Supplemental Appendix

The Unequal Economic Consequences of Carbon Pricing

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A. Data

A.1. 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://climate.ec.europa.eu/news-your-voice/news_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.

To mitigate the risk of including events that are potentially confounded by other macroeconomic news, in particular due to news related to demand or the oil market, I performed a detailed narrative analysis of the regulatory event dates. Specifically, I studied the reporting from leading newswires on Factiva, searching for news related to the European carbon market around each of the collected events. Based on this news coverage, I was able to identify a number of events that were likely confounded by other economic news, related to the oil market, the sovereign debt crisis, or Brexit. I mark these events in the fourth column of Table A.1 and provide the exact reason for the exclusion in the last column.

Table A.1: Regulatory Update Events

	Date	Event description	Type	Exclude	Reason
1	25/05/2005	Italian phase I NAP approved	Free alloc.	x	Bullish market data driving oil prices up
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	European commission rejects UK NAP amendment	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	European Commission ruled that Belgium and the Netherlands must make additional emission cuts	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	European Commission orders cuts to Austrian phase II NAP	Free alloc.		
15	16/04/2007	European Commission orders cuts to Hungarian phase II NAP	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.		

	Date	Event description	Type	Exclude	Reason
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	x	EUA prices fell as recession fears grew
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	x	EUA prices collapsed due to recession fears
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.	x	EUA prices fell due to Grexit fears
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.		
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.		

	Date	Event description	Type	Exclude	Reason
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	x	EUA prices fell ahead of bearish emissions data
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	x	EUA prices fell due to weak economic outlook
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.	x	EUA prices plunge amid weakening demand
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.	x	Brexit vote
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 modernisation	Auction	x	Uncertainty in oil markets due to OPEC meeting
114	04/01/2019	Amendment to the ETS auctioning regulation	Auction		
115	15/01/2019	Commission publishes status update for New Entrants' Reserve	Free alloc.		
116	15/02/2019	Adoption of the Delegated Decision on the carbon leakage list for 2021-2030	Free alloc.	x	EUA prices fell due to bearish economic data and worries ahead of Brexit deadline
117	23/04/2019	Iceland, Liechtenstein and Norway to start auctions on the common auction platform soon	Auction	x	Oil price jump after US Iranian sanctions
118	15/05/2019	ETS Market Stability Reserve to reduce auction volume by almost 400 million allowances	Auction		
119	16/05/2019	Revised 2019 auction calendars including EEA EFTA volumes published	Auction		

	Date	Event description	Type	Exclude	Reason
120	12/06/2019	Poland's 2020 auction volume to include allowances not used for power sector modernisation	Auction	x	Oil prices fell due to weak economic outlook and trade policy uncertainty
121	19/06/2019	Updated information on exchange and international credit use	Intl. credits		
122	11/07/2019	2020 and revised 2019 auction calendars of the common auction platform published	Auction		
123	15/07/2019	Commission publishes status update for New Entrants' Reserve	Free alloc.		
124	28/08/2019	Commission amends ETS auctioning regulation for phase 4	Auction		
125	31/10/2019	Commission adopts the Regulation on adjustments to free allocation due to activity level changes	Free alloc.		
126	08/11/2019	Auctioning regulation amendment for phase 4 of the EU ETS published and to enter into force	Auction		

A.2. Macro data

In this Appendix, I provide details on the financial and macroeconomic data used in the paper. Table A.2 provides information on the source of the data, its construction and coverage.

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

Variable	Description	Source	Sample
Instrument			
CFI2ch	Annual *h*th EUA futures front contract (settlement price)	Eikon	22/04/2005-31/12/2019
LEXC.hh (PS)	Quarterly *h*th EUA futures front contract (settlement price)	Datastream	22/04/2005-31/12/2019
ELECWAVG	Wholesale electricity price, constructed as weighted average of EEX, APX, Nordpool, Powernext, OMEL, GME, and the EPX spot price, converted to EUR/tCO2 using GHG emissions intensity of electricity generation	Datastream/European Environment Agency/own calculations	22/04/2005-31/12/2019
News variables			
EUGNEMUQ	Real GDP advance release and survey surprise (EA)	Bloomberg	2005M4-2019M12
UMRTEMU	Unemployment rate release and survey surprise (EA)	Bloomberg	2005M4-2019M12
ECCPEMUY	CPI release and survey surprise (EA)	Bloomberg	2005M4-2019M12
EUPPEMUM	PPI release and survey surprise (EA)	Bloomberg	2005M4-2019M12
SX5E	EURO STOXX 50 index	Bloomberg	2005M4-2019M12
IGEUR10D	Euro area 10-year government bond yield	Global Financial Data	1999M1-2019M12
BCOM	Bloomberg commodity index	Bloomberg	2005M4-2019M12
CO1	Brent crude oil price	Bloomberg	2005M4-2019M12
NG1	Natural gas price	Bloomberg	2005M4-2019M12
oilprod_nor_uk_ita	Petroleum production: Norway, UK, Italy	EIA	2005M4-2019M12
petroleum_cons_euoecd	Petroleum consumption (EU-OECD)	EIA	2005M4-2019M12
HDD	Heating degree days (EU-27)	Eurostat	2005M4-2019M12
CDD	Cooling degree days (EU-27)	Eurostat	2005M4-2019M12
Baseline variables			
EKESCPENF	HICP energy (EA-19)	Datastream	1999M1-2019M12
GHGTOTAL	Total GHG emissions excluding LULUCF and including international aviation (EU)	Eurostat/own calculations	1999M1-2019M12
EKCPHARMF	HICP all items (EA-19)	Datastream	1999M1-2019M12
EKIPTOT.G	Industrial production excl. construction (EA-19)	Datastream	1999M1-2019M12
EMECB2Y.	Two-year government bond yield	Datastream	1999M1-2019M12
EKESUNEMO	Unemployment rate (EA-19)	Datastream	1999M1-2019M12
DJSTO50	Euro STOXX 50	Datastream	1999M1-2019M12
DCOILBRENTEU	Brent Crude price	FRED	1999M1-2019M12
Additional outcome variables			
BAMLHE00EHYIOAS	ICE BofA euro high yield index option-adj. spread	FRED	1999M1-2019M12
VSTOXX	Euro STOXX 50 volatility	stoxx.com	1999M1-2019M12
RBXMBIS	Broad REER (EA)	FRED	1999M1-2019M12
EKGDP...D	Real GDP (EA-19)	Datastream	1999Q1-2019Q4
EKESENMZD	Final consumption expenditure (EA-19)	Datastream	1999Q1-2019Q4
EKGFCF..D	Gross fixed capital formation (EA-19)	Datastream	1999Q1-2019Q4
EMESJSABB	Wages and salaries: all activities (EA-19)	Datastream	1999Q1-2019Q4
UKCONPRCF	CPI all items (UK)	Datastream	1999M1-2019M12
UKGDP...D	Real GDP (UK)	Datastream	1999Q1-2019Q4
UKCNPER.D	Final consumption expenditure (UK)	Datastream	1999Q1-2019Q4
UKGFCF..D	Gross fixed capital formation (UK)	Datastream	1999Q1-2019Q4
UKESZRNRB	Wages and salaries: all activities (UK)	Datastream	1999Q1-2019Q4

As discussed in the main text, emissions data from Eurostat is unfortunately not available at the monthly frequency. For a large part of our sample, data on emissions are only available at the annual frequency. Only starting from 2010, Eurostat also started to publish quarterly figures.

As GHG emissions are a key outcome of interest, we would like to include a measure of emissions in our baseline model. To this end, I construct a monthly emissions series by temporally disaggregating the annual emissions data using a selection of relevant monthly indicators, following the method by Chow and

Lin (1971).[2] As the relevant monthly indicators I use petroleum and other fuels consumption, industrial production and harmonized consumer prices (energy and headline). This choice is motivated by a validation exercise based on the quarterly Eurostat emission figures. However, the results are relatively robust to the exact indicators included.[3]

Figure A.1 shows the resulting interpolated monthly GHG emissions series together with a naive series that is obtained by uniformly distributing the annual total. The interpolated series looks meaningful and behaves as we would expect. A nice feature is also that by construction, the interpolated monthly series will aggregate to the annual total.

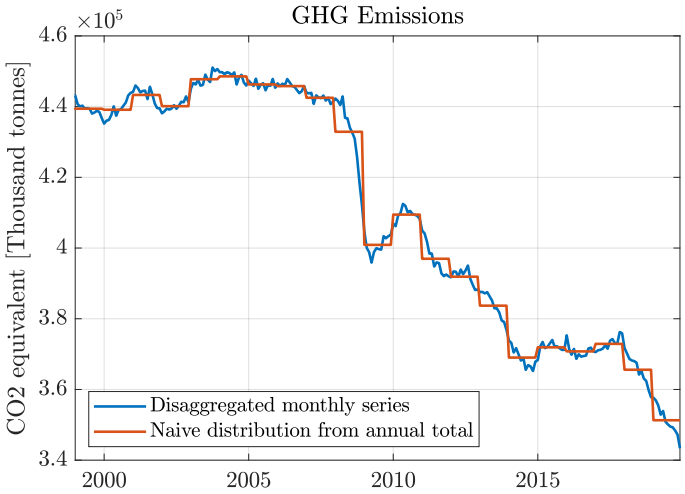


Figure A.1: The Monthly GHG Emissions Series

Notes: This figure shows the disaggregated monthly GHG emissions series, constructed with the Chow and Lin (1971) approach using petroleum and other fuels consumption, industrial production and harmonized consumer prices (energy and headline) as the relevant monthly indicators, together with a naive series that is obtained by uniformly distributing the annual total.

The transformed series used in the baseline VAR are depicted in Figure A.2. We can see a big spike in the two-year rate associated with the sovereign debt crisis. As this may potentially confound the two-year rate as a measure of the monetary stance, I account for this spike using a dummy variable. The results are robust to using a shadow rate instead.

[2] I implement the approach using the Quilis's (2020) Matlab code suite.

[3] I make the disaggregated monthly emissions data available on the following Github repository: https://github.com/dkaenzig/monthlyGHGemissions.

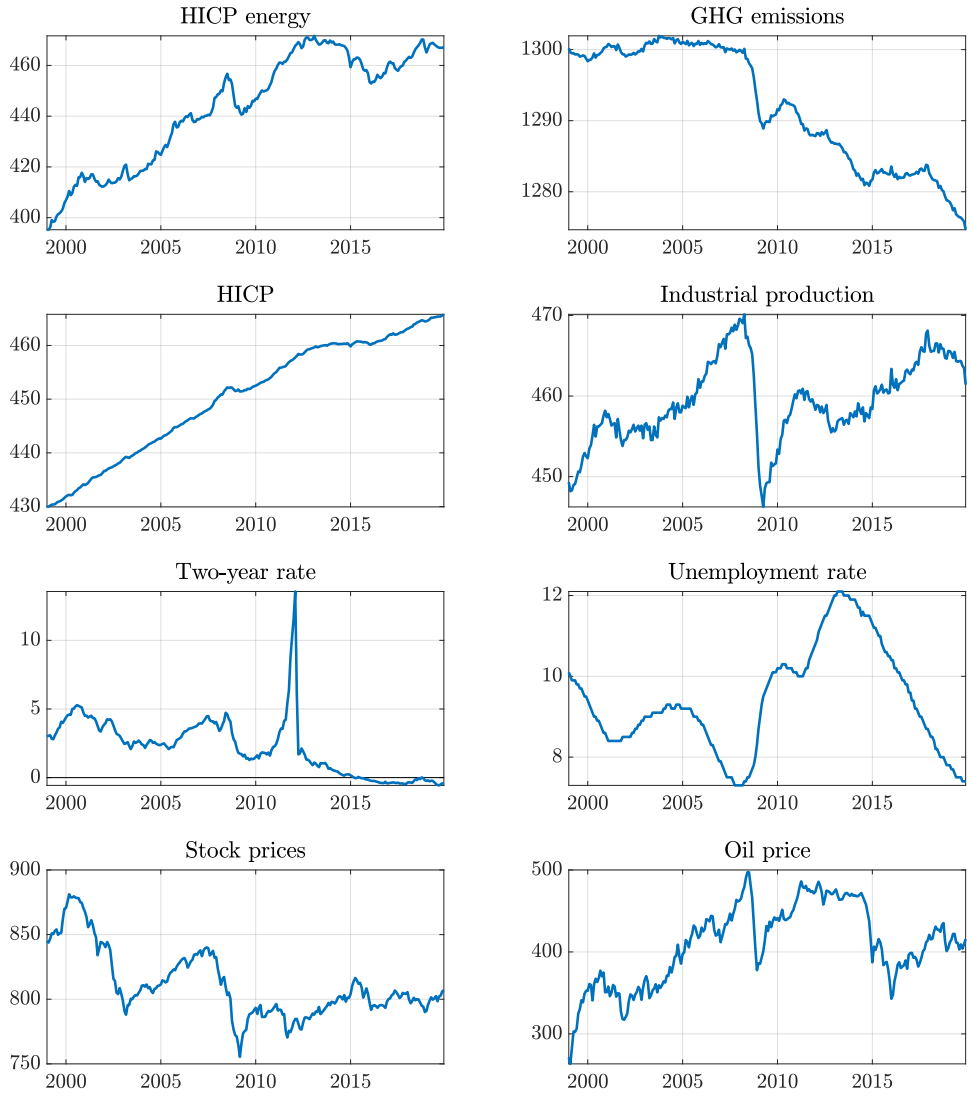


Figure A.2: Transformed Data Series

A.3. Patent data

For the patent data, I rely on the World Patent Statistical Database (PATSTAT), which encompasses bibliographic information for close to the universe of patents globally. I use the autumn 2023 edition (version 5.22) with data for 2005-2019.

I follow the literature (e.g. Hémous et al., 2025) and focus on patent families, i.e. patents representing the same innovation filed at different patent offices. For each patent family I use the original application date to capture the time of the innovation and assign nationality based on the respective filing office. I restrict the analysis to biadic patents, i.e. patents that are filed in at least two jurisdictions (e.g. at the USPTO and the EPO), to screen out low-quality patents.

To measure green innovation, I rely on the International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes. Specifically, I use the

OECD (Haščič and Migotto, 2015) subclasses Y02 and Y04S of the C/IPC, which include climate change mitigation and adaptation technologies. I classify patent families with multiple C/IPC codes as green if any of the respective codes falls into the relevant subclasses.

To study which green patents are responding the most, I consider three subgroups of Y02/Y04S: (i) mitigation in energy generation, transportation, and buildings (Y02E, Y02T, Y02B, Y02W, Y04S), (ii) mitigation in industry/manufacturing (Y02P, Y02D), (iii) adaptation or carbon capture technologies (Y02A, Y02C). Table A.3 shows that the majority of green patent filings in my sample is associated with energy generation, transportation, and buildings.

Table A.3: Descriptive Statistics on Green Patenting

Patent type	Share
Overall green	11.17
Green narrow definition	9.78
Energy, transportation, buildings	87.02
Industry and enabling technologies	22.38
Adaptation and carbon removal	10.63

Notes: Descriptive statistics on green patenting, including the share of overall green patents relative to all patents filed, the share of green patents according to the narrower definition of Acemoglu et al. (2023), as well as the sub shares within green patents (energy, transportation and buildings; industry and enabling technologies; adaptation and carbon removal—all expressed relative to overall green patents filed). Note that these shares do not sum to 100 because patents can belong to multiple groups.

A.4. Panel data

For the analysis in Section 5.1, I construct a quarterly panel of 15 advanced European countries that were part of the EU ETS, spanning the period from 1999Q1 to 2019Q4. Specifically, the panel includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom. The choice of countries is guided primarily by data availability and the desire to focus on a more homogeneous set of advanced economies. Real GDP data is from Eurostat, while country characteristics are drawn from Almgren et al. (2022) and the EU Transaction Log. Table A.4 provides more information on the variables used as well as their source.

Table A.4: Panel Data Description

Variable	Description	Source
NAMQ_10_GDP	Real Gross Domestic Product (Millions of Chained 2010 Euros, Seasonally Adjusted)	Eurostat
rgdppc_na	Real GDP per capita (sample average)	PWT
emission_intensity	GHG emissions intensity (total GHG emissions over GDP, sample average)	Känzig and Konradt (2024)
h2m	Share of hand-to-mouth households	Almgren et al. (2022)
Employment_laws_index	Employment protection index by Botero et al. (2004)	Almgren et al. (2022)

A.5. Household data

In this Appendix, I provide detailed information on the micro data used in Section 5.2 of the paper. I use data from a selection of different surveys, which are discussed in detail below.

A.5.1. LCFS

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

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

For energy expenditure, I use expenditure on fuel, light and power (p537t). Constructing measures of non-durable, services and durable expenditure is not

trivial in the LCFS data, as the broader available expenditure categories do not allow a clean split, e.g. personal goods and services (p544t) is a mix of non-durable goods and services while household goods (p542t) includes both non-durable and durable goods. To construct clean measures of non-durables, services and durables expenditure, I split these broader subcategories into non-durable, services and durable parts by grouping the items in a particular subcategory accordingly, following closely the COICOP guidelines. A further challenge in doing so is that the code names for disaggregated expenditure items changed when the FES became the EFS in 2001. In Table A.5, I detail how the non-durable, services and durable expenditure measures are constructed. At the item level, I provide both, the relevant codes in the FES and the EFS/LCFS. Note that semi-durables are subsumed under non-durables, and services do not include housing.

Table A.5: Expenditure Classification in LCFS

Category	Subcategories	Items
Non-durables	Fuel, light power (p537t)	
	Food, alcoholic drinks, tobacco (p538t, p539t, p540t)	
	Clothing and footwear (p541t)	
	Non-durable household goods (subset of p542t)	*LCFS codes:* c52111t, c52112t, c53311t, c55214t, c56111t, c56112t, c56121t, c56123t, c93114t, c93313t, c93411t, c95311t, c95411t, cc1311t *FES codes:* d070104t, d070105t, d070211t, d070209t, d070401t, d070402t, d070302t, d070601t, d120304t, d070501t
	Non-durable personal goods (subset of p544t)	*LCFS codes:* c61112t, c61211t, c61311t, c61313t, cc1312t, cc1313t, cc1314t, cc1315t, cc1316t, cc1317t, cc3211t, cc3222t, cc3223t, cc3224t *FES codes:* d090402t, d090102t, d090501t, d090101t, d090103t, d090104t, d090105t, d090301t, d090202t, d090302t, d090303t
	Non-durable motoring expenditure (subset of p545t)	*LCFS codes:* c72114t, c72211t, c72212t, c72213t *FES codes:* d100405t, d100301t, d100302t, d100303t
	Non-durable leisure goods (subset of p547t)	*LCFS codes:* c91126t, c91411t, c91412t, c91413t, c91414t, c93111t, c93113t, c93311t, c95111t, c95211t, c95212t *FES codes:* d120114t, d120108t, d120110t, d120109t, d120401t, d120113t, d070703t, d120303t, d120301t, d120302t
	Miscellaneous non-durable goods (subset of p549t)	*LCFS codes:* ck5511c, cc3221t *FES codes:* d070801t, d140601c, d090701t
Services	Household services (p543t)	
	Fares and other travel costs (p546t)	
	Leisure services (p548t)	
	Service part of household goods (subset of p542t)	*LCFS codes:* c53312t, c53313t, c53314t, c93511t, cc5213t *FES codes:* d070212t, d070213t
	Personal services (subset of p544t)	*LCFS codes:* c61111t, c61312t, c62111t, c62112t, c62113t, c62114t, c62211t, c62212t, c62311t, c62321t, c62322t, c62331t, c63111t, cc1111t *FES codes:* d090401t, d090502t, d090403t, d090404t, d090601t

Category	Subcategories	Items
	Service part of motoring expenditure (subset of p545t)	*LCFS codes:* b187-b179, b188, b249, b250, b252, c72313t, c72314t, c72411t, c72412t, c72413t, ck3112t, c72311c, c72312c, cc5411c *FES codes:* b187-b179, b188, b249, b250, b252, d100403t, d100406t, d100407t, d100404t, d100408t, d100201c, d100204c, d100401c
	Leisure services (subset of p547t)	*LCFS codes:* c91511t, c93112t, c94238t, c94239t, c94246t *FES codes:* d120111t, d120112t
	Miscellaneous services (subset of p549t)	*LCFS codes:* b237, b238, ck5315c, ck5213t, ck5214t *FES codes:* b237, b238, d140402, d140406c
Durables	Durable household goods (subset of p542t)	*LCFS codes:* b270, b271, c51111c, c51211c, c51212t, c51113t, c51114t, c53111t, c53121t, c53122t, c53131t, c53132t, c53133t, c53141t, c53151t, c53161t, c53171t, c53211t, c54111t, c54121t, c54131t, c54132t, c55111t, c55112t, c55213t, c56122t, c93212t, c93312t, c93412t, cc1211t *FES codes:* b270, b271, d070101c, d070102c, d070103t, d070304t, d070704t, d070203t, d070202t, d070204t, d070207t, d070208t, d070201t, d070206t, d070303t, d070301t, d070205t, d070701t, d070305t, d070306t, d070702t, d070602t
	Durable personal goods (subset of p544t)	*LCFS codes:* cc3111t *FES codes:* d090201t
	Durable motoring expenditure (subset of p544t)	*LCFS codes:* b244, b2441, b245, b2451, b247, c31315t, c71112t, c71122t, c71212t, c92114t, c92116t, c71111c, c71121c, c71211c, c92113c, c92115c, c72111t, c72112t, c72113t, c91112t *FES codes:* b244, b245, b247, d100105t, d100106t, d100107t, d100101c, d100102c, d100104c, d100203t, d100202t, d100205t
	Durable leisure goods (subset of p547t)	*LCFS codes:* c91124t, c82111t, c82112t, c82113t, c91111t, c91113t, c91121t, c91122t, c91123t, c91125t, c91211t, c91311t, c92211t, c92221t, c93211t *FES codes:* d120104t, d080202t, d080205t, d080207t, d120105t, d120101t, d120102t, d120103t, d120115t, d120402t, d120106t, d120107t, d120201t

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

A.5.2. LFS

To get information on the sector of employment, I use data from the UK Labour Force Survey (LFS). The LFS studies the employment circumstances of the UK population. It is the largest household study in the UK and provides the official measures of employment and unemployment. Apart from detailed information on employment, it also contains a wide range of related topics such as occupation,

training, hours of work and personal characteristics of household members aged 16 years and over. The data can be obtained from the UK Data Service. I use the quarterly waves from 1999-2019 to construct a pooled cross-section. For the employment sector, I use the variable indsect, which describes the industry sector in the main job based on the SIC 2003 classification. To proxy income, I use the net pay from the main and second job (netwk and netwk2).

A.5.3. BSA

To proxy public attitudes towards climate policy, I use data from the British social attitudes (BSA) survey. The data can also be obtained from the UK Data Service. I use the waves from 1999-2019 to construct a pooled cross-section. To construct the income groups, I use the income quartiles that are provided from 2010 onwards (hhincq). For the years before, I use the household income variable (hhincome) to construct the quartiles. The survey contains many questions on the attitudes towards climate change, the environment and climate/environmental policy, but unfortunately most variables are not part of the main set of questions that are asked in every year. One exception concerns a question about taxes for car owners (cartaxhi), in particular it asks whether you agree with the following statement: "For the sake of the environment, car users should pay higher taxes", which was fielded for all years up to 2017. Thus, I use the proportion of households agreeing with this statement as a proxy for the public attitude towards climate policy.

B. Instrument Diagnostics

In this Appendix, I examine several properties of the carbon policy surprise series, related to instrument validity and strength.

B.1. Validity checks

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 displays the monthly carbon policy surprise series, aggregated by summing over the surprises in a given month.

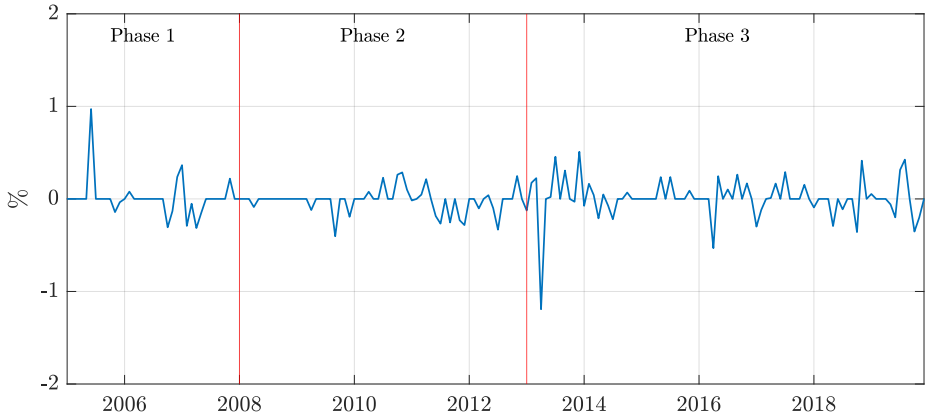


Figure B.1: Monthly Carbon Policy Surprise Series

Notes: The figure shows the refined carbon policy surprise series, aggregated to the monthly frequency by summing over the surprises in a given month.

