The Geographic Effects of Carbon Pricing

Giacomo Mangiante[*]

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November 2022

Abstract

This paper studies the heterogeneous impacts of carbon pricing on European regions. I follow the approach of Känzig (2022) and identify carbon policy shocks from changes in carbon futures price around regulatory events. The shock series is then combined with granular data on economic activity at the city- and county-level in Europe. I document that poorer regions are significantly more exposed to these shocks. Two years after a carbon policy shock the output of regions at the bottom quartile of the gross value added per capita distribution decreases more than twice as much relative to the output of regions in the top quartile. I investigate which channels might explain this result and find that the most important driver is across-country variation rather than sectoral compositions or within-country variation. The empirical evidence provided strongly encourages better coordination among European countries to avoid the economic costs of carbon pricing being unequally borne.

Keywords: Carbon pricing, macroeconomic effects, regional heterogeneity, sectoral heterogeneity
JEL classification: E32, H23, Q54, R11

[*]University of Lausanne, Lausanne, Switzerland, email: giacomo.mangiante@unil.ch
I am indebted to my advisors Florin Bilbiie and Jean-Paul Renne for invaluable guidance and support. I would also like to thank Brendan Berthold and Diego R. Känzig for sharing their data. I am also grateful to Philippe Bacchetta, Kenza Benhima, Brendan Berthold, Maximilian Konradt, and the seminar and conference participants at the Lausanne Research Days for their helpful comments. All errors are my own.

1 Introduction

The mitigation of climate change can be considered one of the most important challenges of our generation. Several policies have been adopted over the last decades to tackle the worldwide long-term shifts in temperatures and weather patterns. Among those policies, carbon pricing, i.e., setting the price of carbon to capture the external costs of greenhouse gas (GHG) emissions paid by the public, is one of the most important tools currently available. Nonetheless, the empirical evidence on the impact of this policy on the economy is rather limited. This is especially true at the regional level.

This paper studies the regional effects of carbon pricing in the Euro Area. A carbon policy shock tightening the carbon pricing regime causes a persistent fall in overall GHG emissions but also results in a strong contraction of the aggregate economy. The impact is extremely heterogeneous across regions. I document that the output of poorer regions in terms of gross value added (GVA) per capita is more affected by changes in the carbon price. I then evaluate plausible channels that can explain this finding. I show that variation across- rather than within-country or sectoral composition is the main driver behind the heterogeneous responses along the GVA per capita distribution.

To measure exogenous changes in the carbon price, I use the carbon policy shock series recently developed by Känzig (2022). He identifies 113 regulatory events that influenced the supply of emission allowances in the European Union Emissions Trading System (EU ETS). The series of carbon policy surprises is then computed from the change in the carbon futures price in a tight window around the regulatory news. The surprise series can be used as an instrument to estimate the dynamic causal effects of a carbon policy shock on the aggregate economy.

I then evaluate whether regions are heterogeneously exposed to carbon pricing policies. To do so, I combine the carbon policy shock series with regional data at an extremely granular level (city- and county-level). The geographic data on gross value added and employment are taken from the European Regional Database (ERD) by Cambridge Econometrics and the responses of region-level economic activity are computed adopting a panel Local Projection à la Jordà (2005). I document that the output of poorer regions responds significantly more to carbon policy shocks than the output of rich regions.

Different channels that might explain this result are tested. On the one hand, the output of poorer regions tends to be produced more by labor-intensive sectors. On the other hand, capital- and labor-intensive sectors do not significantly differ in their sensitivity to carbon policy shocks so the heterogeneous regional sectoral composition cannot account for the different responses of rich and poor regions. Neither does within-country heterogeneity. No significant difference is detected between the responses of rich and poor regions within the four largest countries in the sample, i.e., France, Germany, Italy, and Spain. Therefore, across-country variation is the most important driver behind the main finding. The result holds even once controlling for other country characteristics as well.

Carbon pricing has been found to be extremely effective in reducing GHG emissions. At the same time, some empirical evidence suggests that it can have detrimental effects on the economy. Different regions are heterogeneously exposed to changes in the price of carbon. Correctly understanding how and through which channels the regional characteristics influence the transmission of carbon policy shocks is of pivotal importance for policymakers to reduce the economic costs of carbon pricing. The findings of this paper suggest that fiscal policies coordinated at the European level to support poorer countries through the transition towards a greener economy might help to mitigate these adverse effects.

Related literature. This paper contributes to two strands of the literature. First, the results complement the large body of empirical evidence on the effects of carbon pricing on the economy. On the one hand, the effectiveness of carbon pricing for emission reductions is extensively supported by empirical evidence (Ralf et al., 2014, Andersson, 2019). On the other hand, the impact on macroeconomic variables has been found to be negligible.

Metcalf (2019) and Bernard and Kichian (2021) focus on the effects of the British Columbia carbon tax on the GDP finding no significant impacts on GDP. Similarly, Metcalf and Stock (2020b) and Metcalf and Stock (2020a) do not find a negative relationship between the carbon taxes in European countries and employment or GDP growth. The result is extended to inflation by Konradt and di Mauro (2021) who focus on carbon taxes in Europe and Canada. Benmir and Roman (2022) find that carbon pricing shocks in the California cap-and-trade market have sizable effects on the economy, they result in an increase in the price of energy and in a decrease in energy consumption, wages, and asset returns.

