The economic consequences of putting a price on carbon

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Motivation

The looming climate crisis

The looming climate crisis

- The looming **climate crisis** is one of the greatest challenges of our time
- On the current path of emissions, temperature to increase by **3-5°C** by 2100
  $\Rightarrow$ devastating effects on the environment, human health and the economy
- **Pigou:** internalize costs of polluting by putting a price on emissions
  - Difficult to implement in a global world with many stakeholders
  - More progress at the national level, **but:**
  - **Little known** about the effects of carbon pricing on **emissions** and the **economy** in practice

This paper

- New evidence from the European **Emissions Trading Scheme** (**ETS**), the **largest** carbon market in the world
- Exploit **institutional features** of the EU ETS and **high-frequency data** to estimate the dynamic causal effects of **carbon pricing**
  - Cap-and-trade system: **Market price** for carbon, liquid **futures markets**
  - Regulations in the market have **changed** considerably over time
  - Isolate **exogenous** variation in carbon price by measuring price change in **tight window** around **policy events**
  - Use as **instrument** to estimate dynamic causal effects of a **carbon policy shock**

Preview of results

- Carbon policy has **significant** effects on emissions and the economy
- A shock **tightening** the **carbon pricing regime** leads to
    - a significant **increase in energy prices** and a persistent **fall in emissions**
    - not without **cost**: **economic activity falls**, consumer prices increase
    - costs **not** borne **equally** across society: **poor** lower their consumption significantly, **rich** barely affected

Related literature

- **Carbon pricing and emissions**: Lin and Li (2011); Martin, De Preux, and Wagner (2014); Andersson (2019); Pretis (2019)
- **Carbon pricing and economic activity**: Metcalf (2019); Bernard, Kichian, and Islam (2018); Metcalf and Stock (2020*a*,*b*)
- **Carbon pricing and inequality**: Pizer and Sexton (2019); Ohlendorf et al. (2021)
- **Macroeconomic effects of tax changes**: Blanchard and Perotti (2002); Romer and Romer (2010); Mertens and Ravn (2013); Cloyne (2013)
- **High-frequency identification**: Kuttner (2001); Gürkaynak, Sack, and Swanson (2005); Gertler and Karadi (2015); Nakamura and Steinsson (2018); Känzig (2021)
- **Event studies on regulatory news in the ETS**: Mansanet-Bataller and Pardo (2009); Fan et al. (2017); Bushnell, Chong, and Mansur (2013)

Identification

European ETS

- **Largest** carbon market in the world
- Established in 2005, long implementation history
- Covers around **40%** of EU GHG emissions
- Cornerstone of the EU's policy to combat climate change

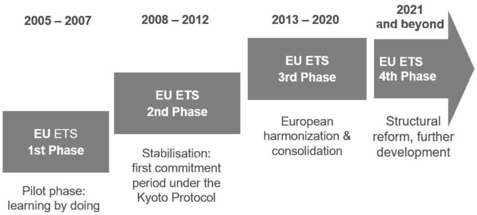
European carbon market

Cap and trade system

- **Cap** on total emissions covered by the system, reduced each year
- **Emission allowances** (**EUA**) allocated within the cap
  - free allocation
  - auctions
  - international credits
- Companies must surrender **sufficient** EUAs to cover their yearly emissions
  - enforced with heavy fines
- Allowances are **traded** on secondary markets (spot and **futures** markets)

European carbon market

- Establishment of EU ETS followed **learning-by-doing** process
- Three main **phases**, **rules updated continuously**
  - address market issues
  - expand system
  - improve efficiency
- Lots of **regulatory events**



Carbon price

Figure 1: EUA price

Regulatory events

- Collected **comprehensive list** of **regulatory update** events
  - Decisions of European Commission
  - Votes of European Parliament
  - Judgments of European courts
- Of interest in this paper: regulatory news on the **supply of allowances**
  - National **allocation plans**
  - **Auctions**: timing and quantities
  - Use of international credits
- **Identified 113** relevant **events** from 2005-2018

Example events

Table 1: Regulatory update events (extract)

	Date	Event description	Type
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

High-frequency identification

- **Idea**: Identify carbon policy surprises from changes in EUA futures price in tight window around regulatory event

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

where $F_{t,d}$ is log settlement price of the EUA front contract on event day d in month t

- Aggregate surprises to **monthly** series

$$CPSurprise_t = \begin{cases} CPSurprise_{t,d} & \text{if one event} \\ \sum_i CPSurprise_{t,d_i} & \text{if multiple events} \\ 0 & \text{if no event} \end{cases}$$

Carbon policy surprises

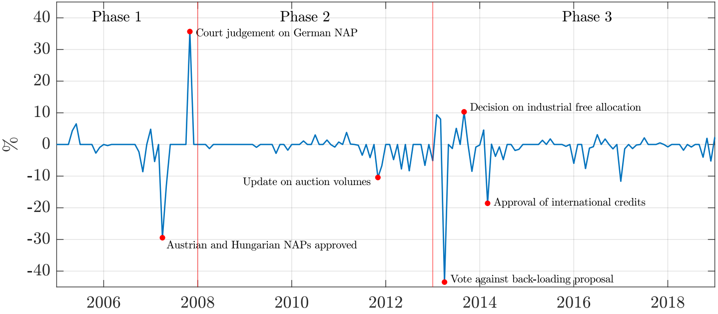


Figure 2: The carbon policy surprise series

Diagnostics

- **Narrative account**:
- **Autocorrelation**:
- **Forecastability**:
- **Orthogonality**:
- **Background noise**:

More

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- **Narrative account**: ✓ Accords well with accounts on historical episodes
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- **Background noise**: ✓ Variance on event days 6 times larger than on control days

More

Econometric framework

- **Carbon policy surprise series** has good properties but is only imperfect shock measure
  $\Rightarrow$ Use it as an **instrument** to estimate dynamic causal effects on emissions and activity
- I use two approaches
  - **External instrument** approach: efficient, assumes invertibility
  - **Internal instrument** approach: robust to non-invertibility
- For estimation I rely on VAR techniques given the short sample

Empirical specification

- 8 variable system:
  - **Carbon block**: HICP energy, total GHG emissions
  - **Macro block**: headline HICP, industrial production, unemployment rate, policy rate, stock market index, REER
- 6 lags as controls
- Estimation sample: 1999M1-2018M12

▸ Data

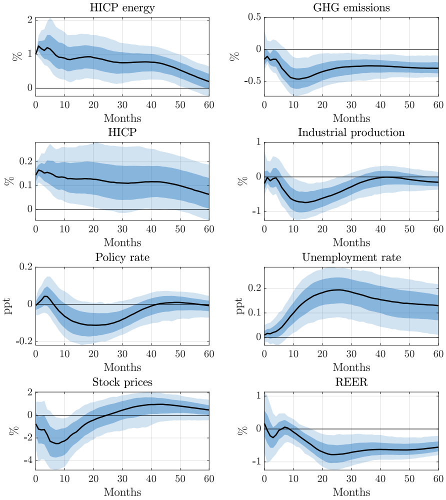
Results

First stage

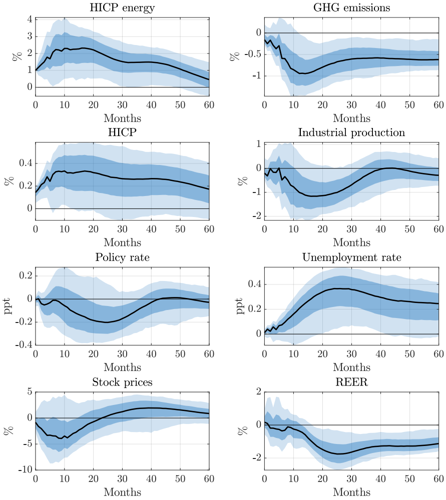
- Weak instrument test by Montiel Olea and Pflueger (2013)
- Heteroskedastcitity-robust **F-statistic**: **20.95**
- Larger than critical value of **15.06** (assuming worst case bias of 20% with 5% size)
- **No** evidence for **weak instrument** problems

The aggregate effects of carbon pricing

Panel A: External instrument approach



Panel B: Internal instrument approach



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

The aggregate effects of carbon pricing

Restrictive **carbon policy shock** leads to

- strong, immediate **increase** in **energy prices**
- significant and persistent **fall** in **emissions**

This has **consequences** for the **economy**:

- Consumer prices increase
- **Industrial production falls**
- **Unemployment rate rises**
- Stock prices fall initially but then reverse
- REER depreciates

$\Rightarrow$ **Trade-off** between reducing **emissions** and economic **activity**

Historical importance

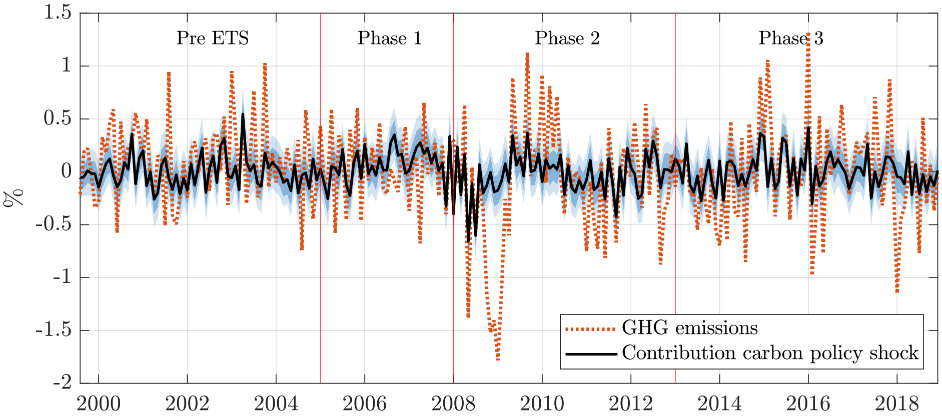


Figure 3: Historical decomposition of emissions growth

Historical importance

- **Carbon policy shocks** have **contributed meaningfully** to historical variations in energy prices, emissions and macro variables
- **But**: they did **not** account for the fall in emissions following the global financial crisis
  - supports the **validity** of the identified shock