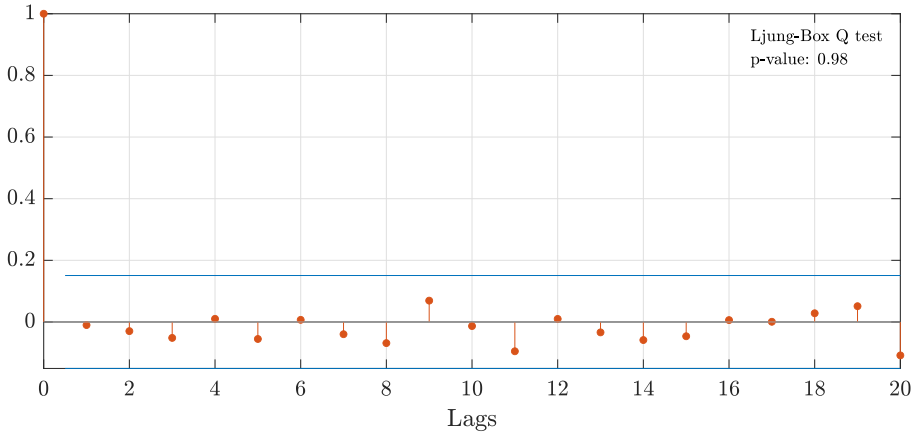


Figure B.2: The Autocorrelation Function of the Carbon Policy Surprise Series

The series looks well behaved, with approximately as many positive as negative surprises. The series is also not serially correlated, as can be seen from the autocorrelation function in Figure B.2.

I also perform a series of Granger causality tests. Table B.1 shows that the monthly series is not forecastable by past macroeconomic variables.

Table B.1: Granger Causality Tests

Variable	p-value
Instrument	0.9724
EUA price	0.7377
HICP energy	0.2063
HICP	0.7327
Industrial production	0.7199
Two-year rate	0.9568
Unemployment rate	0.6601
Stock prices	0.7170
REER	0.3049
Oil price	0.9825
Joint	0.9795

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

Table B.2: Correlation with Other Shock Measures

Shock	Source	ρ	p-value	n	Sample
Monthly measures					
Global oil market					
	Kilian (2009) (updated)	-0.06	0.46	164	2005M05-2018M12
	Caldara, Cavallo, and Iacoviello (2019)	-0.01	0.89	128	2005M05-2015M12
	Baumeister and Hamilton (2019)	-0.09	0.24	176	2005M05-2019M12
	Känzig (2021) (updated)	0.04	0.62	176	2005M05-2019M12
Global demand	Kilian (2009) (updated)	0.04	0.61	164	2005M05-2018M12
	Baumeister and Hamilton (2019)	-0.02	0.78	176	2005M05-2019M12
Oil-specific demand	Kilian (2009) (updated)	0.02	0.76	164	2005M05-2018M12
Consumption demand	Baumeister and Hamilton (2019)	0.05	0.49	176	2005M05-2019M12
Inventory demand	Baumeister and Hamilton (2019)	-0.05	0.53	176	2005M05-2019M12
Monetary policy					
Monetary policy shock	Jarociński and Karadi (2020)	0.05	0.52	140	2005M05-2016M12
Central bank info	Jarociński and Karadi (2020)	0.06	0.51	140	2005M05-2016M12
Financial & uncertainty					
Financial conditions	BBB spread residual	-0.02	0.75	176	2005M05-2019M12
Financial uncertainty	VIX residual (Bloom, 2009)	-0.00	0.97	176	2005M05-2019M12
	VSTOXX residual	0.00	0.97	176	2005M05-2019M12
Policy uncertainty	Global EPU (Baker, Bloom, and Davis, 2016)	0.03	0.72	176	2005M05-2019M12
Quarterly measures					
Fiscal policy	Euro area (Alloza, Burriel, and Pérez, 2019)	0.09	0.58	43	2005Q2-2015Q4
	Germany	0.22	0.15	43	2005Q2-2015Q4
	France	0.03	0.86	43	2005Q2-2015Q4
	Italy	0.01	0.97	43	2005Q2-2015Q4
	Spain	-0.02	0.90	43	2005Q2-2015Q4

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

Finally, I study how the series correlates with other shock series from the literature and find that it is not correlated with other structural shock measures,

including oil demand, uncertainty, financial, fiscal and monetary policy shocks, see Table B.2.[4]

B.2. First stage

Having provided suggestive evidence on the validity of the carbon policy surprise series, I now evaluate instrument strength. Table B.3 presents the results of the weak instruments test for a selection of instruments. I include the raw carbon policy surprise series, normalized by electricity prices or expressed as percentage changes in carbon prices, along with refined surprises purged using different information sets. The results indicate that carbon policy surprises serve as strong instruments, with heteroskedasticity-robust F-statistics typically exceeding the conventional threshold of 10.

Table B.3: Tests on instrument strength

Instrument	Raw		Refined baseline			
	Baseline	$\Delta\log(F)$	(a) Macro	(b) Financials	(c) Oil	(d) Climate
Coefficient	0.610	0.026	0.589	0.590	0.667	0.891
Robust F-stat	12.54	12.85	9.62	9.53	11.69	16.85
R^2	1.40	1.29	1.23	1.22	1.46	2.38
Adj. R^2	0.99	0.89	0.82	0.82	1.05	1.98

Notes: Results of first-stage regressions of the energy price residual $\hat{u}_{1,t}$ on a selection of different instruments: the raw baseline surprise series based on (1), the variant based on the percentage change in the carbon price as well as refined baseline surprise using different information sets: (a) controls for macro news, (b) adding financials, (c) adding oil market variables, (d) adding climatic variables, based on (2). Reported are coefficient estimates, robust F-statistics allowing for heteroskedasticity, the R^2 and adjusted R^2. The number of observations is 246.

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

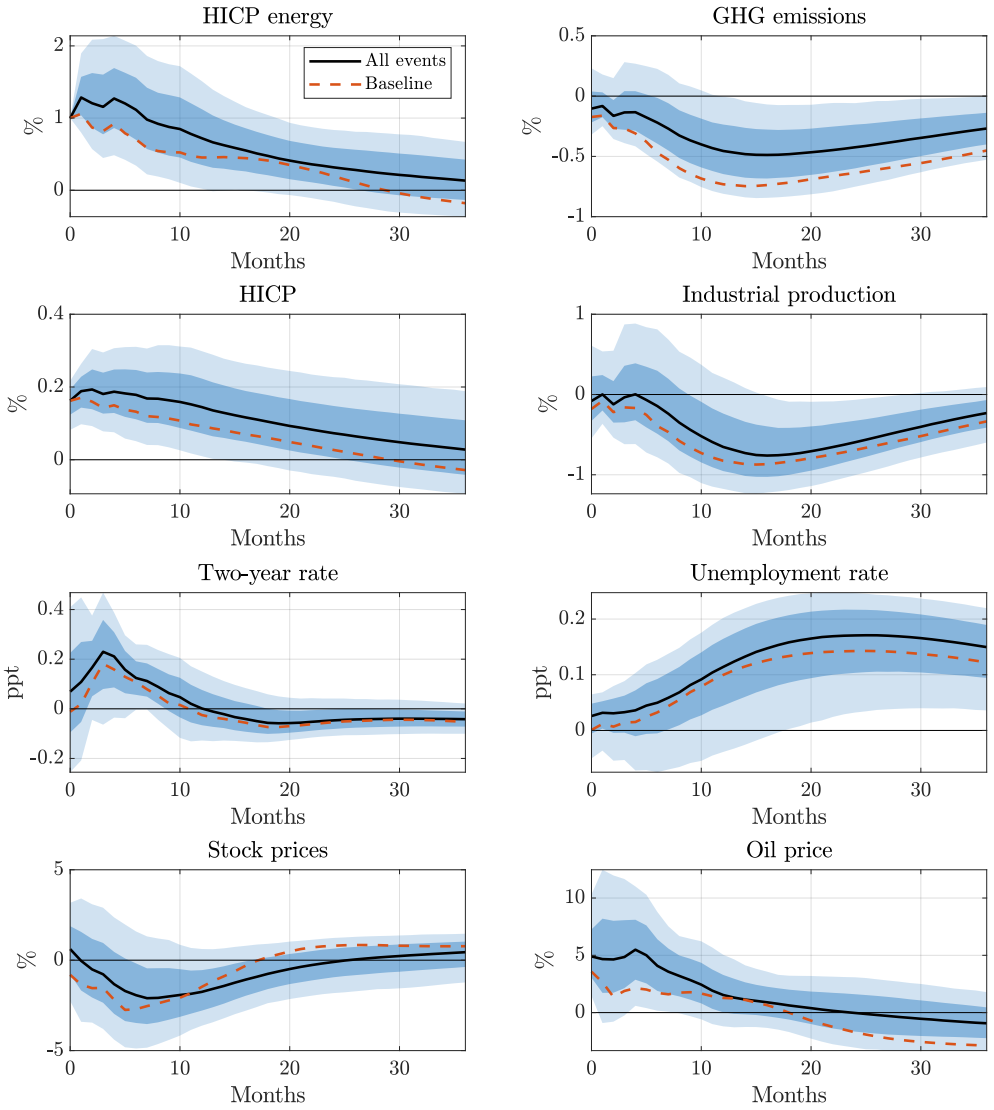
C. Sensitivity Analysis

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

C.1. Instrument construction

Selection of relevant events. A crucial choice in the high-frequency event study approach concerns the selection of relevant events. For the exclusion restriction to be satisfied, the events should only release information about the supply of emission allowances and not about other factors such as macroeconomic or geopolitical news. To this end, I have not included more high level events such as the Paris agreement or other COP meetings but limited the analysis to specific events in the European carbon market.

As discussed in Section 2.2, I also performed a narrative analysis to identify events that are potentially confounded. Figure C.1 shows how excluding these events affects the results. Accounting for these potentially confounded events makes some difference, particularly for the oil price and the emissions responses, even though the differences are not statistically significant. To mitigate concerns about potentially confounded events, I exclude the flagged events in the baseline analysis.



First stage regression: F-statistic: 22.36, R^2: 3.38%

Figure C.1: 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.

In a series of additional sensitivity checks, I show that the results are not driven by a particular subset of events. To ensure that the results are not driven by surprises in times of economic distress, I exclude (i) events during the Great Recession, (ii) events during the European sovereign debt crisis, and (iii) the 2014-16 oil shock. As an additional check, I also exclude events from the the first, trial phase of the EU ETS, where markets were not as liquid and regulations not as strict.

The results are shown in Figure C.2. The results are very robust to the selection of events. The responses based on these alternative instruments all lie within the 68 percent confidence bands of the baseline model. This suggests that the results

are not driven by some specific influential periods such as the sovereign debt crisis or the 2014 oil shock.

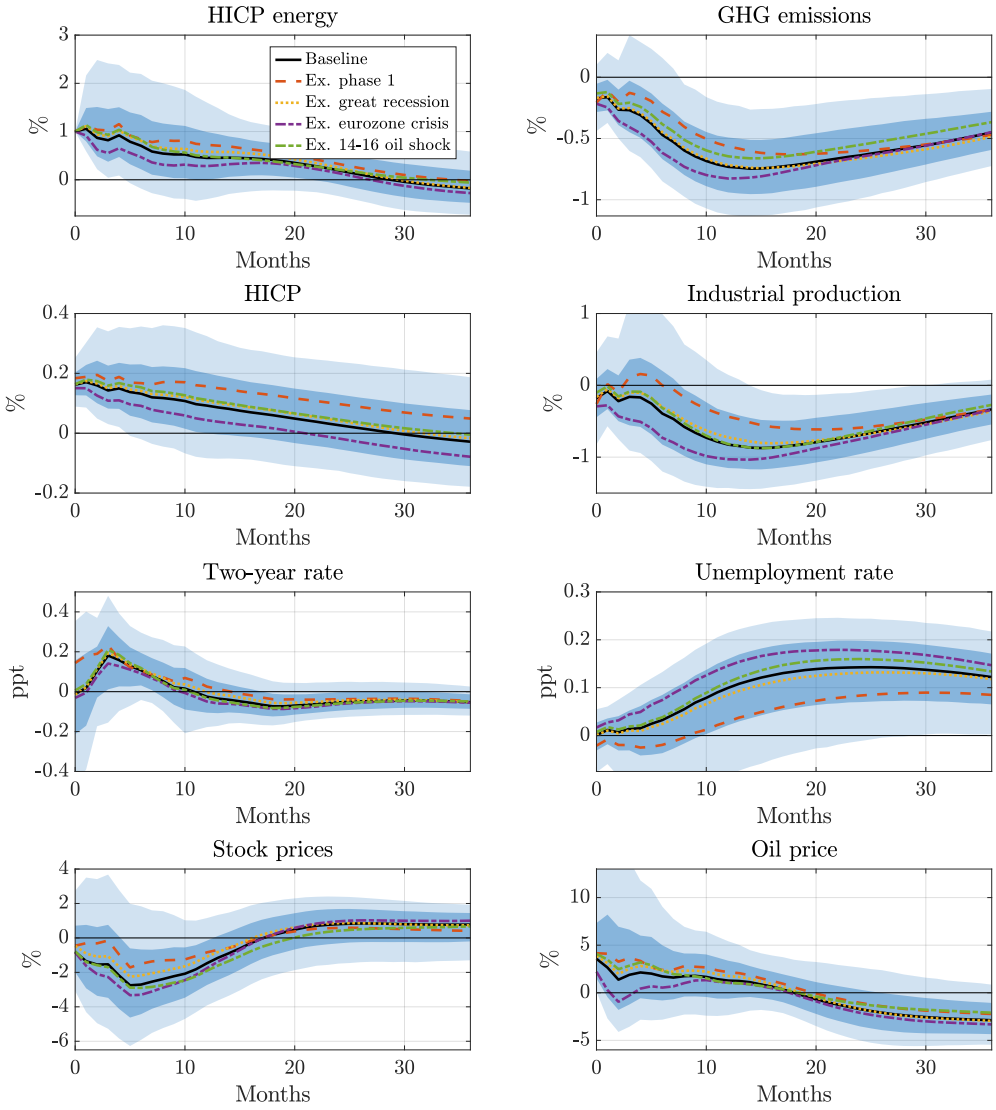


Figure C.2: Excluding Certain Periods from Instrument Construction

To analyze the role of influential events more systematically, I perform a jackknife exercise. Specifically, I censor one value of the carbon policy surprise series at a time to zero, and re-run the external instruments VAR. Figure C.3 shows our baseline response in black, together with the responses from the jackknife exercise in gray. The estimated responses are not driven any single extreme carbon policy surprise. When censoring certain surprises the impacts can get even bigger, while when dropping others the effects can be somewhat attenuated. In all cases, the responses always lay squarely within the 68 percent confidence bands of the baseline model.

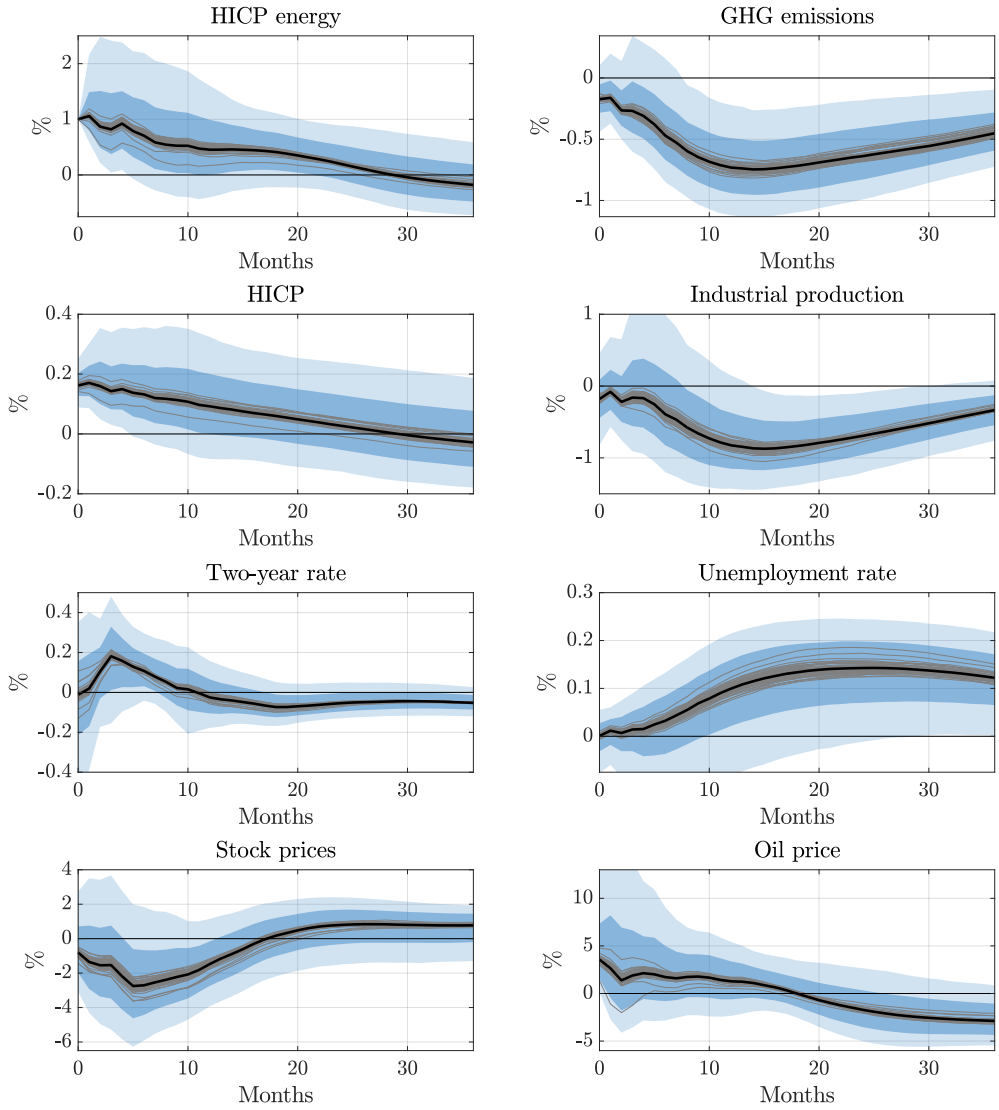


Figure C.3: Results from Jackknife Exercise

Finally, I also perform some robustness with respect to the event type. Specifically, I (i) exclude events concerning the cap as they tend to be broader in nature, (ii) exclude events about international credits, which affect the supply of allowances more indirectly, and (iii) exclude events about data updates which affect the supply of allowances indirectly, e.g. by triggering the market stability reserve. Figure C.4 presents the results. Reassuringly, the results turn out to be robust across the different type of events, and excluding the events described above does not change the responses meaningfully compared to the baseline model.

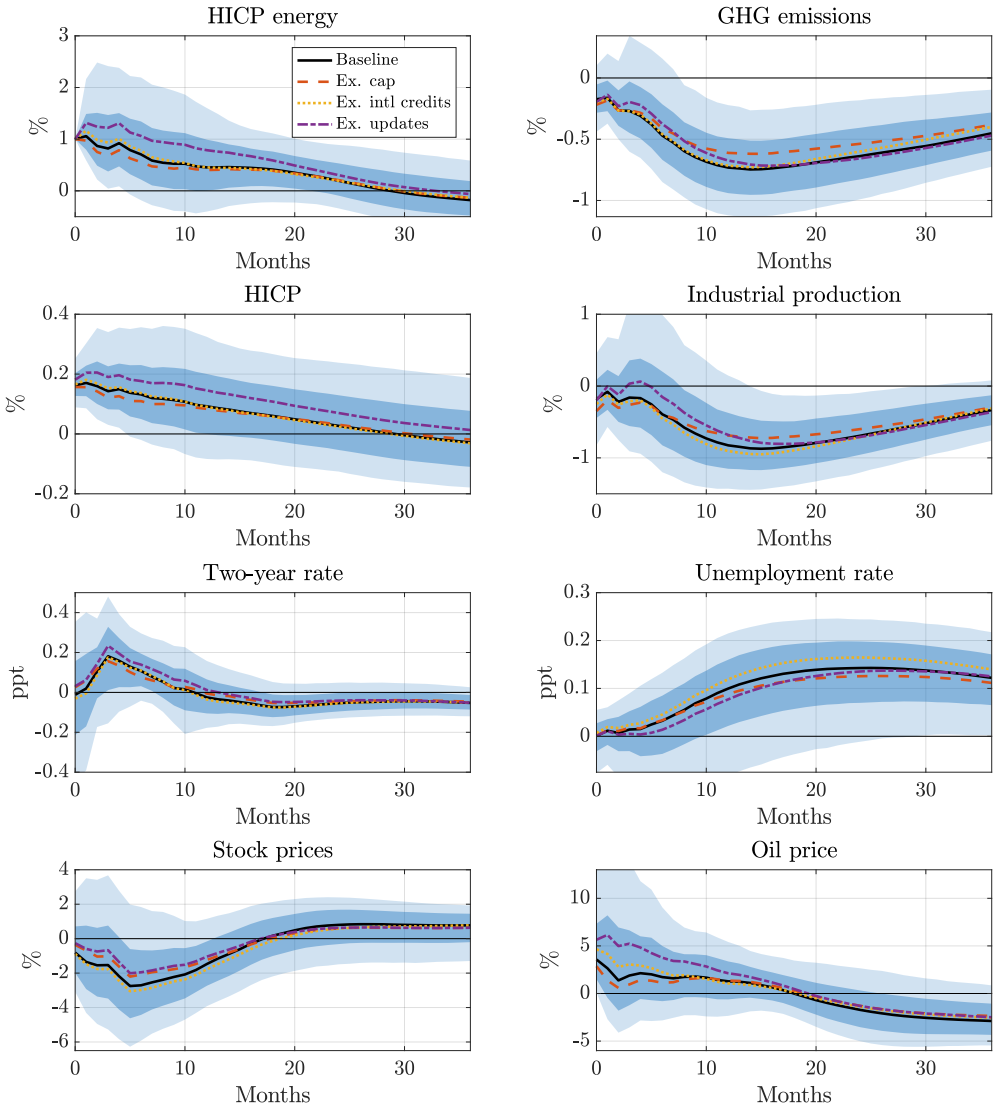
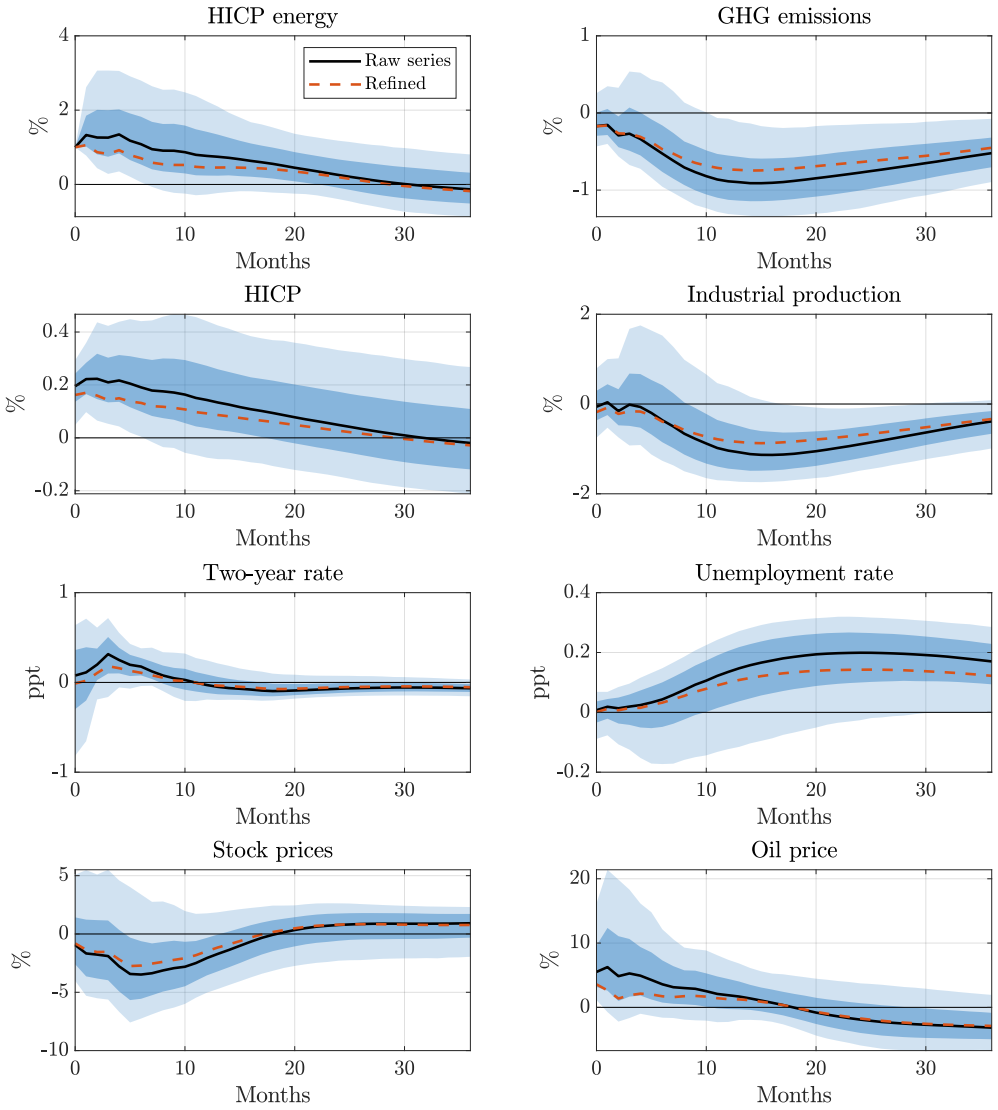


Figure C.4: Sensitivity With Respect to Event Types

Removing predictability. In Section 2.2, we have seen that there is some potential predictability in the carbon policy surprise series, driven by oil market specific and climate related variables. Figure C.5 shows how accounting for this predictability affects the results.

Accounting for the potential predictability makes some difference, particularly for the oil price response, even though the differences are not statistically significant. To mitigate any identification concerns related to the predictability of the surprise series, I use the refined carbon policy surprise series as the baseline.