The impact of carbon policies might not be limited to aggregate variables. Ohlendorf et al. (2021) adopt a meta-analysis approach on 53 empirical studies containing covering 39 countries and document that carbon pricing in the EU has affected substantially more lower-income households than richer ones. The carbon policy shocks used in this paper are developed by Känzig (2022). He shows that exogenous variation in the carbon price due to regulatory events leads to a fall in economic activity. On top of that, the consumption of poorer households decreases significantly more than those of richer households and this is mainly due to general equilibrium effects. Finally, Berthold et al. (2022) uses the same carbon policy shocks and study how different countries and firms respond to them. By adopting a panel VAR with 30 countries they document that more carbon-intensive countries are generally more affected. Moreover, brown sectors do not respond differently than the green sector but within a sector, brown firms tend to suffer more. I contribute by documenting how different regions are heterogeneously exposed to carbon pricing. Poorer regions are more sensitive to changes in carbon price mainly due to different country characteristics.

The second strand is the literature that answers macroeconomic questions with granular data at the regional level. Most macroeconomic variables are often limited over the time dimension. Therefore, more and more researchers have compensated for the lack of time variation by exploiting the cross-sectional variation in geographical data. Auerbach and Gorodnichenko (2012) and Cloyne et al. (2020) use cross-country panel data to estimate the fiscal multipliers. Similarly, Nakamura and Steinsson (2014) estimate the effects of government spending using regional variation across U.S. states in military build-ups.

Regional heterogeneity has been exploited as well to estimate the slope of the Phillips curve (Hazell et al., 2021) or to evaluate which regional characteristics matter the most in the transmission of monetary policy shocks. Gallegos et al. (2022) show that the share of financially constrained households strongly correlates with the output responsiveness to monetary shocks across Euro Area country. Leahy and Thapar (2020) and Mangiante (2022) document that the economic activity of U.S. states with an older demographic structure is more sensitive to shocks. Herreno and Pedemonte (2022) show that poorer U.S. cities respond more to monetary shocks. Hauptmeier et al. (2020) find a similar result for poorer Euro Area regions. I extend this literature by exploiting the geographical variation across Euro Area regions to study which country characteristics matter the most in the transmission of carbon policy shocks.

Road map. The remaining paper is organized as follows. Section 2 describes the data used in this paper. In section 3, I describe how carbon policy shocks are identified following the approach proposed by Känzig (2022). Section 4 shows the results of the main analysis. In Section 5, I perform a battery of robustness checks to strengthen the validity of the baseline results. Finally, Section 6 concludes.

2 Data

2.1 Macroeconomic data

The EA-19 macroeconomic variables used in the Proxy-VAR are the same as in Känzig (2022). The climate policy surprises are computed from the EUA futures front contract (settlement price). The other variables included are the energy component of the HICP, total GHG emissions, the headline HICP, industrial production, the unemployment rate, the policy rate, a stock market index, as well as the real effective exchange rate (REER). All variables are taken from Datastream with the exception of the total GHG emissions which are computed by Känzig (2022). The sample spans the period from January 1999 to December 2018.

2.2 Regional data

The source of the geographical data is the European Regional Database (ERD) by Cambridge Econometrics[1]. The ERD is based on Eurostat's REGIO database and uses national statistics from the European Commission's AMECO database and interpolation methods to fill some of the gaps. The data are based on Eurostat's Nomenclature of Territorial Units for Statistics (NUTS), a hierarchical system that divides the economic territory of the EU into four levels. The highest level (NUTS0) corresponds to the nation-state and the lowest (NUTS3), roughly corresponds to the city and county levels. I will mainly focus on data at the NUTS3 level.