More

Propagation channels

- **Energy prices** play an important role in the transmission
- Significant **pass-through** of carbon to energy prices

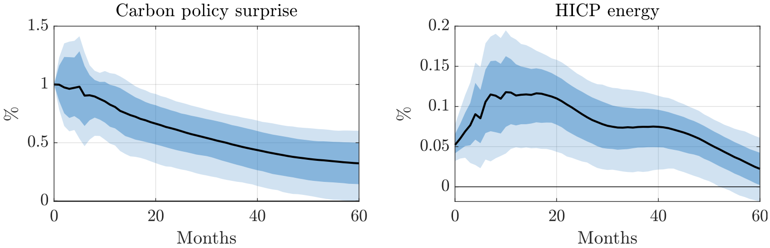


Figure 4: Carbon and energy prices

The role of energy prices

To better understand **role** of **power sector** perform event study using daily futures and stock prices

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

- $q_{i,d+h}$: (log) price of asset i, h days after event d
- $CPSurprise_d$: carbon policy surprise on event day
- ψ_h^i: effect on asset price i at horizon h

The role of energy prices

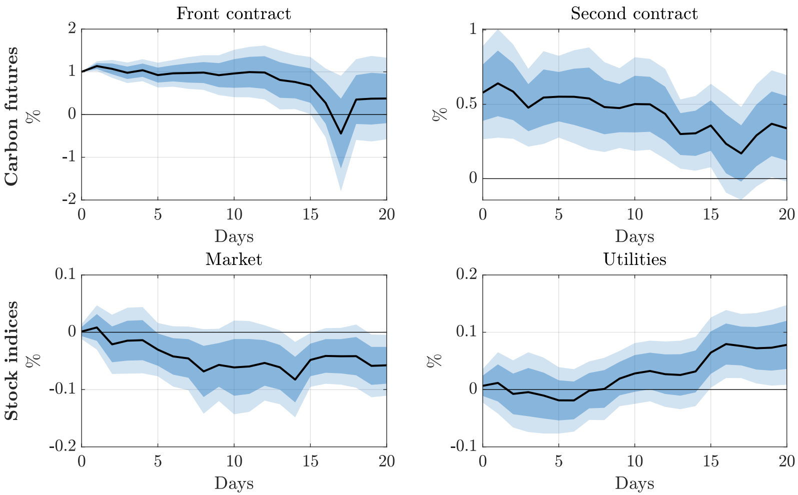


Figure 5: Carbon price and stock market indices

The role of energy prices

- **Carbon futures** prices **increase** significantly after carbon policy surprise
- **Stock market** does not respond on impact but only **falls** with a lag
- **Utilities sector** is the **only** sector displaying a **positive** response
  - Consistent with interpretation that utility sector **pass-through** emissions cost to their customers

The transmission to the macroeconomy

- **Higher energy prices** can have significant effects on the economy via direct and indirect channels
- Estimate effects on **GDP components** using local projections

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

The transmission to the macroeconomy

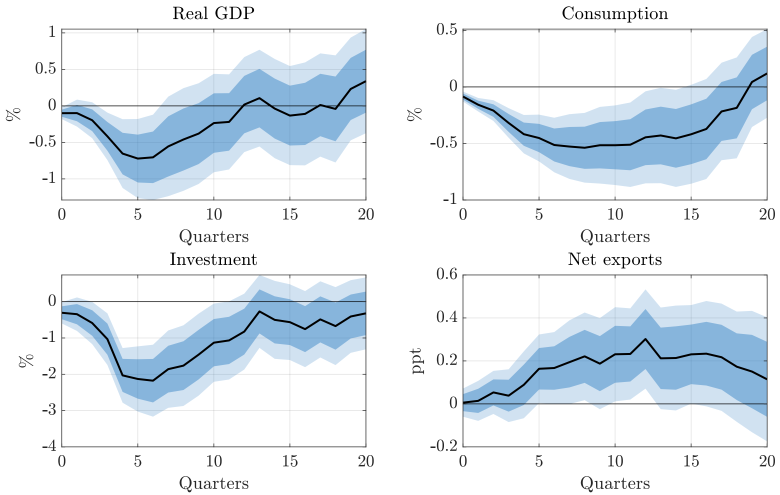


Figure 6: Effect on GDP and components

The transmission to the macroeconomy

- **Fall in GDP** similar to industrial production
- Looking at components, fall seems to be driven by **lower consumption and investment**
  - magnitudes much larger than can be accounted for by **direct effect** on discretionary income
  - **indirect effects** seem to be important

The heterogeneous effects of carbon pricing

Having characterized the aggregate effects, look into **heterogeneous effects** of carbon pricing on **households**

- Sharpen understanding of **transmission channels** at work
- Characterize **redistributive** effects

Problem: Household-level micro data not available at the EU level for long enough and regular sample

- Focus on **UK** where high-quality micro data on **income** and **expenditure** is available
- Check external validity using data for Denmark and Spain.