First stage regression: F-statistic: 12.54, R^2: 1.40%

Figure C.5: The Role of Removing Predictability

Alternative instrument. As discussed in Section 2.2, I measure the carbon policy surprises as the change in the EUA futures price on the day of the regulatory event relative to the prevailing wholesale electricity price on the day before the event.[5]

The main advantage of this approach is that it directly gives a notion of how economically relevant a carbon policy surprise is. In particular, it gives less weight to large percentage changes in carbon prices that occurred in an environment where carbon prices were very low. An alternative approach is to simply measure the surprise as the percentage change in the carbon price on event days.

[5]To mitigate the influence of extreme observations in the wholesale electricity price, I use an average of the price over the last 5 trading days before the event.

To fix ideas, the carbon policy surprise is in this case computed as follows:

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

where d and t indicate the day and the month of the event, respectively and $F_{t,d}$ is the settlement price of the EUA futures contract. To account for the fact that percentage surprises are not really meaningful in late 2007 when carbon prices were approaching zero, I exclude these events from the analysis. Finally, I also purge the surprise series from macro, financial, oil market and climate related news to remove any potential remaining predictability. The daily surprises are shown in Figure C.6.

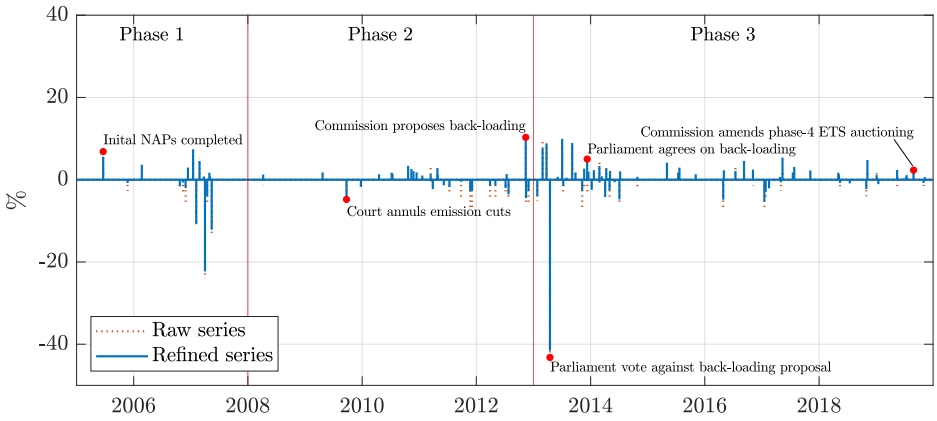


Figure C.6: Alternative Carbon Policy Surprise Series, Daily

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

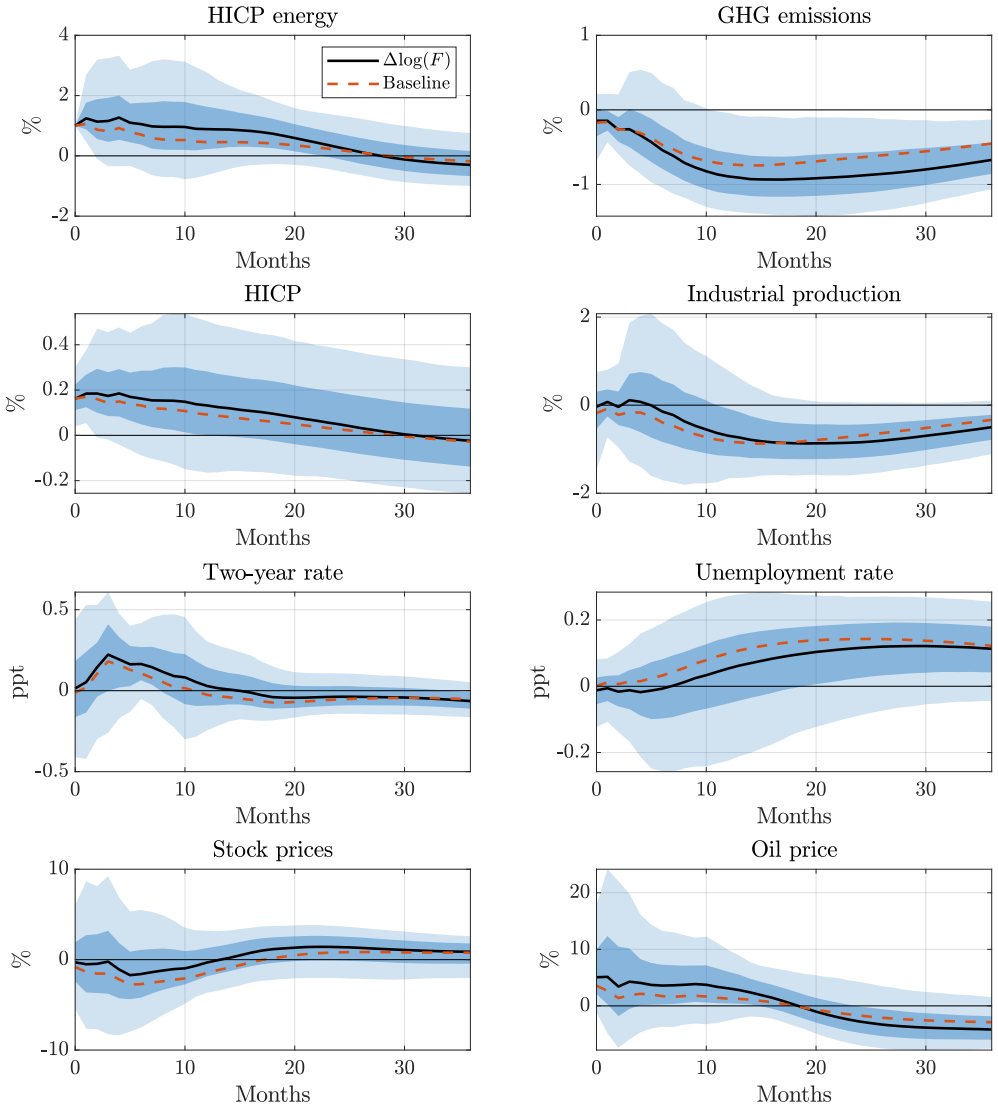
Figure C.7 shows the corresponding aggregated monthly carbon policy surprise series, compared to the baseline surprise series. The two series are fairly similar, particularly during phase two and the beginning of the third phase. The correlation coefficient between the two series stands at around 0.76.

Figure C.8 presents the impulse responses to a carbon policy shock using the alternative instrument, together with the baseline responses. Using the alternative instrument produces similar results, however, the responses are somewhat less precisely estimated. This illustrates the importance of measuring the surprise series in economically relevant terms.



Figure C.7: Alternative Carbon Policy Surprise Series, Monthly

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



First stage regression: F-statistic: 12.24, R^2: 1.49%

Figure C.8: Responses Based on Alternative Surprise Series

Futures contracts. EUA futures are traded on both annual and quarterly cycles. Annual contracts expire in December and are available multiple years out, while quarterly contracts expire at the end of each quarter. As a baseline, I use the current December contract, which is the main contract used and typically the most liquid. However, at the start of the year, its distant expiry may raise concerns about risk and term premia. As an alternative, I use the front quarterly contract—the one with the nearest expiry. Figure C.9 shows that results are virtually identical across annual and quarterly futures.

I also examine how the results change when using contracts with longer maturities. Results from one-year, two-year, and four-year contracts are similar, further suggesting that risk premia do not significantly affect the findings.

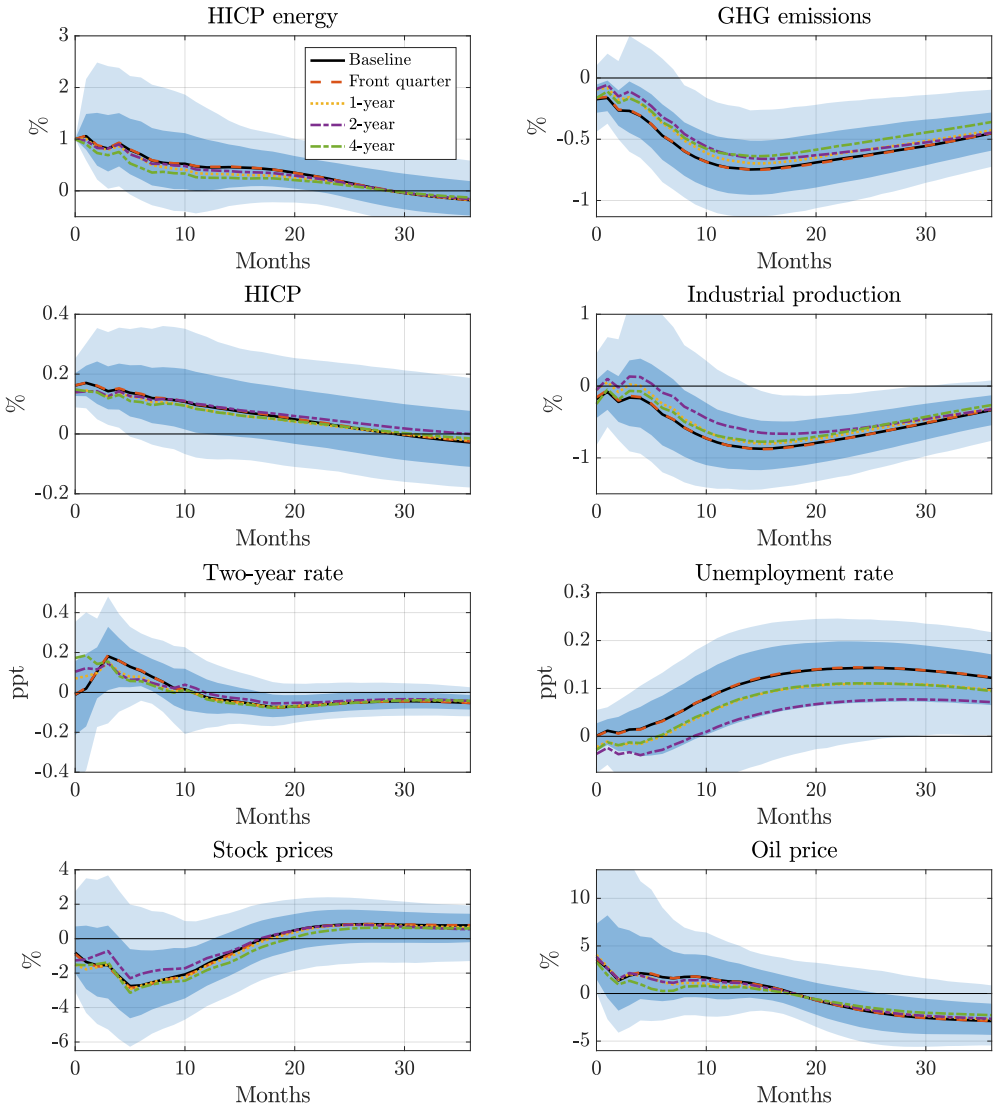


Figure C.9: Using Different Futures Contracts

C.2. Confounding news

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

To mitigate concerns about other news confounding the carbon policy surprise series, I employ an alternative identification strategy exploiting the heteroskedasticity in the data (Rigobon, 2003; Nakamura and Steinsson, 2018*a*). 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.

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

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

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

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

$$\begin{aligned} \sigma^2_{\varepsilon_1,R1} &> \sigma^2_{\varepsilon_1,R2} \\ \sigma^2_{\varepsilon_j,R1} &= \sigma^2_{\varepsilon_j,R2}, \quad \text{for } j = 2, \ldots, n. \\ \sigma^2_{v,R1} &= \sigma^2_{v,R2}. \end{aligned} \tag{1}$$

Under these assumptions, the structural impact vector is given by

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

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

To implement this approach, I construct a sample of control days. In particular, I use the changes in carbon futures prices on the same weekday and week in the months prior a given regulatory event. For the samples of event and control days, I compute surprises as the percentage change in EUA futures, purged from information available prior to the day. I use percentage changes in carbon prices as opposed to the change relative to the wholesale electricity price to capture the variance in carbon prices more directly.

The assumption that the variance is much larger on event days than on a sample of controls days is indeed supported by the data. Figure C.10 shows the carbon policy surprise series together with the control series. We can see that the policy surprise series is much more volatile than the control series, and a Brown–Forsythe test for the equality of group variances confirms that this difference is also statistically significant.

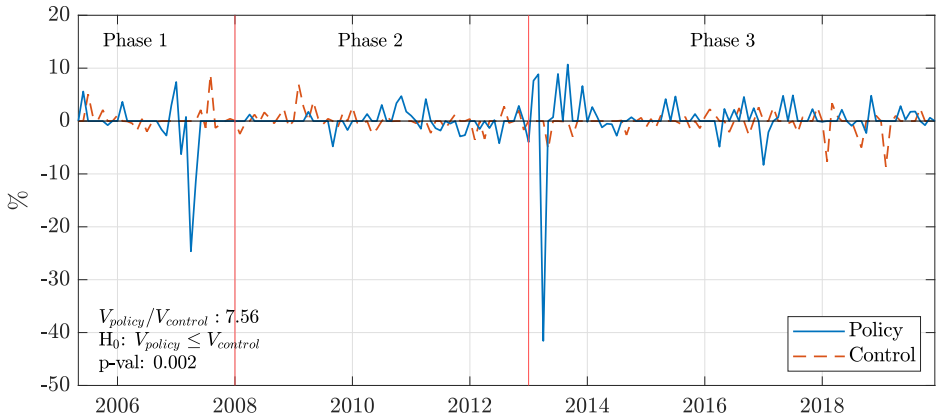


Figure C.10: The Alternative Carbon Policy and the Control Series

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

Figure C.11 shows the impulse responses estimated from this alternative approach. The results turn out to be consistent with the baseline results from the external instrument approach, even though the responses are a bit less precisely estimated. These results suggest that the bias induced by background noise is likely negligible in the present application. However, part of the statistical strength un-

der the external instrument approach appears to come from the stronger identifying assumptions.

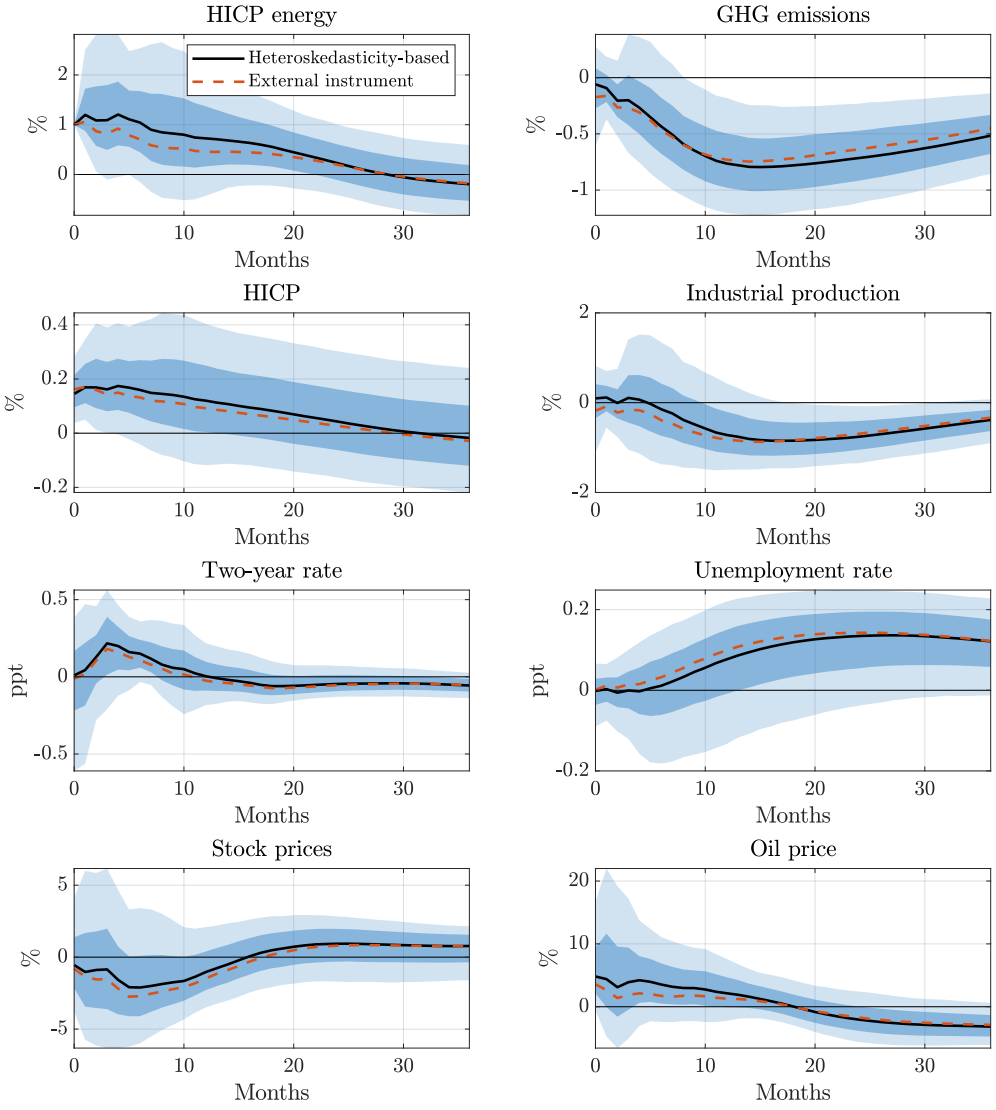


Figure C.11: Heteroskedasticity-based Identification

C.3. Placebo exercise

In Appendix C.2, I exploit the heteroskedasticity between event and non-event days explicitly for identification. In this appendix, I show that randomly-drawn placebo dates do not lead to systematic changes in energy prices, emissions and economic activity.

The exercise proceeds as follows. I first draw 114 placebo dates from the sample of non-event dates. Next, I construct a placebo surprise series, measuring changes in carbon prices on these dates, and remove any predictability using my extended set of predictive variables (d). I then aggregate the refined surprises

into a monthly placebo series. Using this series as an external instrument in my baseline VAR model, I estimate impulse responses. I repeat these steps a 1,000 times.

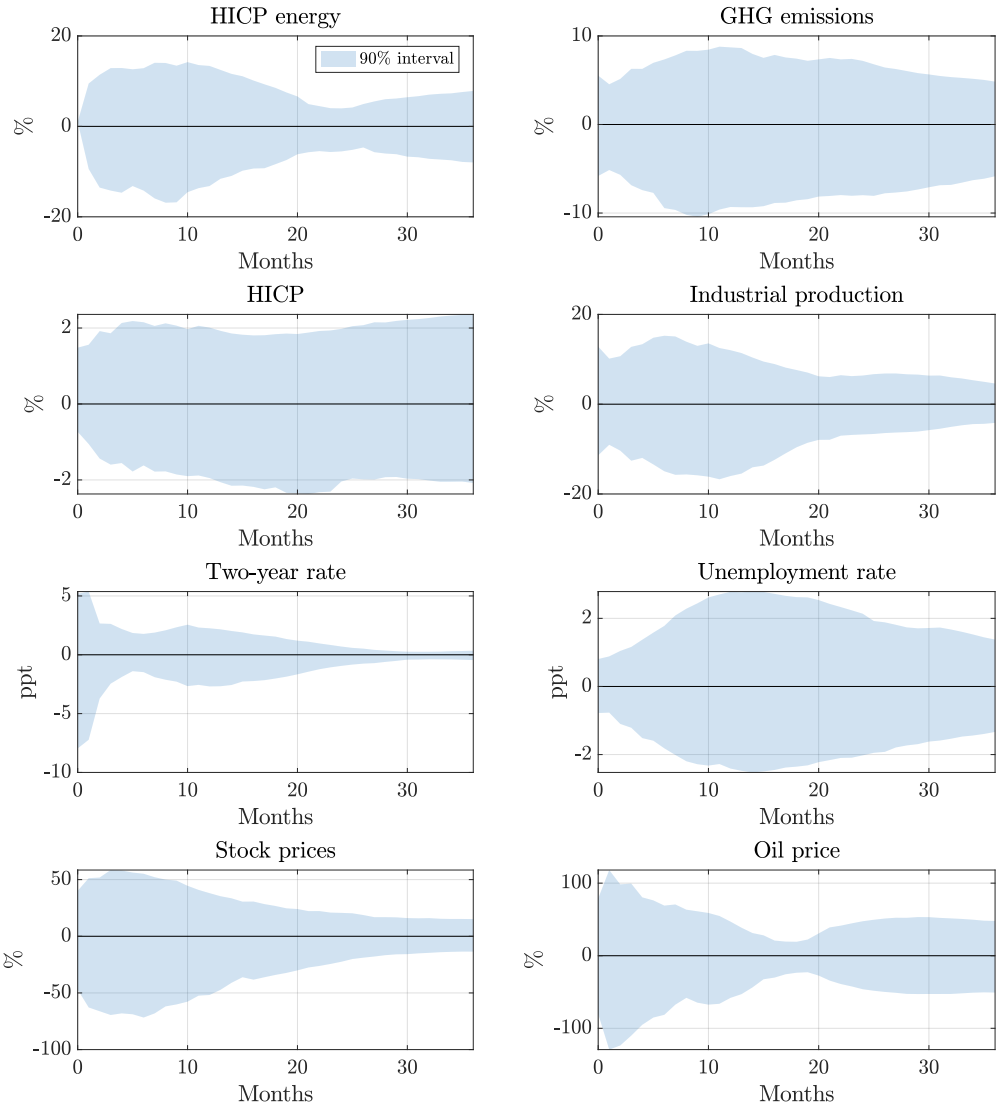


Figure C.12: Placebo Responses

Figure C.12 shows the 5th and 95th percentiles of the placebo responses. News on placebo dates are not associated with systematic effects on energy prices, emissions and economic and financial variables. This is not merely due to offsetting positive and negative responses—all responses are normalized to increase the HICP energy by 1 percent on impact. The width of the interval further underscores this point. Overall, this evidence suggests that the external instrument VAR approach is not picking up spurious correlations in the data.

Another way to assess this is by examining the first stage. Random placebo dates should capture a mix of different shocks, and as such, they should not pro-

duce a systematic response in energy prices. Consequently, the placebo surprises should be weak instruments. This intuition is confirmed by the distribution of F-statistics from the first-stage regressions, where placebos serve as instruments for the HICP energy residual.

Figure C.13 shows the histogram of the (robust) F-statistics. Most values cluster near zero and virtually all of the mass is below the relevant threshold of 10. The contrast with the F-statistic for the actual carbon policy surprise series is even more pronounced. These results confirm that the placebos are weak instruments, explaining the wide range of possible effects they produce.

