 distributive consequences of carbon pricing. In this sense, I also contribute to a growing literature studying the distributional impact of carbon pricing. While the available empirical evidence on carbon pricing is sill rather limited given the relatively short history of such policies (see Ohlendorf et al., 2021 for a meta-analysis of the existing evidence), a large literature has studied the distributional effects of energy taxes, with ambiguous results. The incidence of energy taxes appears to depend on the targeted fuels and pollutants, the characteristics of taxed populations and their communities, the measurement of household income, and, importantly, how tax revenues are used (see Pizer and Sexton, 2019 for a review). My findings suggest that carbon pricing in the EU has been regressive, burdening lower-income households more than richer ones, and that this heterogeneity also matters for the transmission of carbon 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. 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 then 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).

## 2.1. 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 three different phases of the EU ETS. The unit of trading is 1,000 EUA, each being an entitlement to emit one tonne of carbon dioxide equivalent gas.

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 possibly expand the scope of the EU ETS, with the aim to achieve a climate-neutral EU by 2050 (see European Comission, 2020*a*).

## 2.2. 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.

# 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 very 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. 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). Thus, high-frequency changes in EUA futures are likely to be valid measures of changes in carbon price expectations since risk premia are differenced out.

EUA futures are traded at different maturities. I focus here on the front contract, which is the most liquid and has the longest coverage. 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. Interestingly, however, the results turn out to be quite robust to using different contracts, indicating that risk premium effects are not driving the empirical results.[2]

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 surprises occurred at the beginning of the third phase. On April 16, 2013 the Eu-

[2]See Figure B.33 in the Appendix for a comparison of the results based on different contracts. While using different contracts produces comparable results, the first stage becomes weaker when using contracts further out.

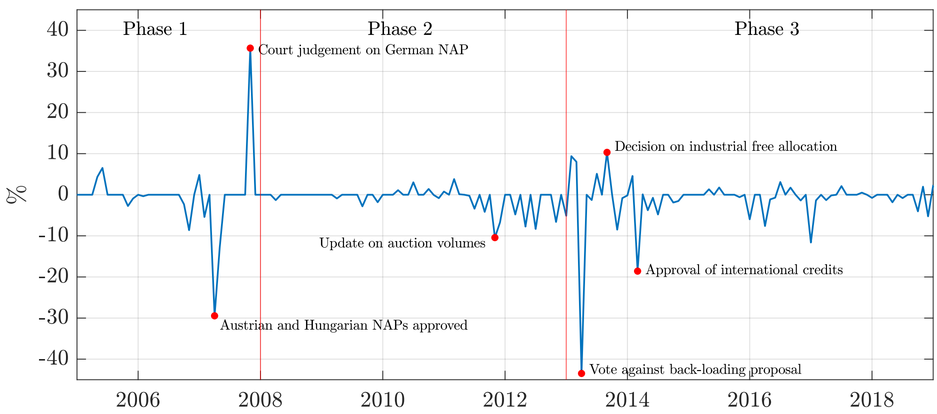



Figure 2: The carbon policy surprise series

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

ropean 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 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 will also present results from a heteroskedasticity-based approach that allows for background noise in the surprise series.

Finally, to be able to interpret the resulting series as a carbon policy surprise series, it is crucial that the events do not contain 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.[3]

**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 will 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 will 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 external instrument approach, the surprise series is used as an instrument external to the VAR model. While this approach tends to be very efficient, it will provide biased estimates if the VAR is not invertible. In contrast, the internal instrument

[3]See e.g. https://www.bbc.com/news/science-environment-22167675.

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 much 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 $\text{Var}(\mathbf{u}_t) = \mathbf{\Sigma}$, $\mathbf{b}$ is a $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices.

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

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

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

We are interested in characterizing the causal impact of a single shock. Without loss of generality, let us denote the carbon policy shock as the first shock in the VAR, $\varepsilon_{1,t}$. Our aim is to identify the structural impact vector $\mathbf{s}_1$, which corresponds to the first column of $\mathbf{S}$.

**External instrument approach.** Identification using external instruments works as follows. Suppose there is an external instrument available, $z_t$. In the application at hand, $z_t$ is the carbon policy surprise series. For $z_t$ to be a valid instrument, we need

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

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

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

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

provided that $E[z_t \mathrm{u}_{1,t}] \neq 0$.[4] To facilitate interpretation, we scale the structural impact vector such that a unit positive value of $\varepsilon_{1,t}$ has a unit positive effect on $\mathrm{y}_{1,t}$, i.e. $\mathrm{s}_{1,1} = 1$. I implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\hat{\mathbf{u}}_t$ on $\hat{\mathrm{u}}_{1,t}$ using $z_t$ as the instrument. To conduct inference, I employ a residual-based moving block bootstrap, as proposed by Jentsch and Lunsford (2019), 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, $\bar{\mathbf{s}}_1 = [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{.,1} / [\mathrm{chol}(\bar{\boldsymbol{\Sigma}})]_{1,1}$. 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. To conduct inference, I rely again on a residual-based moving block bootstrap.

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

## 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.[5] 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).[6] 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.[7]

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.

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

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

[6]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.

[7]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).

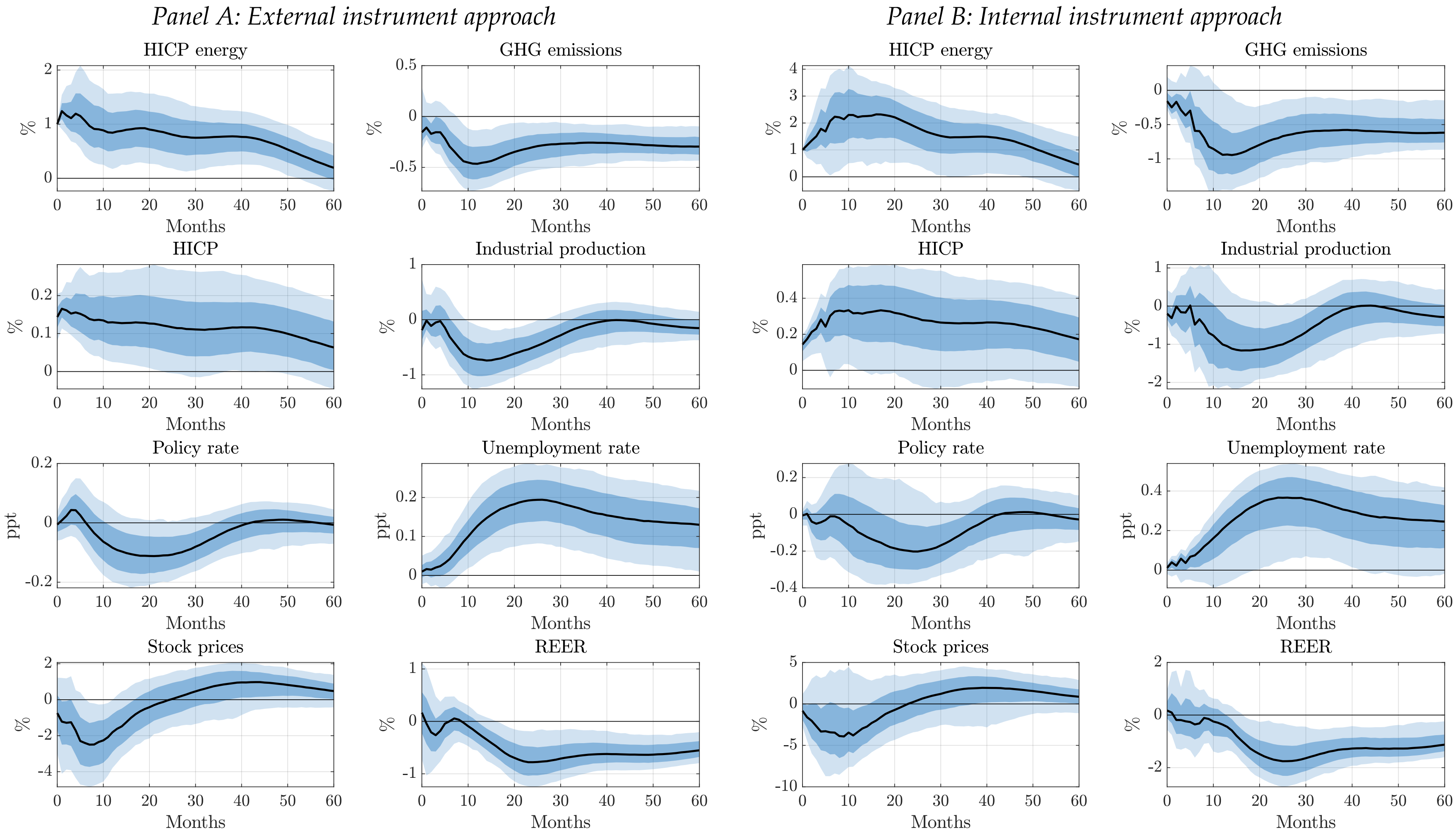
The heteroskedasticity-robust F-statistic in the first stage of the external instrument VAR is 20.95. Assuming a worst-case bias of 20 percent with a size of 5 percent, the corresponding critical value is 15.06. As the test statistic lies clearly above the critical value, we conclude that the instrument 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 baseline 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 in reducing emissions. Turning to the macroeconomic variables, we can see that the persistent 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, which is 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. Stock prices fall significantly on impact but recover quite quickly and even turn positive after two years. Finally, the real exchange rate depreciates significantly.

The internal instrument responses turn out to be very similar to the external instrument ones. The signs are all consistent and the responses also have similar shape. The main difference lies in the response of energy prices, which turns out to be stronger and more persistent in the internal instrument VAR. 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 results suggest that the results are robust to relaxing the assumption of invertibility.




First stage regression: F-statistic: 20.95, $R^2$: 3.65%

Figure 3: Impulse responses to 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.

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. From the first stage of the external instrument VAR, we get an elasticity of energy to carbon prices of about 0.05 percent. Figure 4 shows the elasticity obtained from the internal instrument VAR. On impact, the elasticity is very close to the one obtained from the external instrument VAR. Subsequently, the elasticity increases and reaches its peak after about a year at close to 0.12 percent.[8]

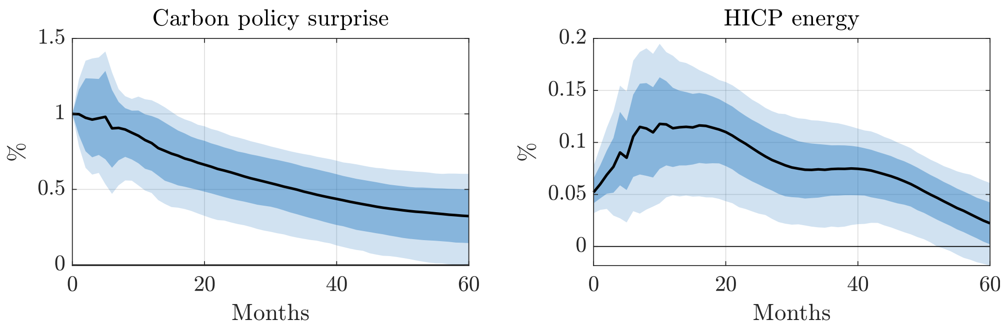



Figure 4: Carbon and energy prices

*Notes*: Impulse responses of the carbon policy surprise and the HICP energy, normalized to increase the surprise series by 1 percent on impact.

## 5.3. Historical importance

In the previous section, we have established that carbon policy shocks can have significant effects on emissions, macroeconomic and financial variables. An equally important question, however, is how much of the historical variation in these variables can carbon policy account for? To answer this question, I perform a variance decomposition exercise. 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.

[8] Alternatively, we can also obtain the elasticity from a model augmented by the 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. The results from a VAR on the shorter sample, augmented by carbon prices point to similar elasticities, see Appendix B.2.

The forecast variance ratio for variable $i$ at horizon $h$ is given by

$$FVR_{i,h} = 1 - \frac{\text{Var}(y_{i,t+h}|\{y_\tau\}_{-\infty<\tau\leq t}, \{\varepsilon_{1,\tau}\}_{t<\tau<\infty})}{\text{Var}(y_{i,t+h}|\{y_\tau\}_{-\infty<\tau\leq t})}, \tag{8}$$

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 1. 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 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.

Table 1: 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.

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.

The variance decomposition is informative about the average contribution of carbon policy shocks over the sample of interest. However, it is potentially even more interesting to see how carbon policy shocks have contributed in specific historical episodes. To this end I perform a historical decomposition of HICP energy inflation and GHG emissions growth based on the baseline VAR.

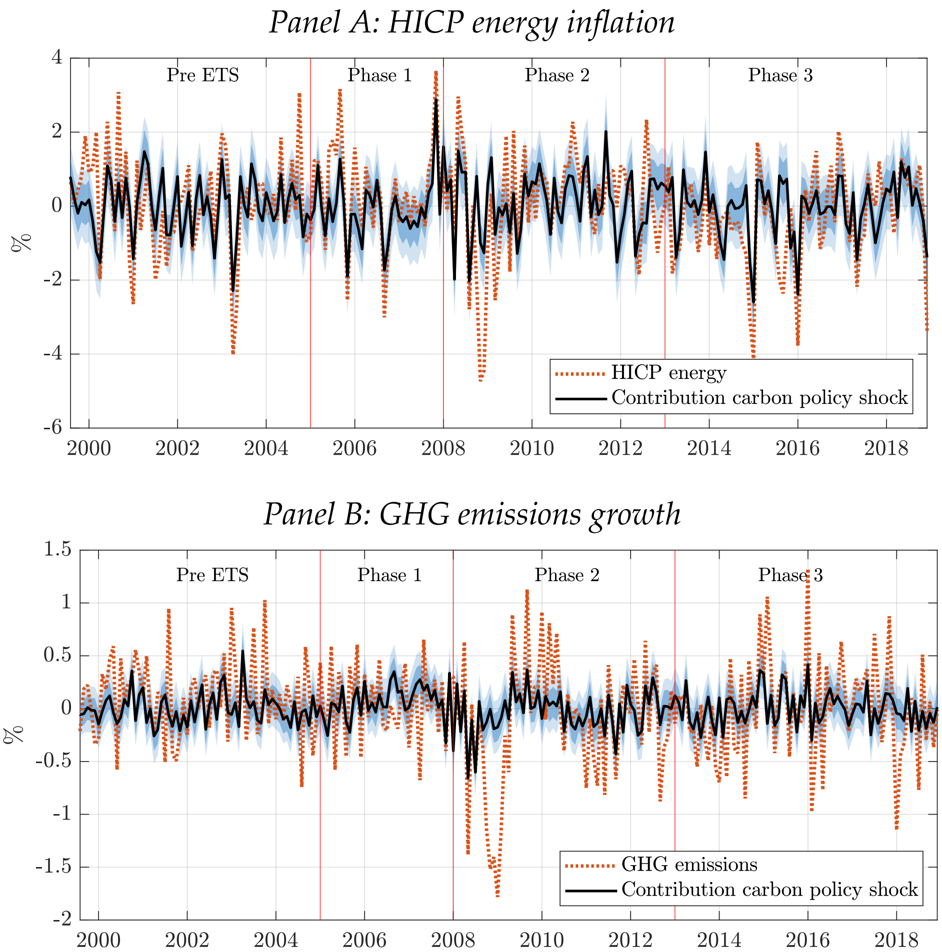



Figure 5: Historical decomposition of inflation and emissions growth

*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 shocks 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.

Figure 5 shows the results. We can see that carbon policy shocks have contributed meaningfully to variations in energy prices and GHG emissions in many episodes. For energy price inflation, the contribution is particularly stark in the third phase of the EU ETS. 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-side factors.

## 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 are suggestive 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 on the sectoral effects of the EU ETS (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:

$$q_{i,d+h} - q_{i,d-1} = \beta_0^i + \psi_h^i CPSurprise_d + \beta_{h,1}^i \Delta q_{i,d-1} + \ldots + \beta_{h,p}^i \Delta q_{i,d-p} + \xi_{i,d,h}, \tag{9}$$

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. $\psi_h^i$ 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).

The results are shown in Figure 6. We can see that the carbon policy surprises lead to a significant increase in carbon futures prices. The front contract increases significantly for about three weeks. The effect on carbon prices turns out to be quite persistent as the price of the second contract, which expires in December the following year, 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 two weeks, the index starts to fall significantly. This may reflect the fact that the EU ETS is a relatively new market and thus stock market participants need some time to process the regulatory news. I have also

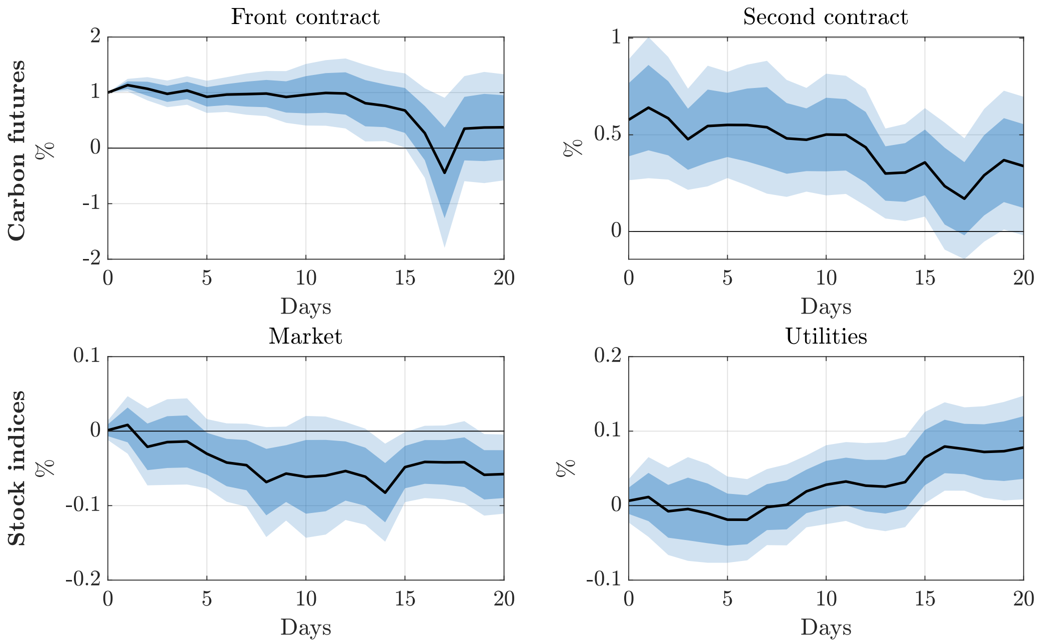



Figure 6: Carbon price and stock market indices

*Notes*: Responses of the carbon price 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 and the confidence bands are constructed using heteroskedasticity-robust standard errors.

looked at the stock price response of different sectors. Among the 11 GICS sectors, utilities is the only sector that displays a response that is significantly different from the market response: after a couple of weeks, the price starts to increase significantly.

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. 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 $CPShock_t = \mathbf{s}_1' \boldsymbol{\Sigma}^{-1} \mathbf{u}_t$ (for a derivation, see Stock and Watson, 2018) and estimate the dynamic causal effects using simple local projections:

$$y_{i,t+h} = \beta_0^i + \psi_h^i CPShock_t + \beta_{h,1}^i y_{i,t-1} + \ldots + \beta_{h,p}^i y_{i,t-p} + \xi_{i,t,h}, \tag{10}$$

where $\psi_h^i$ 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.[9] Throughout the paper, I normalize the shock to increase the HICP energy component by one percent on impact.