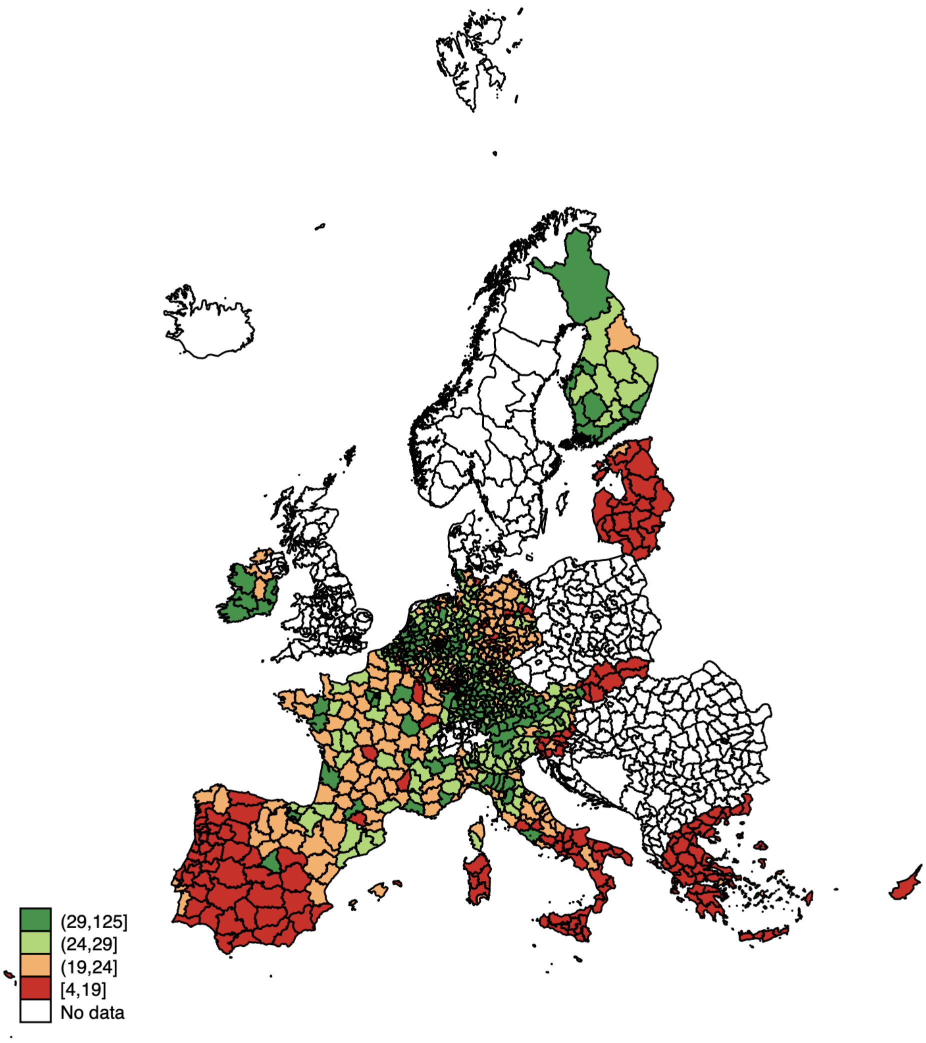
The main variables of interest are the gross value added, deflated to 2005 price levels, total employment, and population size. I will also focus on the breakdown of regional gross value added and employment into six sectors of the economy, corresponding to the disaggregation in NACE Rev.2 as agriculture, forestry, and fishing; industry less construction; construction; financial and business services; wholesale, retail, transport, accommodation, and food services, information and communication; and last, non-market services. I define the capital-intensive sector as the merging of the industry and construction sectors. Similarly, I merge the sectors of financial and business services, wholesale, retail, transport and food services, information and communication, and non-market services and define this as the labor-intensive sector.

The sample includes all NUTS3 regions from the EA-19 member states, over the period 1999-2018. The countries considered are Austria (AT), Belgium (BR), Cyprus (CY), Estonia (EE), Germany (DE), Greece (EL), Finland (FI), France (FR), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU), Malta (MT), Netherlands (NL), Portugal (PT),

[1] Further details can be found in Econometrics (2017).

Slovenia (SI), Slovakia (SK), Spain (ES). The data are available only at an annual frequency and the final sample consists of 964 NUTS3 regions.

Figure 1: Heterogeneity in GVA per capita (thousands of euro)



Notes: The figure reports the real GVA per capita in 2015 at the NUTS3 level.

Figure 1 reports the real GVA per capita in 2015 at the NUTS3 level. As can be noticed, the geographic data displays an extremely high level of heterogeneity. This is true within as well as across countries.

2.3 Country-level data

The shares of financially constrained households at the country level are taken from Gallegos et al. (2022). The authors rely on the Eurosystem Household Finance and Consumption Survey (HFCS) to compute a measure of the share of Hand-to-Mouth (HtM) households for each country. They categorize a household as HtM if its liquid wealth is smaller than a certain share of monthly income. They further divide households into wealthy and poor HtM. A household is categorized as (*Wealthy HtM*) if it also has positive illiquid wealth otherwise is categorized as (*Poor HtM*). The average age of household heads is labeled *Age*.

Other country characteristics include a measure of trade openness defined as the sum of imports and exports as a share of GDP (*Trade openess*), a measure of how regulated labor markets (*ROL*) are, and the house price growth (*HP Growth*) calculated as the average quarterly year-on-year change in the house price index.

The remaining country characteristics are taken from Eurostat. They include the amount of CO2 emission per capita (*CO2 Emiss.*), the share of natural gas in gross available energy (*Gas Share in Energy*), the share of oil and petroleum product in gross available energy (*Petroleum Share in Energy*), and the ratio between gross available energy and GDP (*Energy intensity*).