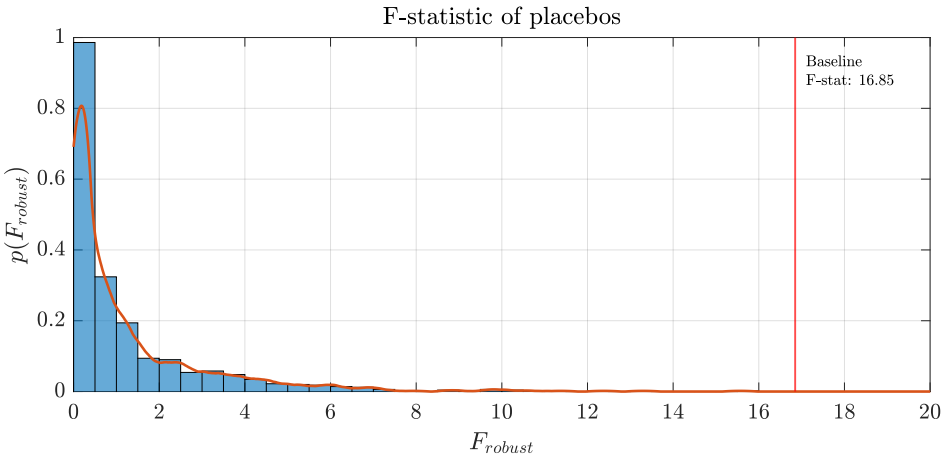
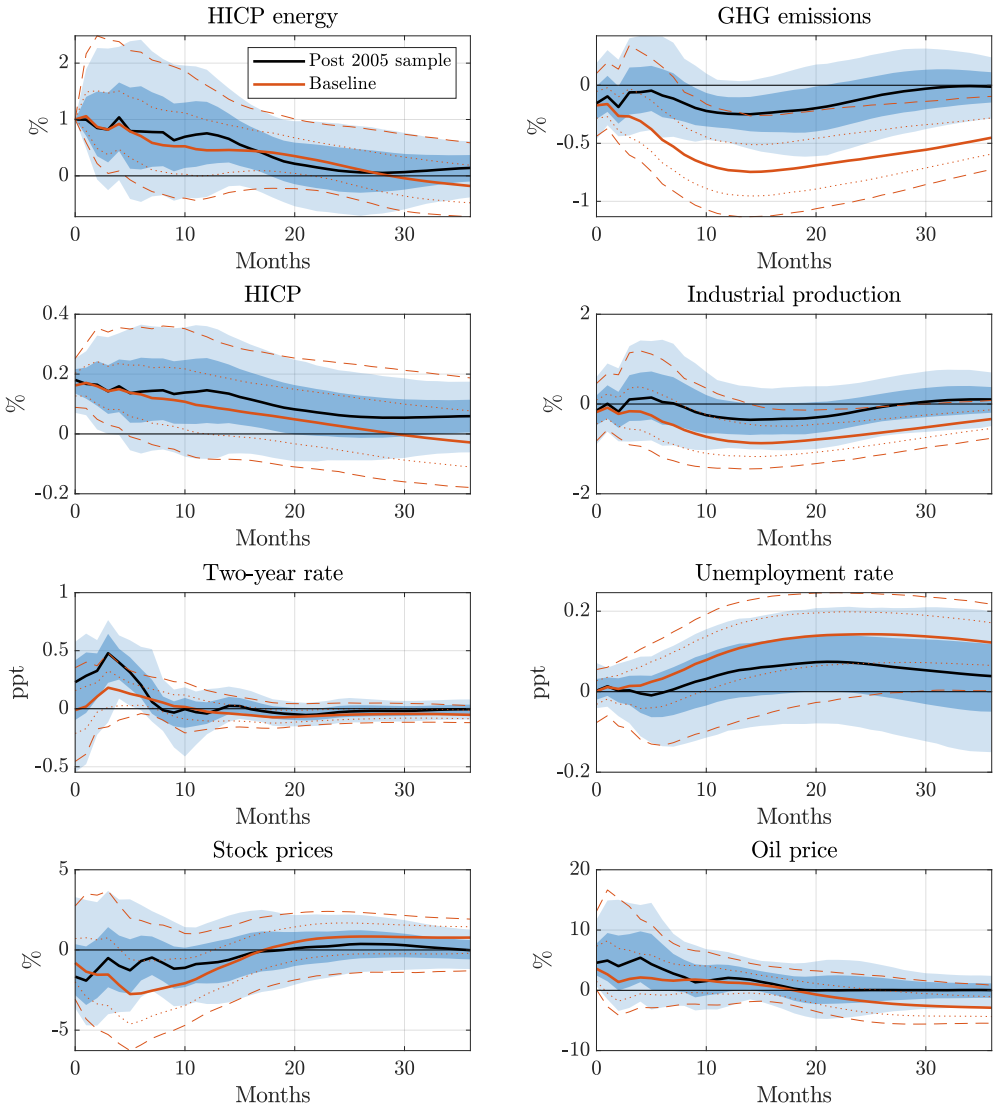


Figure C.13: Placebo F-Statistics

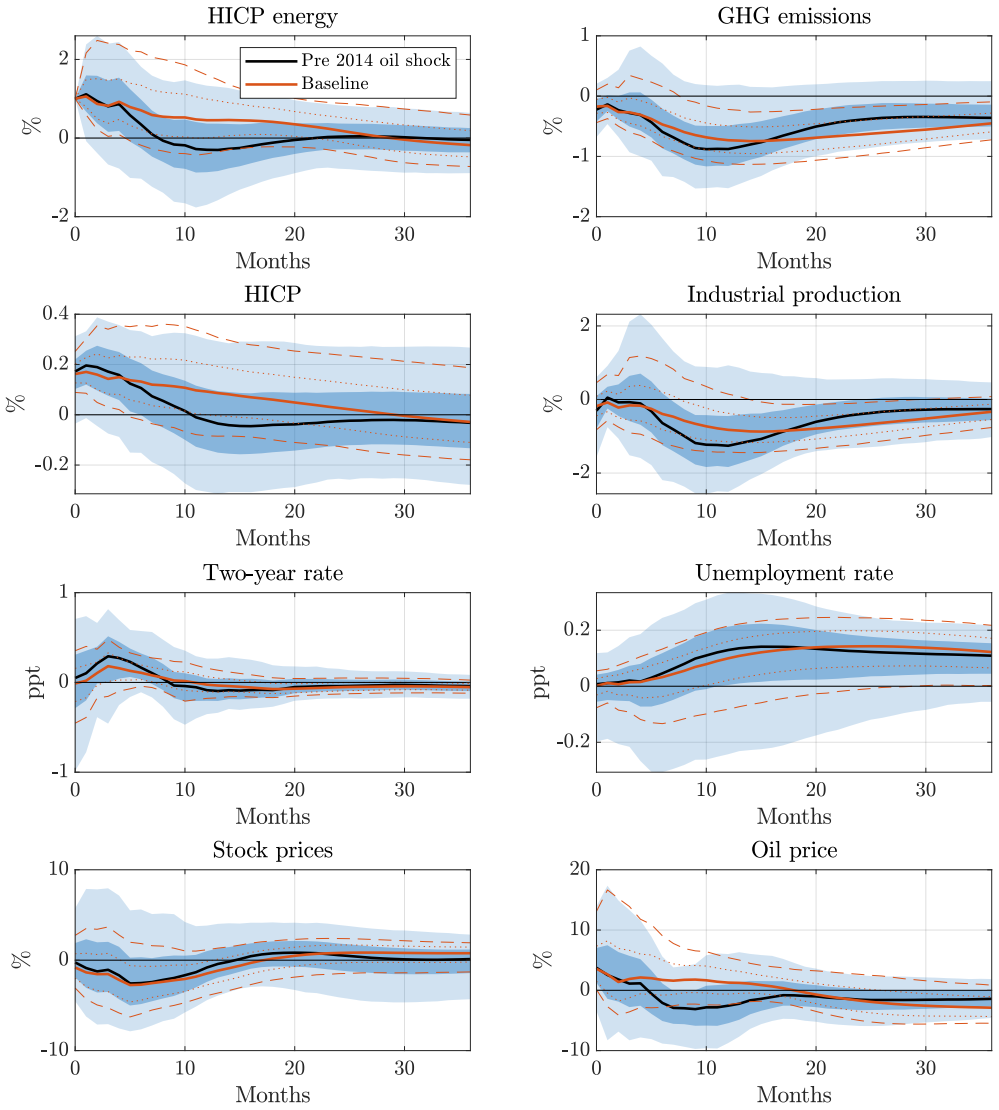
C.4. Sample and specification choices

An important robustness check concerns the estimation sample. Recall, the baseline sample goes back to 1999, which is longer than the instrument sample that only starts in 2005. The main motivation for using the longer sample is to increase the precision of the estimates. As a robustness check, I restrict the overall sample to the 2005-2019 period. The responses are shown in Figure C.14. Overall, the results are similar to the ones using the longer sample. However, the responses of emissions and industrial production turn out to be less pronounced. Some responses also turn out to be less stable, pointing to difficulties in estimating the model dynamics on the relatively short sample. As a second check, I stop the estimation sample before the oil shock in mid-2014. From Figure C.15, we can see that the responses turn out to be very similar to the baseline case. However, the responses overall are less precisely estimated, again illustrating the challenges of estimating the model on an even shorter sample.



First stage regression: F-statistic: 10.95, R^2: 3.98%

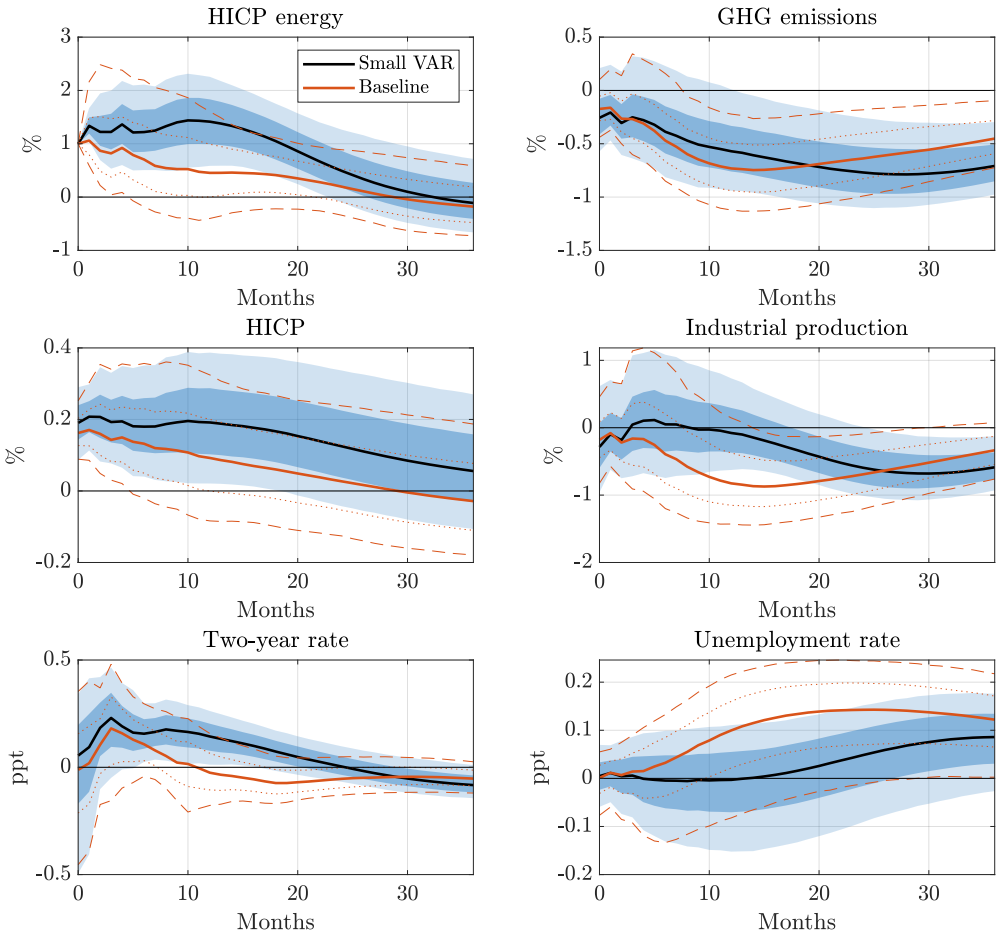
Figure C.14: Results Using 2005-2019 Sample



First stage regression: F-statistic: 10.94, R^2: 2.83%

Figure C.15: Results Using 1999-2014 Sample

I also perform a number of other sensitivity checks on the specification of the model. The baseline VAR includes 8 variables, which is relatively large given the short sample. As a robustness test, I use a 6-variable model, excluding stock and oil prices. As can be seen from Figure C.16, the results from this smaller model turn out to be consistent with the larger baseline model. The results are also robust to the lag order (Figure C.17 shows the responses using 3 or 9 lags) and the choice of deterministics (Figure C.18 shows responses of a model with a linear trend and a model excluding the dummy for the sovereign debt crisis).



First stage regression: F-statistic: 6.49, R^2: 1.12%

Figure C.16: Responses from Smaller VAR

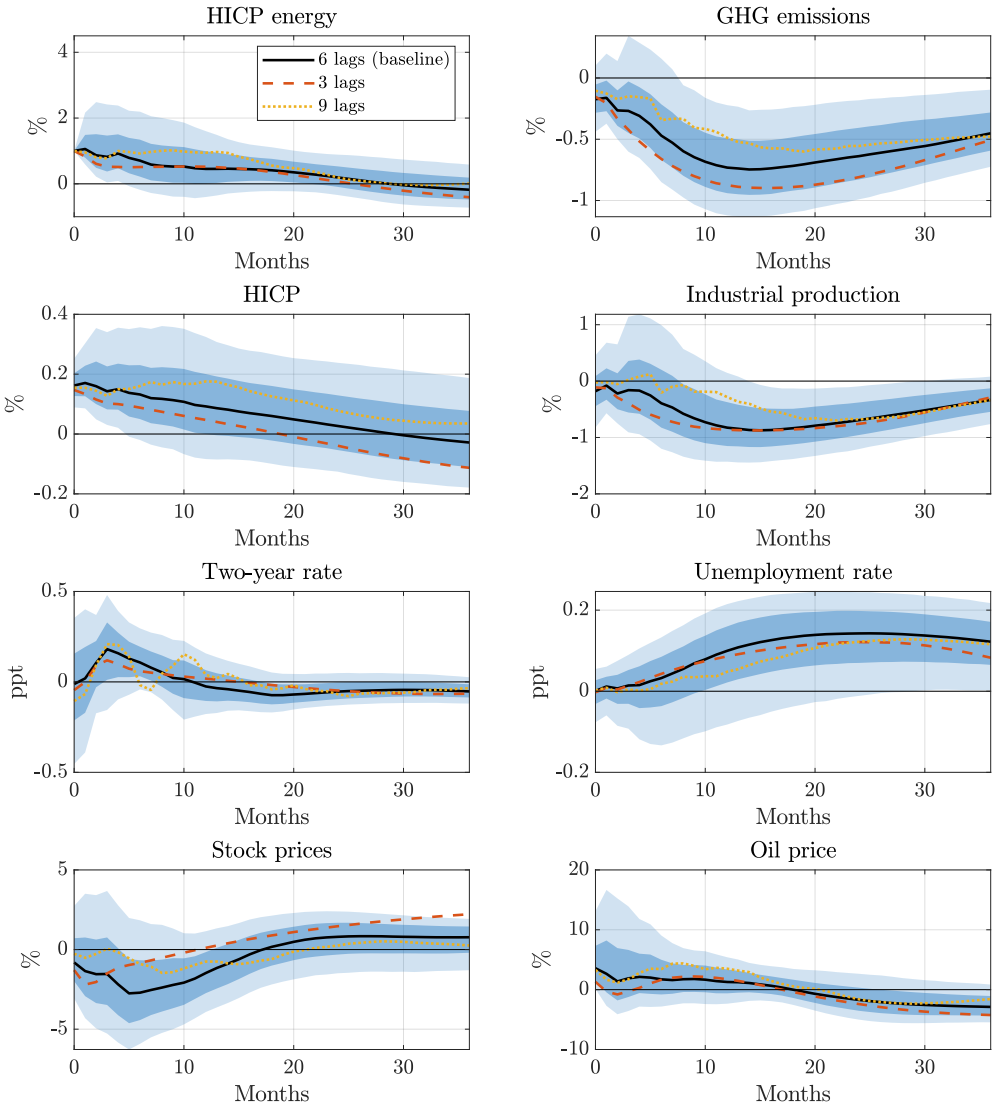


Figure C.17: Sensitivity to Lag Order

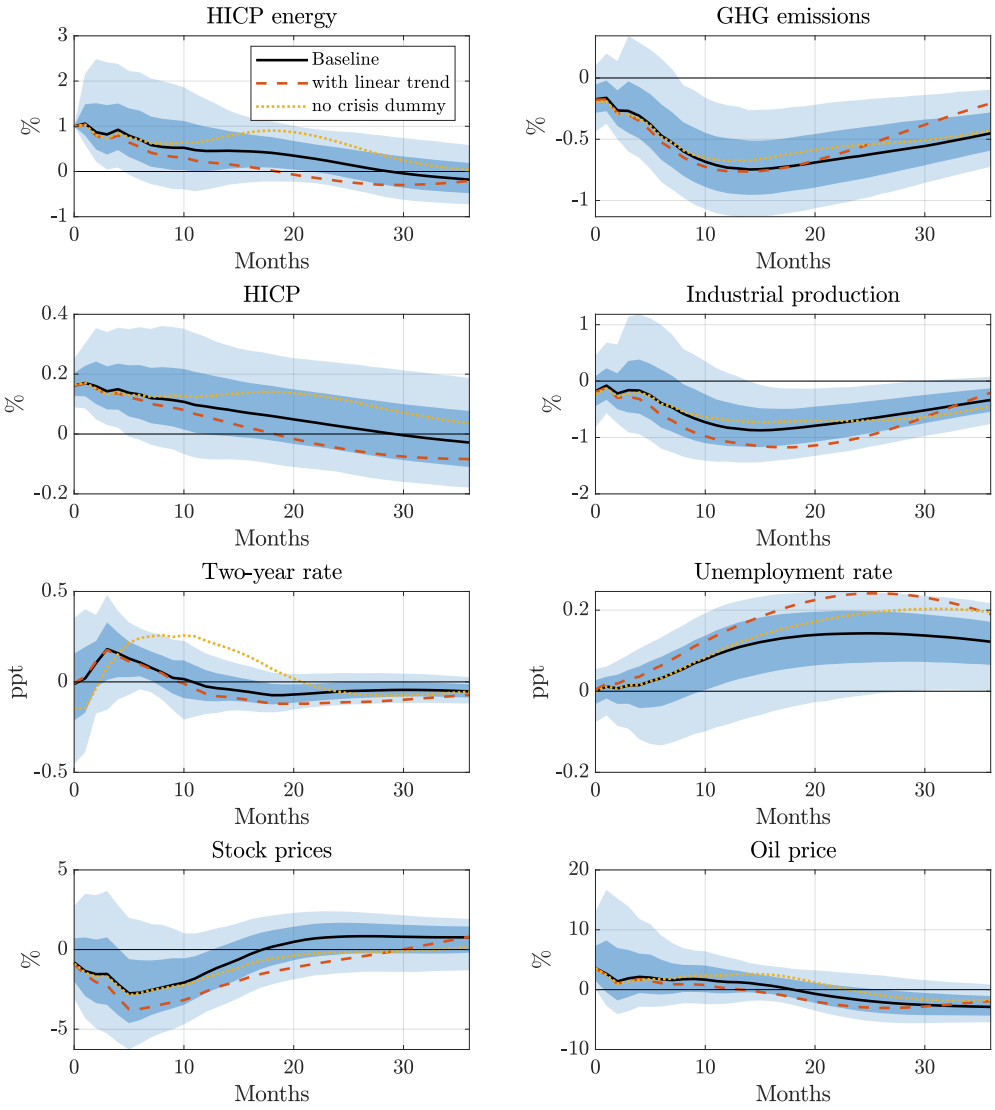


Figure C.18: Sensitivity to Deterministic Variables

C.5. Relaxing the invertibility requirement

A key advantage of the external instruments approach lies in its efficiency. However, this comes at the cost of assuming (partial) invertibility. If the invertibility assumption is not satisfied, this can lead to biased results (Li, Plagborg-Møller, and Wolf, 2024). To mitigate concerns about invertibility, I perform two additional exercises.

Internal instruments approach. First, I present results using the internal instruments approach (Ramey, 2011; Plagborg-Møller and Wolf, 2021), which involves placing the instrument first in a recursive VAR. This method is robust to non-invertibility.

Figure C.19 compares impulse responses from the internal instruments VAR

with the external instrument baseline. Since the system is now larger, I reduce the number of lags to three, improving stability without materially affecting the results. The responses remain qualitatively and quantitatively similar, though the estimated response of the two-year rate is somewhat less stable. Notably, the internal instrument responses are much less precisely estimated, as indicated by wider confidence bands. Overall, these findings suggest that the results are robust to relaxing the invertibility assumption, but assuming invertibility improves precision.

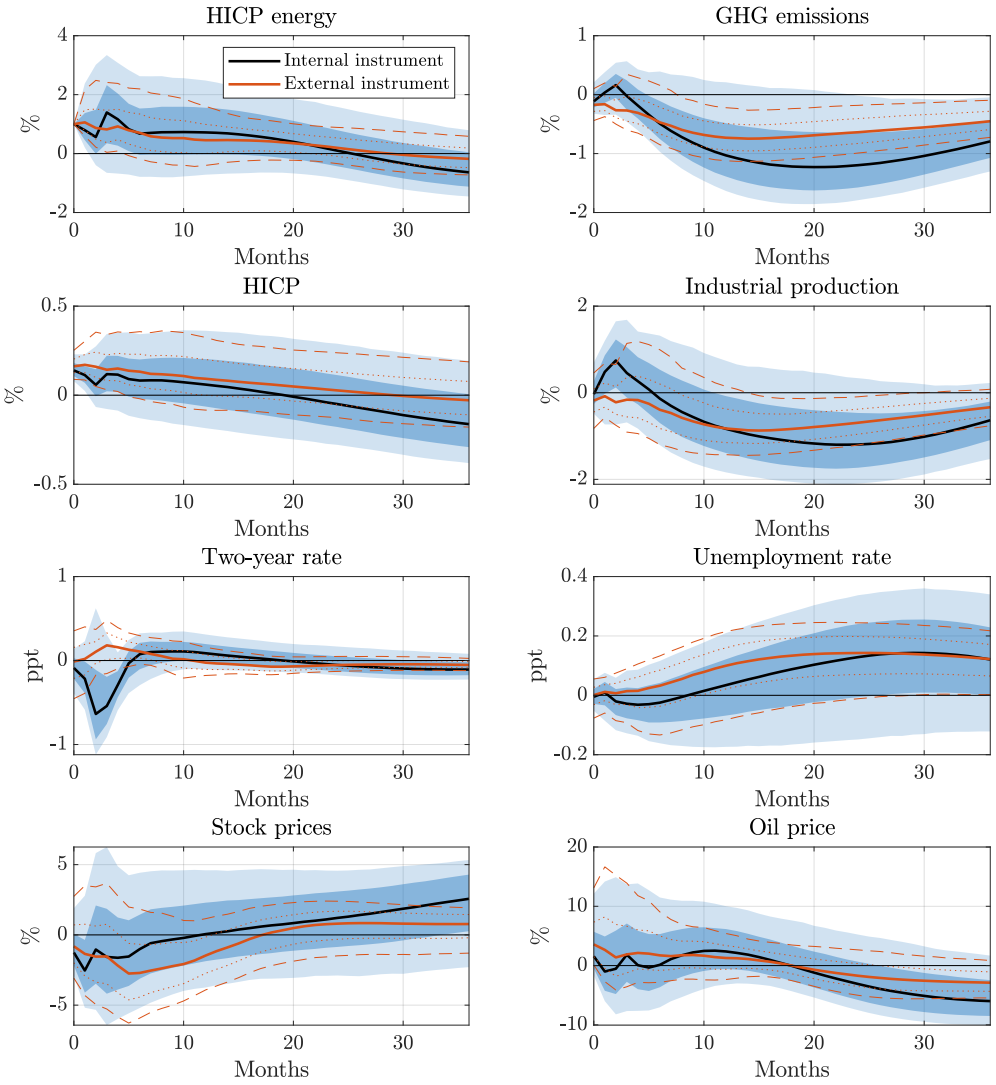


Figure C.19: Internal Versus External Instrument VAR

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

Local projection-instrumental variable approach. As an invertibility-robust alternative, I estimate the impulse responses using a local projections instrumental variable (LP-IV) approach à la Jordà, Schularick, and Taylor (2015) and Ramey and Zubairy (2018). To fix ideas, the dynamic causal effects, θ_h^i, can be estimated from the following set of regressions:

$$y_{i,t+h} = \beta_h^i + \theta_h^i y_{1,t} + \boldsymbol{\beta}_h^{i\prime} \mathbf{x}_{t-1} + \xi_{i,t,h}, \tag{3}$$

using z_t as an instrument for $y_{1,t}$. Here, $y_{i,t+h}$ is the outcome variable of interest, $y_{1,t}$ is the endogenous regressor, $\mathbf{x}_{t-1}$ is a vector of controls, $\xi_{i,t,h}$ is a potentially serially correlated error term, and h is the impulse response horizon. I use the same controls as in the internal instruments VAR. For inference, I follow again the lag-augmentation approach from Montiel Olea and Plagborg-Møller (2021).

As the impacts of carbon policy are potentially quite persistent, we want to look at the dynamic causal effects relatively far out. This is challenging in the LP-IV framework because of a power problem (Nakamura and Steinsson, 2018*a*): the macroeconomic outcomes several quarters or years out are affected by a myriad of other shocks, rendering the signal-to noise ratio from the relatively small carbon policy shocks too low to credibly identify the effects of interest. Additionally, each increase in the impulse horizon h reduces the degrees of freedom, further complicating estimation given the short sample. To address these limitations, I restrict the impulse horizon in the LP-IV regressions to 12 months.

Figure C.20 compares the responses from the LP-IV approach to those from the internal instrument VAR. Both methods rely on the same invertibility-robust identifying restrictions but differ in their estimation techniques. The results are broadly consistent, particularly for horizons up to one year. At longer horizons the differences tend to be larger, however, the responses are also much less precisely estimated.

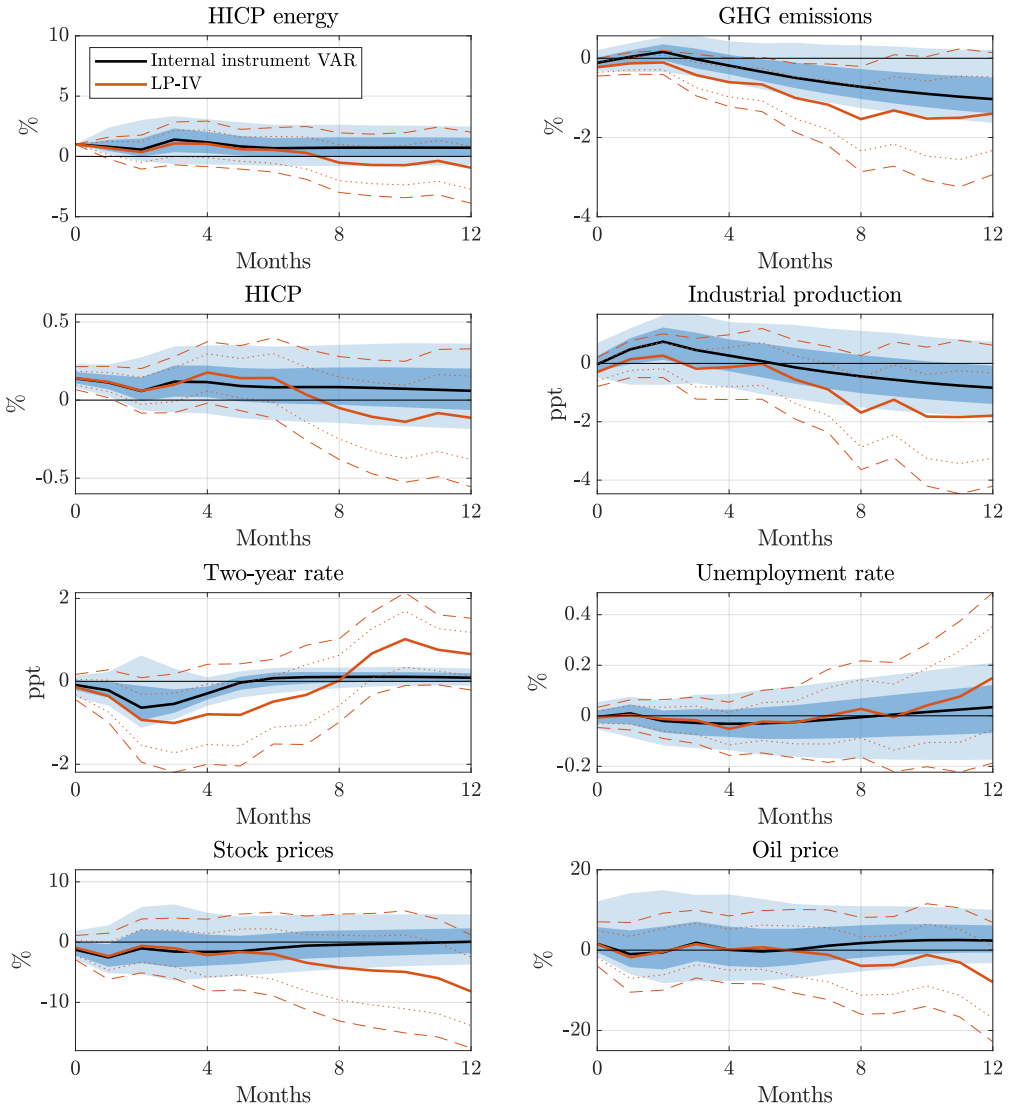


Figure C.20: Internal Instrument VAR Versus LP-IV

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

C.6. Estimation method

As discussed in the main text, I use VAR techniques for estimation because the sample is relatively short, and VARs offer a parsimonious characterization of the data. Another important assumption underlying this approach is that the finite-order VAR adequately approximates the data generating process, implying negligible lag truncation bias.