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. 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 household expenditure and firms' investment 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 7. 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

[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.

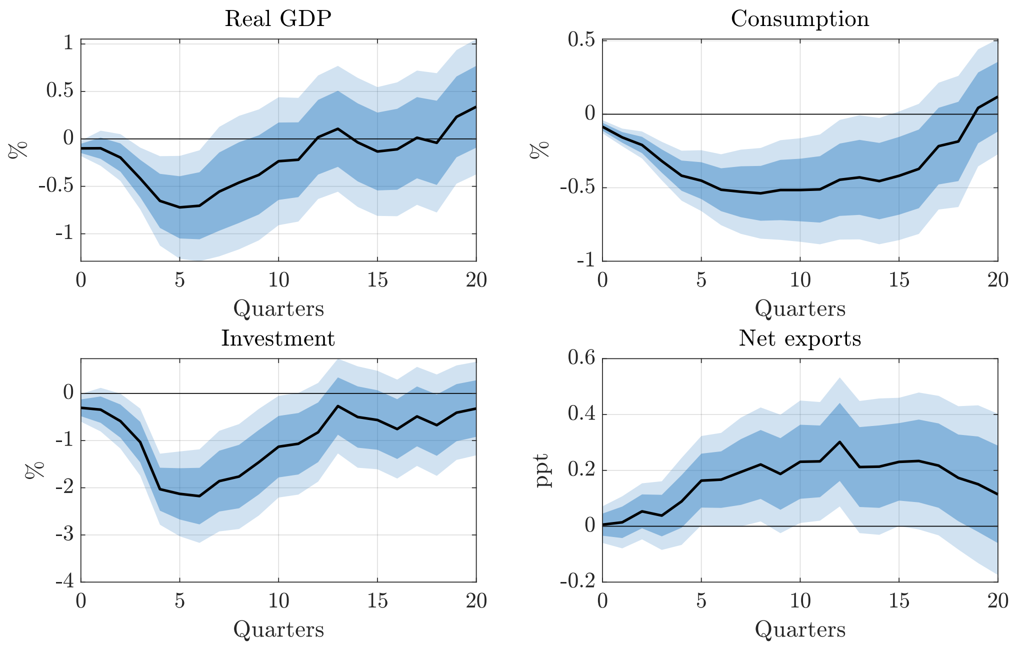



Figure 7: Effect on GDP and components

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

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 could be expected from the direct discretionary income effect. Therefore, indirect effects likely play a crucial role in the transmission of the shock. In Section 6, I will shed more light on the role of different transmission channels using detailed household micro data.

The above results support the notion that higher energy prices 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 market 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.4 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.** The above results illustrate 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 driving 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 (CCMT).

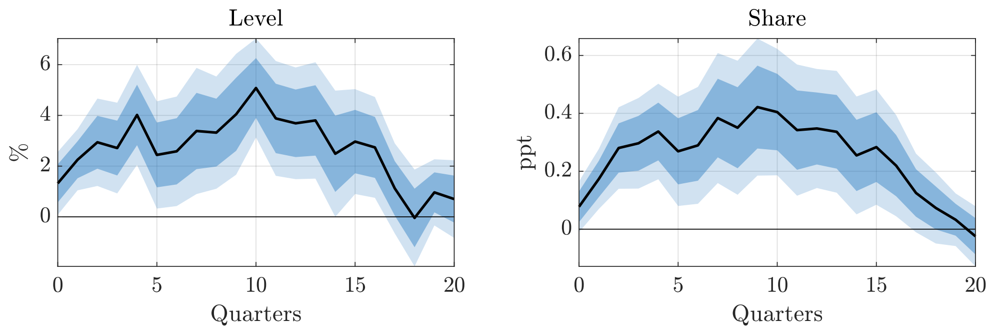



Figure 8: Patenting in climate change mitigation technologies

*Notes*: Impulse responses of patenting activity in climate change mitigation technologies. Depicted is the response of the number of CCMT 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 8. 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 CCMT. These results are in line with 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

So far we have studied the effects of carbon pricing at the aggregate level. In this section, we look into the heterogeneous effects of carbon pricing with a particular focus on households. The motivation for doing so is twofold. First, looking into potential heterogeneities in the consumption response can help to better understand the transmission channels at work. Second, studying the heterogeneous effects on households is interesting per se, as it sheds light on the distributive impacts of carbon pricing policies.

There is reason to believe that there are important heterogeneities at play. First, the direct, discretionary income effect discussed above 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 their income composition or the sector of employment.

## 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 expenditures 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).[10]

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 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

[10]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.5 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.24.

the income may endogenously respond to the shock of interest, we cannot use the current household income as the grouping variable. Luckily, the LCFS does not only collect information about current household income but also about normal household income, which should by construction not be affected by temporary shocks.[11] Thus, I use the normal disposable household income to group households into three pseudo-cohorts: low-income, middle-income, and high-income households.[12] 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 2 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, as 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.7 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 by 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

[11] While it may still 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.9 in the Appendix.

[12] In Appendix B.2, I alternatively 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.

higher frequency (see Figure B.8 in the Appendix).

Table 2: 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 some 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 inequality responses

We are now in a position to study how households' expenditure and income respond to carbon policy shocks. As a validating exercise, we first look at the median household expenditure response and compare it to the consumption response based on national statistics.[13] As can be seen from the left panel of Figure

[13]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.13 in the Appendix.

9, the median response aligns very well with the response from national statistics, both in terms of shape and magnitude (see Figure 7).

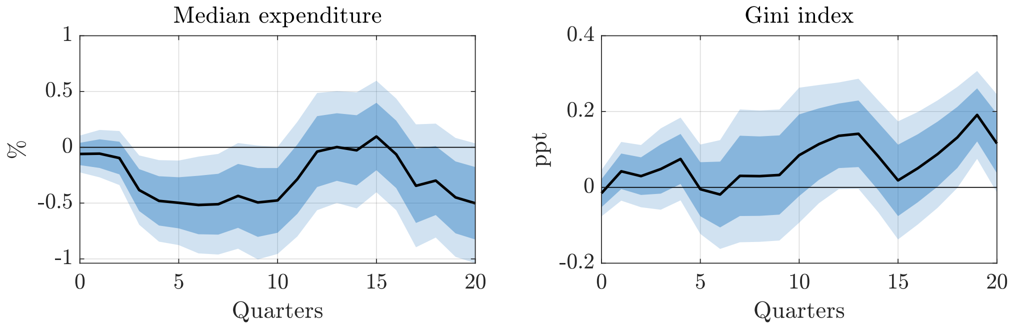



Figure 9: Response of household consumption expenditure

*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 9. 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 10 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 a bit less persistent.[14] The finding that expenditure of high-income households does nevertheless not respond significantly points to the fact

[14]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.14 in the Appendix.

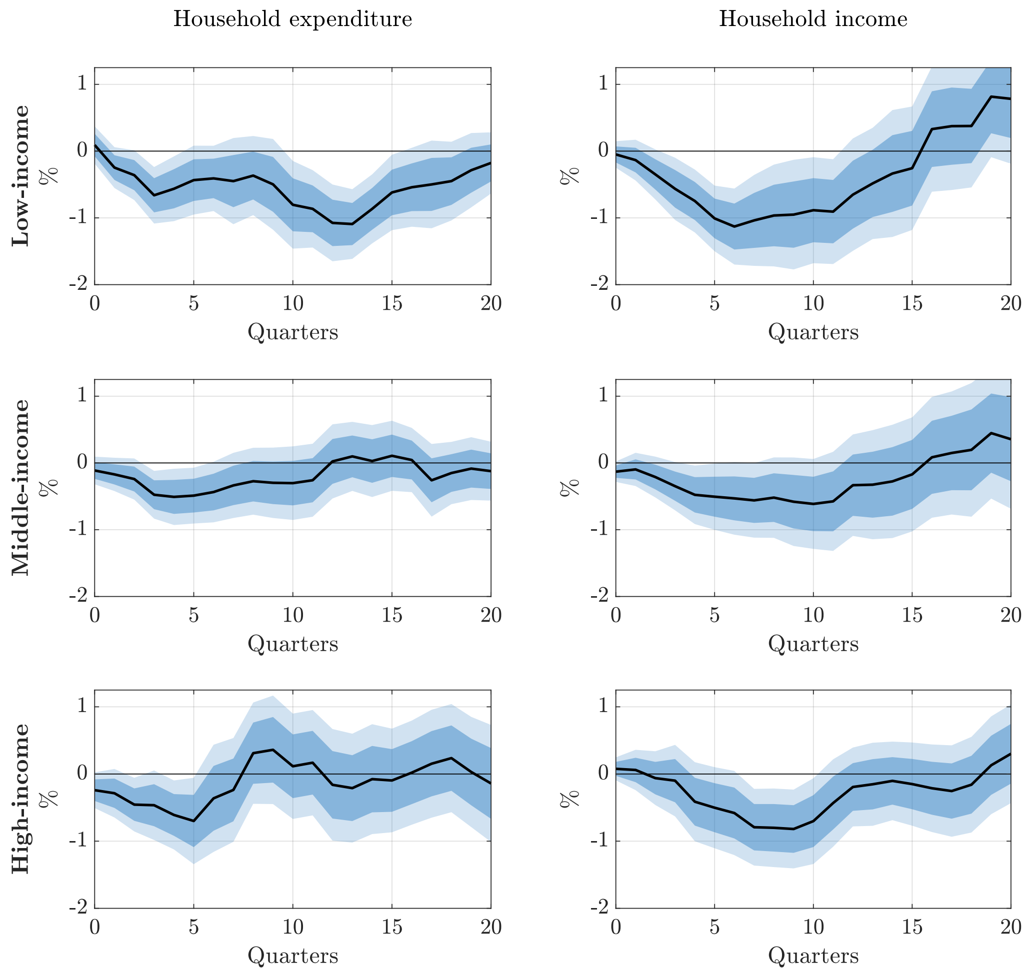



Figure 10: Household expenditure and income responses by income groups

*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.

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. 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.[15] Second, they experience the largest fall in income, as they are more likely to work in sectors that are most hardly affected by the carbon policy shock.[16] 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.

While the expenditure responses are, as expected, more pronounced the higher the energy share, the magnitudes are much larger than 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. However, the peak response of low-income households is around one percent – close to ten times the energy share of that group. This suggests that indirect, general equilibrium effects via income account for a large part of the overall effect on household expenditure.

To better understand the different channels at play, we decompose total expenditure into its non-durable, services and durable components. The responses are shown in Figures B.18-B.19 in the Appendix. We can see that all expenditure groups fall significantly. 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. This result supports 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 pro-

[15]Energy expenditure does indeed turn out to be pretty inelastic. Figures B.15-B.16 in the Appendix show the response of energy expenditure as well as the share of energy in total expenditure. The response is close to zero in the short run and then tends to increase slightly even though the response is not statistically significant. Higher-income households display a somewhat higher price elasticity, especially in the short run.

[16]Unfortunately, the LCFS does not include any information on the job sector. However, data from the UK Labour Force Survey (LFS) corroborates this explanation. Lower-income households tend to work disproportionally in sectors such as construction, wholesale and retail trade, hospitality, and entertainment and recreation. These are also the sectors that display the strongest fall in the median net pay after a carbon policy shock, see Table B.3 and Figure B.17 in the Appendix.

nounced for high-income households given their higher share of durables in total expenditure (see also Edelstein and Kilian, 2009). 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 low share of durables in total expenditure, these other direct channels do likely not play a dominant role in terms of the overall effect on expenditure.

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.20-B.22 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. The role of the energy share

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. Descriptive statistics on these groups can be found in Table B.4 in the Appendix. Note that the heterogeneity in the energy share is now much starker: close to 16 percent in the high-share group against only around 2 percent for low-share households. We can also see that the high-share group tends to be poorer as reflected by lower levels of income and expenditure.

Figure 11 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

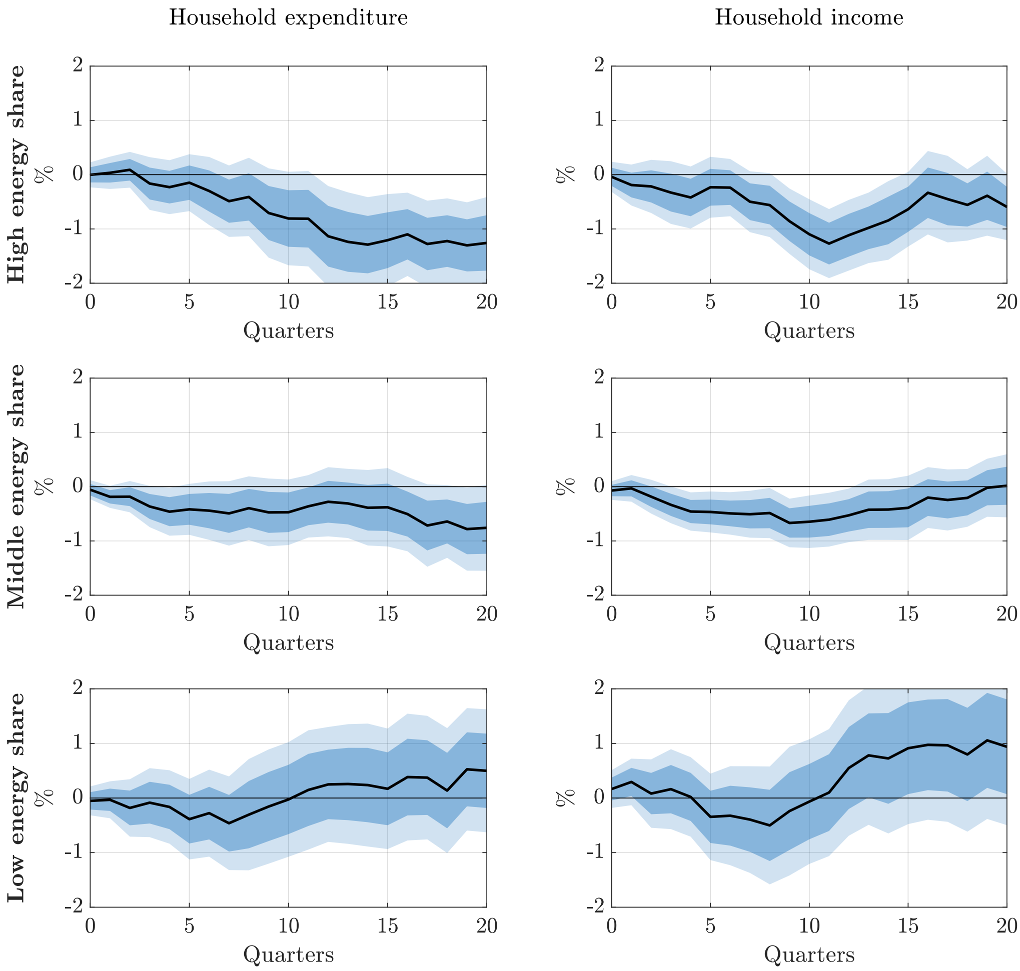



Figure 11: Household expenditure and income responses by energy share

*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.

for reasons dicussed above. 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.

To better understand the roles of the energy share and the income level, I group households along these two dimensions. In particular, 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. Not only are these households more exposed to carbon pricing because of their higher energy share but they also experience a sharper decline in their incomes. The role of these indirect effects via the decrease in household income can also be nicely seen 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 the 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 wages and labor income.

**Discussion.** 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 poor and middle income households that are the most hardly affected, having to reduce their expenditures the most, and who are driving the aggregate response. In fact, the overall pound change in expenditure over the five-year period following a carbon policy shock is $-$£316.4 for low-income, $-$£175.9 for middle-income, and $-$£155.6 for high-income households.[17] These heterogeneities are striking against the backdrop that low-income households have much lower levels of expenditure to start with, see Table 2. Put differently, low-income households account for about 40 percent of the aggregate effect of carbon pricing on consumption, despite the fact that they only represent 25 percent of the population.

[17]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.

The results also highlight the importance of energy prices in the transmission of carbon policy shocks through direct and indirect effects that disproportionally affect lower-income households, who also tend to be the households that are financially constrained and have a higher marginal propensity to consume. My findings suggest that fiscal policies targeted to the households that are most affected by carbon pricing 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 were freely allocated, auctioning became the default method 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 spent for such purposes, with many countries using all of the revenues for such climate actions. While this should help to further propel emission reductions and increase energy efficiency, 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 – increasing the public support of such policies.

## 6.5. Effect on attitude towards climate policy

As we have seen, carbon pricing leads to higher energy prices, a consequence that tends to be highly unpopular (see e.g. Knittel, 2014). Public opposition can be an impediment for climate policy as the yellow vest movement in France, which started as a demonstration against higher fuel taxes, has shown for instance. 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 ant thus, it is possible to analyze how certain attitudes have changed over time.

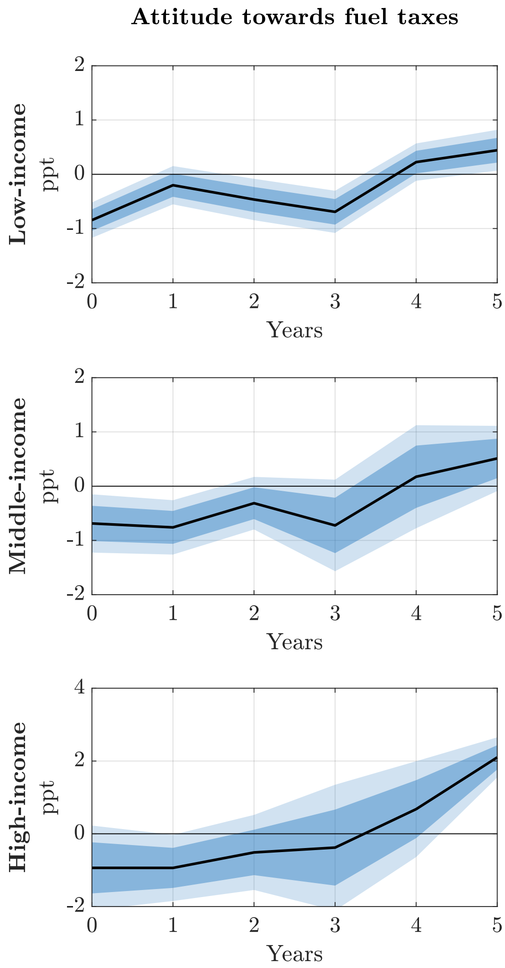



Figure 12: Effect on attitude towards climate policy by income group

*Notes*: Impulse responses of public attitude towards climate policy by income group. 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, middle-income to the middle 50 percent, and high-income households to the top 25 percent of the income distribution.

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.25 in the Appendix shows how the attitude towards fuel taxes has changed among low-, middle- and high-income households. The support tends to be higher among richer households and has increased significantly in the last decade. In contrast, the support is lower among poorer households and has stayed at rather low levels, even in recent years.

Figure 12 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 particularly significant for lower 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 much less precisely estimated and even turns positive in the longer run.

These results suggest that compensating households that are most exposed to carbon pricing may indeed help to increase the public support of climate change mitigation policies. This is in line with recent evidence by Anderson, Marinescu, and Shor (2019), who show that resistance to higher energy prices played an important role in two failed carbon tax initiatives in Washington State, US.

# 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.3.[18]

**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.26, the results turn out to be robust. I have also tried to exclude the events about international credits, which affect the supply of allowances only indirectly, by changing the number of

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

credits from international projects that can be exchanged for allowances. From Figure B.27, we can see that the results turn out to be very similar. As an additional check, I only include the core events on free allocation and auctions, see Figure B.28. The results are again very similar to the baseline case. 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.29). 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 slightly less precisely estimated (see Figure B.30).