Living costs and food survey

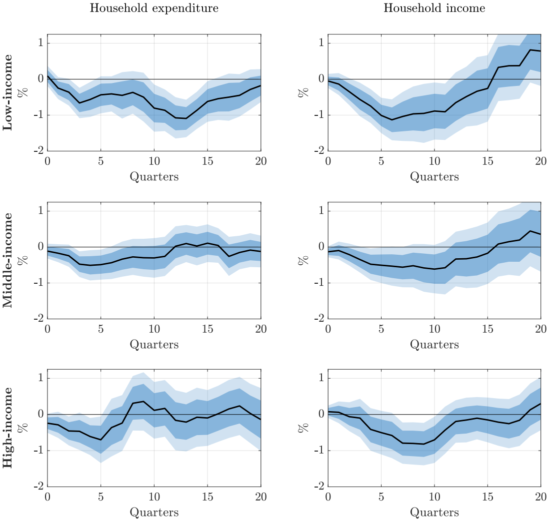
- **LCFS** is the major UK survey on household spending
  - provides detailed information on **expenditure, income**, and household **characteristics**
  - fielded every year but interview date allows to construct **quarterly** measures
- I compile a **repeated cross-section** spanning the period 1999 to 2018
  - each wave contains around 6,000 households, generating over 120,000 observations in total
- To estimate effects, I use a **grouping estimator** using **normal disposable income** as the grouping variable:
  - **Low-income**: Bottom 25%
  - **Middle-income**: Middle 50%
  - **High-income**: Top 25%

Descriptive statistics

Table 2: Descriptive statistics on households in the LCFS

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

Heterogeneity by income group



Heterogeneity by income group

- **Low-income** households **lower** their **consumption** significantly and persistently
- Response of **high-income** housheolds barely significant
  - Low-income households are more exposed because of **higher energy share**
  - But also experience **stronger fall** in their **income**
- **Low-income** households account for ∼**40%** of the aggregate effect on consumption even though they only represent 25% of the population

▸ Sectoral employment ▸ More on grouping ▸ Other income ▸ Other countries

Policy implications

- Fiscal policies **targeted** to the **most affected** households can **reduce** the economic **costs** of climate change mitigation policy
- Crucial for a **sustainable transition**, which should not come at the cost of the most vulnerable
- To the extent that energy demand is **inelastic**, this should **not compromise** emission reductions
  - Turns out to be particularly the case for low-income households

Policy implications

- Especially relevant given recent surge in European carbon prices

Robustness

Check **robustness** with respect to

- **Selection of events**: robust to just using NAP/auction events, robust to dropping largest events
- **Background noise**: robust to controlling for confounding news using a heteroskedasticity-based approach
- **Sample and specification choices**: robust to estimating on shorter sample, to lag order, and to using a smaller system to estimate effects

Details

Conclusion

Conclusion

- New evidence on the **economic effects** of **carbon pricing** from the European carbon market
- Policy successful in **reducing emissions**, but comes at an **economic cost**
- These costs are **not borne equally** across society, policy is **regressive**
- Targeted fiscal policy can reduce these costs without compromising emission reductions

Thank you!

Autocorrelation

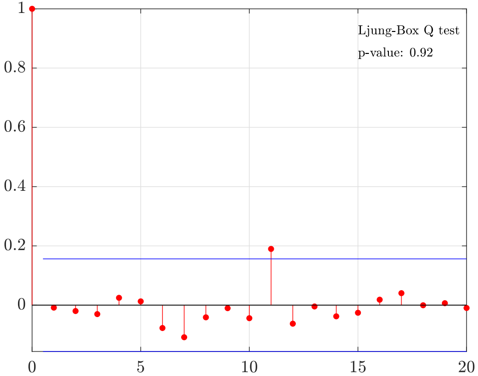


Figure 7: The autocorrelation function of the carbon policy surprise series

Forecastability

Table 3: Granger causality tests

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

Orthogonality

Shock	Source	ρ	p-value	n	Sample
Monthly measures					
Global oil market					
Oil supply	Kilian (2008) (extended)	-0.05	0.61	104	2005M05-2013M12
	Kilian (2009) (updated)	-0.02	0.76	164	2005M05-2018M12
	Caldara, Cavallo, and Iacoviello (2019)	-0.05	0.57	128	2005M05-2015M12
	Baumeister and Hamilton (2019)	-0.11	0.17	164	2005M05-2018M12
	Känzig (2021) (updated)	0.02	0.83	164	2005M05-2018M12
Global demand	Kilian (2009) (updated)	0.01	0.93	164	2005M05-2018M12
	Baumeister and Hamilton (2019)	-0.03	0.69	164	2005M05-2018M12
Oil-specific demand	Kilian (2009) (updated)	0.05	0.55	164	2005M05-2018M12
Consumption demand	Baumeister and Hamilton (2019)	0.05	0.51	164	2005M05-2018M12
Inventory demand	Baumeister and Hamilton (2019)	-0.03	0.68	164	2005M05-2018M12
Monetary policy					
Monetary policy shock	Jarociński and Karadi (2020)	0.02	0.80	140	2005M05-2016M12
Central bank info	Jarociński and Karadi (2020)	0.03	0.75	140	2005M05-2016M12
Financial & uncertainty					
Financial conditions	BBB spread residual	0.06	0.43	164	2005M05-2018M12
Financial uncertainty	VIX residual (Bloom, 2009)	0.10	0.22	164	2005M05-2018M12
	VSTOXX residual	0.05	0.50	164	2005M05-2018M12
Policy uncertainty	Global EPU (Baker, Bloom, and Davis, 2016)	0.03	0.71	164	2005M05-2018M12
Quarterly measures					
Fiscal policy	Euro area (Alloza, Burriel, and Pérez, 2019)	0.12	0.44	43	2005Q2-2015Q4
	Germany	0.22	0.15	43	2005Q2-2015Q4
	France	-0.06	0.69	43	2005Q2-2015Q4
	Italy	0.28	0.07	43	2005Q2-2015Q4
	Spain	0.10	0.52	43	2005Q2-2015Q4