To assess the extent of lag truncation bias, I conduct two exercises. First, I estimate the responses using local projections, relaxing the dynamic VAR struc-

ture while maintaining the invertibility assumption. Second, I employ Bayesian methods to estimate a VAR with a longer lag order.

Frequentist approach. Section 3 in the main text discusses how local projections can be used to estimate effects on additional outcome variables. Here, I apply this approach to re-estimate the responses of the baseline model variables. This involves regressing each variable of interest on the identified VAR shock and its own lags, as in (8).

Alternatively, I employ the approach originally proposed in Jordà (2005). This amounts to directly estimating the reduced-form responses $\boldsymbol{\psi}_0^h$:

$$\mathbf{y}_{t+h} = \mathbf{b} + \boldsymbol{\psi}_0^h \mathbf{y}_t + \cdots + \boldsymbol{\psi}_p^h \mathbf{y}_{t-p} + \mathbf{u}_{t+h}, \tag{4}$$

and computing the structural responses as $\boldsymbol{\theta}_h = \boldsymbol{\psi}_0^h \boldsymbol{\theta}_0$. Both estimators are similar in spirit: they rely on the invertibility assumption but relax the dynamic structure of the VAR. In other words, both approaches allow for a more robust estimation of the autocovariance function. The key difference is that the first approach directly estimates structural impulse responses, whereas the second estimates reduced-form responses and translates them into structural responses using the structural impact vector.

Figure C.21 presents the results. The responses closely resemble those from the baseline VAR, with the most notable difference appearing in the emissions response, which is somewhat less stable. In addition, the local projection estimates are less precisely estimated.

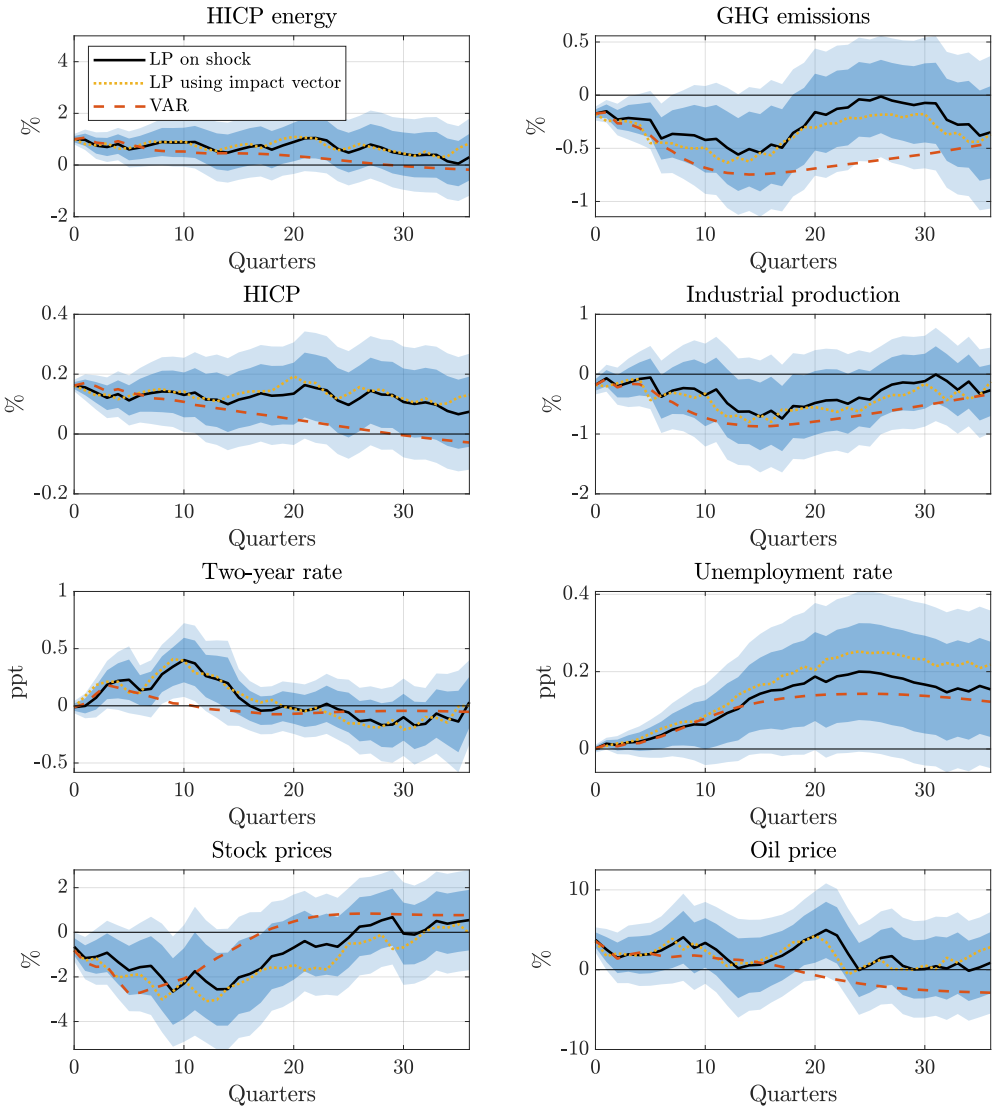


Figure C.21: Alternative Frequentist Estimation

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, estimated using (i) simple local projections on the carbon policy VAR shock and (ii) based on reduced-form LP responses and the structural impact vector from the VAR, compared to the baseline VAR responses. Solid and dashed lines: point estimates. Dark and light shaded areas: 68 and 90 percent confidence bands based on lag-augmentation approach.

Bayesian approach. Alternatively, I use Bayesian techniques for estimation. Specifically, I estimate a Bayesian VAR with shrinkage priors, allowing me to extend the number of lags up to 18. Specifically, I use a Minnesota prior with tightness 0.3 and a decay of 1. Figure C.22 presents the results. The responses based on the Bayesian models align well with the responses from the baseline VAR estimated using frequentist methods.

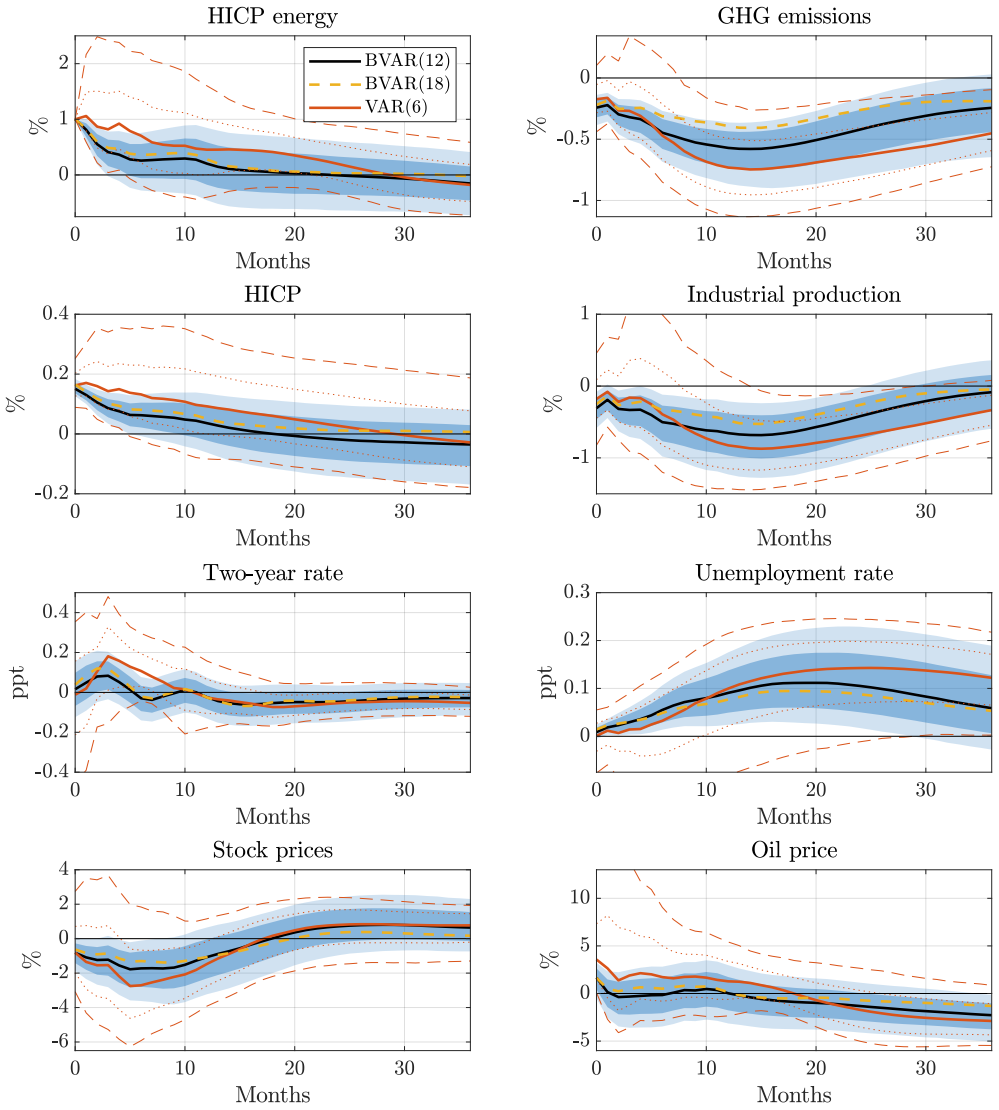


Figure C.22: Alternative Bayesian Estimation

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, estimated using a Bayesian VAR with Minnesota priors (tightness=0.3, decay=1). We consider BVARs with 12 and 18 lags, compared to the baseline frequentist VAR(6) responses. Solid and dashed lines: posterior medians/point estimate. Dark and light shaded areas: 68 and 90 percent HPD intervals. Light dashed lines: 68 and 90 percent bootstrapped confidence bands.

Overall, these findings suggest that the results are robust to the estimation method, suggesting that lag truncation bias is unlikely to be a major concern in this application.

C.7. Inference in local projections

The lag-augmentation approach used for inference in the local projections (8) does not account for the estimation uncertainty in the VAR shock, treating the estimated shock as if it were directly observed. To assess how consequential this

potential generated regressor problem is for inference, I alternatively compute the standard errors using bootstrapping techniques. Specifically, I independently sample from the residuals of the local projection model and the carbon policy shock, taking the sampling error of the carbon policy shock into account.

Figure C.23 compares the confidence bands for the responses of real GDP, consumption, investment and wages based on the baseline standard errors from the lag-augmentation approach to the standard errors constructed based on the bootstrap.

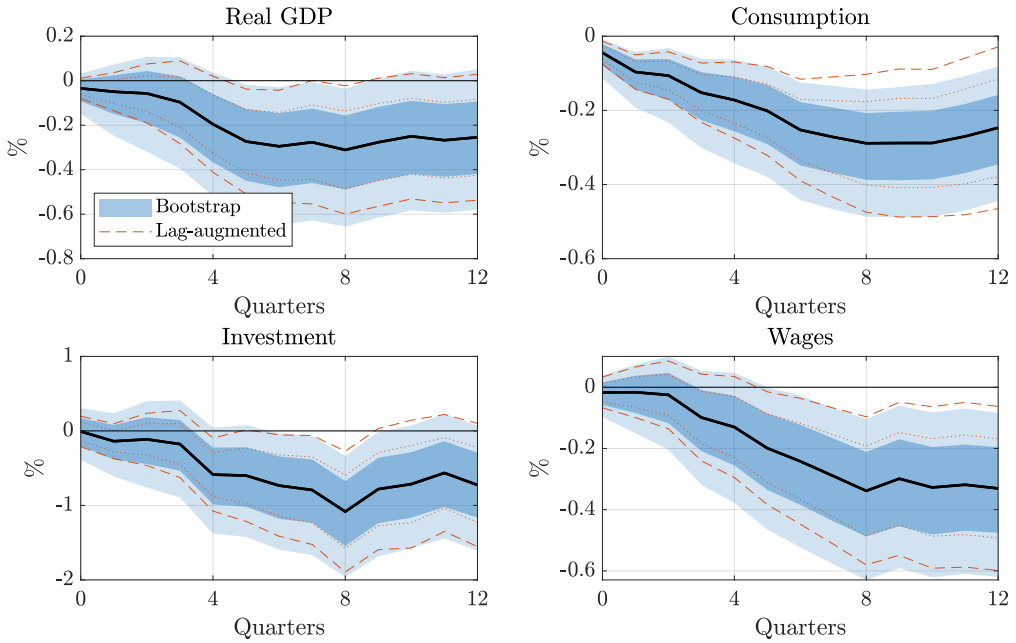


Figure C.23: Inference in Local Projections on Carbon Policy Shock

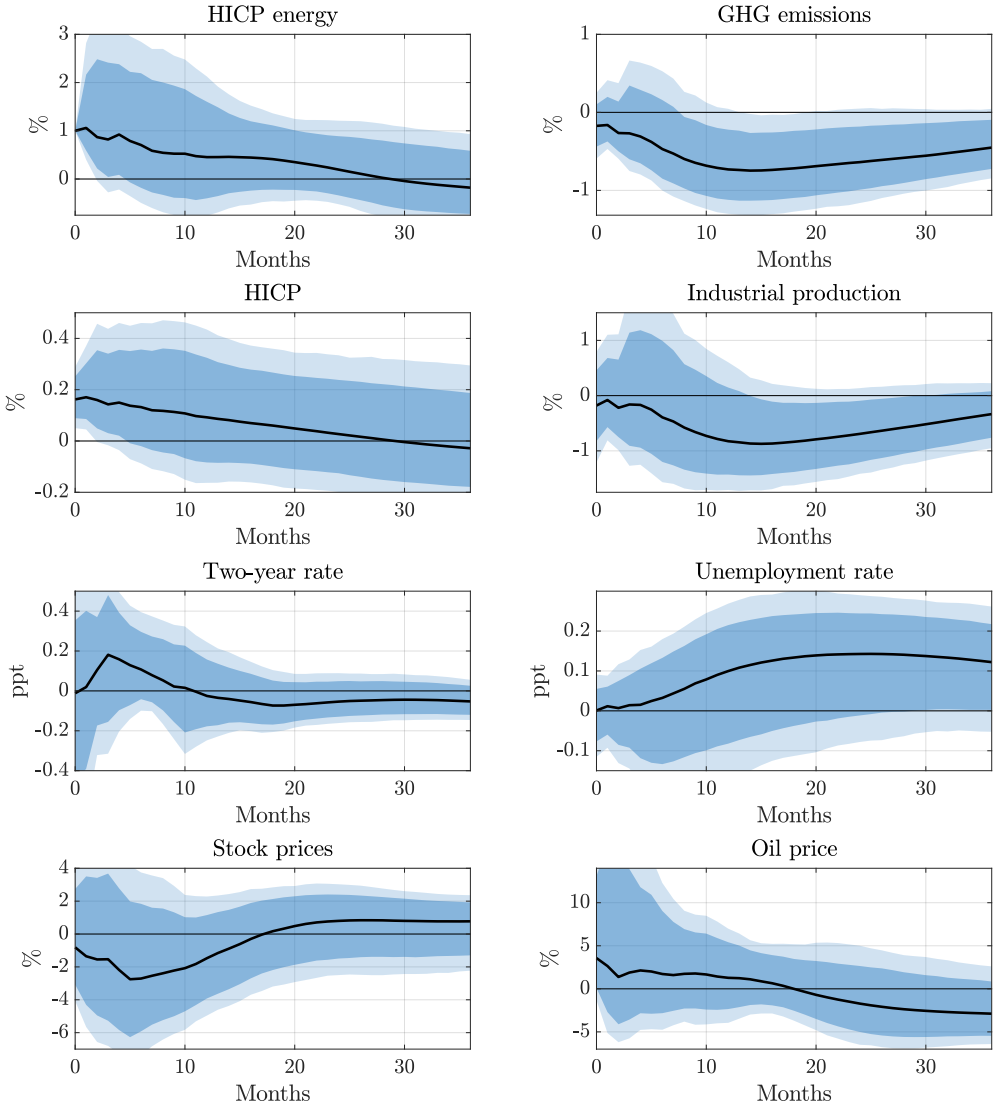
Notes: Impulse responses of a selection of quarterly variables estimated using local projections on the carbon policy shock. The responses are normalized to have the same quarterly peak effect on HICP energy as in the baseline model. The bootstrapped 68 and 90 percent confidence bands are depicted as the light and dark blue shaded areas, respectively. For comparison, the confidence bands based on the lag-augmentation approach, that do not account for sampling uncertainty of the carbon policy shock, are included as the dashed and dotted orange lines.

Interestingly, the confidence bands from both methods are very similar, with the bootstrap-based bands being only marginally wider. This suggests that accounting for the sampling error in the generated regressor does not significantly alter the conclusions in the present application.

D. Additional Aggregate Results

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

D.1. Main results with 95 percent bands



First stage regression: robust F-statistic: 16.85, R^2: 2.38%

Figure D.1: VAR Responses with 95 Percent Bands

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, estimated based on the VAR model (4) using the refined carbon policy surprise series from specification (d) as an instrument. Lag order: 6. Solid line: point estimate. Dark and light shaded areas: 90 and 95 percent confidence bands based on moving-block bootstrap.

Throughout the paper, I report 68 and 90 percent confidence bands, which is standard practice in the macroeconomics literature, acknowledging the power

problems resulting from the relatively short available sample periods. In microeconomic work and in science, 90 and 95 percent confidence bands are more standard. To allow for better comparability with these literatures, I reproduce the main results from the paper with 90 and 95 percent bands in Figures D.1-D.2.

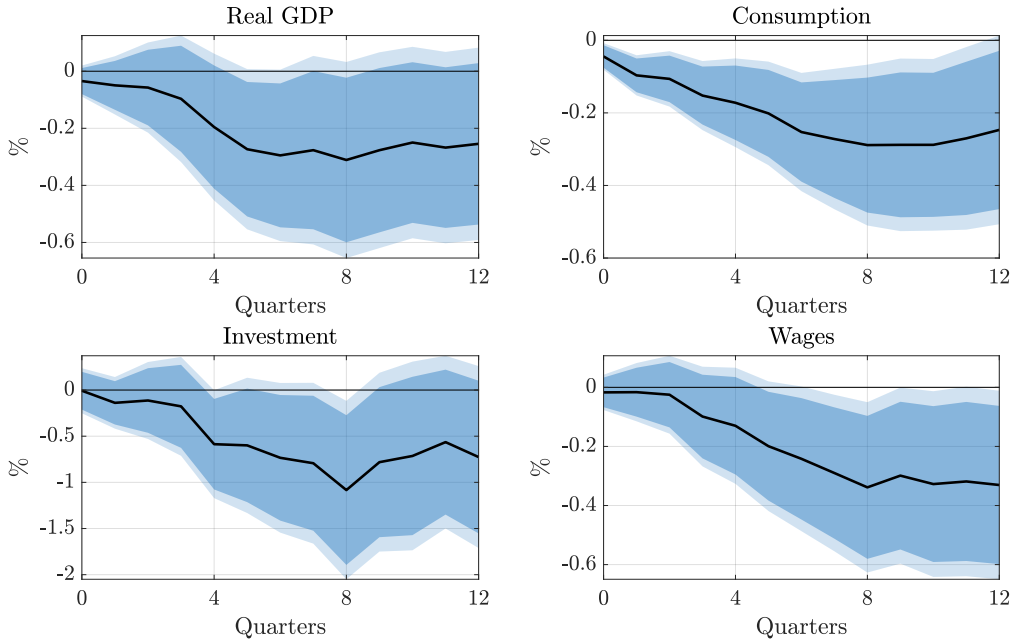


Figure D.2: Local Projection Responses with 95 Percent Bands

Notes: Impulse responses of a selection of quarterly variables, estimated using local projections (8) of the variable of interest on the carbon policy shock from the baseline VAR. Responses are normalized to have the same quarterly peak effect on HICP energy as in the baseline VAR. Controls: 3 lags of outcome variable and linear trend. Solid line: point estimate. Dark and light shaded areas: 90 and 95 percent confidence bands based on lag-augmentation approach.

D.2. Core versus headline HICP

In the main text, I document a significant and persistent increase in headline HICP. An important question that has also relevant implications for the conduct of monetary policy is how the shock transmits to core consumer prices. To this end, I re-estimate the model substituting headline for core HICP. Figure D.3 presents the response for core HICP together with the HICP headline and energy component from the baseline model. The response of core consumer prices is more muted and less precisely estimated. This illustrates that this is really a shock to relative prices. Reassuringly, all other responses from the model with core HICP are very similar to the baseline case.

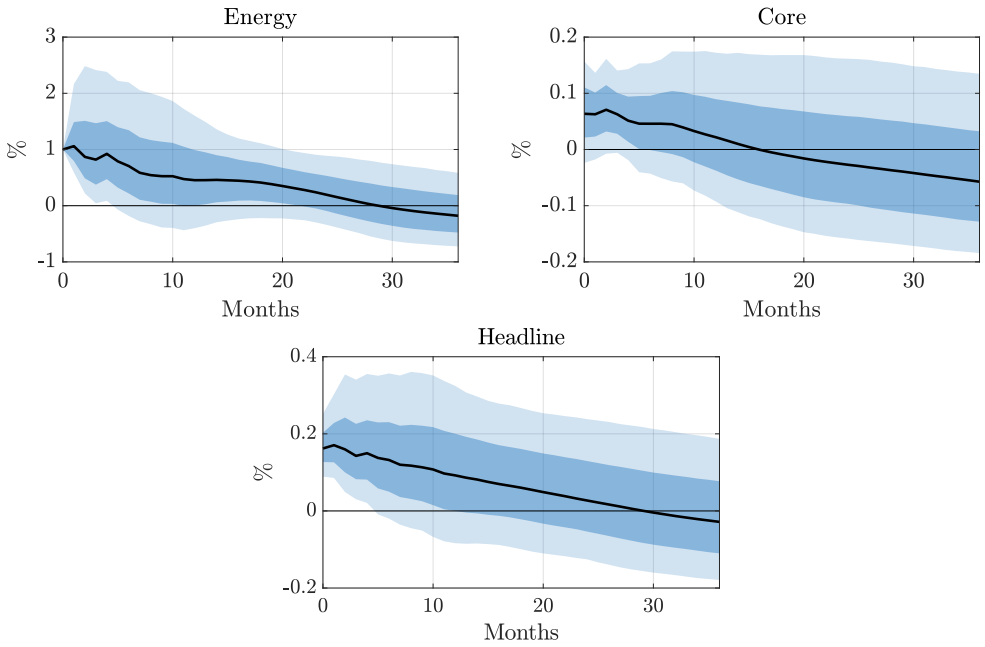


Figure D.3: Headline Versus Core HICP

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

D.3. Variance Decomposition

To better understand how carbon policy shocks have contributed to variations in macroeconomic and financial variables, I perform a variance decomposition exercise in addition to the historical decomposition presented in the paper. I do so both under the invertibility assumption maintained in the external instrument VAR as well as under weaker assumptions in the context of a general SVMA model, as proposed by Plagborg-Møller and Wolf (2022). In particular, I perform a standard forecast error variance decomposition in the SVAR and compute forecast variance ratios for the SVMA. The forecast variance ratio for variable i at horizon h is given by

$$FVR_{i,h} = 1 - \frac{\text{Var}(y_{i,t+h}|\{y_\tau\}_{-\infty<\tau\leq t}, \{\varepsilon_{1,\tau}\}_{t<\tau<\infty})}{\text{Var}(y_{i,t+h}|\{y_\tau\}_{-\infty<\tau\leq t})}, \tag{5}$$

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 (2022) show that this statistic is interval-identified under the assumption that a valid instrument is available. Under the assumption of recoverablity, the ratio is point-identified by the upper bound.