**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.5 in the Appendix. More details on the underlying assumptions and how to implement the heteroskedasticity-based approach are provided in Appendix C.

Figure B.31 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.32 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.34. 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.35, 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 thus present the results from a 6 variable model, excluding stock prices and the real exchange rate. As can be seen from Figure B.36, 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.38-B.39 show the responses using 3 or 9 lags) and the choice of deterministics (Figure B.37 includes a linear trend). Finally, I also present results from a Bayesian VAR model with 12 lags and using shrinkage priors.[19] The results turn out to be again very similar to the baseline VAR (see Figure B.40).

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

# 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, exploiting institutional features of the European carbon market and high-frequency data. 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, redistributing 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 increasing public support of climate policy.

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# Online Appendix

## The economic consequences of putting a price on carbon


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## Contents




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# A. Data

## A.1. Details on regulatory events

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

Table A.1: Regulatory update events

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

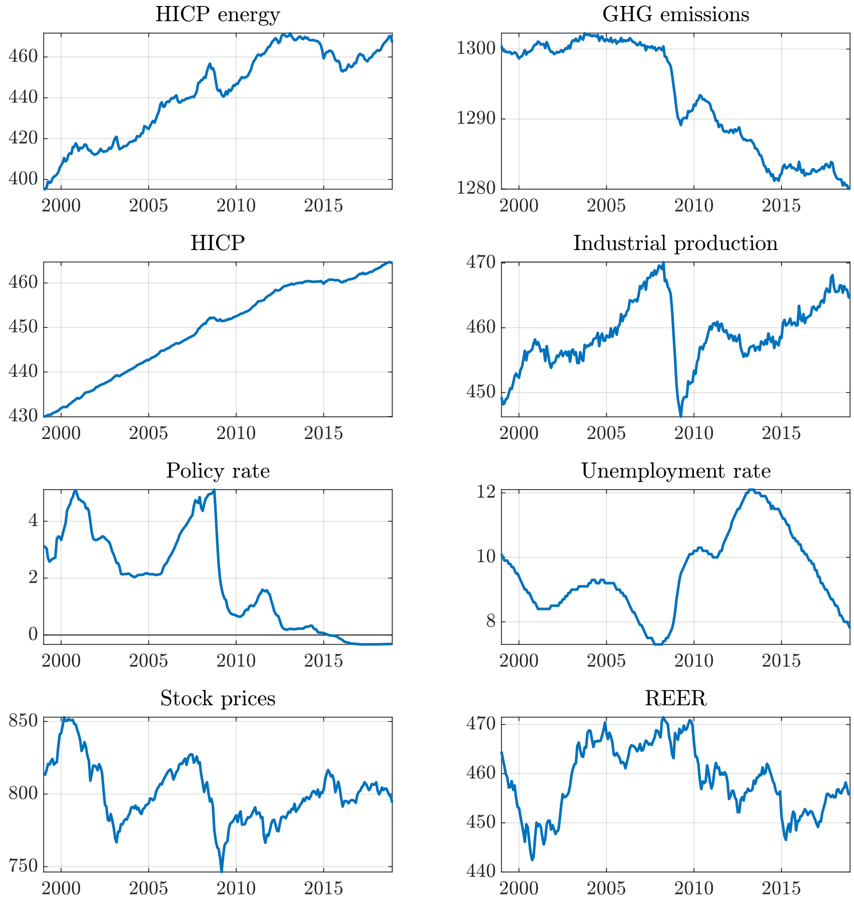



Figure A.1: Transformed data series

## 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. All variables, except the age at which full-time education was completed, are available in the derived household datasets. The age at which fulltime education was completed, as well as current wages, is aggregated from the personal derived datasets by using the maximum age at which one of the household members completed a full-time education.

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 variables that are available do not allow a clean split between these categories, 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 serviced 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<br>*FES codes:* d070104t, d070105t, d070211t, d070209t, d070401t, d070402t, d070302t, d070601t, d120304t, d070501t |

| Category | Subcategories | Items |
|---|---|---|
| | Non-durable personal goods (subset of p544t) | *LCFS codes:* c61112t, c61211t, c61311t, c61313t, cc1312t, cc1313t, cc1314t, cc1315t, cc1316t, cc1317t, cc3211t, cc3222t, cc3223t, cc3224t<br>*FES codes:* d090402t, d090102t, d090501t, d090101t, d090103t, d090104t, d090105t, d090301t, d090202t, d090302t, d090303t |
| | Non-durable motoring expenditure (subset of p545t) | *LCFS codes:* c72114t, c72211t, c72212t, c72213t<br>*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<br>*FES codes:* d120114t, d120108t, d120110t, d120109t, d120401t, d120113t, d070703t, d120303t, d120301t, d120302t |
| | Miscellaneous non-durable goods (subset of p549t) | *LCFS codes:* ck5511c, cc3221t<br>*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<br>*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<br>*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<br>*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<br>*FES codes:* d120111t, d120112t |
| | Miscellaneous services (subset of p549t) | *LCFS codes:* b237, b238, ck5315c, ck5213t, ck5214t<br>*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<br>*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<br>*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<br>*FES codes:* b244, b245, b247, d100105t, d100106t, d100107t, d100101c, d100102c, d100104c, d100203t, d100202t, d100205t |

| Category | Subcategories | Items |
|---|---|---|
| | Durable leisure goods (subset of p547t) | *LCFS codes:* c91124t, c82111t, c82112t, c82113t, c91111t, c91113t, c91121t, c91122t, c91123t, c91125t, c91211t, c91311t, c92211t, c92221t, c93211t<br>*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 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.

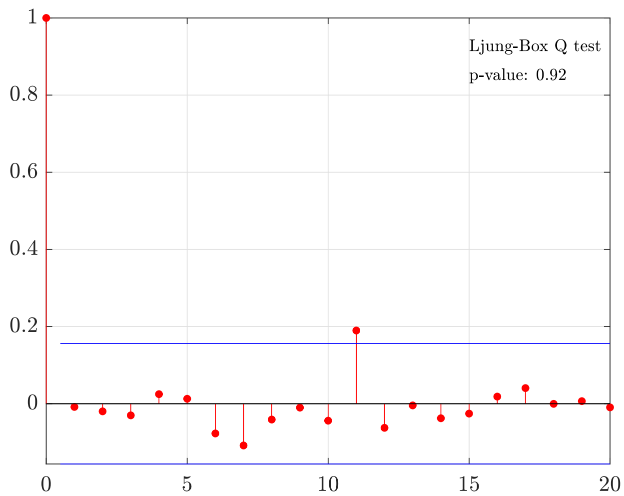



Figure B.1: The autocorrelation function of the carbon policy surprise series

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. The only variables that have some power in forecasting the carbon policy surprises are proxies for the perception of the importance of climate change, such as Google Trends data for climate change search queries or newspaper-based indices for climate news, supporting the interpretation of the surprise series. 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 from the literature, 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 | $\rho$ | 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. $\rho$ 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. Additional results

### B.2.1. Aggregate effects

In this Appendix, I present some additional results pertaining to the analysis in Section 5 in the paper. 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 local projections instrumental variable (LP-IV) approach à la Jordà, Schularick, and Taylor (2015); Ramey and Zubairy (2018). To fix ideas, the dynamic causal effects, $\psi_h^i$, 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 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.

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 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.

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 de-

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

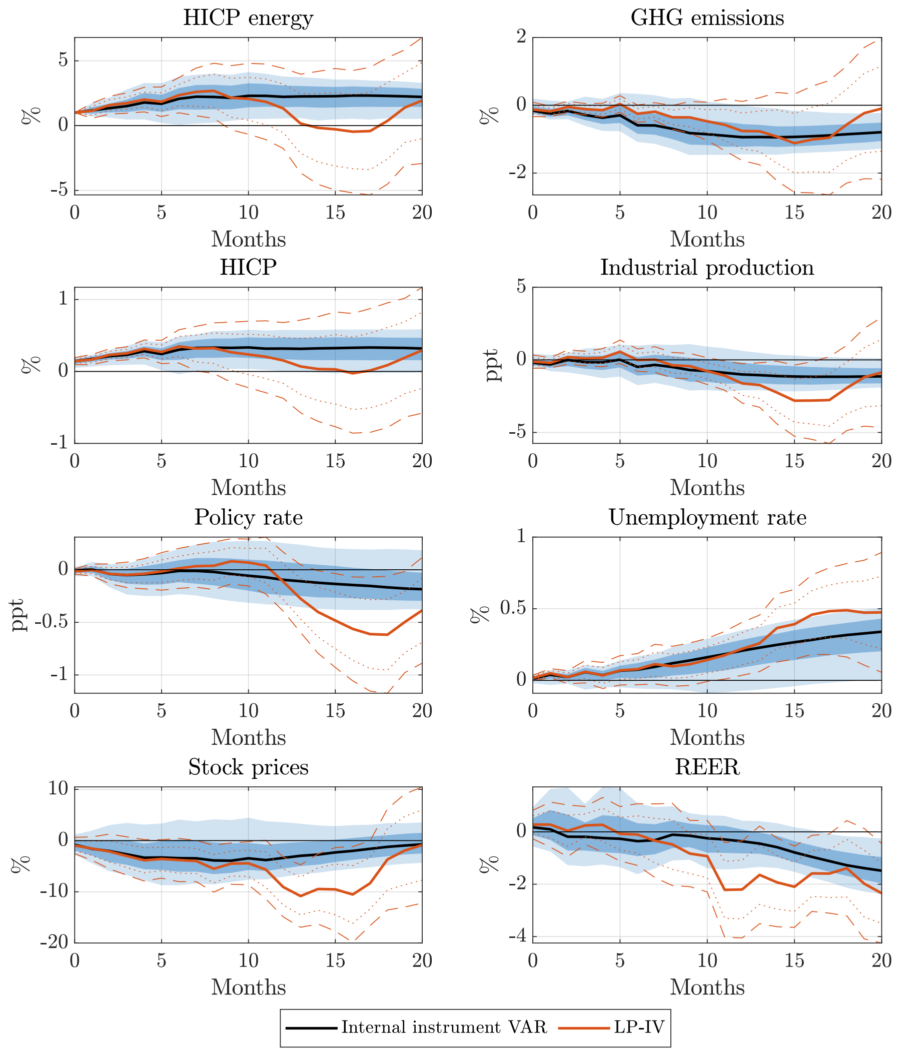
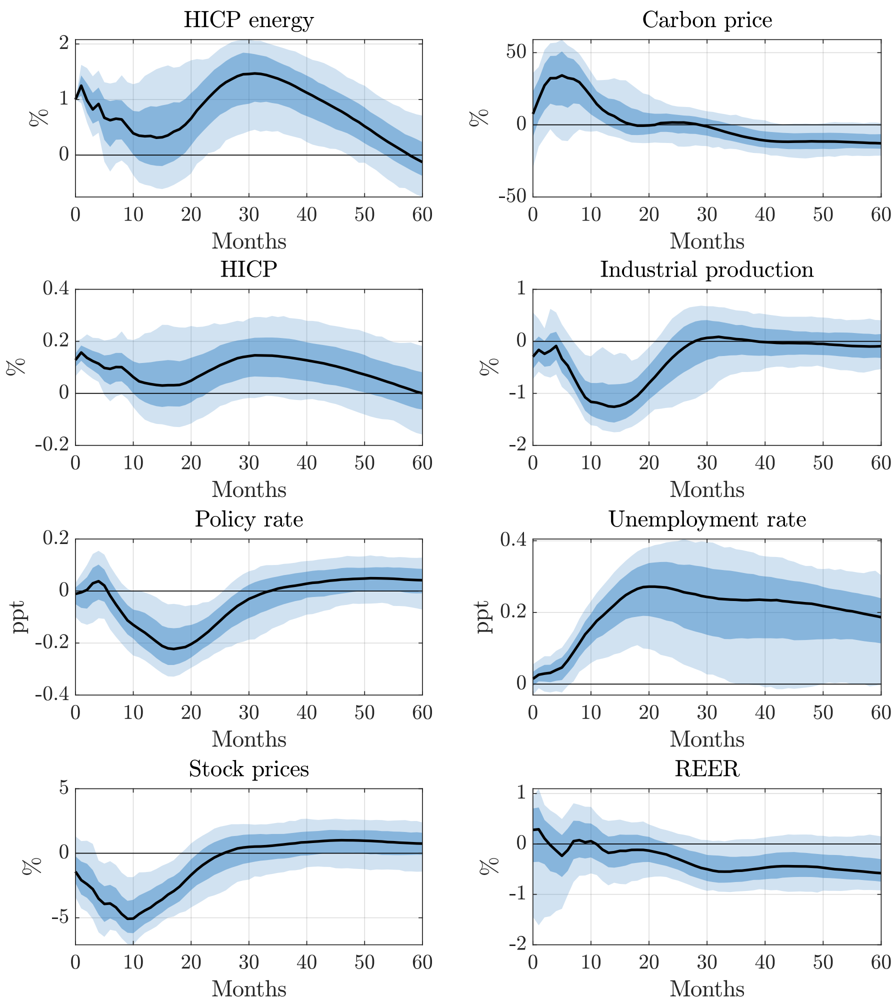



Figure B.2: Robustness with respect to estimation strategy

*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.

picted in Figure B.3. 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.




First stage regression: F-statistic: 15.30, $R^2$: 5.48%

Figure B.3: 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.

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.4. However, these variables do not appear to play a dominant role in the transmission of the carbon policy shock.

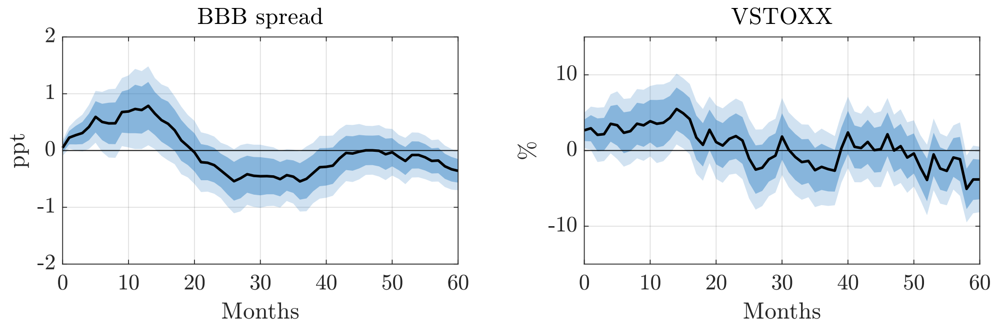



Figure B.4: Financial and uncertainty indicators

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

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.5.

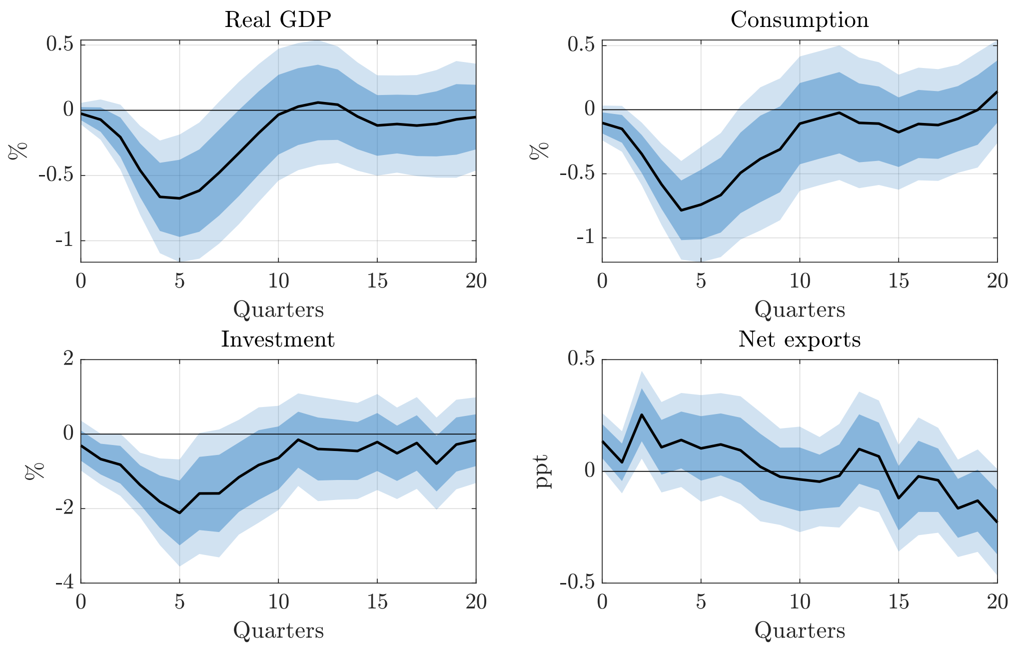
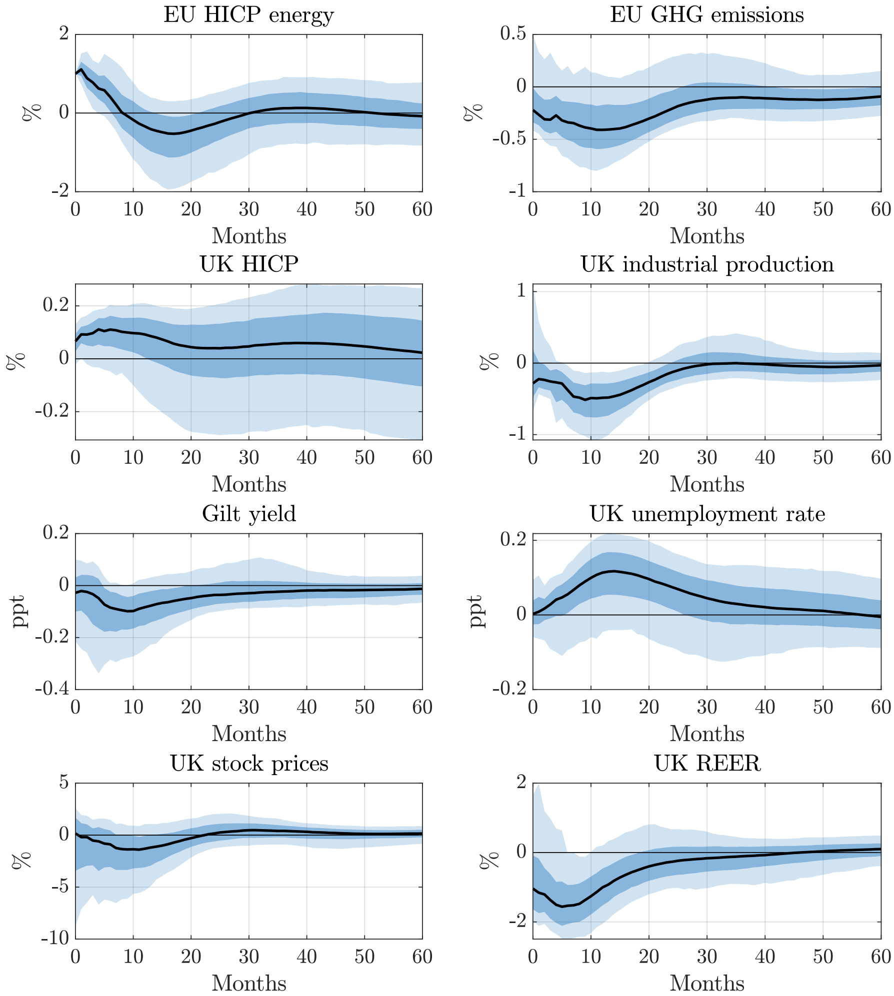



Figure B.5: Effect on UK GDP and components

*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.6. 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.