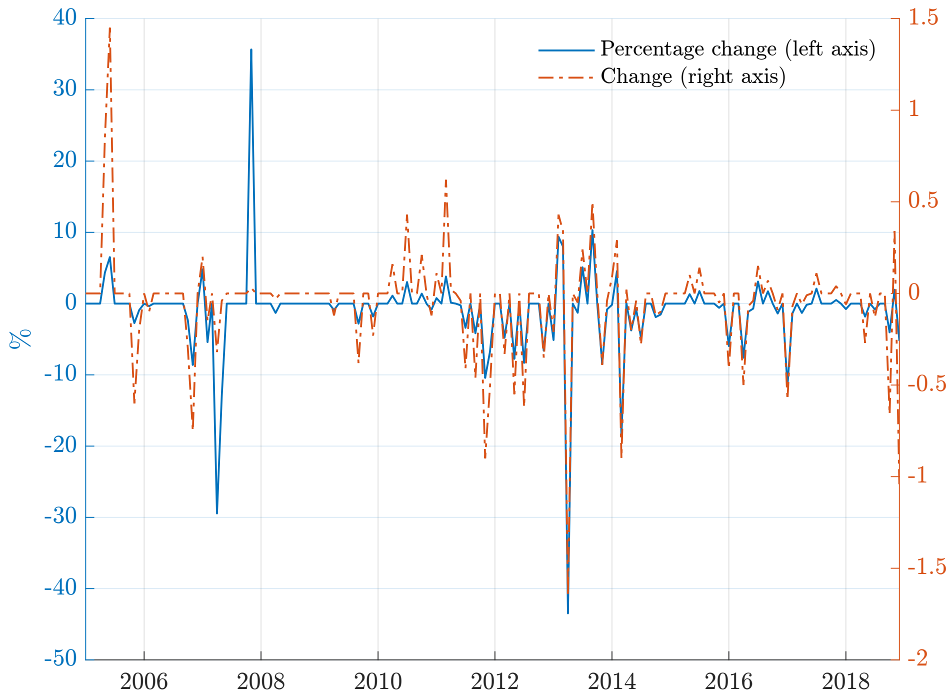
3 Identifying carbon policy shocks

The carbon policy shocks are computed as in Känzig (2022). I here briefly summarise his approach but I refer to the original paper for a detailed description. The author exploits the fact that the European carbon market, established in 2005, operates under the cap and trade principle. This means that a cap is set on the overall amount of certain greenhouse gases that can be emitted by, for instance, power plants and industry factories. Within the cap, emission allowances are auctioned off and traded in different organized markets. Each year the cap decreases ensuring that total emissions fall.

Känzig (2022) identify 113 events during the period between 2005 and 2018 concerning the overall cap in the European Union Emissions Trading System (EU ETS), the free allocation of allowances, the auctioning of allowances as well as the use of international credits. He then defines carbon policy surprises from the changes in the futures price of the EU emission allowances (EUA) in the ICE since it is the most liquid market. In particular, the surprises are defined as the difference in the log settlement price of the EUA futures contract between the day of the event and the day before. Since in some periods, the futures price is close to zero, as robustness checks, I also considered the simple difference in settlement price rather than the percentage change. The results for this alternative specification are reported in Section 5.

The daily surprises are then aggregated into a monthly series by summing over the daily surprises in a given month. In months without any regulatory events, the series takes zero value. The resulting carbon policy surprise series, computed as percentage change as well as simple difference, are shown in Figure 2. The two series are poorly correlated up until 2008 when the EUA futures price was relatively close to zero, but highly correlated afterward. Given the high correlation between the series, the main results hold under both specifications.

Figure 2: The carbon policy surprise series



Notes: This figure shows the carbon policy surprise series, constructed by measuring the percentage change (blue solid line, left axis) as well as the change (red dashed line, right axis) of the EUA futures price around regulatory policy events.

The carbon policy surprise series can be considered only a partial measure of the shock of interest. Indeed, it may not capture all relevant instances of regulatory news in the carbon market and could be subject to measurement errors. Therefore, as in Känzig (2022), I do not use it as a direct shock measure but as an instrument. To estimate the dynamic causal effects of a carbon policy shock on the aggregate economy, I rely on the external instrument approach (Mertens and Ravn, 2013, Gertler and Karadi, 2015).

Starting from the standard VAR model:

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

with p the number of lags, y vector of variables of dimension n x 1, u the vector of reduced-form innovations with covariance matrix $\text{Var}(\mathbf{u}_t) = \mathbf{\Sigma}$, $\mathbf{b}$ is the vector of constant and $\mathbf{B}_1, ..., \mathbf{B}_p$ are coefficient matrices.

Assuming that the VAR is invertible, the residuals can be expressed as a function of structural shocks ε_t:

$$\mathbf{u}_t = \mathbf{S}\varepsilon_t. \tag{2}$$

Our aim is to estimate the causal impact on the economy of a single shock, i.e., the carbon policy shock. Therefore, without loss of generality, we can denote the carbon policy shock as the first shock in the VAR, $\varepsilon_{1,t}$. We are interested in identifying only the structural impact vector $\mathbf{s_1}$ which corresponds to the first column of $\mathbf{S}$.

The identification can be achieved by using an external instrument z_t. In our case, the external instrument is the carbon policy surprise series obtained from the changes in EUA futures price. For z_t to be a valid instrument we need two assumptions to hold:

$$\begin{aligned} \mathbb{E}\left[z_t \varepsilon_{1,t}\right] &= \alpha \neq 0 \\ \mathbb{E}\left[z_t \varepsilon_{2:n,t}\right] &= \mathbf{0}. \end{aligned} \tag{3}$$

The first assumption is the relevance requirement: the instrument z_t has to be strongly correlated with the shock of interest $\varepsilon_{1,t}$. The second assumption is the exogeneity condition: the instrument needs to be exogenous to the other structural shocks $\varepsilon_{2:n,t}$. These assumptions, plus invertibility, identify s_1 up to sign and scale:

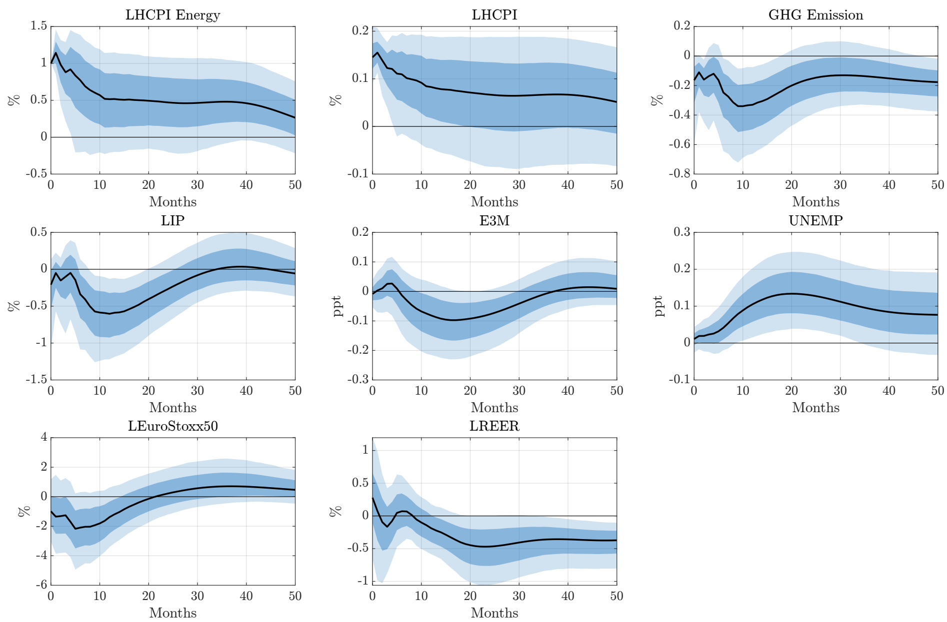
$$\mathbf{s}_1 \propto \frac{\mathbb{E}\left[z_t \mathbf{u}_t\right]}{\mathbb{E}\left[z_t \mathbf{u}_{1,t}\right]'}. \tag{4}$$

To ease interpretation, the structural impact vector is scaled such that a unit positive value of $\varepsilon_{1,t}$ has a unit positive effect on $y_{1,t}$, i.e., $s_{1,1} = 1$. Therefore, the carbon policy shock is normalized to increase the first variable of the VAR, i.e., the energy component of the HICP, by one percent on impact. Inference is conducted with residual-based moving block bootstrap by Carsten and Lunsford (2019).

Following Känzig (2022), the baseline VAR specification consists of eight variables: the energy component of the HICP (*LHCPI Energy*), total GHG emissions, the headline HICP (*LHCPI*), industrial production (*LIP*), the unemployment rate (*UNEMP*), the policy rate (*E3M*), a stock market index (*LEuroStoxx50*), as well as the real effective exchange rate ((*LREER*)). The sample spans the period from January 1999 to December 2018. The carbon policy surprise series is only available from 2005 when the carbon market was established. Therefore, the missing values in the surprise series are censored to zero. The VARs are estimated in levels using as controls six lags of all variables. Apart from unemployment and the policy rate, all variables enter in log levels.

Figure 3 reports the impulse responses to the identified carbon policy shock, normalized to increase the HICP energy component by one percent on impact. The solid black lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands based on 10,000 residual-based moving block bootstrap replications.

Figure 3: Impulse responses to a carbon policy shock



Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid lines are the point estimate and the dark and light-shaded areas are 68 and 90 percent confidence bands, respectively. The percentage change of the EUA futures price is used as an instrument.

A restrictive carbon policy shock results in an increase in overall inflation and in a strong decrease in greenhouse gas emissions as well as industrial production while the unemployment rate rises. Financial markets are affected as well, stock prices fall significantly, and the real exchange rate depreciates. The macroeconomic responses show how carbon policies successfully result in a reduction in GHG emissions. However, the aggregate economy is negatively affected by them.

4 The heterogeneous impact of carbon policy shocks on regional output

I now focus on how different European regions are heterogeneously exposed to carbon policy shocks. I extract the carbon policy shock from the monthly VAR as $CPShock_t = \mathbf{s}_1' \Sigma^{-1} \mathbf{u}_t$ (Stock and Watson, 2018) and combine it with regional data at NUTS3 level *European Regional Database* (ERD) by Cambridge Econometrics. The shocks are aggregated to an annual frequency by summing them over to match the frequency of the regional data. Finally, the shock is normalized to increase the HICP energy component by one percent on impact.

The average region-level response to a climate policy shock is estimated using Local Projection à la Jordà (2005):

$$y_{i,t+h} = \alpha_{i,h} + \beta_h CPShock_t + \sum_{l=1}^{L} \theta_{i,h}^l y_{i,t-l} + \gamma_{i,h} X_{i,t-1} + \epsilon_{i,t+h}, \tag{5}$$

for $h = 1, ..., 5$. $y_{i,t}$ is the dependent variable for region i at time t, $CPShock_t$ are the carbon policy shocks extracted from Proxy-VAR. I control for lags of the dependent variable, $\sum_{l=1}^{L} \theta_{i,h}^l y_{i,t-l}$, as well as regional variables, $X_{i,t}$. In the baseline specification L is equal to 2 and region fixed effects and population size are included. Standard errors are clustered at the country-year level. The main dependent variable is the log of real gross value added (GVA) at aggregate as well as sectoral levels. The coefficient of interest is β_h which captures the average response across regions of a carbon policy shock on the dependent variable for each horizon h.