Table D.1: Variance Decomposition

h	HICP energy	Emissions	HICP	IP	Two-year rate	Unemp. rate	Stock prices	Oil price
Panel A: Forecast variance decomposition (SVAR-IV)								
6	0.21	0.22	0.32	0.03	0.04	0.01	0.06	0.04
	[0.03, 0.39]	[0.02, 0.49]	[0.03, 0.52]	[0.01, 0.27]	[0.01, 0.22]	[0.00, 0.30]	[0.01, 0.31]	[0.01, 0.27]
12	0.15	0.35	0.21	0.09	0.03	0.05	0.07	0.04
	[0.03, 0.36]	[0.03, 0.56]	[0.03, 0.45]	[0.01, 0.32]	[0.02, 0.21]	[0.01, 0.32]	[0.01, 0.31]	[0.01, 0.27]
24	0.13	0.42	0.12	0.18	0.05	0.12	0.06	0.05
	[0.03, 0.33]	[0.03, 0.54]	[0.02, 0.38]	[0.02, 0.35]	[0.02, 0.22]	[0.01, 0.36]	[0.01, 0.30]	[0.02, 0.26]
36	0.12	0.40	0.09	0.20	0.06	0.15	0.07	0.07
	[0.03, 0.30]	[0.03, 0.51]	[0.02, 0.35]	[0.03, 0.34]	[0.03, 0.23]	[0.01, 0.36]	[0.02, 0.31]	[0.03, 0.26]
Forecast variance ratio (SVMA-IV)								
6	0.04, 0.25	0.01, 0.05	0.05, 0.30	0.00, 0.03	0.03, 0.22	0.00, 0.03	0.00, 0.01	0.02, 0.12
	[0.01, 0.39]	[0.00, 0.23]	[0.01, 0.44]	[0.00, 0.23]	[0.01, 0.41]	[0.00, 0.23]	[0.00, 0.20]	[0.00, 0.31]
12	0.03, 0.19	0.02, 0.16	0.03, 0.22	0.00, 0.02	0.04, 0.23	0.00, 0.01	0.00, 0.01	0.02, 0.12
	[0.01, 0.38]	[0.00, 0.39]	[0.00, 0.43]	[0.00, 0.28]	[0.01, 0.41]	[0.00, 0.25]	[0.00, 0.28]	[0.01, 0.32]
24	0.02, 0.16	0.05, 0.30	0.03, 0.16	0.01, 0.06	0.03, 0.22	0.00, 0.02	0.00, 0.01	0.02, 0.11
	[0.01, 0.37]	[0.00, 0.47]	[0.00, 0.44]	[0.00, 0.30]	[0.02, 0.37]	[0.00, 0.30]	[0.00, 0.28]	[0.01, 0.31]
36	0.02, 0.14	0.05, 0.31	0.02, 0.13	0.01, 0.09	0.04, 0.23	0.00, 0.03	0.00, 0.01	0.02, 0.11
	[0.01, 0.33]	[0.00, 0.46]	[0.00, 0.42]	[0.00, 0.31]	[0.02, 0.37]	[0.00, 0.33]	[0.00, 0.27]	[0.01, 0.30]

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

The results are shown in Table D.1. Carbon policy shocks have contributed meaningfully to historical variations in the variables of interest. Under the invertibility assumption (Panel A), they account for about 20 percent of the variations in energy prices and around 20 percent of the short-run variations in emissions, which goes up to roughly 40 percent at the 3-year horizon. Turning to the macroeconomic variables, we can see that they explain a substantial part of variations in the headline HICP, especially at shorter horizons, and a non-negligible fraction of the variations in industrial production and the unemployment rate at longer horizons. The shocks explain only little of the variations in the two-year rate, stock prices and oil prices. The forecast variance ratios in Panel B, which dispense from the assumption of invertibility, paint a similar picture.

D.4. Financial conditions and uncertainty

To better understand how the shock transmits to the economy, I study the responses of indicators for financing conditions and financial uncertainty, see Figure D.4. The responses turn out to be largely insignificant, suggesting that these variables do not appear to play a dominant role in the transmission of the carbon policy shock.

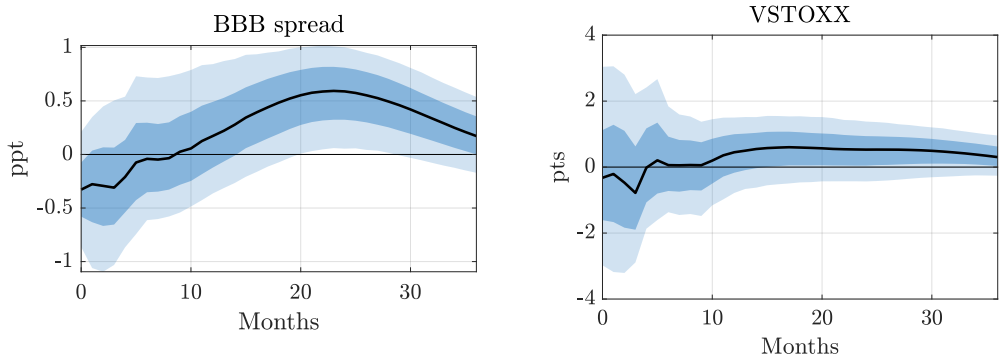


Figure D.4: Financial Conditions and Uncertainty

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

D.5. Green patenting

I perform two robustness checks on the patenting responses. First, to better account for potentially low-quality patents, I further restrict our sample to patents that have been cited more than once. Second, following Acemoglu et al. (2023) I exclude technologies that do not directly compete with fossil-fuel technologies, including those aimed at reducing pollution from fossil-fuel electricity generation (Y02E20), improving grid efficiency (Y02E40) or storage (Y02E60). The results turn out to be robust, see Figure D.5.

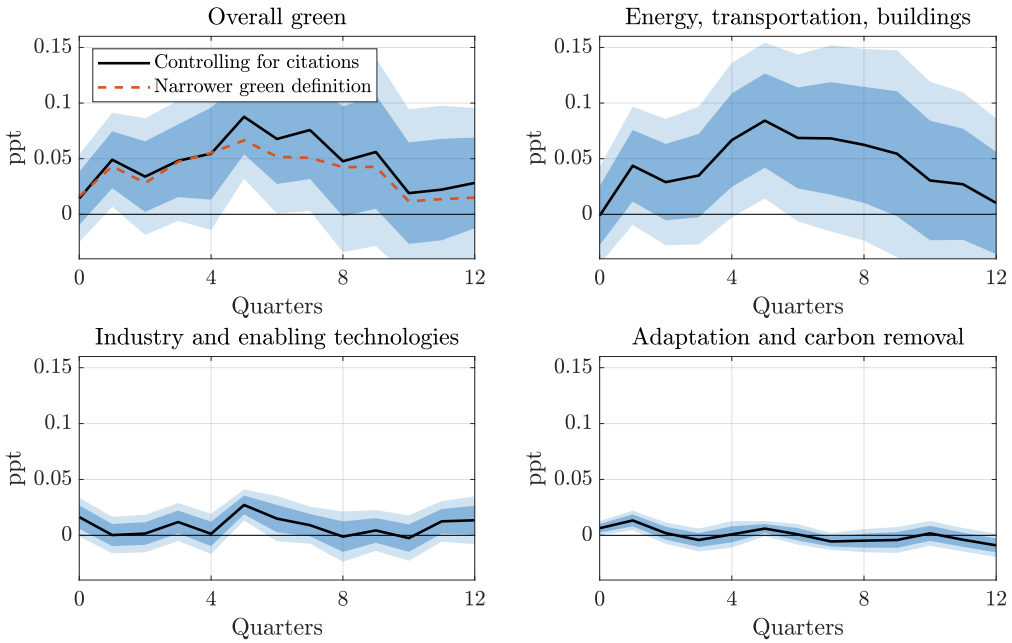


Figure D.5: Controlling for Patent Quality

Notes: Impulse responses of green patenting, as measured by the number of climate change mitigation patents as a share of all biadic patents file, imposing the additional restriction that patents have at least one citation. The figure reports responses for overall green patenting; mitigation technologies in energy generation, transportation, and buildings; mitigation in industry; and adaptation and carbon removal technologies. For overall green patenting, I also show results using a more narrow definition of green patents. Solid and dashed lines: point estimates. Dark and light shaded areas: 68 and 90 percent confidence bands based on lag-augmentation approach.

E. Additional Micro Results

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

E.1. Aggregate effects for the UK

Because of data availability, the household-level analysis is carried out for the UK. As a validating exercise, I have verified that the aggregate effects on the UK, as measured by real GDP, consumption and investment, are comparable to the EU level responses, though somewhat less persistent, see Figure E.1.

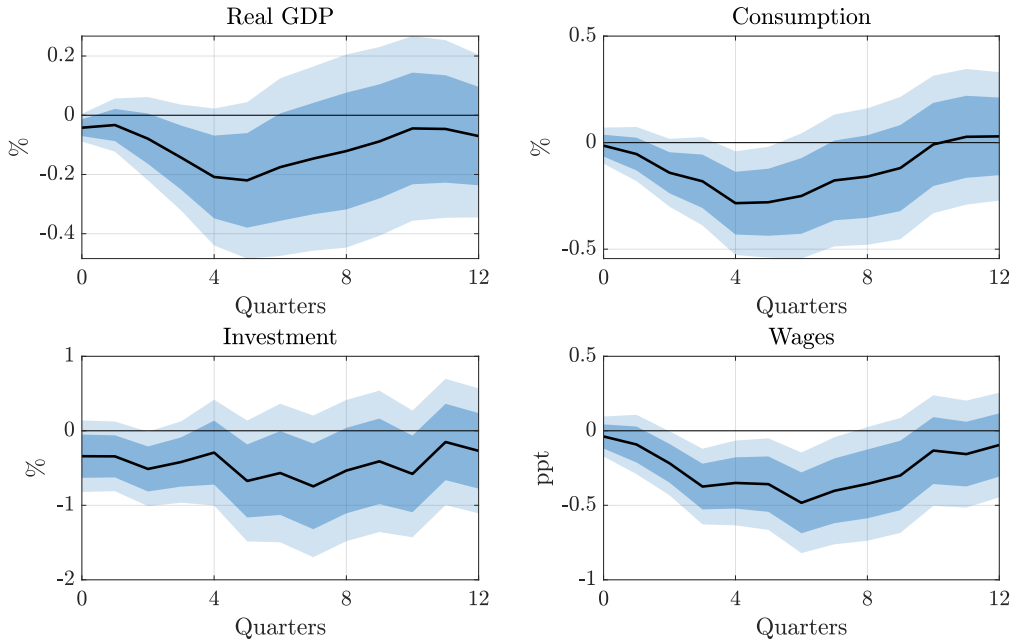


Figure E.1: Effect on GDP, Consumption, Investment and Wages in the UK

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

E.2. Additional descriptive statistics

Figure E.2 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.

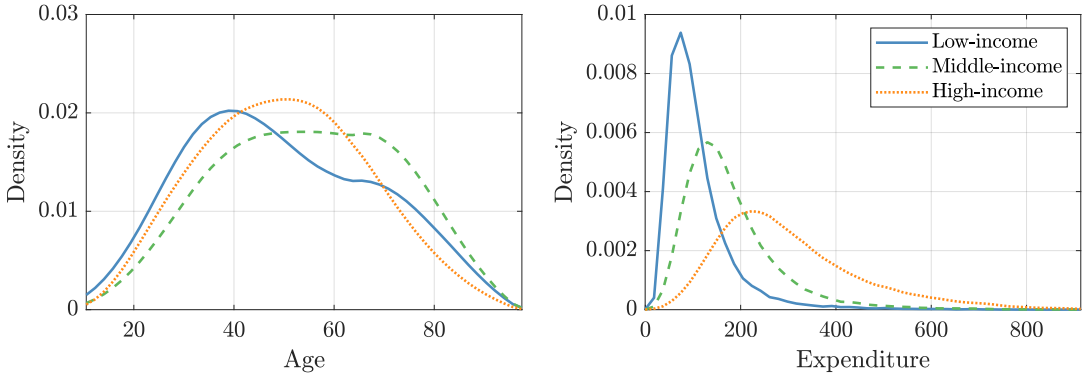


Figure E.2: Empirical Distribution of Age and Total Expenditure in the LCFS

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

Figure E.3 depicts the evolution of different households characteristics, including age, education and housing tenure, over time. 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 E.3: Evolution of Household Characteristics by Income Group

Notes: Evolution of age, education, and housing tenure status over time by income group.

E.3. Aggregate responses

Before studying at the heterogeneous expenditure responses by income group, I look at the aggregate expenditure responses as a validating exercise. The results are shown in Figures E.4. The response of aggregated expenditure from household micro data is very similar to the consumption response from national statistics—both in terms of shape and magnitude. This supports the notion that the survey data is indeed representative for the macroeconomy. For completeness, I also report the aggregated responses for different expenditure categories.

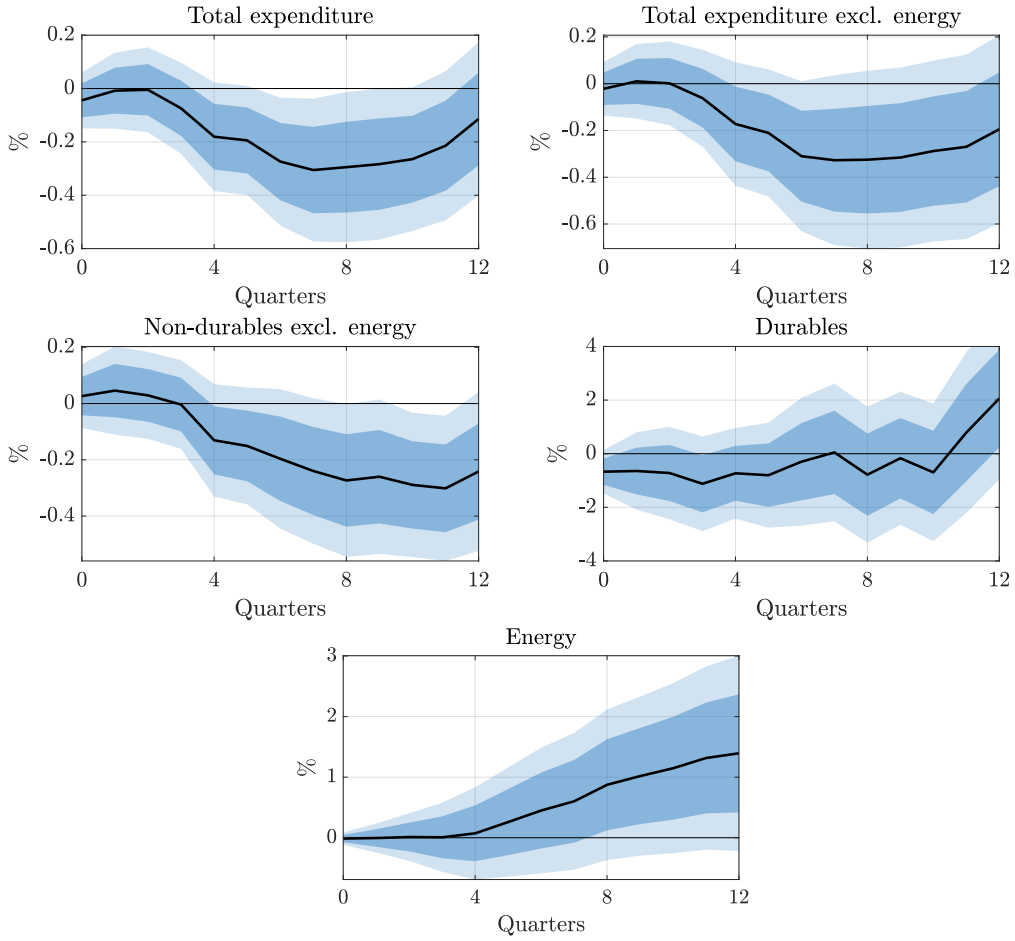


Figure E.4: Aggregate Expenditure Responses

E.4. Smoothing impulse responses

In the LCFS, households interviewed at time t are typically asked to report expenditure over the previous three months (with the exception of non-durable consumption which refers to the previous two weeks). To eliminate some of the noise inherent in survey data, I smooth the expenditure and income measures with a backward-looking (current and previous four quarters) moving average,

as in Cloyne, Ferreira, and Surico (2020). However, as shown in Figure E.5, I obtain similar results 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).

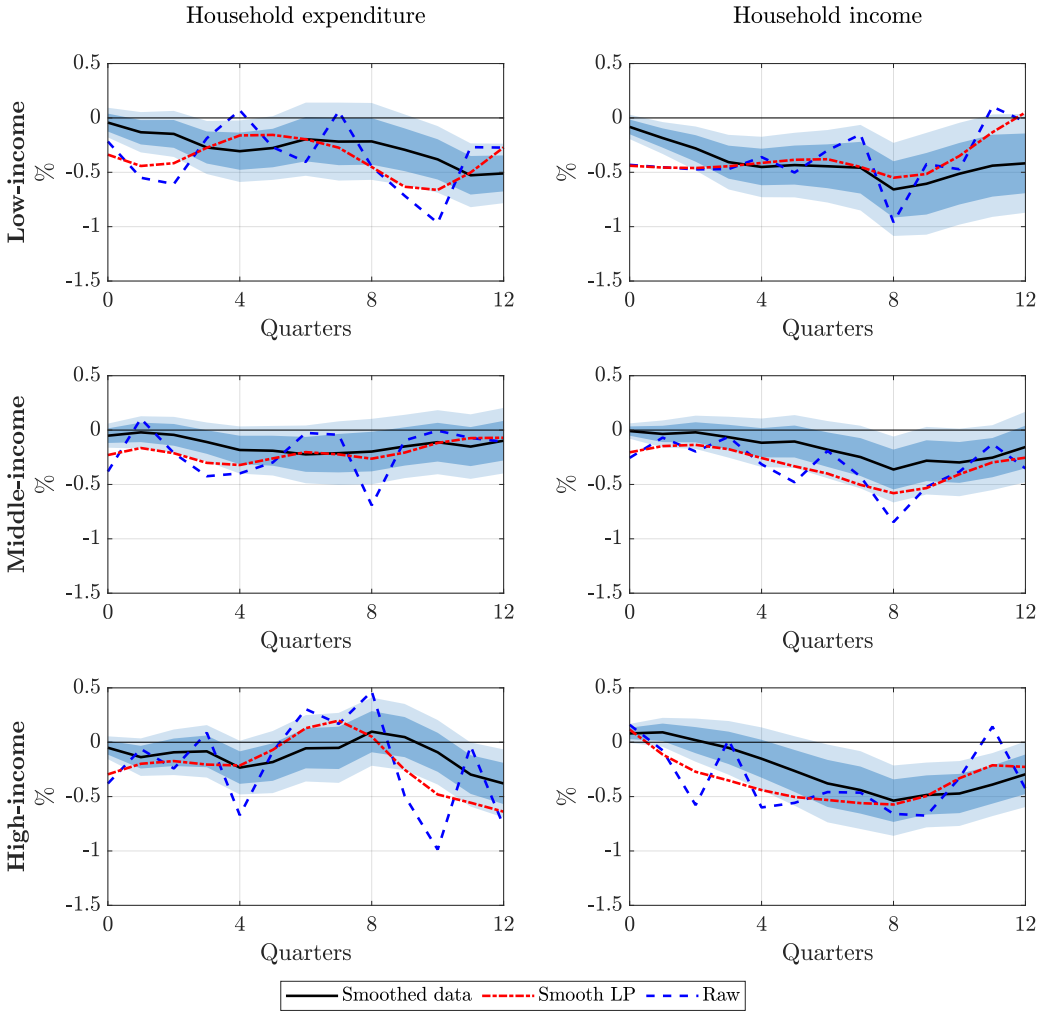


Figure E.5: Sensitivity with Respect to Smoothing of Responses

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

E.5. Robustness concerning grouping

To mitigate concerns about endogenous changes in the grouping variable, I study the responses of current and normal disposable income in Figure E.6. We can see that both variables are rather slow-moving. Current income starts to fall significantly after about a year. In contrast, the response of normal disposable income moves less and is insignificant, supporting its validity as a grouping variable.

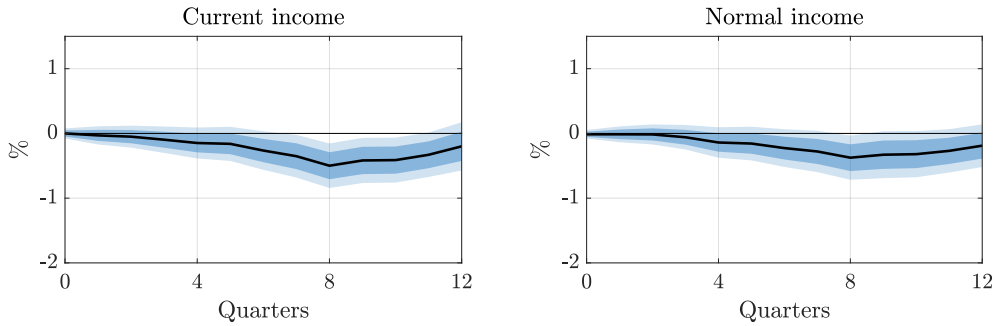


Figure E.6: Responses of Current and Normal Income

As discussed in the main text, the normal income variable can be thought of as a proxy for permanent income. As a robustness check, I compute estimates for permanent income from a Mincerian-type regressions. Specifically, I use age, education, ethnicity, sex, martial status, occupation, the source of the main household income, as well as interactions between age and education, and between age and sex as predictors, as in Alves et al. (2020).

Figure E.7 shows the responses by permanent income group. The results turn out to be robust.

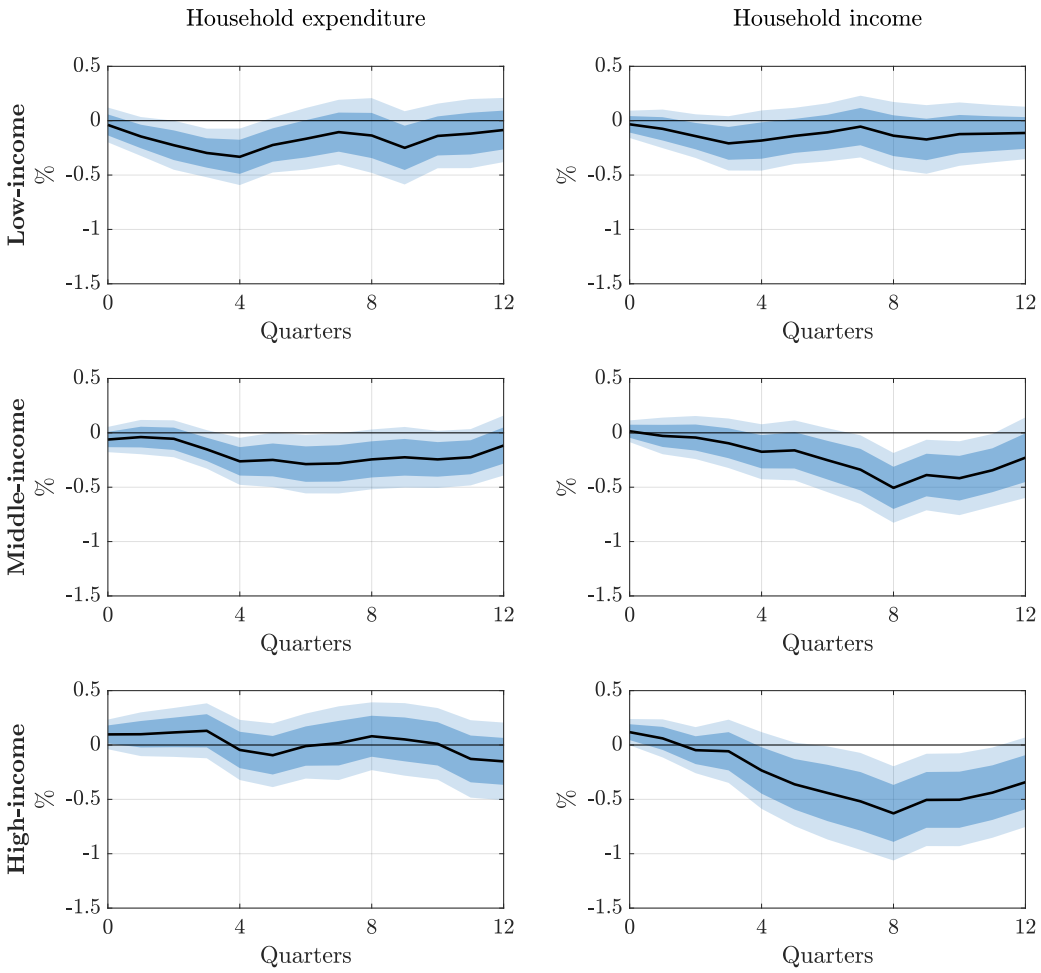


Figure E.7: Expenditure and Income Responses by Permanent Income

Notes: Impulse responses of total expenditure excluding housing and current total 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).

E.6. Selection

To mitigate concerns about selection, I use a number of different grouping variables, including age, education and housing tenure. From Figures E.8-E.10, we can see that none of these alternative grouping variables can account for the patterns uncovered for income, suggesting that the estimates 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.