First stage regression: F-statistic: 4.97, $R^2$: 2.47%

Figure B.6: 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.2.2. Heterogeneous effects

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

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

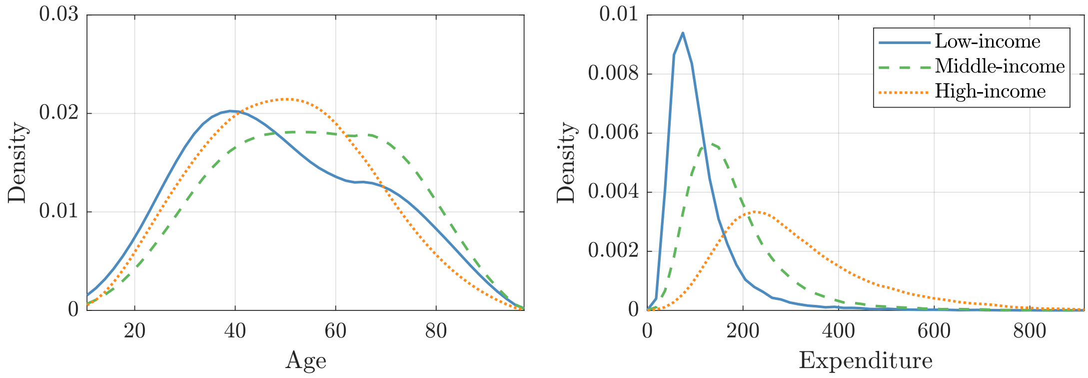



Figure B.7: Empirical distribution of age and total expenditure in the LCFS

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

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

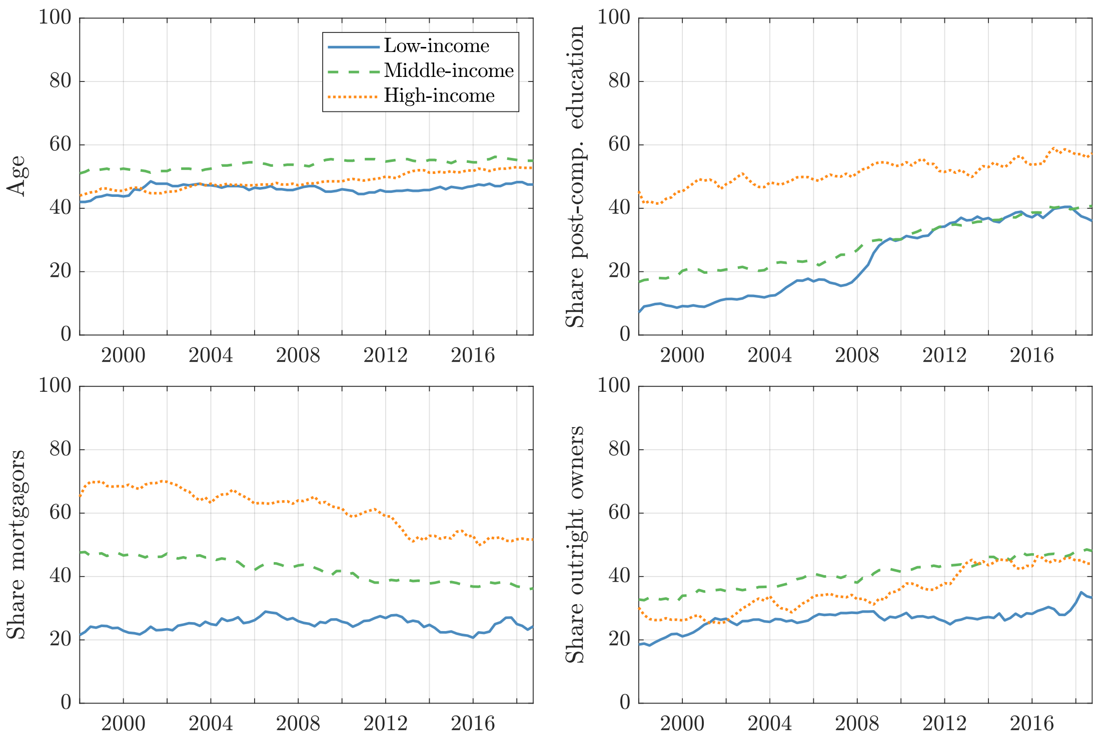



Figure B.8: Evolution of household characteristics by income group

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

To mitigate concerns about endogenous changes in the grouping variable, I look at the responses of current and normal disposable income in Figure B.9. 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.

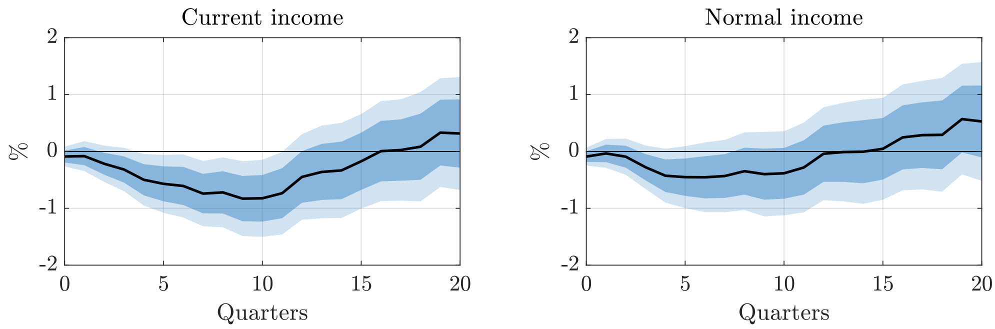



Figure B.9: Responses of current and normal income

*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.10-B.12, we can see that the results turn out to be robust.

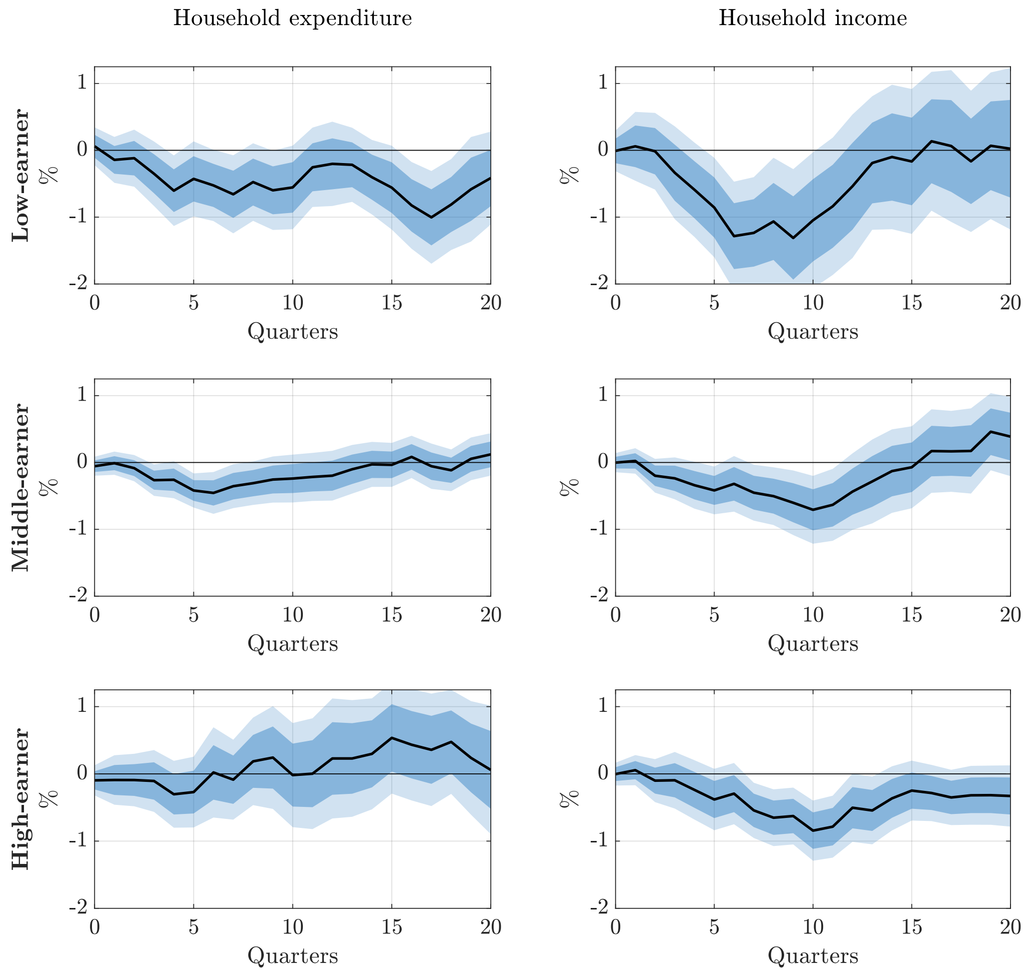



Figure B.10: Household expenditure and income responses by earnings groups

*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).

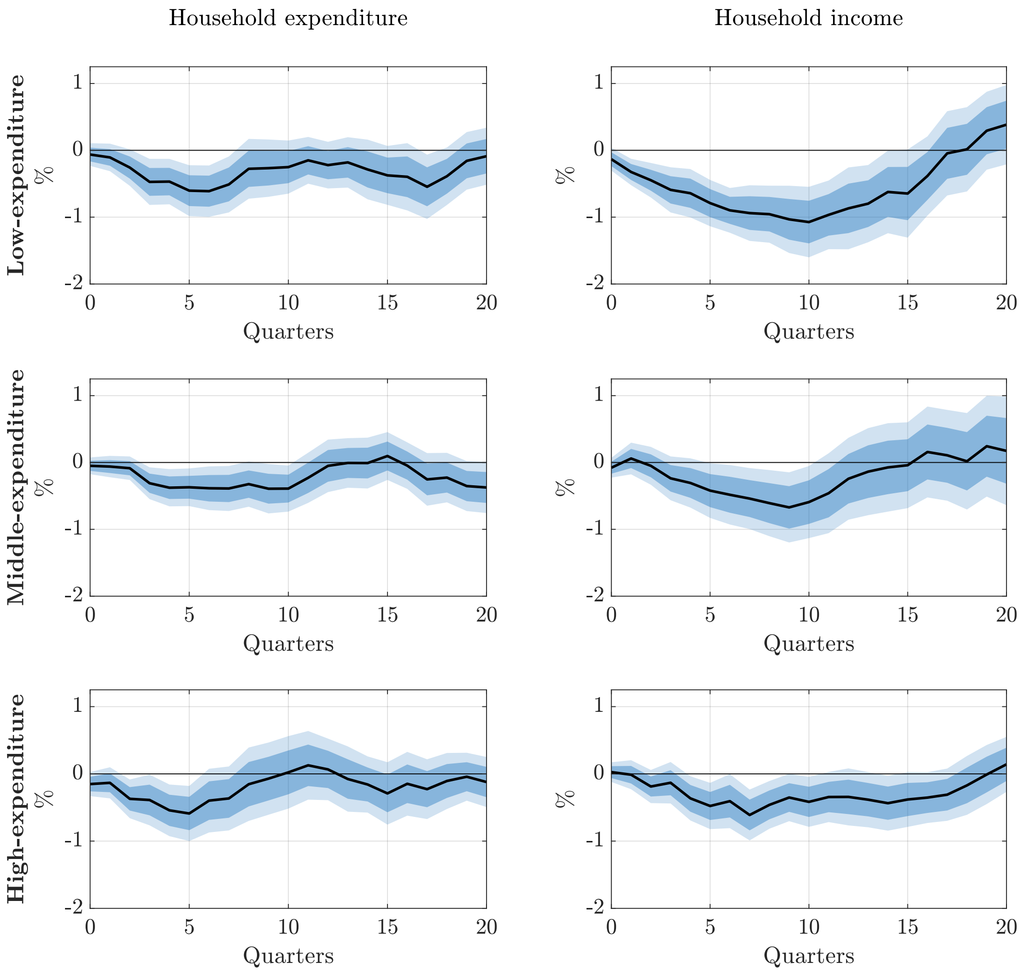



Figure B.11: Household expenditure and income responses by expenditure groups

*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).

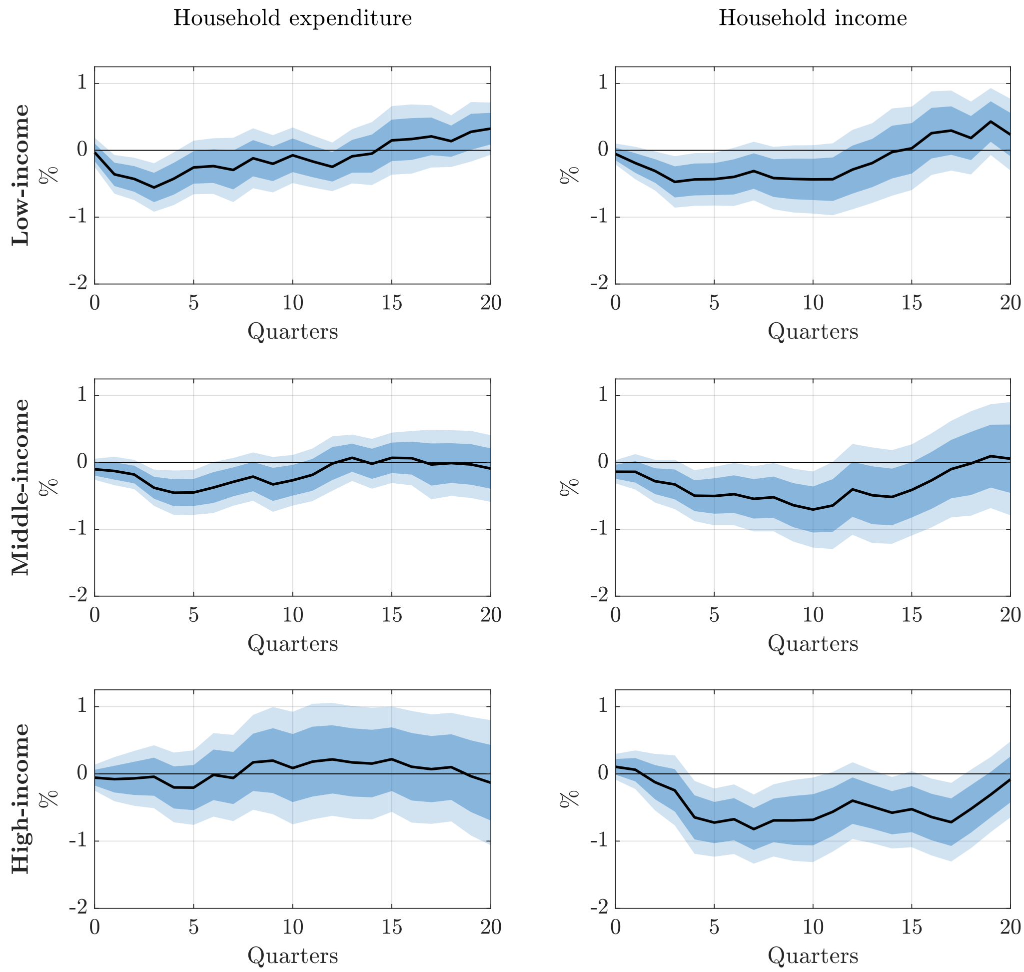



Figure B.12: Household expenditure and income responses by permanent income

*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).

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.13, 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).

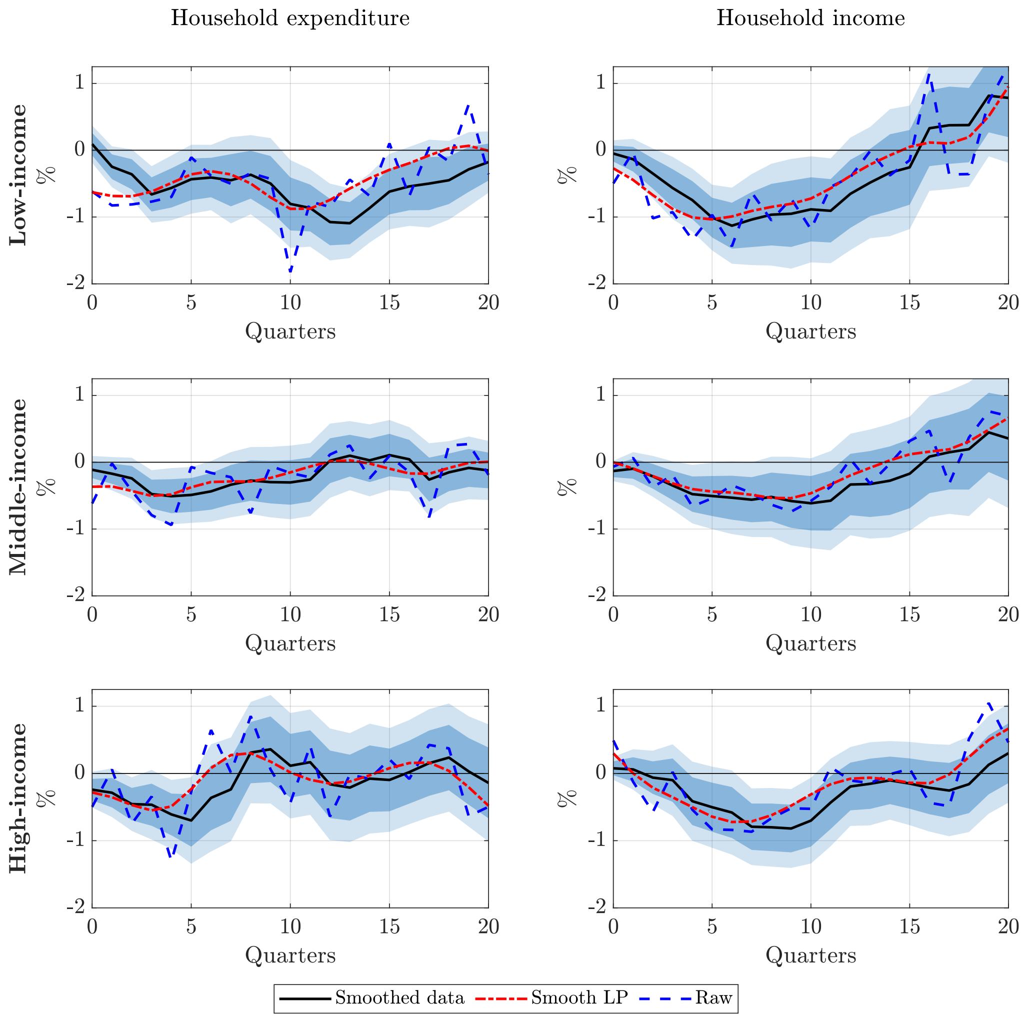



Figure B.13: Sensitivity with respect to smoothing of responses

*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).

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).