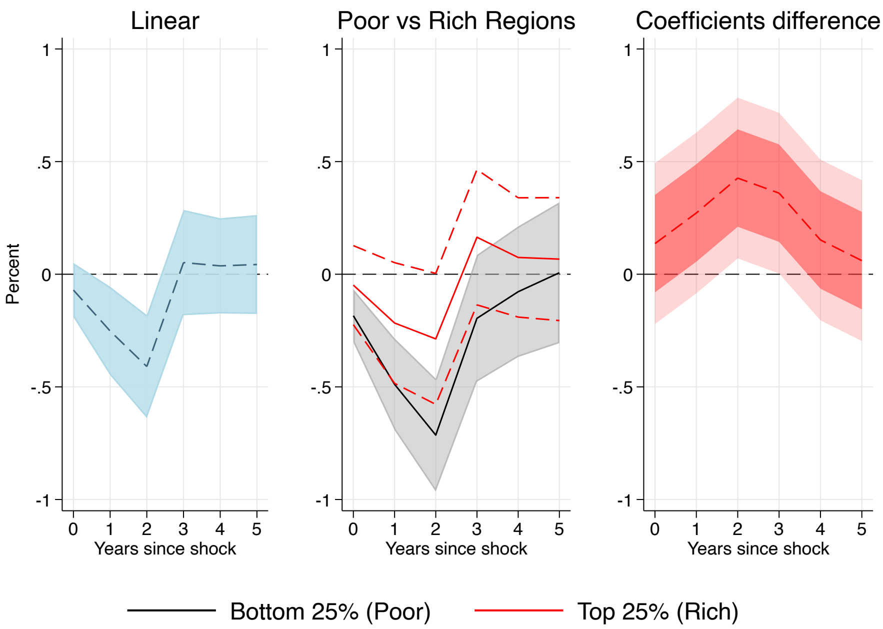
To evaluate how different regions are affected by carbon policy shocks, I follow the approach proposed by Cloyne et al. (2018). I define dummy variables for different percentiles P of the GVA per capita distribution and interact them with the climate policy shock $CPShock_t$:

$$y_{i,t+h} = \alpha_{i,h} + \sum_{p=1}^{P} \gamma_h D_{i,t}^p + \sum_{p=1}^{P} \beta_h^p D_{i,t}^p CPShock_t + \sum_{l=1}^{L} \theta_{i,h}^l y_{i,t-l} + \gamma_{i,h} X_{i,t} + \epsilon_{i,t+h}, \tag{6}$$

where $D_{i,t}^p$ is a dummy equal to 1 if the GVA per capita of the region i belongs to the p-th percentile at time t and 0 otherwise. The coefficients β_h^p, which are different for each percentile included in the regression, capture how regions are heterogeneously affected by carbon policy shocks according to their position in the GVA per capita distribution.

The responses of regional real gross value added to a climate policy shock are reported in Figure 4. The left panel plots the estimated β_h coefficient at different horizons h from equation (5). The shaded area is the 90 percent confidence interval. Following a carbon policy

Figure 4: Impact of climate policy shocks on log real GVA



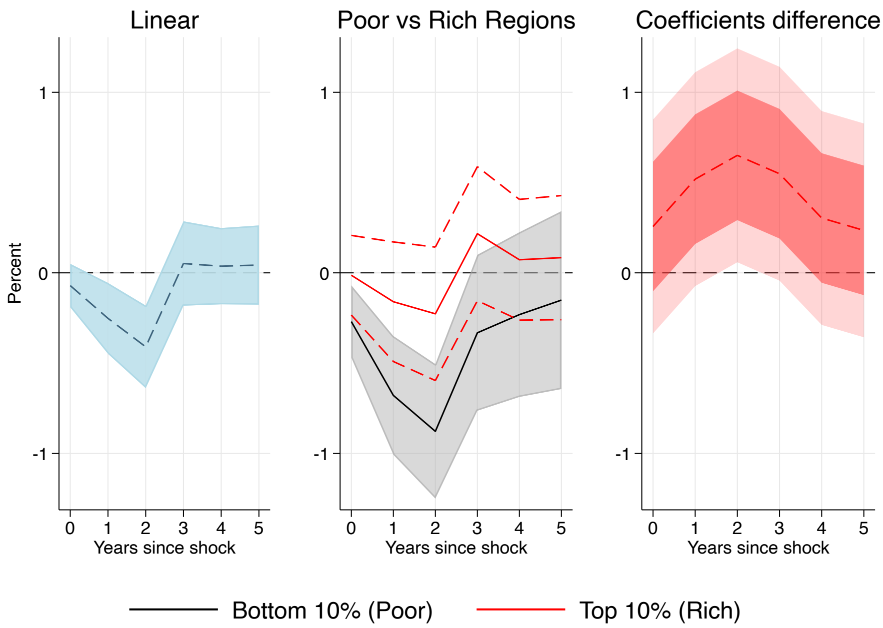
Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The middle panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution. The right panel performs a t-test on the difference between the coefficients of the responses of poor and rich regions. The red-shaded areas are the 68 and 90 percent confidence bands.

shock that results in a one percent increase of the HICP energy component on impact, the gross value added significantly and persistently decreases. The magnitude and the shape of the response are in line with the macro responses from the Proxy-VAR.

The middle panel of Figure 4 plots the estimated β_h^p coefficients from equation (6) for the bottom 25% and top 25% regions in terms of GVA per capita. As one can notice, the response of the "rich" regions (top 25%) is remarkably more muted than the response of the "poor" regions. After 2 years, the gross value added for the regions at the top of the GVA per capita distribution decreases by 0.3% whereas for the regions at the bottom by 0.7%. These results suggest there are sizable and economically meaningful differences in the extent to which poor and rich regions are impacted by carbon policy shocks.

On the right panel, I test whether the difference between the regional responses of poor and rich regions is statistically significant. The red dashed line is the difference in the responses between poor and rich regions and the shaded areas are the one and 1.65 standard deviation confidence intervals of the t-test. The null hypothesis can be rejected at the 10% significance level for the difference of the coefficients two and three years after the shock.