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

Background noise

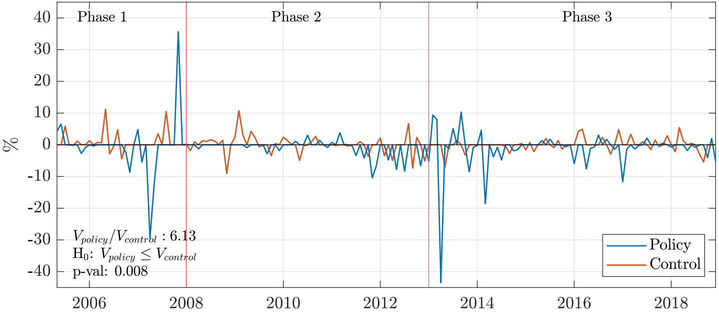


Figure 8: The carbon policy and the control series

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

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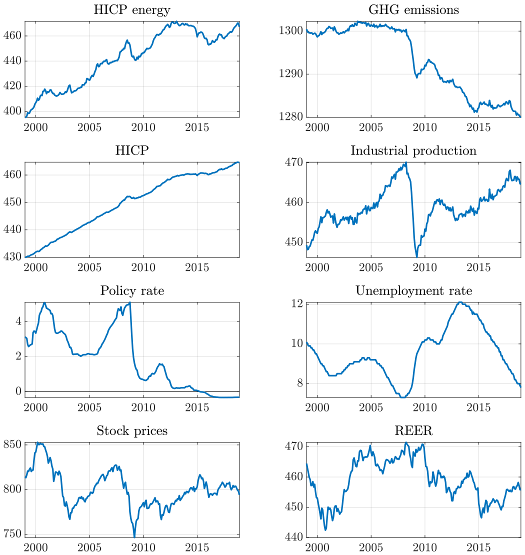
Data


HICP energy
460
440
420
400
2000
2005
2010
2015
GHG emissions
1300
1290
1280
HICP
460
450
440
430
Industrial production
470
460
450
Policy rate
4
2
0
Unemployment rate
12
10
8
Stock prices
850
800
750
REER
470
460
450
440

Historical importance

Table 4: Variance decomposition

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

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Heterogeneity by sector of employment