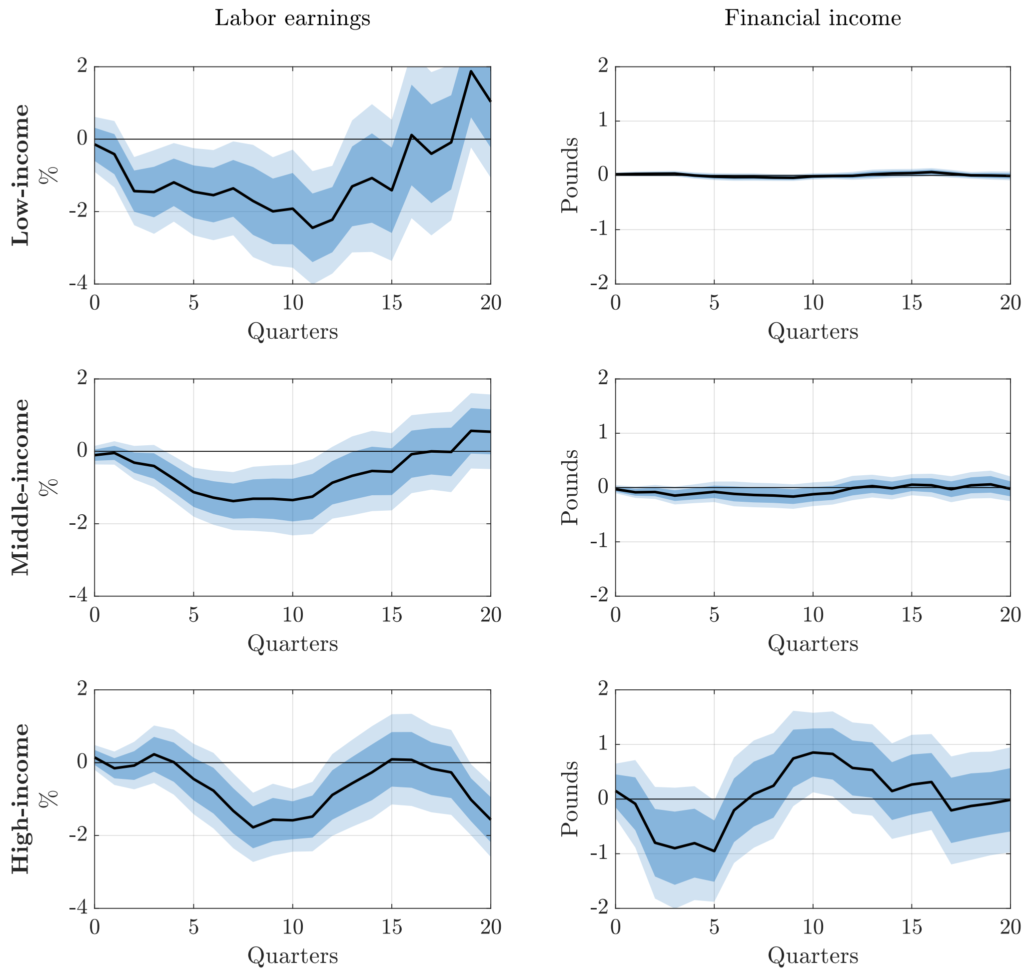



Figure B.14: Responses of earnings and financial income

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

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. From Figure B.15, 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.16 further presents the energy expenditure responses by income group. From this, we can see that energy expenditure turn out to be more elastic for high-income than for low-income households.

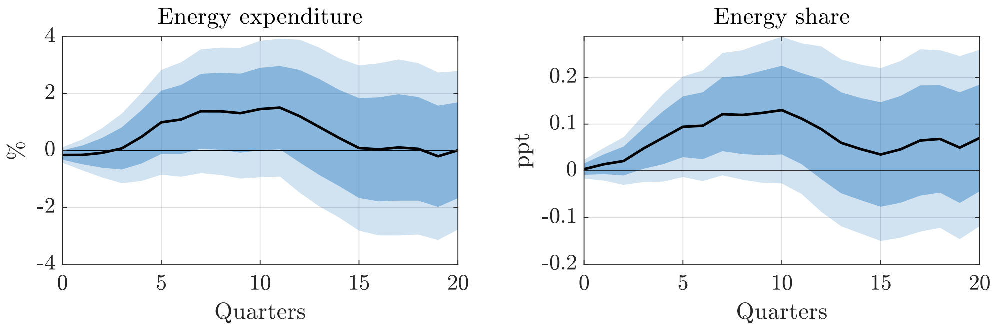



Figure B.15: Responses of energy expenditure and the energy share

*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).

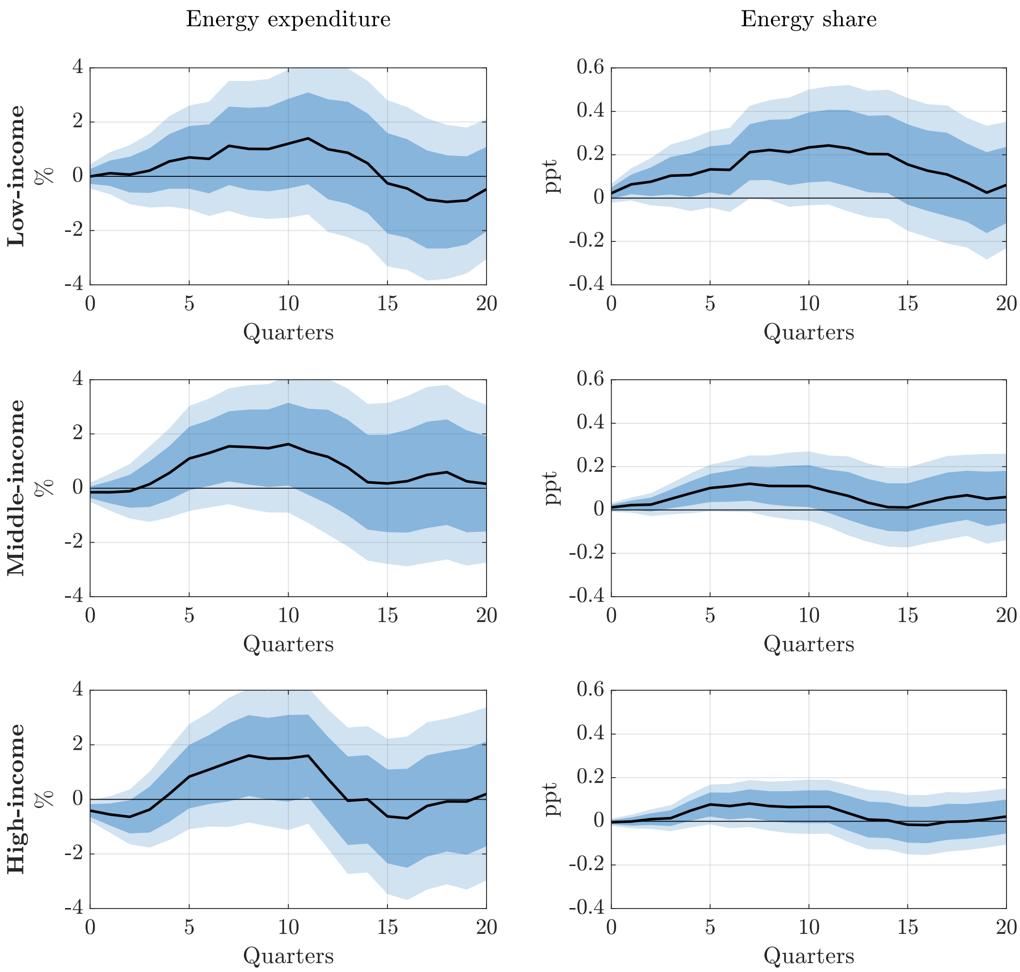



Figure B.16: Energy expenditure and energy share by income group

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

Unfortunately, the LCFS does not feature information on the sector of employment. However, the LFS does have both, detailed information on employment sector and income. As we can see from Table B.3, low-income households work disproportionally in sectors such as construction, wholesale and retail trade, hospitality, and entertainment and recreation. While these are not the sectors with the highest energy intensity (in relation to their gross value added), energy is an important cost driver. Furthermore, these sectors are very concentrated in lower-skilled occupations.

Table B.3: Descriptive statistics on households in the LFS

| Sectors | Overall | By income group | | |
|---|---|---|---|---|
| | | Low-income | Middle-income | High-income |
| High-energy intensity | 21.7 | 9.7 | 25.7 | 25.8 |
| Middle-energy intensity | 30.5 | 49.0 | 27.2 | 18.0 |
| Low-energy intensity | 47.7 | 41.2 | 47.0 | 56.1 |

*Notes*: The table depicts the sectoral distribution of workers in the LFS, both overall and by income group (where income is proxied by net pay in the main and second job). For the sectors, I use the SIC 2003 sections, and group them according to their energy intensity (using data from the ONS for 1999-2018). The first group contains sectors with a very high energy intensity, namely agriculture & fishing, utilites, transportation, and manufacturing. The second group consists of sectors with a middle energy intensity such as construction, wholesale and retail trade, hospitality, and entertainment and recreation. The last group are financial services, public administration and education & health, which have a low energy intensity.

Interestingly, these sectors are also the ones for which we observe the larges fall in net pay after a carbon policy shock, see Figure B.17. This helps explain why low-income households in the LCFS display the strongest and most significant fall in income.

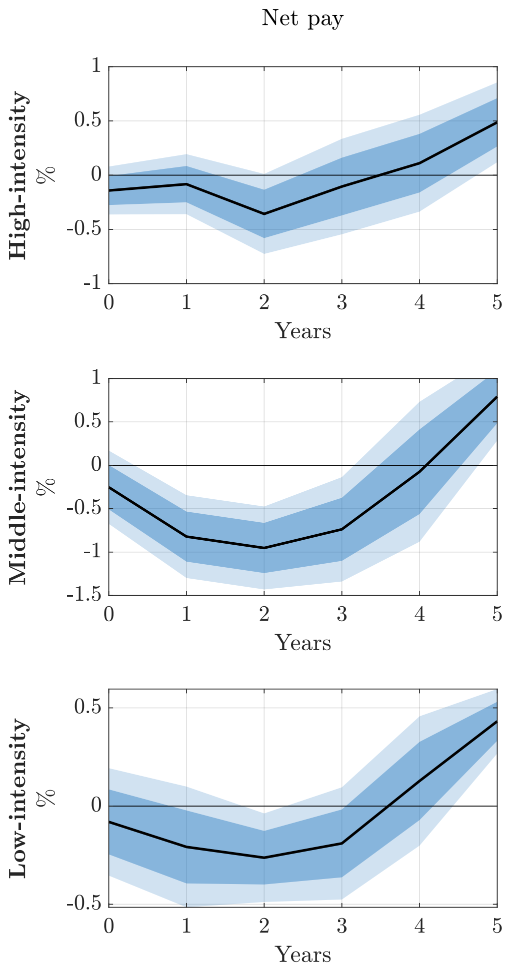



Figure B.17: Income response by sector of employment

*Notes*: Impulse responses of net pay (pay after deductions from main and second job) in sectors with a high-, middle- and low-energy intensity from the LFS. The response is computed based on the median pay in the respective group of sectors. The sector groups are described in detail in Figure B.3.

To be able to better understand the overall expenditure response, 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.18, we can see that all components fall in response to a carbon policy shock. There are also some interesting heterogeneities by income group. While the response of non-durable and services expenditure is very strong for low-income and more muted for higher-income households, the responses of durables are somewhat more homogeneous. Also note that the magnitude of the durable response is larger, in line with the fact that durable expenditure tends to be more volatile.

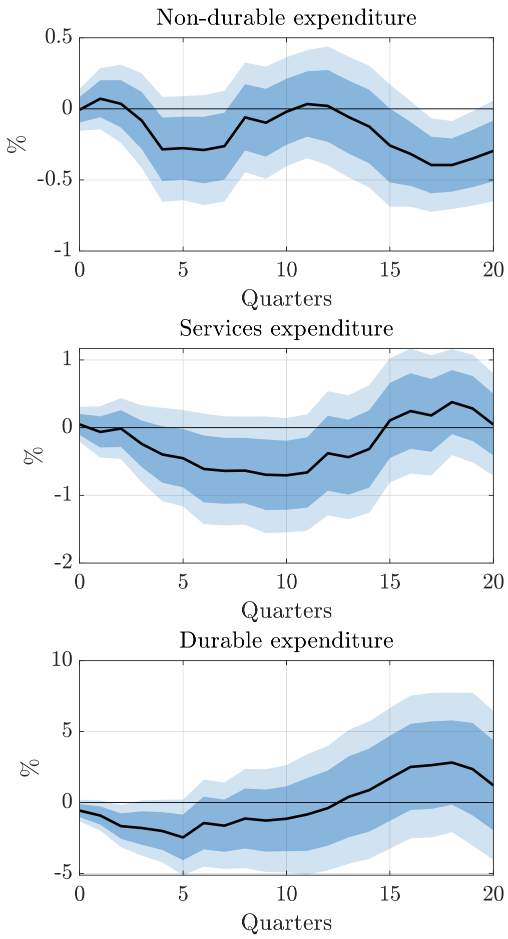



Figure B.18: Responses of non-durable, services, and durable expenditure

*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.

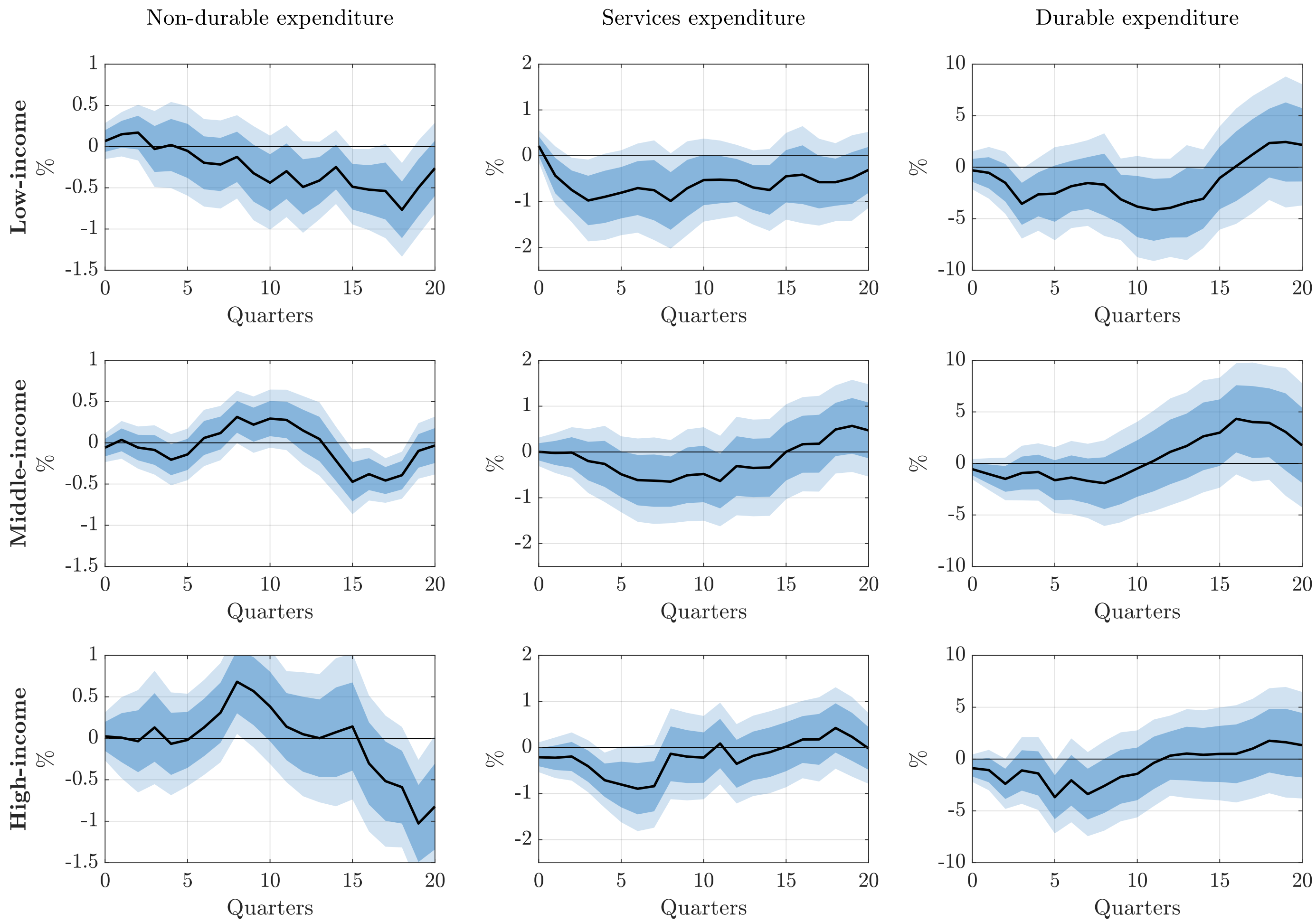



Figure B.19: Responses of non-durable, services, and durable expenditure by income group

*Notes*: Impulse responses of non-durable, services and durable expenditure by income group (bottom 25 percent, middle 50 percent, top 25 percent).

To mitigate concerns about selection, I use a selection of different grouping variables, including age, education and housing tenure. From Figures B.20-B.22, 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.

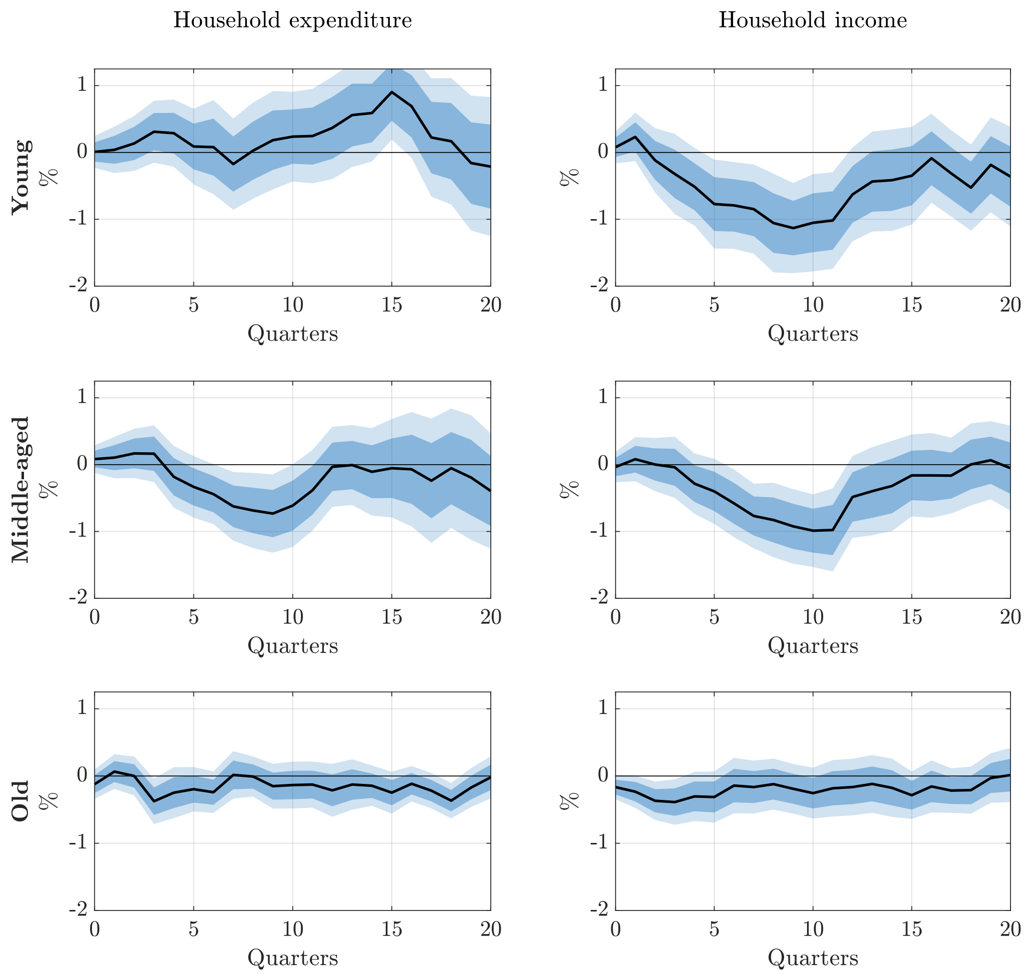



Figure B.20: Household expenditure and income responses by age groups

*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.