Figure 5: Impact of climate policy shocks on log real GVA, top/bottom 10%



Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The middle panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 10% and top 10% of the real GVA per capita distribution. The right panel performs a t-test on the difference between the coefficients of the responses of poor and rich regions. The red-shaded areas are the 68 and 90 percent confidence bands.

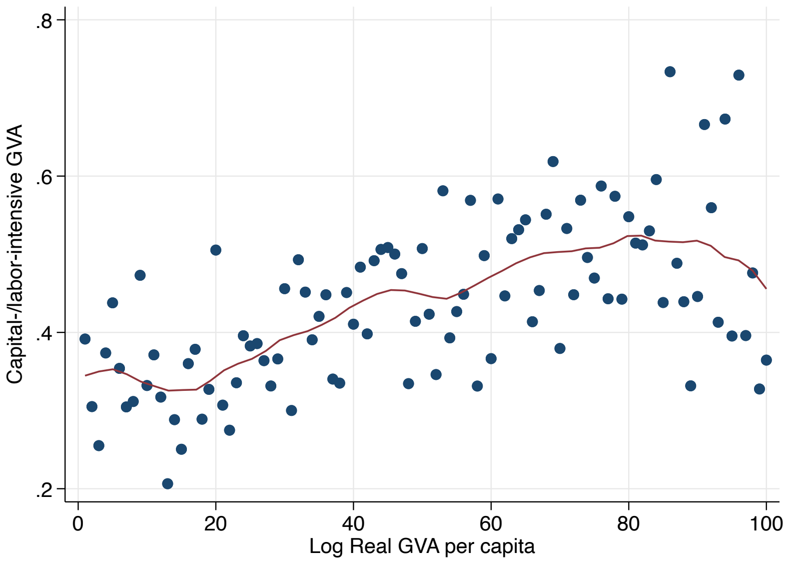
The difference in responses is even more striking if we focus on the top and bottom 10% of the distribution as in Figure 5. The gap between the responses of gross value added across regions between poor and rich regions is larger under this specification. Two years after the shocks the difference in GVA responses between the bottom 25% and top 25% regions in terms of GVA per capita is 0.43 percentage points whereas for the bottom 10% and top 10% regions is 0.65. This reinforces the conclusion that the responsiveness of output to carbon policy shocks is decreasing in the GVA per capita.

What could explain the sizable difference in the regional responses? Two channels might drive the result: sectoral composition and across-country variations. It might be the case that the gross value added of the regions along the GVA per capita distribution is produced by different sectors. If the different sectors do not homogenously respond to carbon policy shocks, the different regional sectoral compositions might result in heterogeneous responses. A second potential explanation is that what I am capturing is variation across countries rather than across regions: poorer countries might be more exposed to these shocks than rich ones and the output of their regions respond more on average. I explore both channels in the next sections.

4.1 The role of sectoral composition

I now evaluate whether regions along the GVA per capita distribution specialize in different sectors. Figure 6 shows the relationship between the ratio of output in the capital-intensive sectors over the output in the labor-intensive sectors across different percentiles of the regional per-capita GVA distribution for 2015. There is a clear positive relationship between the two variables: the richer the region the more its output is produced by capital-intensive sectors. The industry ratio increases from 0.35% for the regions at the bottom of the distribution to 0.55% for those at the top.

Figure 6: Industry structure across percentiles

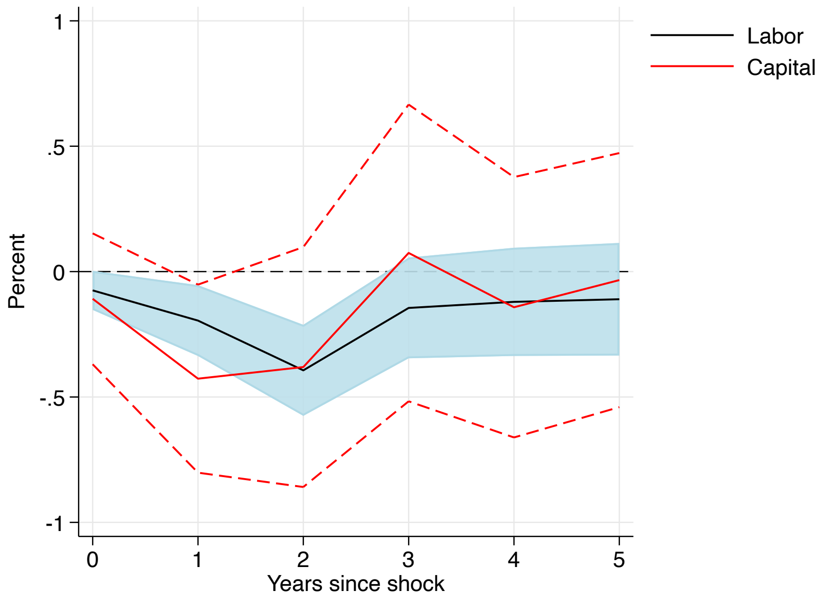


Notes: The figure shows the relationship between the ratio of output in the capital-intensive sectors over the output in the labor-intensive sectors and different percentiles of the regional per-capita GVA distribution for 2015.