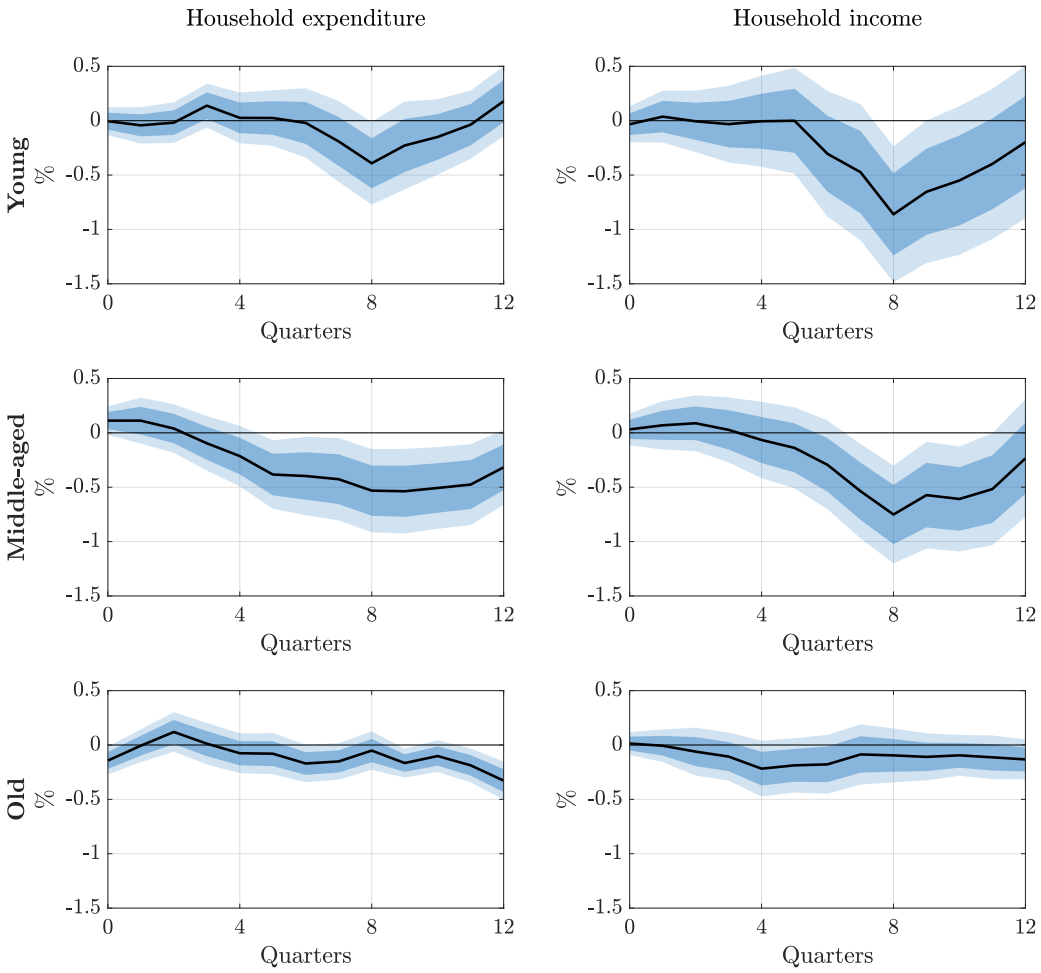


Figure E.8: Household Expenditure and Income Responses by Age Group

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

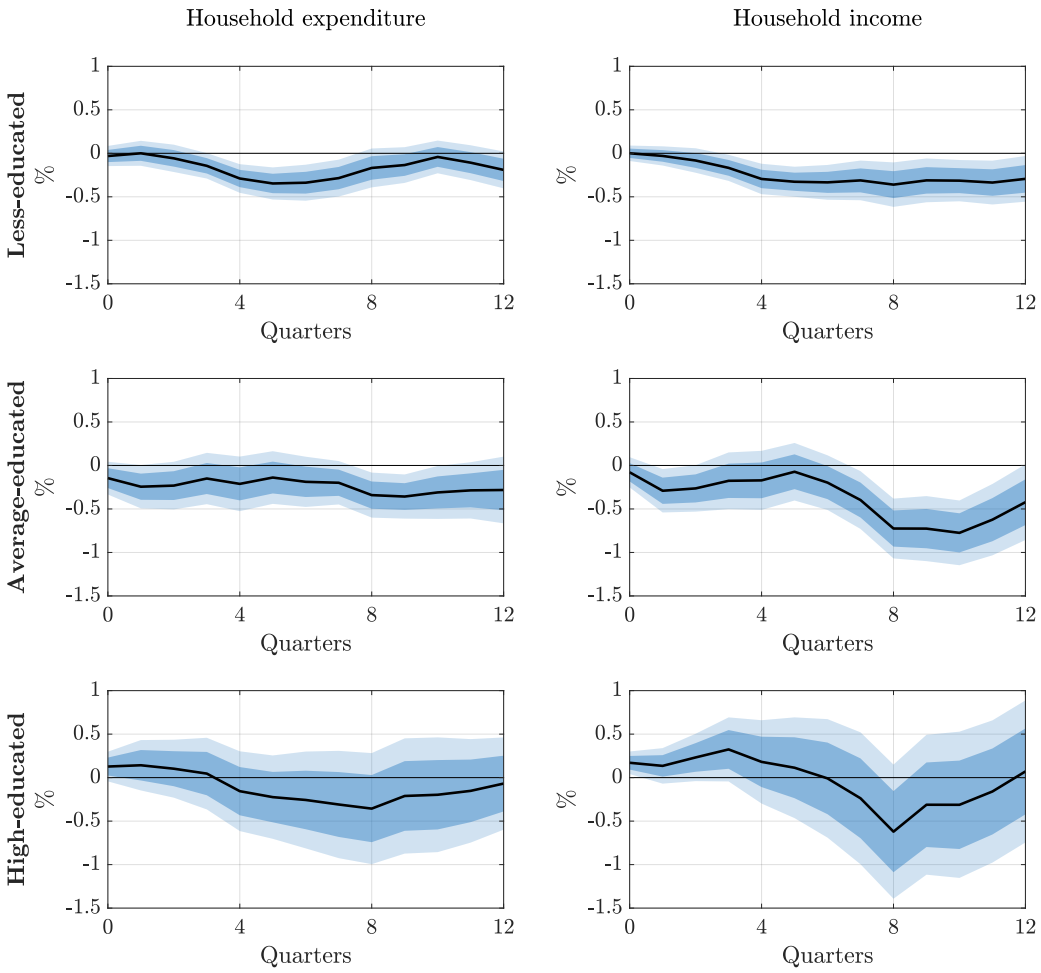


Figure E.9: Household Expenditure and Income Responses by Education Status

Notes: Impulse responses of total expenditure excluding housing and current total 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).

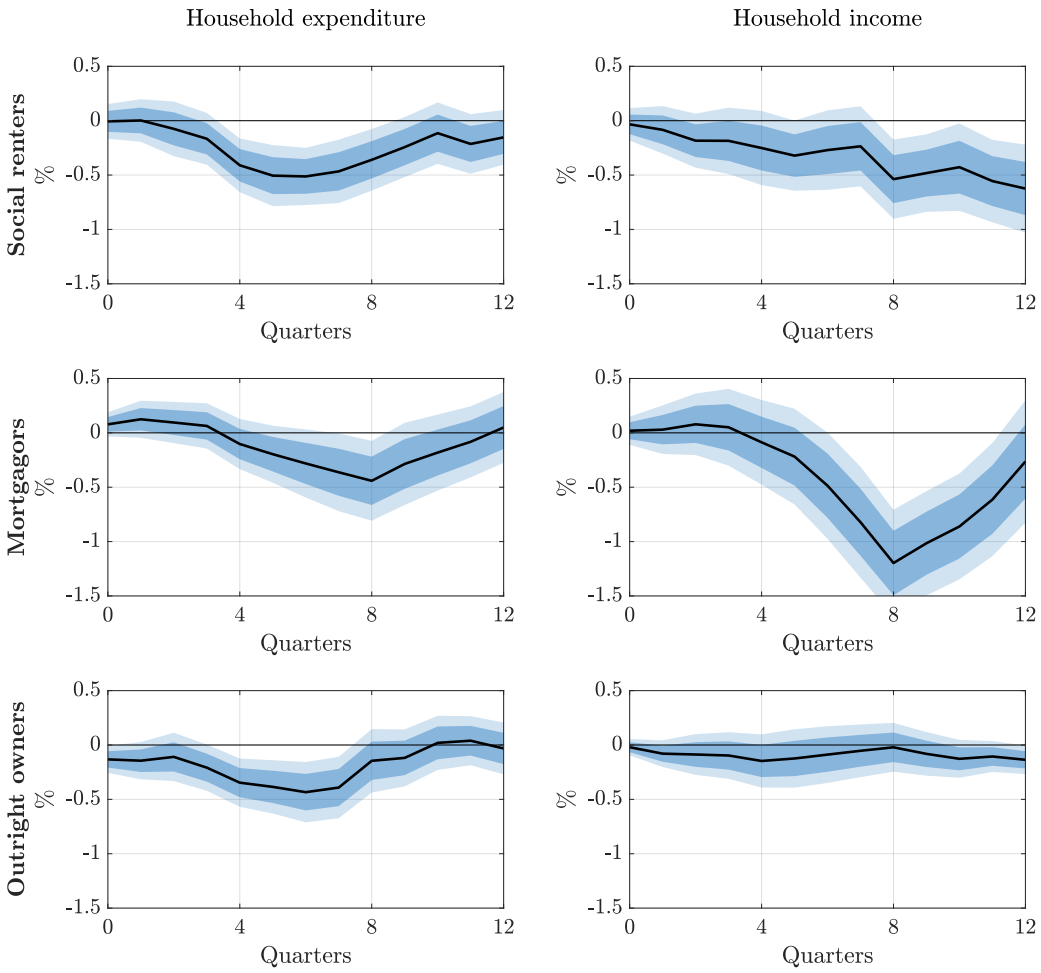


Figure E.10: Household Expenditure and Income Responses by Housing Tenure

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

E.7. Expenditure responses

How do different components of household expenditure respond to carbon policy shocks? Figure E.11 shows the expenditure responses, broken down by energy, non-durables excluding energy and durable spending. These numbers are used to arrive at the cumulative figures in Table 3.

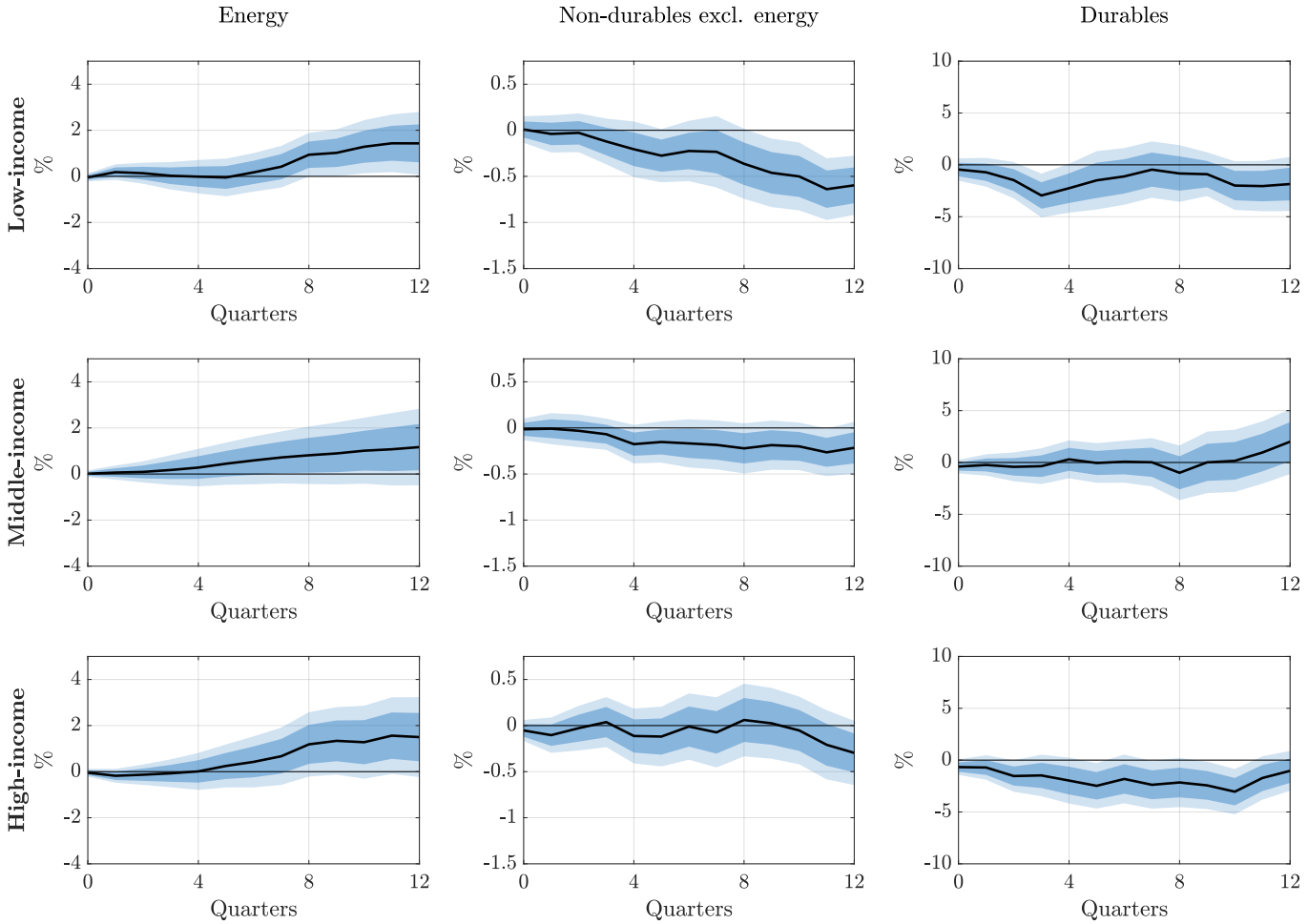


Figure E.11: Energy, Non-durables and Durables Expenditure Responses by Income Group

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

E.8. What drives the income response?

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

Table E.1 shows the data on sectoral energy intensity and estimated demand sensitivity together with the resulting classification. I define high energy intensive sectors as sectors with an energy intensity above 5 and high demand sensitive sectors as sectors with a demand sensitivity in excess of 0.5. Choosing the threshold involves some judgment. As a robustness check, I have excluded/included the sectors closest to the two thresholds for both groupings. The results turn out to be not sensitive to the precise level of the threshold.

Table E.1: Sectors by Energy Intensity and Demand Sensitivity

Panel A: Energy intensity and estimated demand sensitivity

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

Panel B: Sector classification

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

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

Finally, another source of heterogeneity in the income response is the income composition. To better understand this, I study the responses of labor earnings and financial income. The earnings of low-income households fall more promptly than for higher-income households, consistent with the results on total income. On the other hand, the financial income of low- and middle-income households barely shows a response, reflecting the fact that these households own very little

financial assets. In contrast, high-income households experience a temporary fall in their financial income in the short run, which however subsequently reverts (consistent with the stock market response).

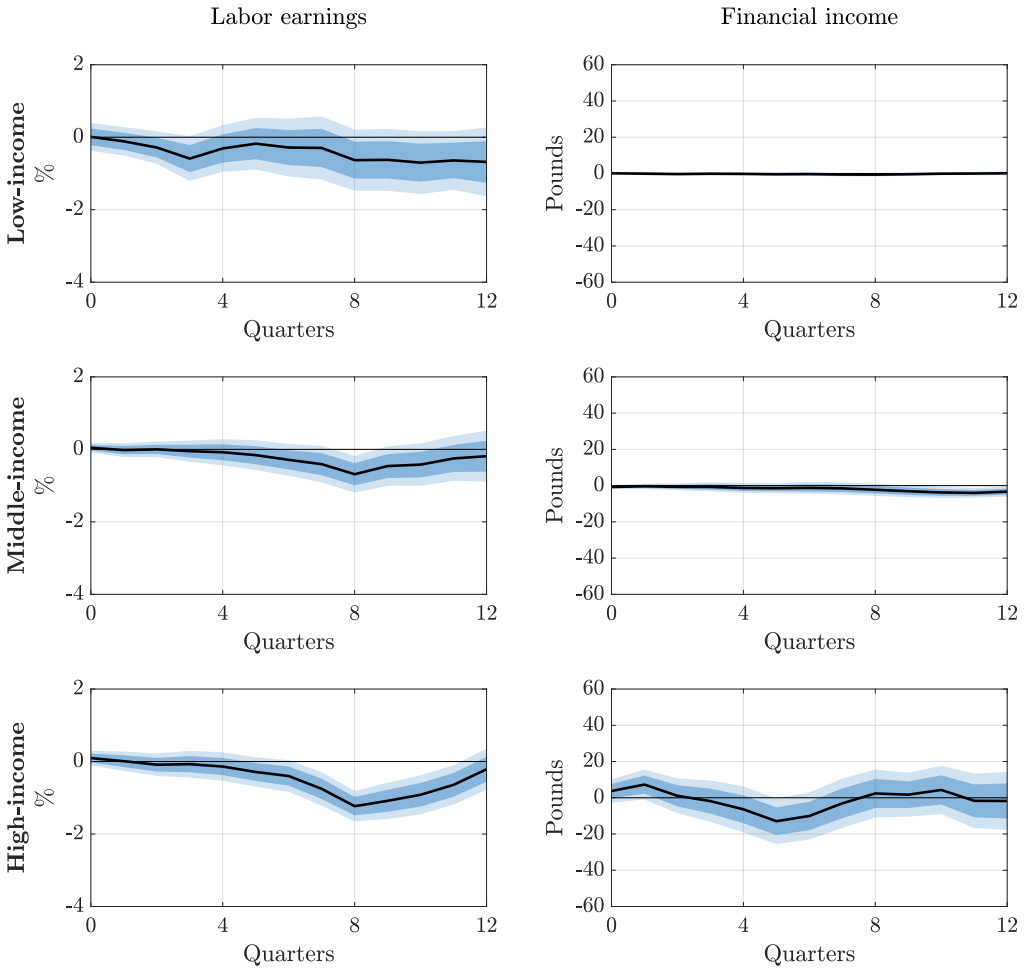


Figure E.12: Responses of Earnings and Financial Income

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

E.9. External validity

To mitigate concerns regarding external validity, I confirm the main results on the heterogeneity in household expenditure by income group using data for Denmark and Spain. As can be seen from Figure E.13, the expenditure response turns out to be significant and persistent for low-income households, while high-income households are much less affected. These findings confirm the results for the UK, supporting the external validity of the results.

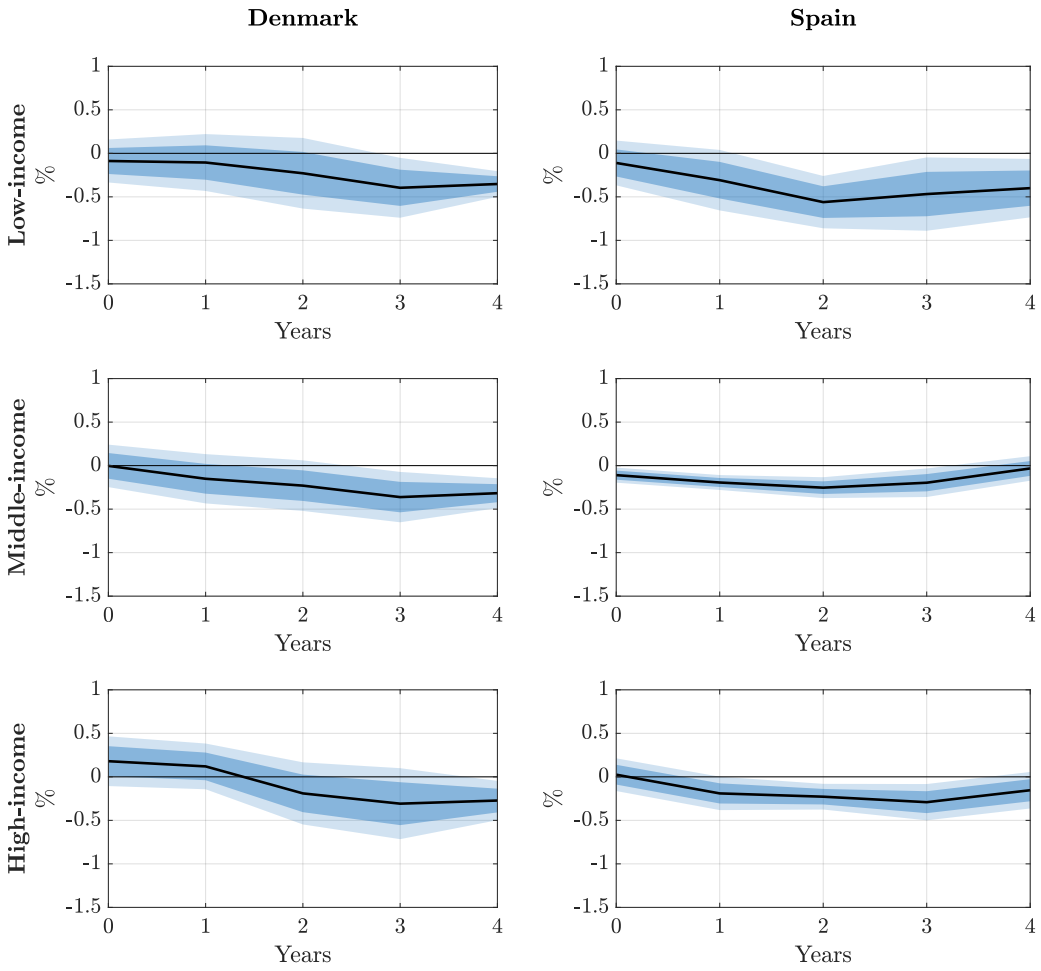


Figure E.13: Expenditure by Income Group for Other European Countries

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

E.10. Attitudes towards climate policy

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

To proxy the public attitude towards climate policy, I rely on a question from the transportation module of the survey, which asks about the attitude towards environmentally-motivated fuel taxes. In particular, the question asks whether the respondent agrees with the following statement: "For the sake of the environment, car users should pay higher taxes". The BSA also includes information about the income of the respondent, thus it is possible to analyze how the attitudes of different income groups have evolved. Figure E.14 shows how the attitude towards climate policy has changed among low- and higher-income households. The support of climate policy has remained relatively stable at moderate levels for a large part of the sample. In the early to middle 2010s, the support started increasing for higher-income households. In contrast, the support of low-income households has remained stable until the end of the sample.

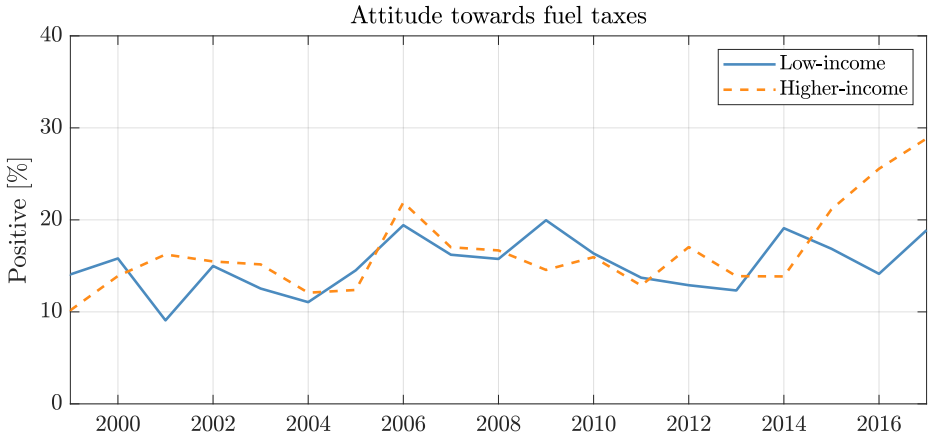


Figure E.14: Public support for climate policy by income group

Notes: Attitudes towards climate policy by income group over time, 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".

F. A Heterogeneous-agent Climate-economy Model

To study the role of redistributing carbon revenues more formally, I build a climate-economy model. The aim is to obtain a framework that can account for the empirical findings and can be used as a laboratory for policy experiments. The model belongs to the dynamic stochastic general equilibrium (DSGE) class. It augments the climate-economy structure in Golosov et al. (2014) with nominal rigidities and household heterogeneity, as in Bilbiie, Känzig, and Surico (2022), to allow for the demand channels identified in the data.

F.1. Households

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

Households face idiosyncratic risk as they switch exogenously between types. In particular, the exogenous change of type follows a Markov chain: the probability to stay a saver is s and the probability to remain hand-to-mouth is h (with transition probabilities $1-s$ and $1-h$, respectively). I focus on the stationary equilibrium with $\lambda = (1-s)/(2-s-h)$, which is the *unconditional* probability of being hand-to-mouth. I assume that only bonds are liquid and can be used to self-insure.

Savers. There is limited asset market participation. Only savers are able to self-insure themselves using liquid bonds.[6]

[6]This is a tractable way of introducing idiosyncratic risk and liquidity in spirit of full-blown HANK models à la Kaplan, Moll, and Violante (2018), see Bilbiie (2020) and Bilbiie, Känzig, and Surico (2022) for a detailed discussion.

Savers maximize their lifetime utility

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(x_{S,t}, h_t) \right], \tag{6}$$

choosing how much to consume $x_{S,t}$, save $b_{S,t+1}$ and invest $i_{S,t}$. Their consumption bundle $x_{S,t}$ is a composite of a non-energy good $c_{S,t}$ and energy $e_{S,t}$: $x_{S,t} = \left(a_{S,c}^{\frac{1}{\epsilon_x}} c_{S,t}^{\frac{\epsilon_x - 1}{\epsilon_x}} + a_{S,e}^{\frac{1}{\epsilon_x}} e_{S,t}^{\frac{\epsilon_x - 1}{\epsilon_x}} \right)^{\frac{\epsilon_x}{\epsilon_x - 1}}$, where $a_{S,c}$ and $a_{S,e}$ are distribution parameters satisfying $a_{S,c} + a_{S,e} = 1$, and ϵ_x is the elasticity of substitution between non-energy and energy goods. This gives rise to standard non-energy and energy demand functions: $c_{S,t} = a_{S,c} \left(\frac{1}{p_{S,t}} \right)^{-\epsilon_x} x_{S,t}$ and $e_{S,t} = a_{S,e} \left(\frac{p_{e,t}}{p_{S,t}} \right)^{-\epsilon_x} x_{S,t}$.