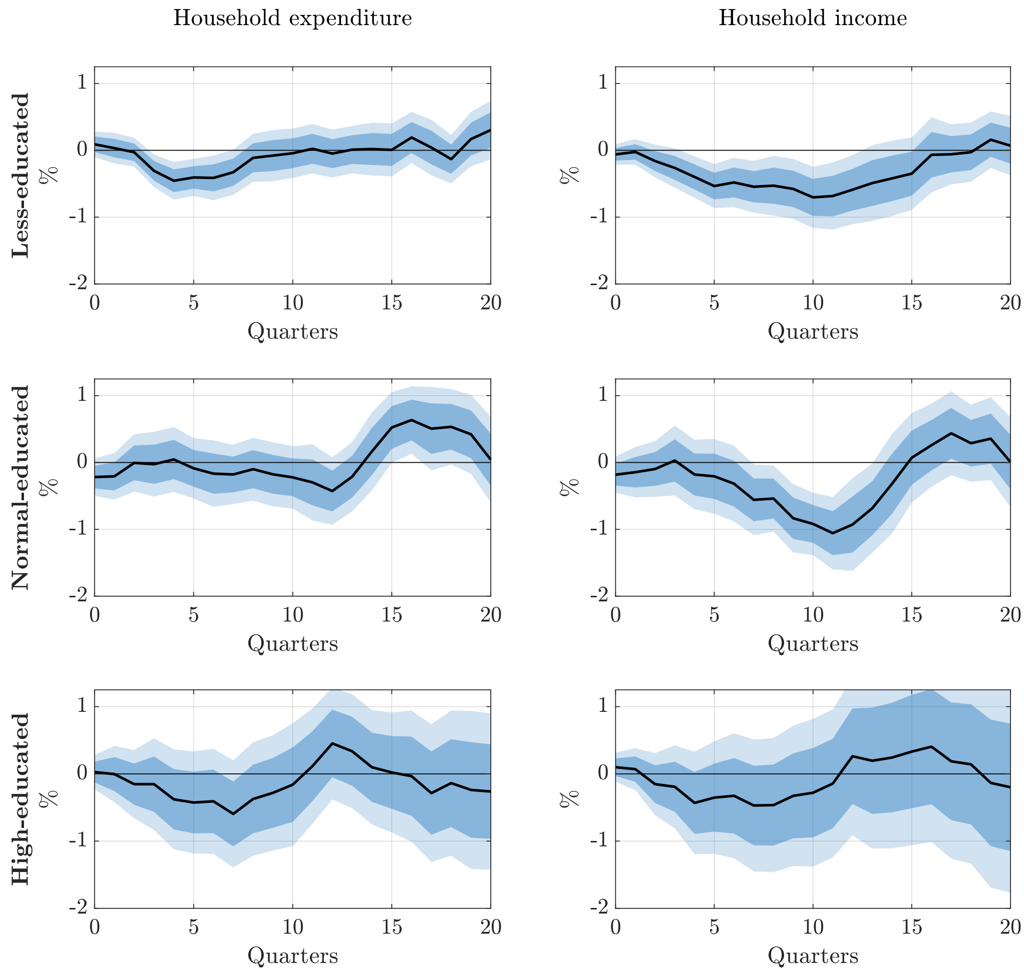



Figure B.21: Household expenditure and income responses by education status

*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).

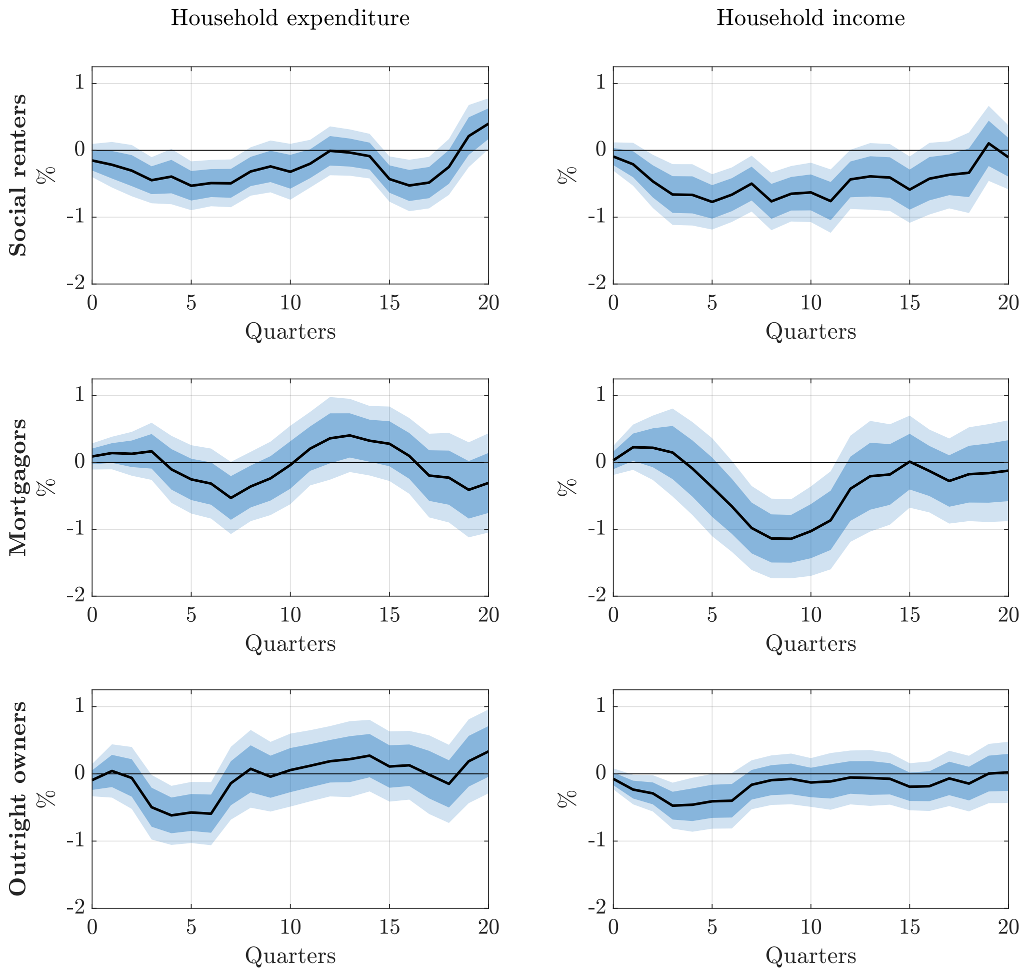



Figure B.22: Household expenditure and income responses by housing tenure

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

To further investigate the role of the energy share, I alternatively group households by their energy share. Table B.4 provides descriptive statistics on income, expenditure and households characteristics by energy share. While the differences in energy share are now (by construction) more pronounced), the high-, middle- and low-energy share groups are 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 some descriptive statistics on weekly per capita income and expenditure (in 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.

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. 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.

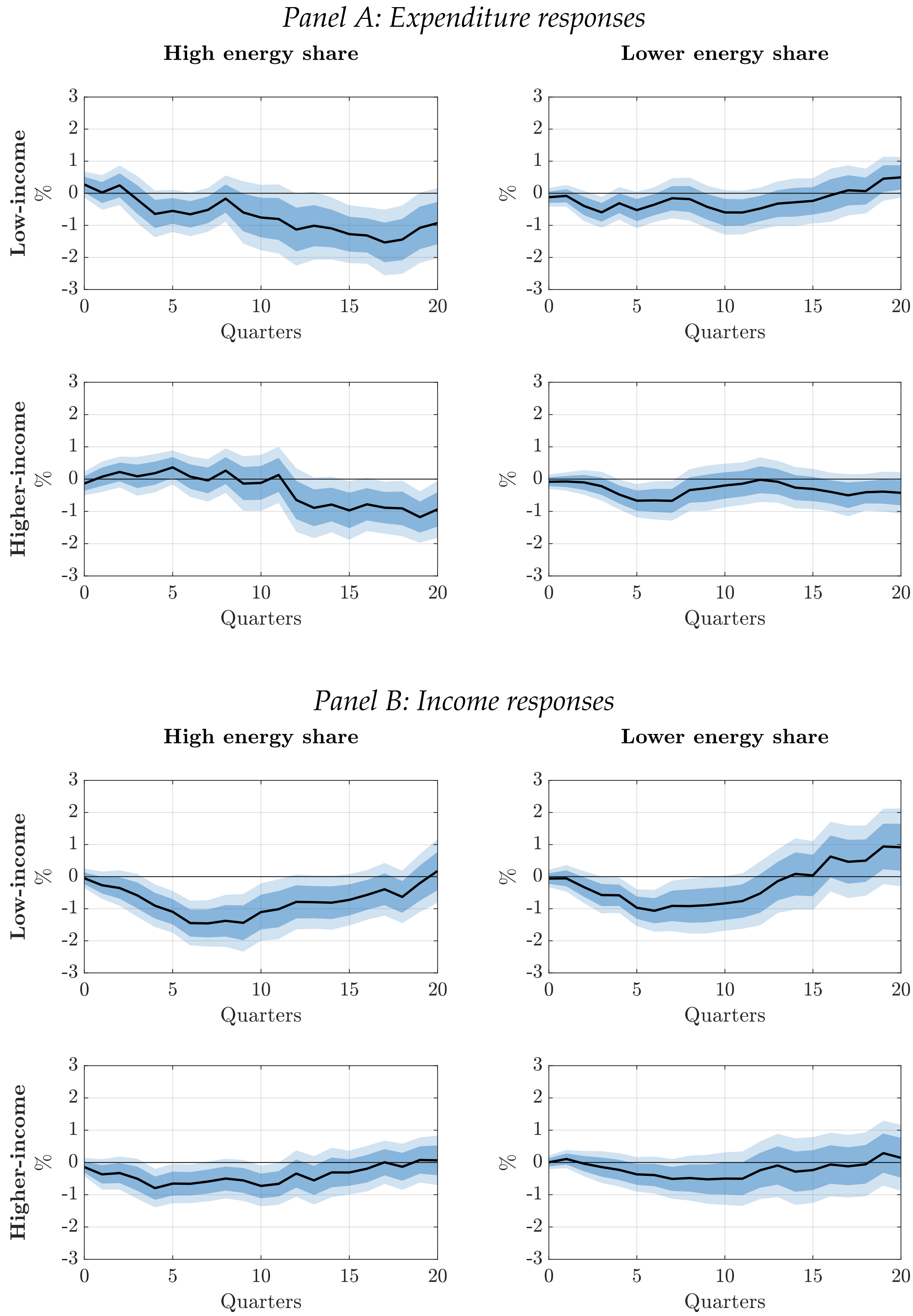



Figure B.23: Responses by income and energy share groups

*Notes*: Impulse responses of total expenditure excluding housing and current total disposable household income by income group, conditioning on households with a high or lower energy share.

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.24, the expenditure response turns out to be much more pronounced for low-income households.

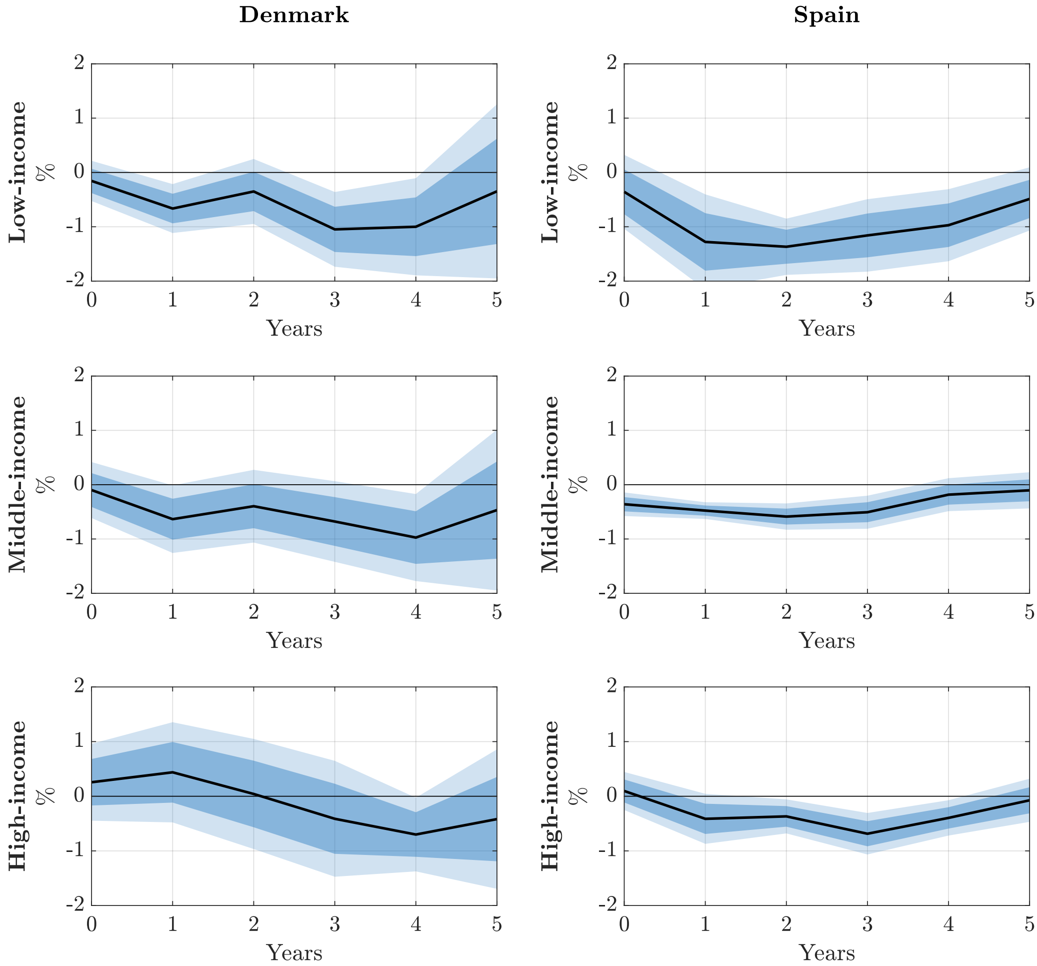



Figure B.24: Expenditure by income groups for other European countries

*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).

Finally, Figure B.25 displays the evolution of the public attitude towards climate policy, as proxied by the positive answers to a question from the BPA, see Figure B.25. 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, especially for high- and middle-income households. In contrast, the support of low-income households has remained stable at lower levels until the end of the sample.

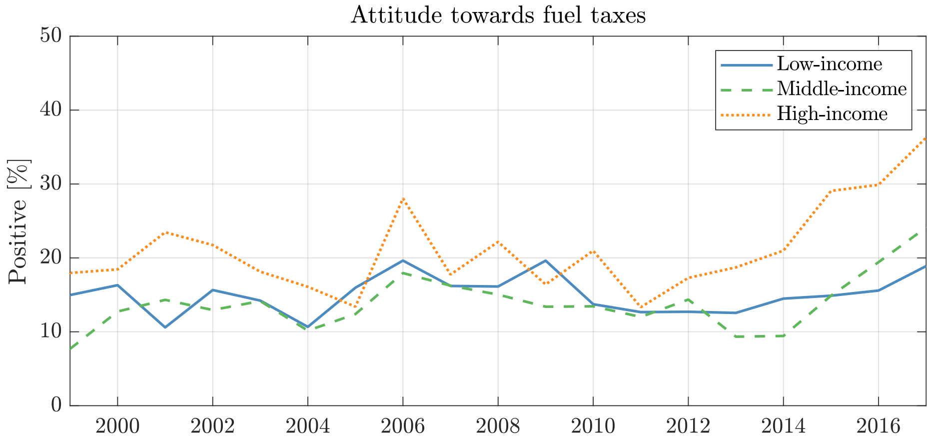



Figure B.25: Public support for climate policy by income group

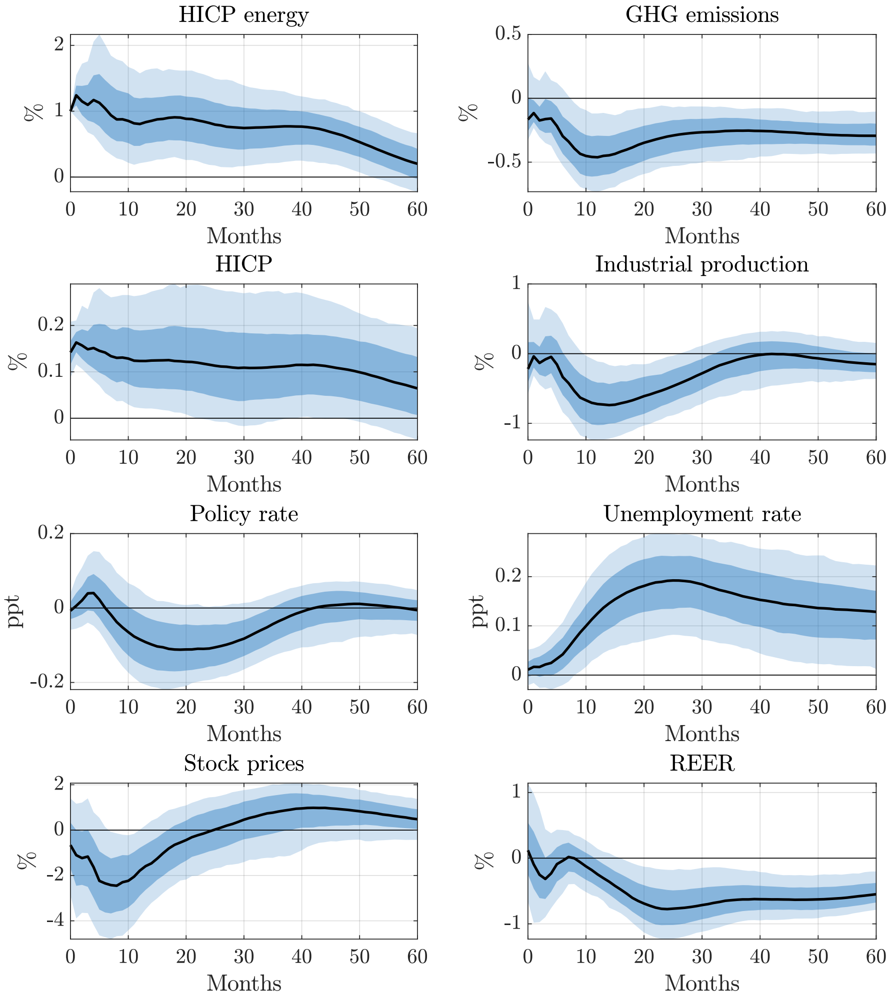
*Notes*: The figure shows the evolution of the attitude towards climate policy by income group, as proxied by the share of households in the British social attitudes survey that agree to the following statement: "For the sake of the environment, car users should pay higher taxes".