Table 5: Sectoral distribution of employment

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

Heterogeneity by sector of employment

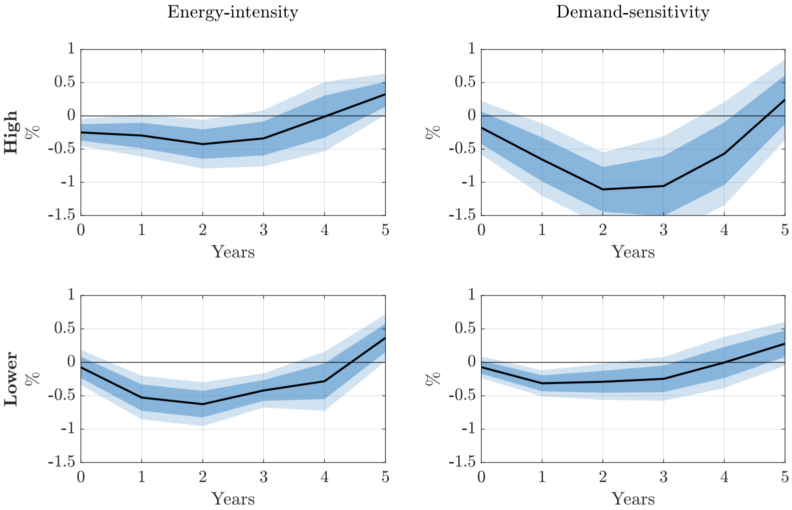

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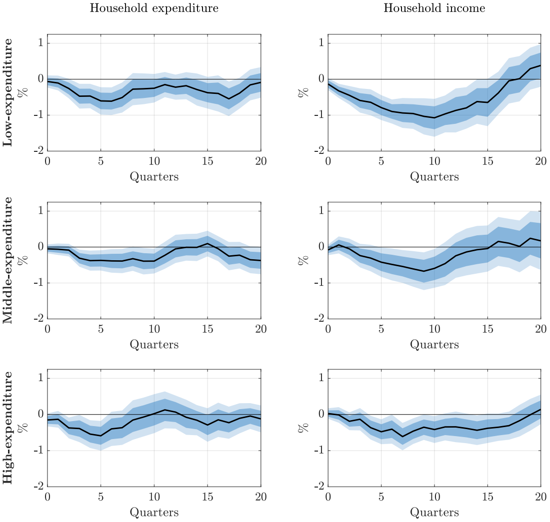
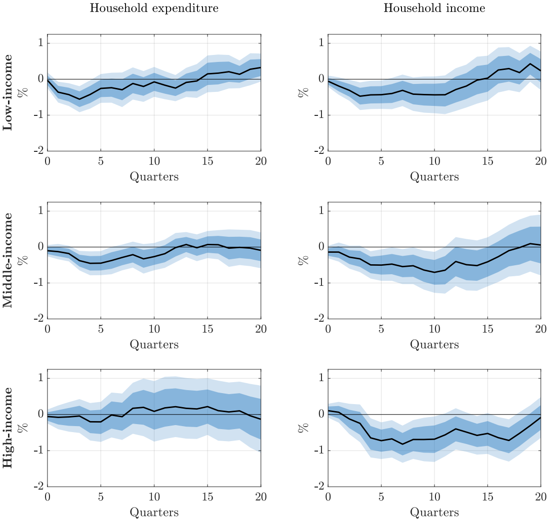
Figure 10: Income response by sector of employment

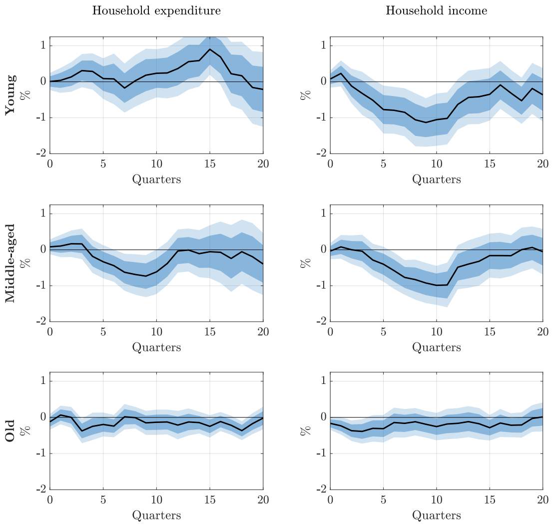
Group by expenditure



Group by permanent income

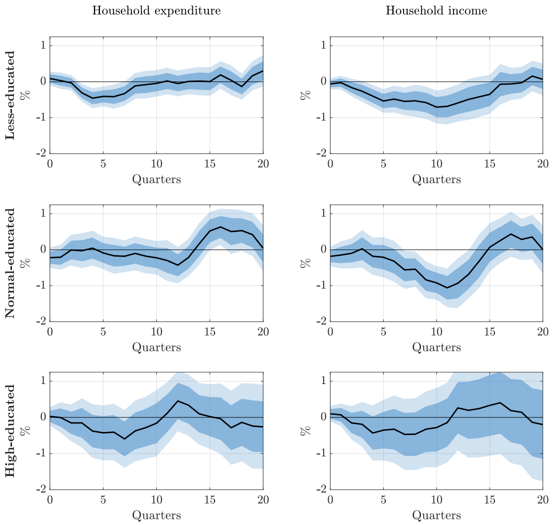


Group by age

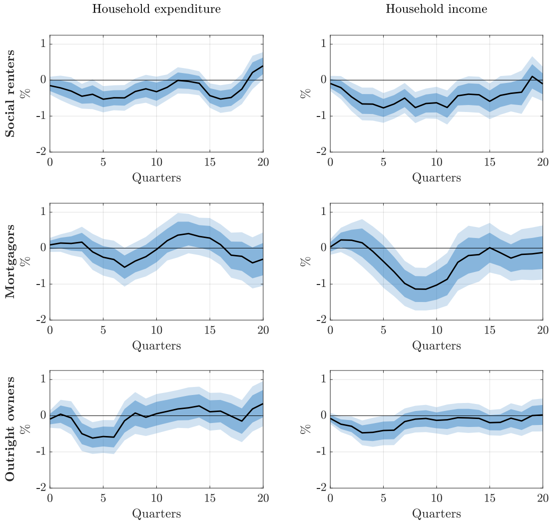


Household expenditure
Household income
Young
Middle-aged
Old
%
Quarters
1
0
-1
-2
0
5
10
15
20