The savers budget constraint equates their consumption, savings and investment to their income, accounting for the flows of liquid assets between types (see Bilbiie, Känzig, and Surico, 2022, for details). Their income is given by $y_{S,t} = w_t h_t + \frac{R^b_{t-1}}{\Pi_t} b_{S,t} + (1 - \tau^k) r_t k_{S,t} + \frac{(1-\tau^d) d_t}{1-\lambda} + \omega_{S,t}$, where $p_{S,t}$ is the price of the savers' final consumption bundle, $\frac{R^b_{t-1}}{\Pi_t}$ is the risk-free rate deflated by inflation, r_t is the rental rate of capital, d_t are dividends, and $\omega_{S,t}$ are transfers from the government. Capital accumulation follows $k_{S,t+1} = i_{S,t} + (1 - \delta) k_{S,t}$.

Maximizing (6) subject to the budget constraint and the capital accumulation equation, we obtain the Euler equations for investment and bond holdings:

$$\frac{U_x(x_{S,t}, h_{S,t})}{p_{S,t}} = \beta \, \mathbb{E}_t \left[\frac{R^b_t}{\Pi_{t+1}} \left(s \frac{U_x(x_{S,t+1}, h_{S,t+1})}{p_{S,t+1}} + (1 - s) \frac{U_x(x_{H,t+1}, h_{H,t+1})}{p_{H,t+1}} \right) \right] \tag{7}$$

$$\frac{U_x(x_{S,t}, h_{S,t})}{p_{S,t}} = \beta \, \mathbb{E}_t \left[(1 + (1 - \tau^k) r_{t+1} - \delta) \frac{U_x(x_{S,t+1}, h_{S,t+1})}{p_{S,t+1}} \right] \tag{8}$$

Note that only the Euler equation for bonds includes the marginal utility in the H-state, reflecting the fact that only bonds are liquid and can be used to self-insure against idiosyncratic risk.

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

$$p_{H,t} x_{H,t} = y_{H,t}. \tag{9}$$

The income of the hand-to-mouth is given by $y_{H,t} = w_t h^d_t + \omega_{H,t}$, where $\omega_{H,t}$ are government transfers. The non-energy and energy demand functions and the associated price index are analogous to the expressions for the savers.

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

$$w_t = \varphi h_t^{\theta} \left(\lambda \frac{1}{p_{H,t}} U_x(x_{H,t}, h_t) + (1-\lambda) \frac{1}{p_{S,t}} U_x(x_{S,t}, h_t) \right)^{-1}, \tag{10}$$

where w_t is the real wage charged by the union, $p_{H,t}$ and $p_{S,t}$ are the relative prices of the hand-to-mouth and the savers' consumption baskets, respectively, and $U_x(\cdot)$ is the marginal utility of consumption. The labor market structure equalizes labor income across households; thus all income heterogeneity in the model will come from heterogeneity in financial income.[7]

F.2. Firms

The firm block of the model consists of two sectors: energy and non-energy producers. Energy firms produce energy using labor as an input. Non-energy firms produce the non-energy consumption good using capital, energy, and labor as inputs. Consistent with the data, I assume that energy firms can adjust their prices flexibly while non-energy firms face nominal price rigidities (Dhyne et al., 2006).

Energy sector. The energy firm produces energy according to the following technology

$$e_t = a_{e,t} h_{e,t}, \tag{11}$$

as in Golosov et al. (2014). I assume that there is only a single source of energy (e.g. coal) that is available in approximately infinite supply. Without loss of generality, energy is measured in terms of carbon content (carbon amount emitted). Energy firms are subject to a carbon sales tax τ_t.[8] The optimal energy supply is characterized by $w_t = (1-\tau_t) p_{e,t} \frac{e_t}{h_{e,t}}$.

Non-energy sector. The non-energy sector consists of standard New Keynesian firms that produce different varieties of non-energy goods and set prices subject to nominal rigidities. The final non-energy good is assembled by a CES aggregator.

The non-energy variety j is produced according to the following technology,

[7] This is a reduced-form way of capturing the income responses observed in the data. In the model, this labor market structure helps to mitigate varying labor supply responses offsetting income heterogeneity.

[8] For simplicity, I consider here a carbon tax, however, I could equivalently consider regulating the quantity (see e.g. the discussion in Heutel, 2012).

using capital $k_t(j)$, energy $e_{y,t}(j)$, and labor $h_{y,t}(j)$ as inputs

$$y_t(j) = e^{-\gamma s_t}\left[(1-\nu)^{\frac{1}{\epsilon_y}}\left(a_t k_t(j)^{\alpha} h_{y,t}(j)^{1-\alpha}\right)^{\frac{\epsilon_y-1}{\epsilon_y}} + \nu^{\frac{1}{\epsilon_y}}\left(e_{y,t}(j)\right)^{\frac{\epsilon_y-1}{\epsilon_y}}\right]^{\frac{\epsilon_y}{\epsilon_y-1}}, \quad (12)$$

where a_t is a technology shifter. The function $e^{-\gamma s_t}$ captures climate damages, where s_t is the atmospheric carbon concentration. This generates a feedback loop between climate and the economy. Higher economic activity increases carbon emissions via higher energy use, which in turn increases the carbon concentration. A higher carbon concentration will have economic damages in turn (e.g. via weather events etc.), which reduce output. The functional form is taken from Golosov et al. (2014), where γ governs the size of climate damages.

The cost-minimization problem gives rise to the factor demands for capital $r_t = \alpha v_{1,t} mc_t \frac{y_t}{k_t}$, labor $w_t = (1-\alpha) v_{1,t} mc_t \frac{y_t}{h_{y,t}}$ and energy $p_{e,t} = v_{2,t} mc_t \frac{y_t}{e_{y,t}}$, where mc_t are real marginal costs and $v_{1,t} = \left(e^{-\gamma s_t} a_t k_t^{\alpha} h_{y,t}^{1-\alpha}/y_t\right)^{\frac{\epsilon_y-1}{\epsilon_y}}$ and $v_{2,t} = \left(e^{-\gamma s_t} e_{y,t}/y_t\right)^{\frac{\epsilon_y-1}{\epsilon_y}}$ are auxiliary terms. Note that factor demands are common across firms.

The price setting problem gives rise to a standard Phillips curve, which in log-linear form reads $\hat{\pi}_t = \kappa \hat{mc}_t + \beta E_t \hat{\pi}_{t+1}$, where hatted variables denote log-deviations from steady state. Finally, profits are given by $d_t = \int_0^1 [\frac{P_t(j)}{P_t} y_t(j) - mc_t y_t(j)] dj$.

F.3. Climate block

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

F.4. Fiscal and monetary policy

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

$$\lambda \omega_{H,t} = \mu \tau_t p_{e,t} e_t \quad \text{and} \quad (1-\lambda)\omega_{S,t} = (1-\mu)\tau_t p_{e,t} e_t. \quad (13)$$

The distribution of carbon tax revenues are governed by the parameter μ. As the baseline, I assume that all carbon revenues accrue to the savers $\mu = 0$. Later, we will study alternative transfer policies. Carbon taxes τ_t are set according to the

following rule: $\tau_t = (1-\rho_\tau)\tau + \rho_\tau \tau_{t-1} + \epsilon_{\tau,t}$. Finally, the monetary authority follows a standard Taylor rule, targeting headline inflation (in log-linear form): $\hat{r}^b_t = \rho_r \hat{r}^b_{t-1} + (1-\rho_r)(\phi_\pi \hat{\pi}_{T,t} + \phi_y \hat{y}_t) + \epsilon_{mp,t}$, where $\hat{\pi}_{T,t}$ is headline inflation.

F.5. Aggregation and market clearing

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

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

Finally, goods market clearing requires that $c_t + i_t = y_{d,t}$.

F.6. Calibration

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

The labor weight in the utility function, φ_i is set such that steady-state hours worked h_i are normalized to one. I calibrate the share of hand-to-mouth λ to 25 percent, corresponding to the low-income threshold used in the LCFS. Such a share is also in line with the estimates of hand-to-mouth households in Kaplan, Violante, and Weidner (2014). Idiosyncratic risk is calibrated to $1-s = 0.04$, as in Bilbiie (2020). The distribution parameters $a_{H,e}$ and $a_{S,e}$ are set to match the energy expenditure shares of 9.5 percent for the hand-to-mouth and 6.5 percent for the savers as observed in the LCFS. Note that the elasticity of substitution ϵ_x is the same as the own price elasticity in this model. I calibrate ϵ_x to 0.2, as my empirical evidence points to rather low sustainability at the horizons considered. The elasticity is consistent with Labandeira, Labeaga, and López-Otero (2017) who perform a meta analysis on the price elasticity of energy demand and find an average short-run elasticity of around 0.21.

Turning to the production side, I set the depreciation rate δ to 0.025, implying an annual depreciation on capital of 10 percent. The capital adjustment cost parameter is set to $\varphi_k = 4$, which implies an elasticity of investment to Tobin's marginal q of 10. I set α to 0.3, implying a steady-state capital share of around 70 percent (see e.g. Smets and Wouters, 2003). Using data on non-household energy consumption and energy prices in the EU, I estimate a energy share of around

7 percent. To approximate that share, I thus set $\nu = 0.07$. The elasticity of substitution between energy and capital/labor is set to 0.21, drawing again on the evidence in Labandeira, Labeaga, and López-Otero (2017). The elasticity of substitution between non-energy varieties is assumed to be 6, which is a standard value and implies a steady-state markup of 20 percent, consistent with the evidence in Christopoulou and Vermeulen (2012). The Calvo parameter θ_p is set to 0.825, which implies an average price duration of 5-6 quarters, in line with the empirical estimates in Alvarez et al. (2006). These parameter choices imply a relatively flat Phillips curve with a slope of 0.04.

For the climate block, I rely on the values in Golosov et al. (2014). I abstract from uncertainty about the damage parameter and use the deterministic, long-run value from Golosov et al. (2014). Note, however, that carbon emissions in my model are in arbitrary units. Thus, following Heutel (2012) I scale the damage parameter to make the increase in output damages from doubling the steady-state carbon stock consistent with the projected increase in damages from doubling CO2 levels in 2005. Turning to the carbon cycle, note that the excess carbon has a half-life of about 300 years (Archer, 2005). This implies a value of $1 - \varphi = 0.9994$.[9] Furthermore, according to the 2007 IPCC reports, about half of the CO2 pulse to the atmosphere is removed after a time scale of 30 years. This implies that $\varphi_0 = \frac{0.5}{(1-\varphi)^{120}} = 0.5359$.

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

All other taxes are assumed to be zero in the baseline case, later I will use them to equalize the income incidence. Furthermore, I assume that all carbon tax revenues accrue to the savers, $\mu = 0$, motivated by the fact that there is no redistribution scheme in the current EU ETS in place. The calibration is summarized in Table F.1.

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

Table F.1: Calibration

Parameter	Description	Value	Target/Source/Comments
β	Discount factor	0.99	Standard value
$1/\sigma$	Intertemporal elasticity of substitution	1	Standard value
$1/\theta$	Labor supply elasticity	1	Standard value
λ	Share of hand-to-mouth	0.2	Share of low-income households, LCFS
$1-s$	Probability of becoming H	0.04	Bilbiie (2020)
$a_{H,e}$	Distribution parameter H	0.078	Energy share of 9.5%, LCFS
$a_{S,e}$	Distribution parameter S	0.056	Energy share of 6.5%, LCFS
ϵ_x	Elasticity of substitution energy/non-energy households	0.2	LCFS, Labandeira, Labeaga, and López-Otero (2017)
ϵ_y	Elasticity of substitution energy/non-energy firms	0.21	Labandeira, Labeaga, and López-Otero (2017)
δ	Depreciation rate	0.025	Standard value
φ_k	Capital adjustment costs	4	Standard value
α	Capital returns-to-scale	0.3	Standard value
ν	Energy returns-to-scale	0.07	Steady-state energy share of $\approx$ 7%; Eurostat
ϵ_p	Price elasticity	6	Steady-state markup of 20%
θ_p	Calvo parameter	0.825	Average price duration of 5-6 quarters
γ	Climate damage parameter	$5.3 * 10^{-5}$	Golosov et al. (2014)
φ_0	Emissions staying in atmosphere	0.5359	Golosov et al. (2014)
$1-\varphi$	Emissions decay parameter	0.9994	Golosov et al. (2014)
ϕ_π	Taylor rule coefficient inflation	1.5	Standard value
ρ_r	Interest smoothing	0.8	Standard value
τ	Steady-state carbon tax	0.039	Implied tax rate from average EUA price
ρ_τ	Persistence carbon tax shock	0.85	Persistence in the data

F.7. Results

Model evaluation. The impulse responses to a carbon policy shock, leading to an increase in the energy price by 1 percent, are shown in Figure F.1. In what follows, we focus on the peak responses, as the model is not designed to match the hump-shaped responses in the data. The model is successful in generating consumption and income responses, overall and by household group, that are in the same order of magnitude as the estimated responses in Section 5. As in the data, consumption and income are more responsive to carbon policy shocks for the low-income, hand-to-mouth households. In contrast, the responses of high-income savers are much less pronounced.

Redistributing carbon revenues. We are now in a position to study how different carbon revenue redistribution schemes affect the transmission of carbon policy shocks. Figure F.1 compares the baseline case when all carbon revenues

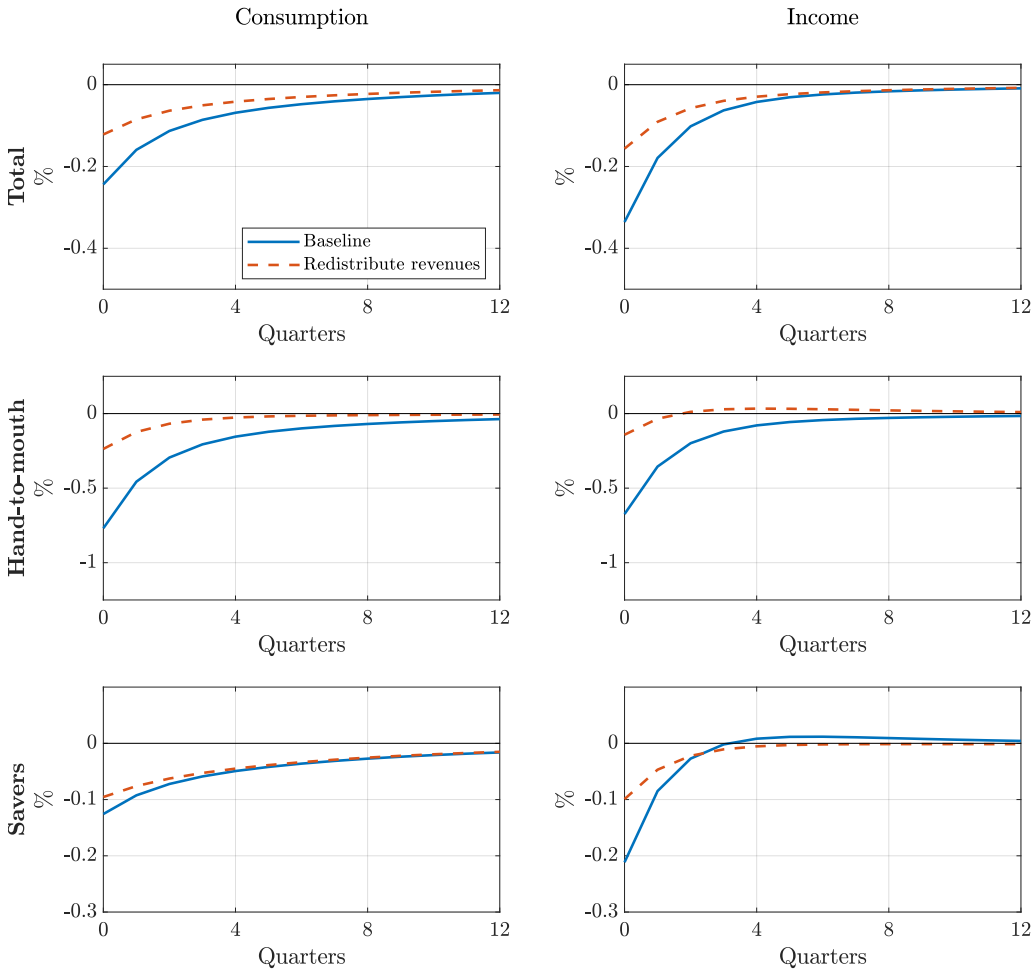


Figure F.1: Model Responses for Consumption and Income

Notes: Impulse responses of consumption and income, in the aggregate as well as for hand-to-mouth and savers, to a carbon policy shock normalized to increase the energy price by 1 percent. The blue line is the baseline response when carbon revenues solely accrue to the savers; the red dashed line is the response when carbon revenues are redistributed equally among hand-to-mouth and savers.

accrue to the savers (blue line) to the case where the revenues are distributed equally across households $\mu = \lambda$ (red dashed line).

Redistributing carbon revenues has important consequences: the aggregate effect on consumption and income is much smaller than in the baseline case of no redistribution. In contrast, redistributing revenues has a smaller impact on the response of emissions, see Figure F.2. The intuition is that the redistribution scheme stabilizes the income of the hand-to-mouth which translates into a significantly smaller consumption response as they have a high MPC. Savers, on the other hand, face a somewhat more prolonged fall in their income but the effect on their consumption is more muted as they are able to smooth the effects of the shock. Thus, redistributing carbon revenues also leads to a reduction in consumption inequality. Emissions on the other hand change by less as low-income

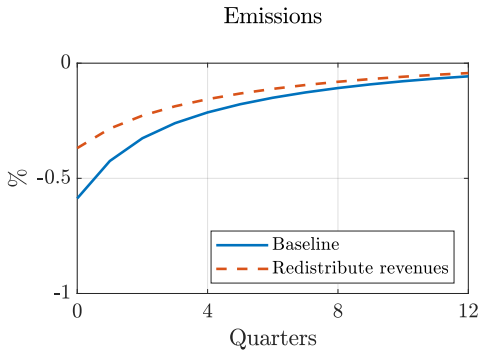


Figure F.2: Emissions Response

households' energy demand is inelastic and they make up only a small share of aggregate emissions to start with.

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

Role of heterogeneity. Household heterogeneity plays an important role for the magnitudes of the responses. In particular, heterogeneity in MPCs linked to heterogeneity in energy shares and income incidence can amplify the responses further. This is illustrated in Figure F.3, which compares the responses of the heterogeneous agent to the corresponding representative agent version of the model.

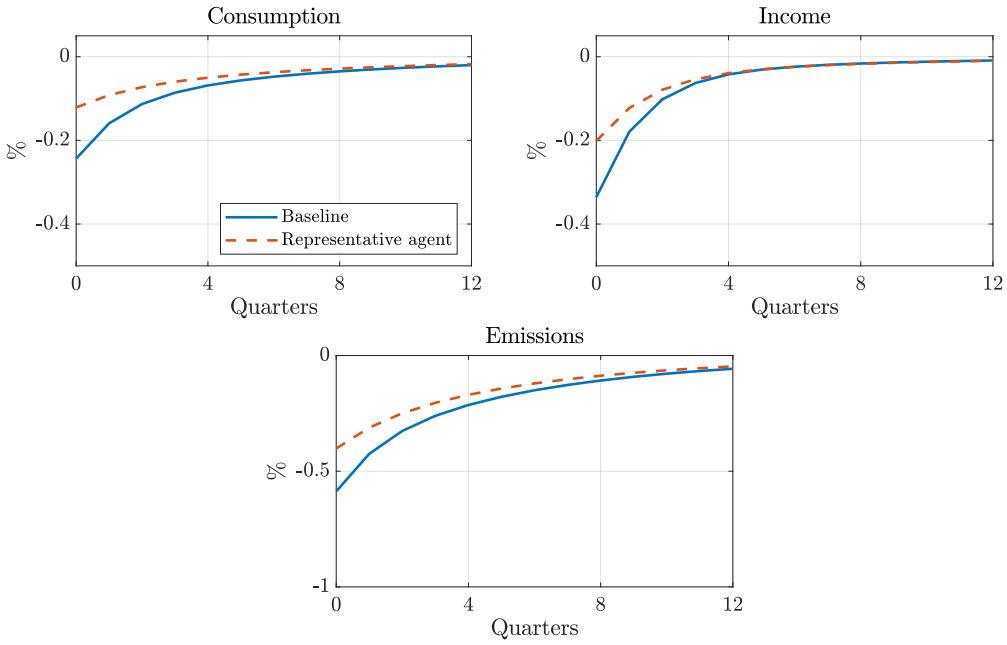


Figure F.3: Heterogeneity Versus Representative Agent

To get a better understanding of how much the heterogeneity matters for the direct and indirect channels I identify, I perform a decomposition. In particular, I compare four different scenarios: (i) a model where there is no heterogeneity in income incidence and energy share (this is achieved by perfectly redistributing income over the cycle and calibrating the energy share for H and S to the same level), (ii) a model with equal incidence but heterogeneity in energy shares, (iii) a model with unequal incidence and no energy share heterogeneity, and (iv) our baseline case with both heterogeneities. From Figure F.4, we can see that the heterogeneity in income incidence turns out to be crucial, accounting for the bulk of the amplification of the aggregate consumption response. This can be seen from the fact that the model with unequal incidence is already very close to the baseline with heterogeneous energy shares and income incidence.

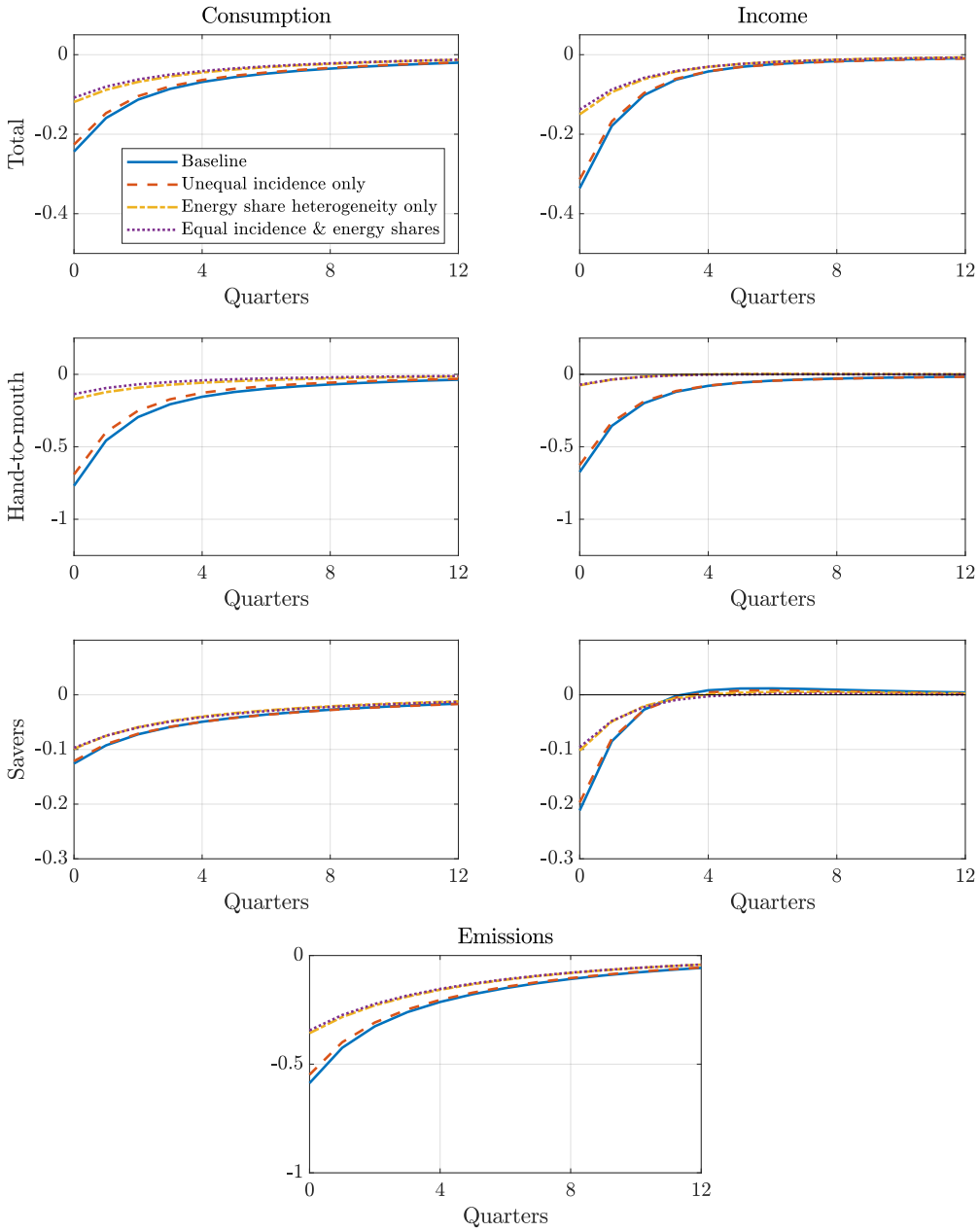


Figure F.4: Role of Unequal Income Incidence and Energy Share Heterogeneity

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