## B.3. Robustness

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

### B.3.1. Selection of events

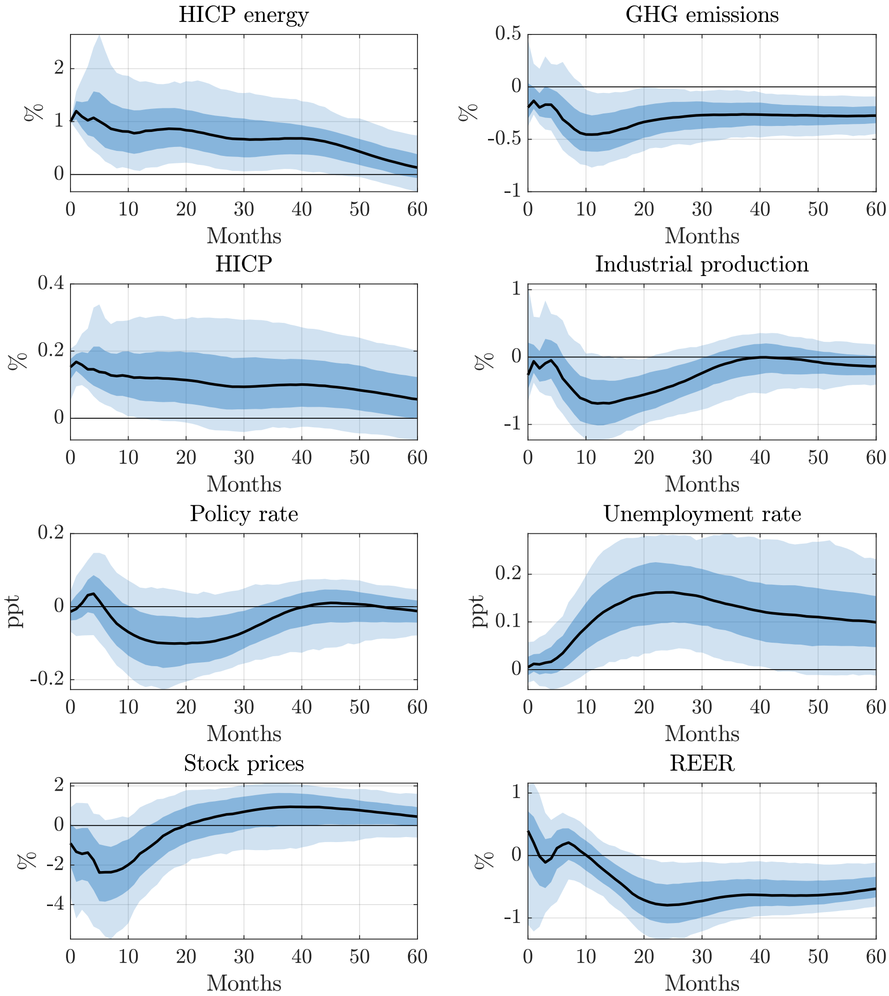
The first check concerns the selection of the relevant events used for identification. As the baseline, I have included all identified events that concern the supply of emission allowances. Figures B.26-B.29 present the results under varying assumptions and show that the results turn out to be very robust to the selection of events. Figure B.30 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.26: Excluding events regarding cap

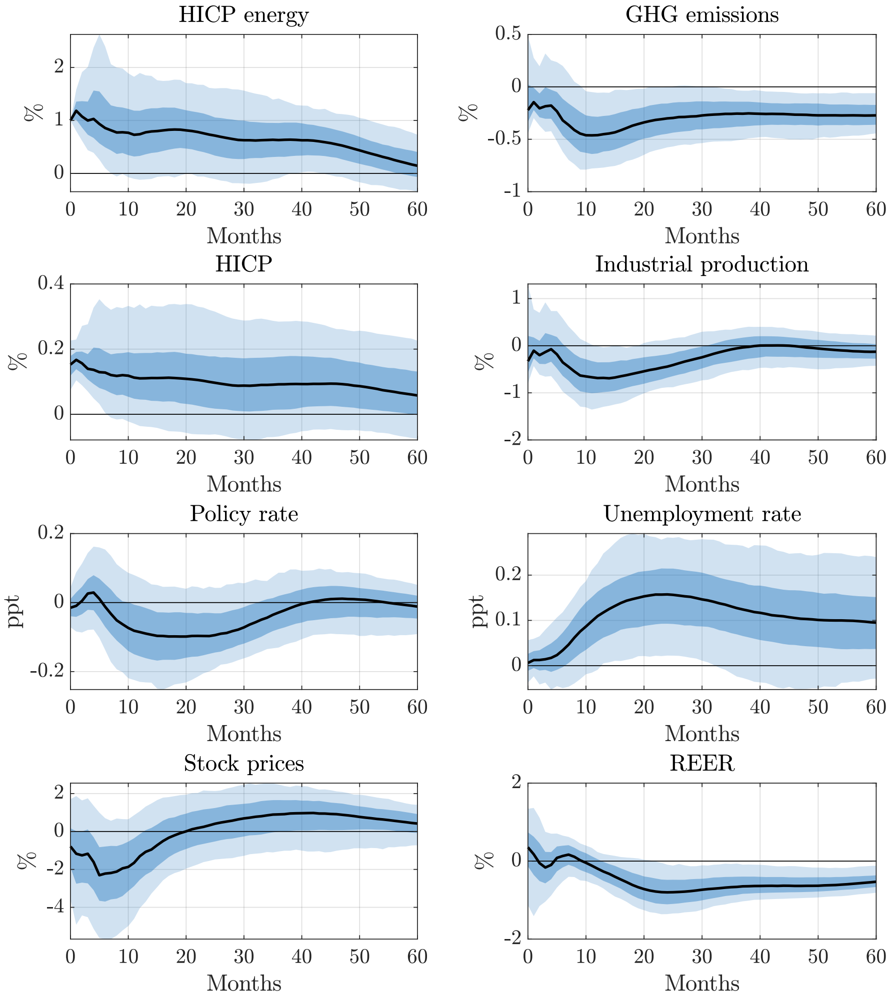
*Notes*: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.




First stage regression: F-statistic: 15.00, $R^2$: 2.90%

Figure B.27: 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.




First stage regression: F-statistic: 14.42, $R^2$: 2.83%

Figure B.28: 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.

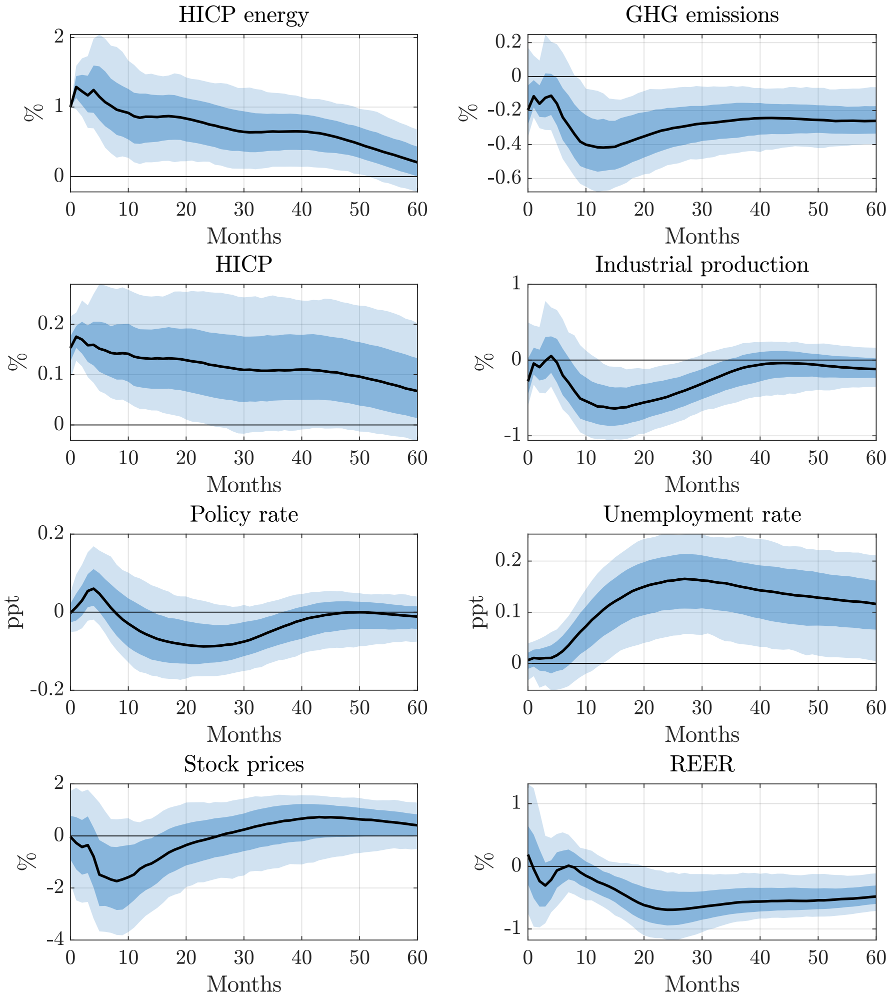
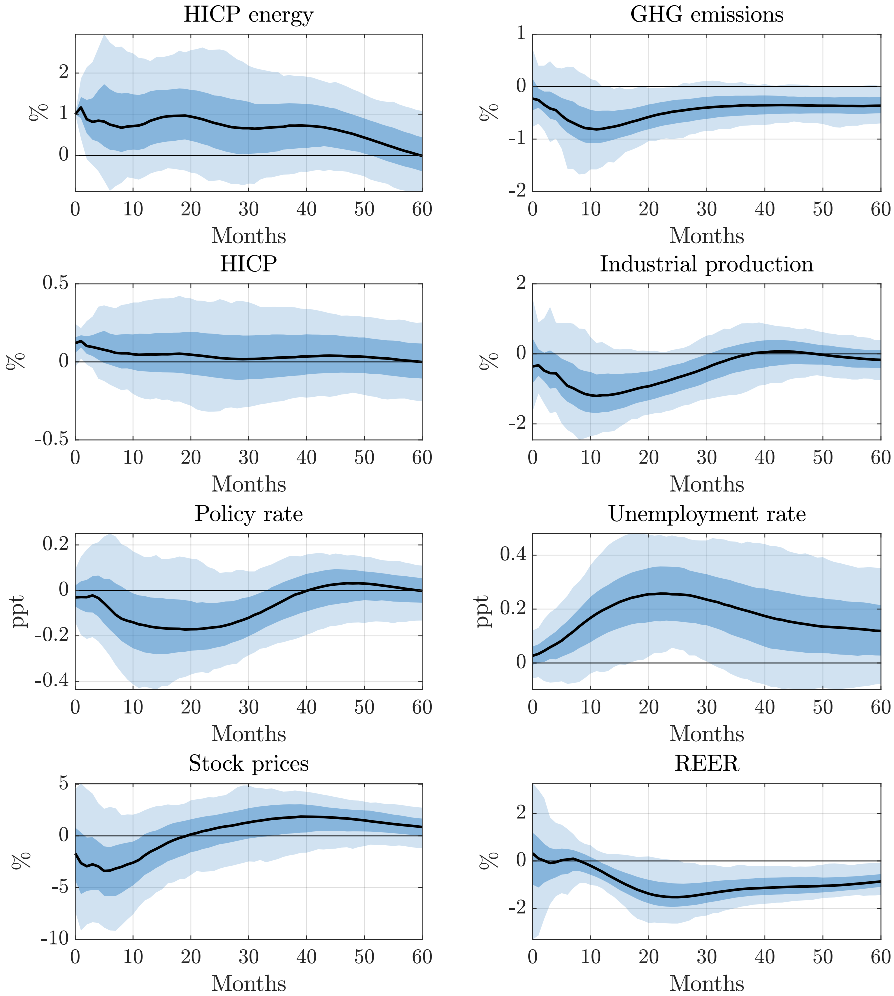



Figure B.29: Excluding potentially confounded events

*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.



First stage regression: F-statistic: 5.77, $R^2$: 1.06%

Figure B.30: 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.3.2. 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.5 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.5: 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 | |

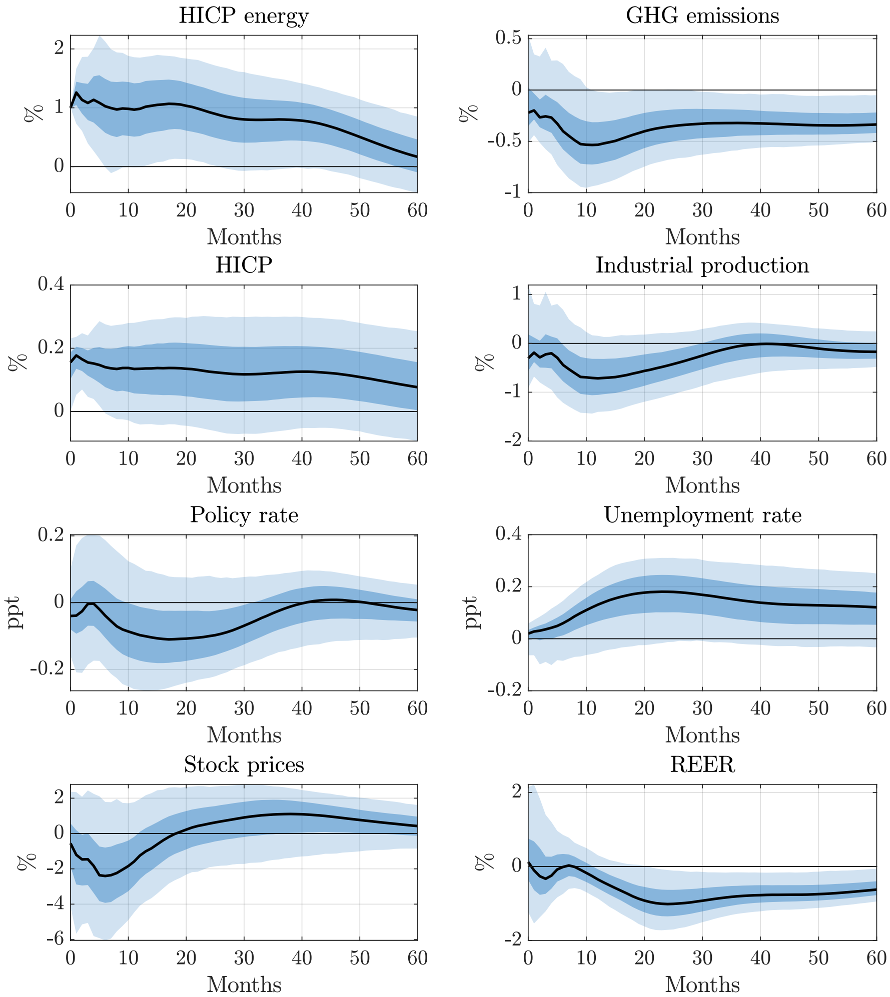
| Month | Policy | Control | Month | Policy | Control |
|---|---|---|---|---|---|
| 2007M06 | | 06/06/2007 | 2014M04 | 04/04/2014 | |
| | | | | 11/04/2014 | |
| | | | | 23/04/2014 | |
| 2007M07 | | 11/07/2007 | 2014M05 | 02/05/2014 | |
| | | | | 05/05/2014 | |
| 2007M08 | | 08/08/2007 | 2014M06 | 04/06/2014 | |
| 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.31: 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.31 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.32: 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.32 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 much 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.3.3. Futures contracts

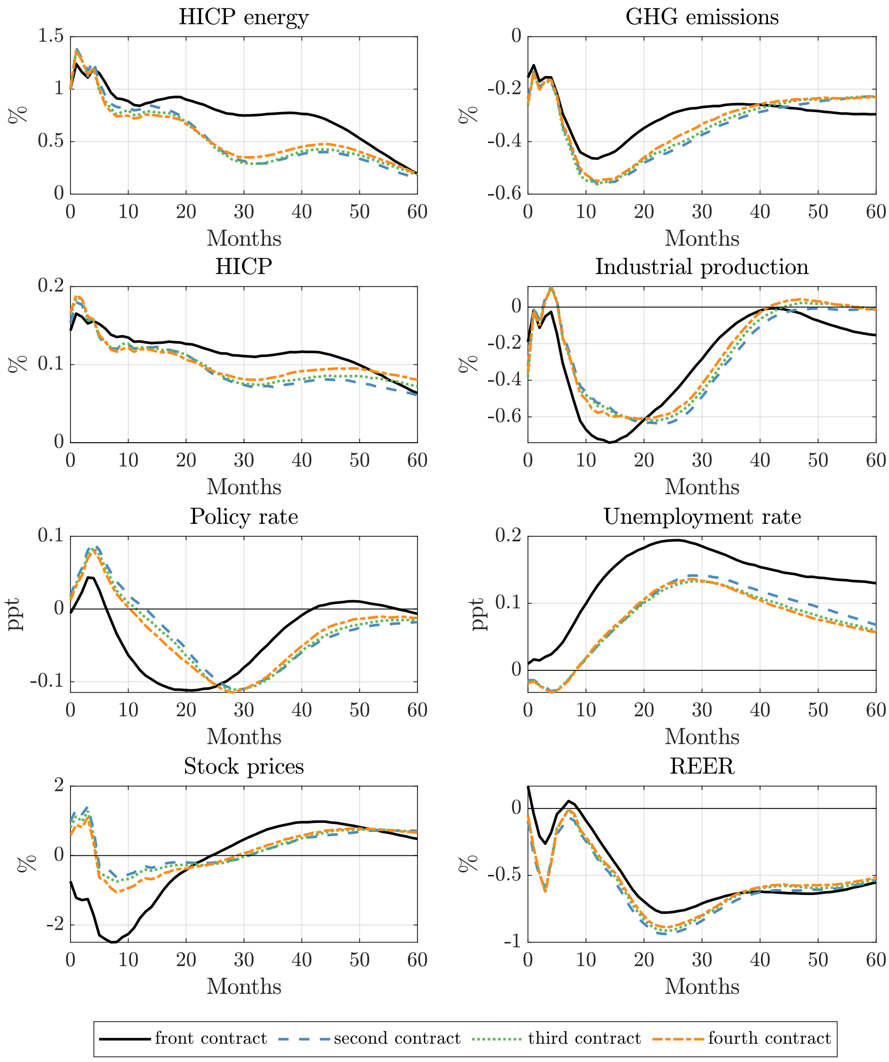



Figure B.33: Using different futures contracts for the instrument

*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.