Group by education

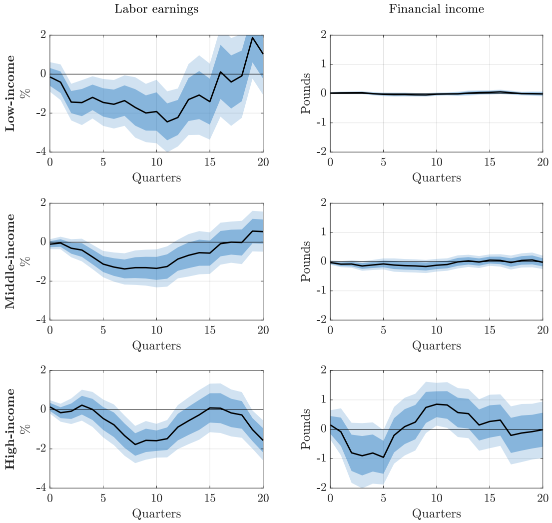


Group by housing tenure



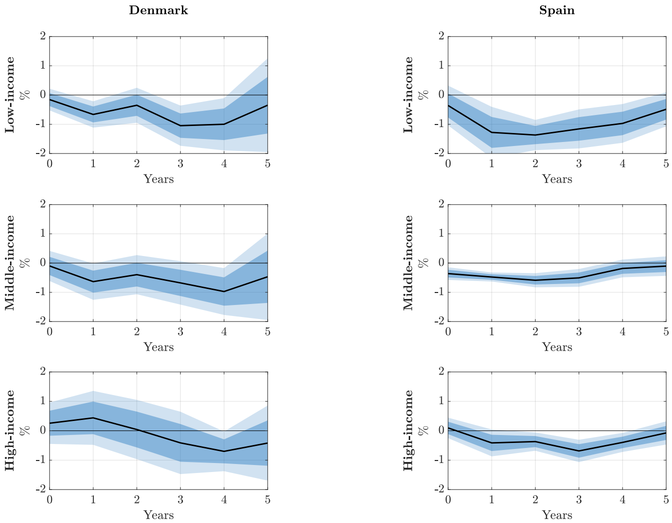
Back

Earnings and financial income



◂ Back

External validity



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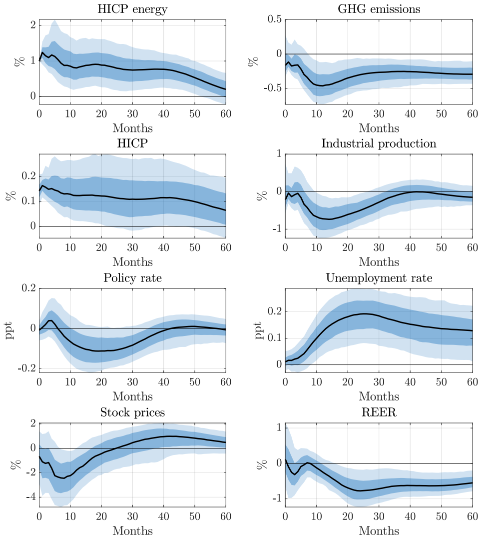
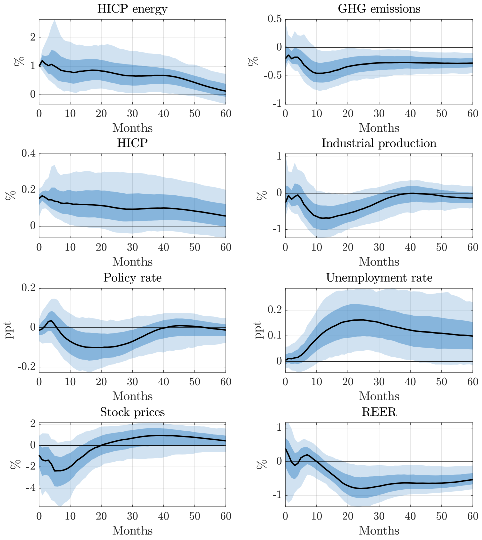
Excluding events regarding cap



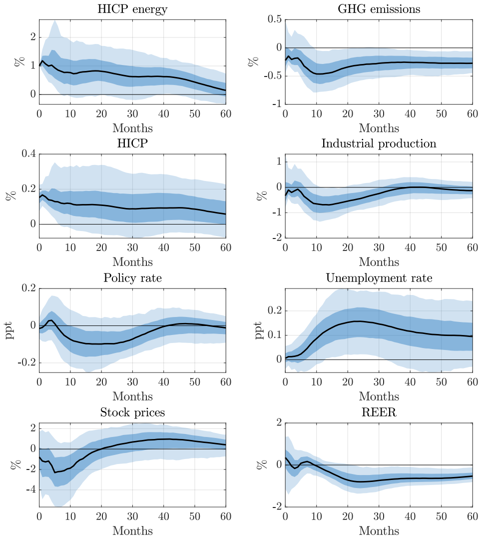
First stage regression: F-statistic: 20.29, R^2: 3.58%

Excluding events regarding international credits



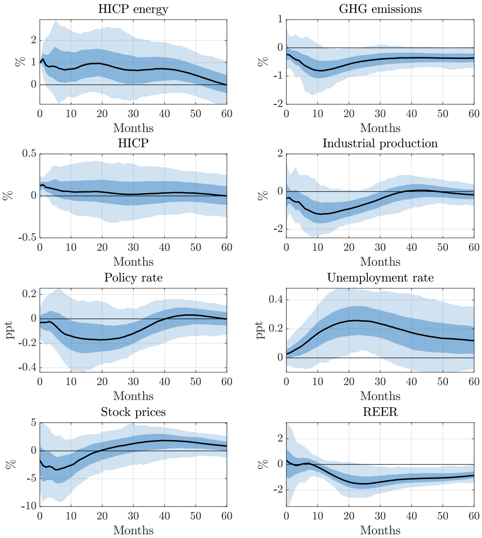
First stage regression: F-statistic: 15.00, R^2: 2.90%