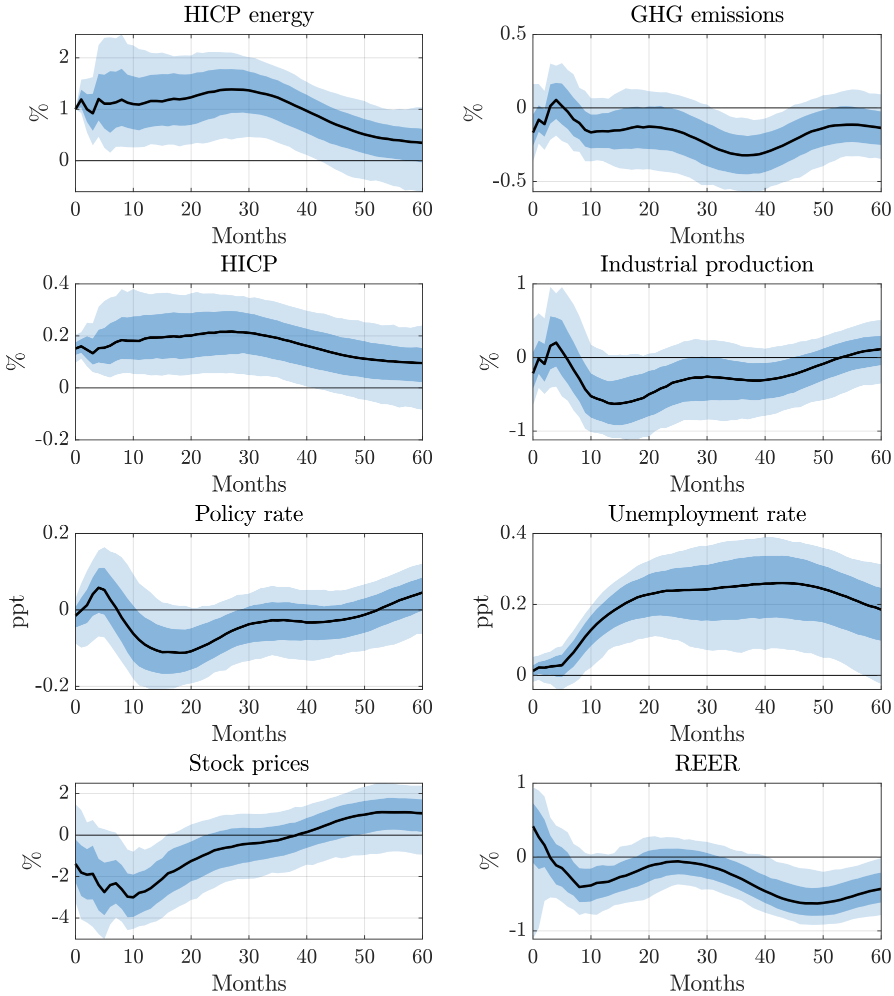
EUA futures are traded at different maturities. The main contracts are annual, with expiry date in December and are traded up to seven years.[2] As a baseline,

[2]There exist now also several quarterly and even monthly contracts, however, these have shorter coverage. Thus, I restrict the analysis on the annual contracts.

I focus here on the front contract, which expires in December of the current year and is the most liquid and has the longest coverage. Figure B.33 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. These results support the focus on the front contract, to mitigate concerns about risk premia.

### B.3.4. Sample and specification choices

Finally, I perform a number of sensitivity checks concerning the sample and model specification. Figure B.34 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.34: 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.35 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.

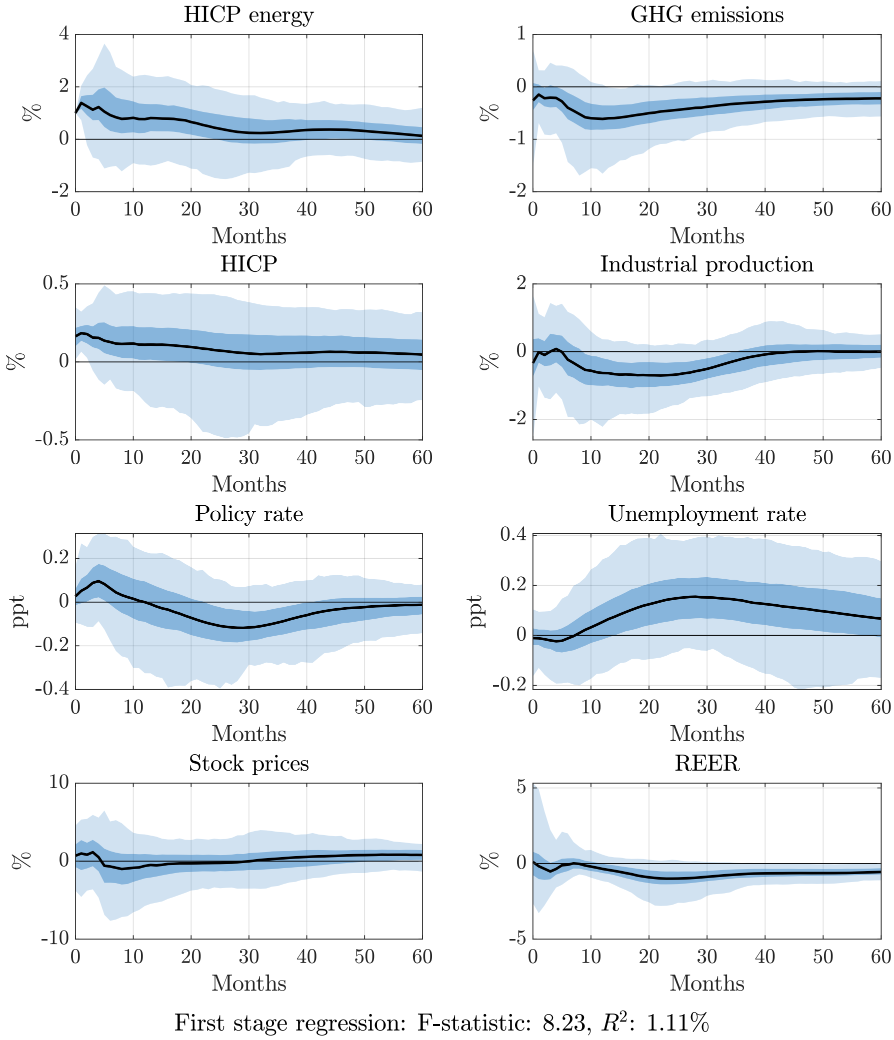
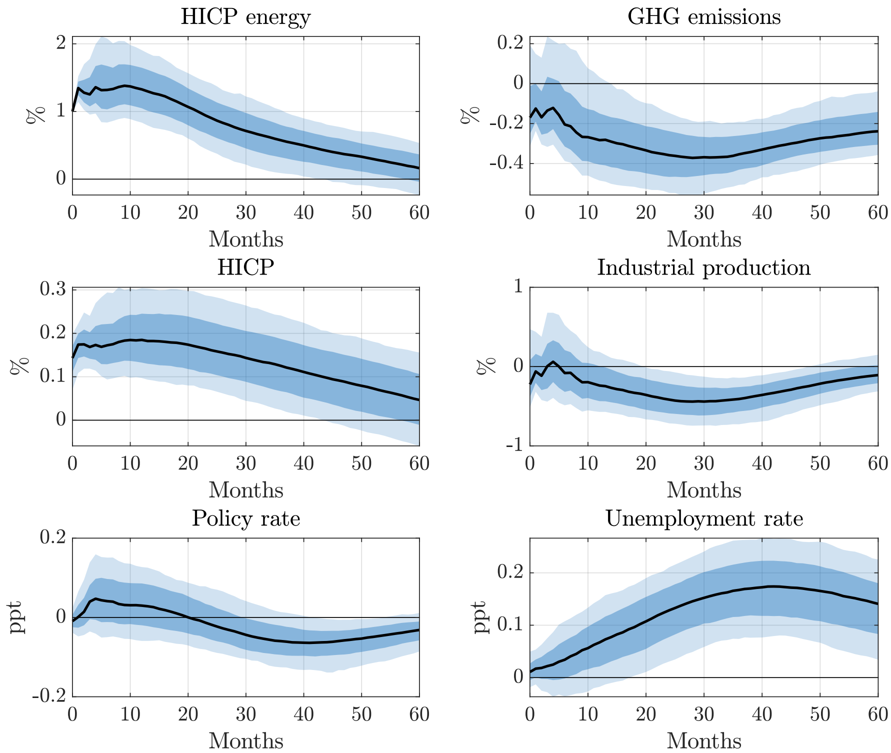



Figure B.35: Excluding phase one events

*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.

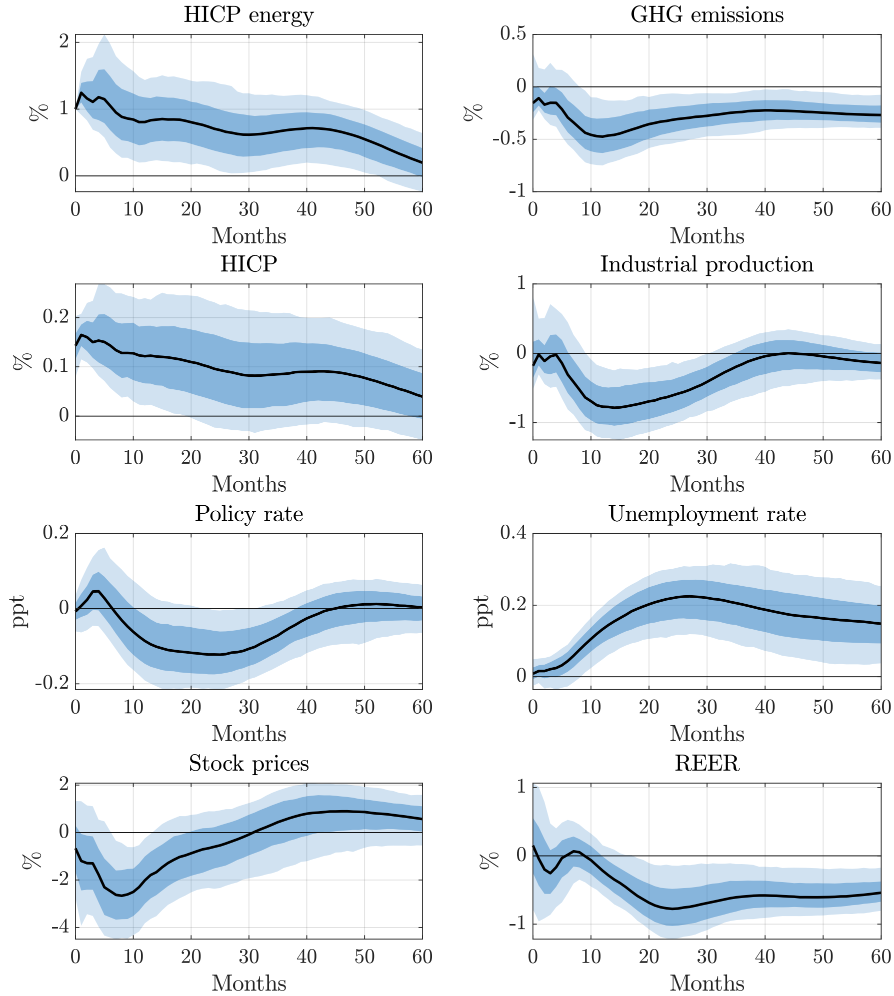
The baseline model includes 8 variables and 6 lags, which is relatively large for a comparably short sample. Therefore, Figures B.36-B.40 analyze the robustness with respect to the variables included and number of lags used. Alternatively, I estimate the model using shrinkage priors. The results turn out to be robust along all these dimensions.




First stage regression: F-statistic: 13.58, $R^2$: 3.32%

Figure B.36: Responses from smaller VAR

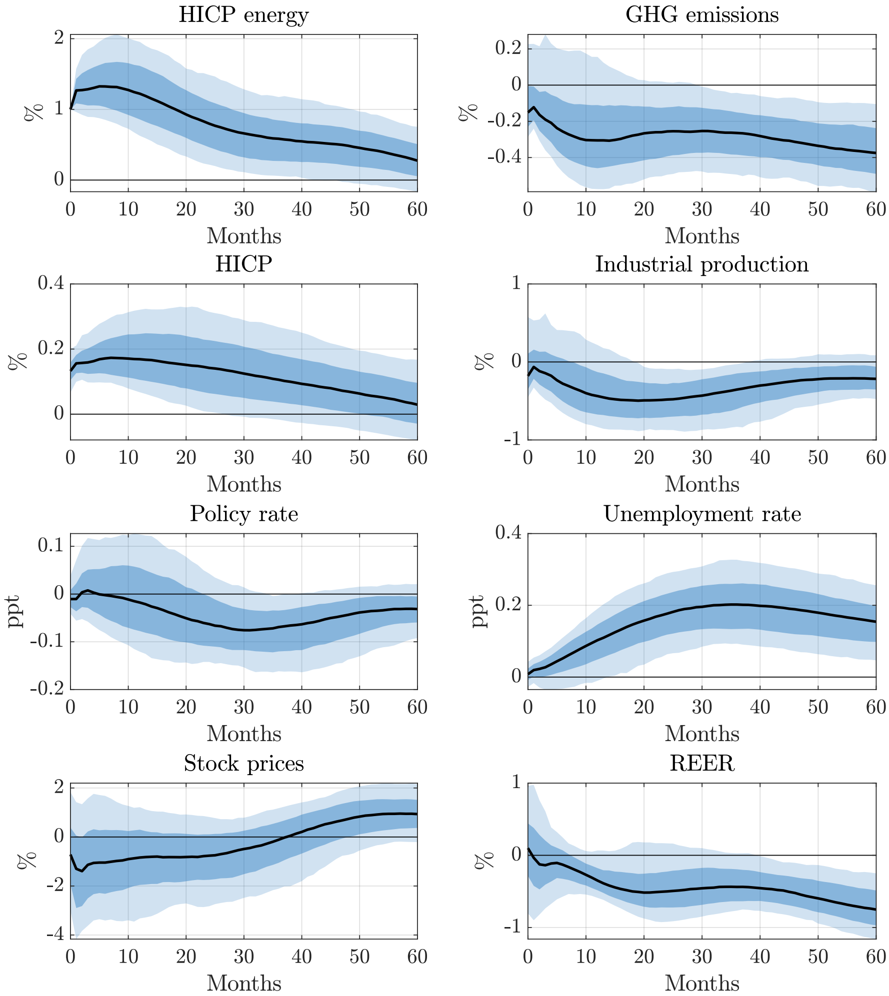
*Notes*: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.




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

Figure B.37: 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.38: 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.

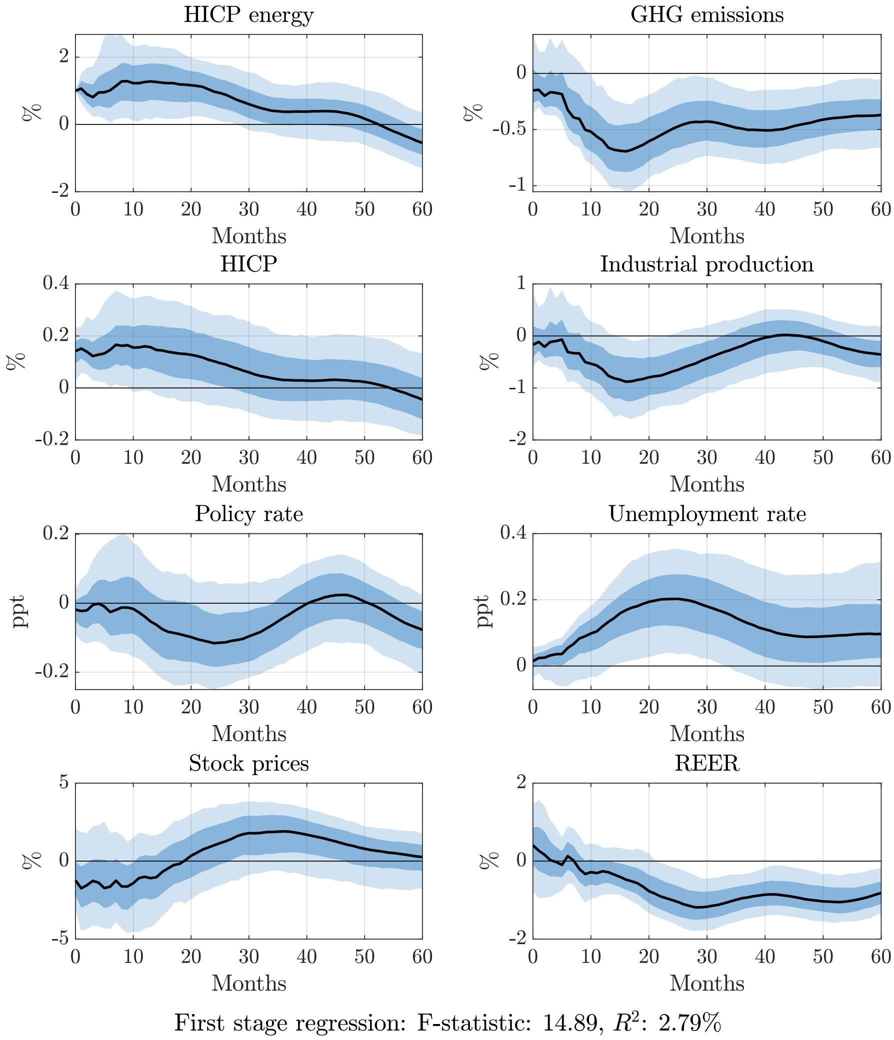



Figure B.39: VAR with 9 lags

*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.

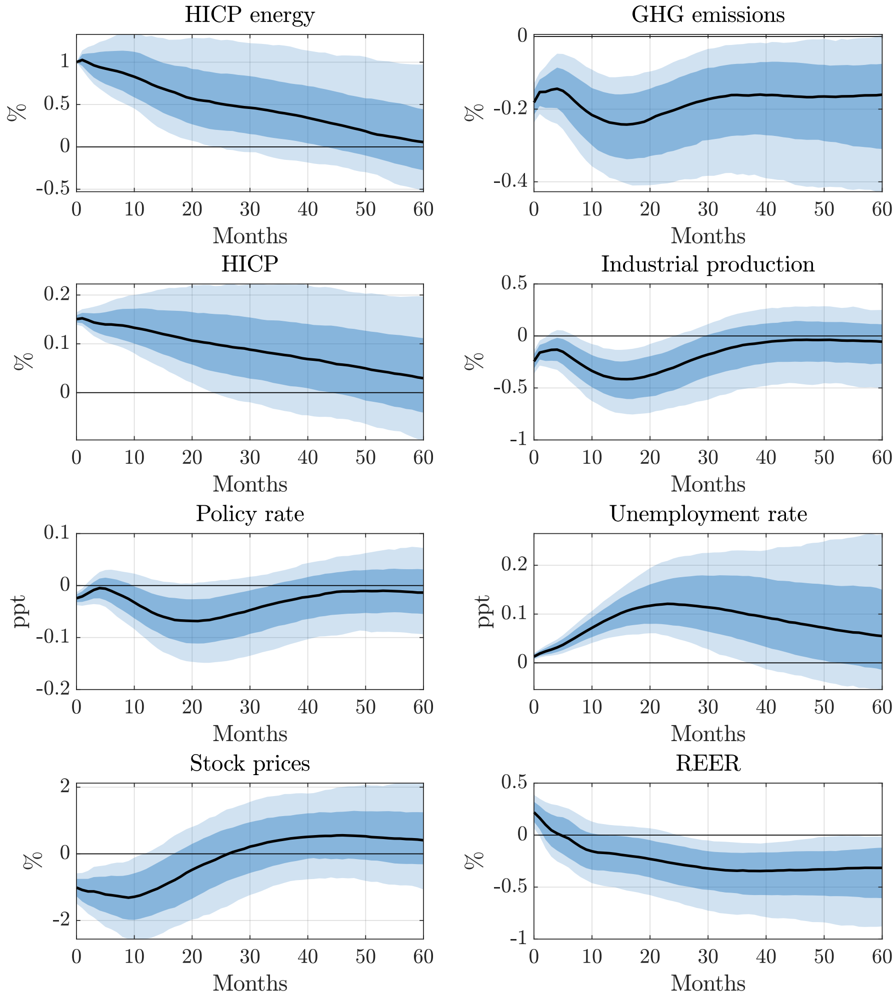



Figure B.40: Bayesian VAR with shrinkage priors

*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.3 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

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

Under these assumptions, the structural impact vector is given by

$$\mathbf{s}_1 = \frac{\mathbb{E}_{R1}[z_t \mathbf{u}_t] - \mathbb{E}_{R2}[z_t \mathbf{u}_t]}{\mathbb{E}_{R1}[z_t^2] - \mathbb{E}_{R2}[z_t^2]}. \tag{3}$$

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

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