Only using events regarding NAPs



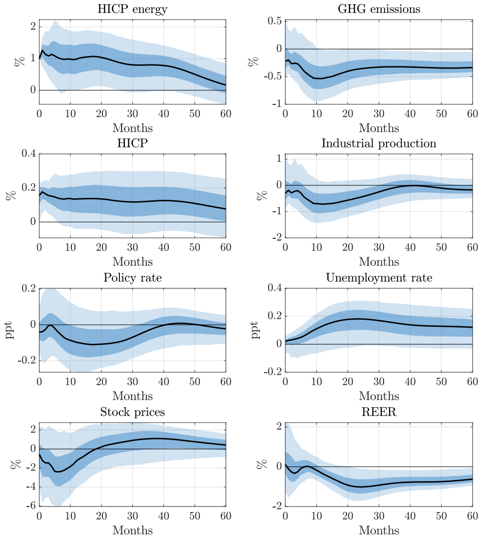
First stage regression: F-statistic: 14.42, R^2: 2.83%

Excluding extreme events



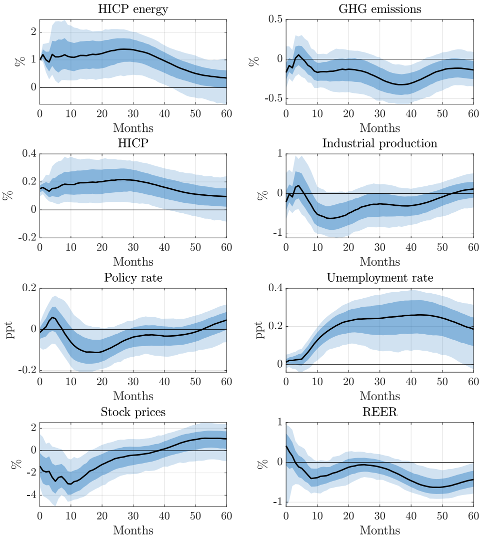
First stage regression: F-statistic: 5.77, R^2: 1.06%

Heteroskedasticity-based identification



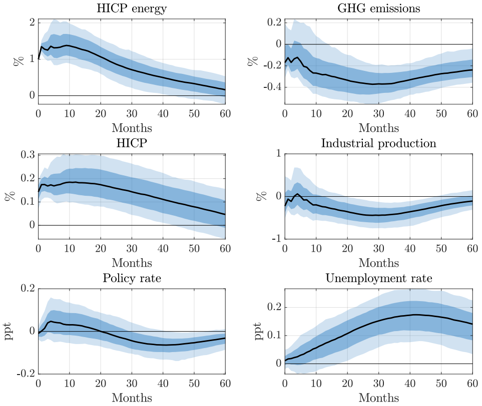
First stage regression: F-statistic: 37.55, R^2: 51.68%

2005-2018 sample



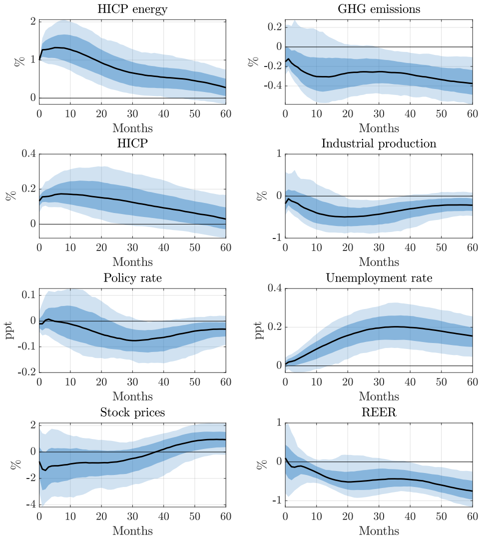
First stage regression: F-statistic: 14.11, R^2: 4.49%

Responses from smaller VAR



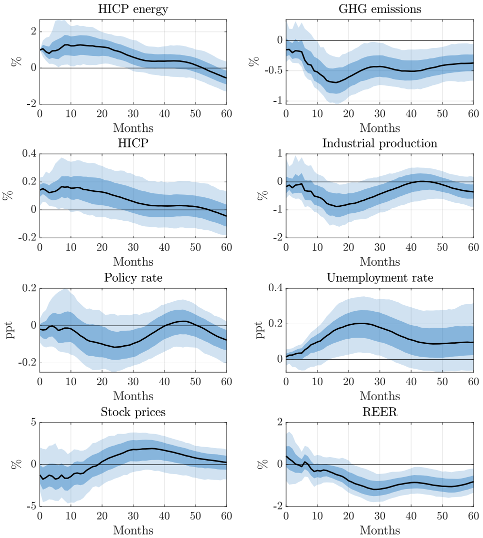
First stage regression: F-statistic: 13.58, R^2: 3.32%

VAR with 3 lags



First stage regression: F-statistic: 9.73, R^2: 2.86%

VAR with 9 lags



First stage regression: F-statistic: 14.89, R^2: 2.79%