Therefore, if the labor-intensive sectors were to react more to carbon policy shocks, this would partially explain the stronger response observed for poorer regions. However, two pieces of evidence speak against industry structure as an explanation for the greater sensitivity of poorer regions.

First, the output of the labor-intensive sectors does not respond more to a climate policy shock than the output of capital-intensive sectors. Second, even within each type of industry, the differential response across the distribution remains intact: both the capital- and the labor-intensive production decrease more strongly and more persistently in the lower than in the upper part of the distribution.

Figure 7: Impact of climate policy shocks on output across industries

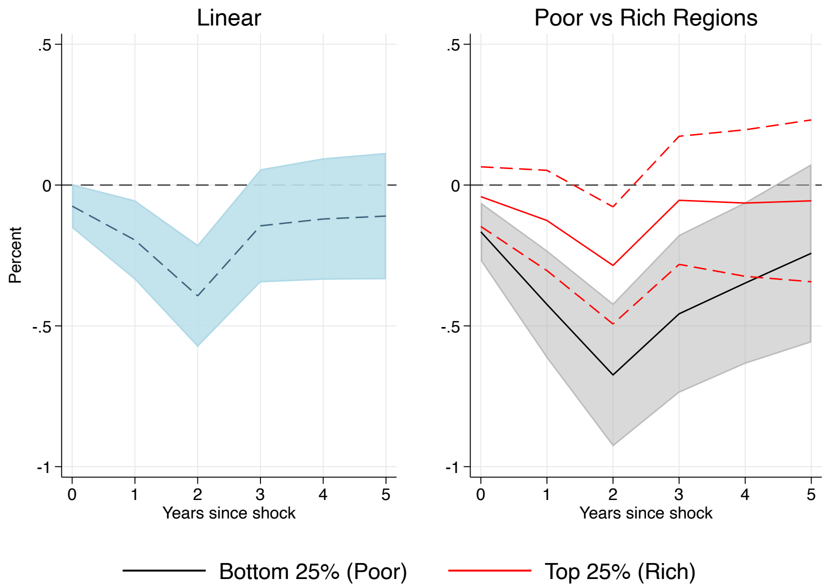


Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region level log real GVA from the capital-, labor-intensive sectors and the construction sector. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

Figure 7 shows the responses of the real gross value added for the capital- and labor-intensive sectors. In the first 2 years after the shock, the output from the capital-intensive sectors decreases slightly more than the output from the labor-intensive sectors although the difference is not statistically significant. This is most likely due to the higher energy use in the former group of sectors which is directly affected by the carbon policy shocks.

Figure 8 and Figure 9 report the output responses for the rich and the poor regions within each type of industry. As it can be noticed, conditioning for the type of industry does not change the fact that the gross value added of the poorer regions decreases remarkably more in response to a carbon policy shock. Overall, we can conclude that sectoral composition does not explain the higher sensitivity to the shock of the poorer regions.

Figure 8: Impact of climate policy shocks on log real GVA from labor-intensive sectors



Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA from labor-intensive sectors. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

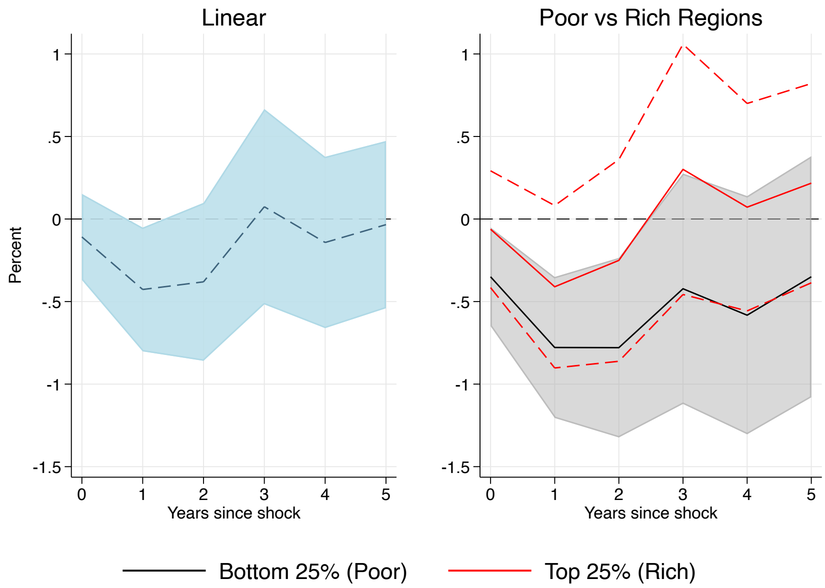
4.2 Across- vs within-country variation

Since sectoral composition at the regional level does not explain the different responses of output along the GVA per capita distribution, I now evaluate whether across-country heterogeneity might. Indeed, it might be the case that across- rather than within-country variation is driving the results.

To test this channel, I estimate the same equation (6) but for one country at a time. I focus in particular on the four largest countries in the sample and which have the highest within-country regional variations in GVA per capita: France, Germany, Italy, and Spain.

The aggregate and percentile responses of the GVA for each country are reported in Figure 10. The four countries are different in the magnitude and shape of the responses. However, looking at the left panel of each plot, the heterogeneous responses along the GVA distribution almost entirely disappear once we condition for the individual country. This suggests that across-country rather than within-country or across-region variation is what matters the most in terms of regional sensitivity to carbon policy shocks.

Figure 9: Impact of climate policy shocks on log real GVA from capital-intensive sectors

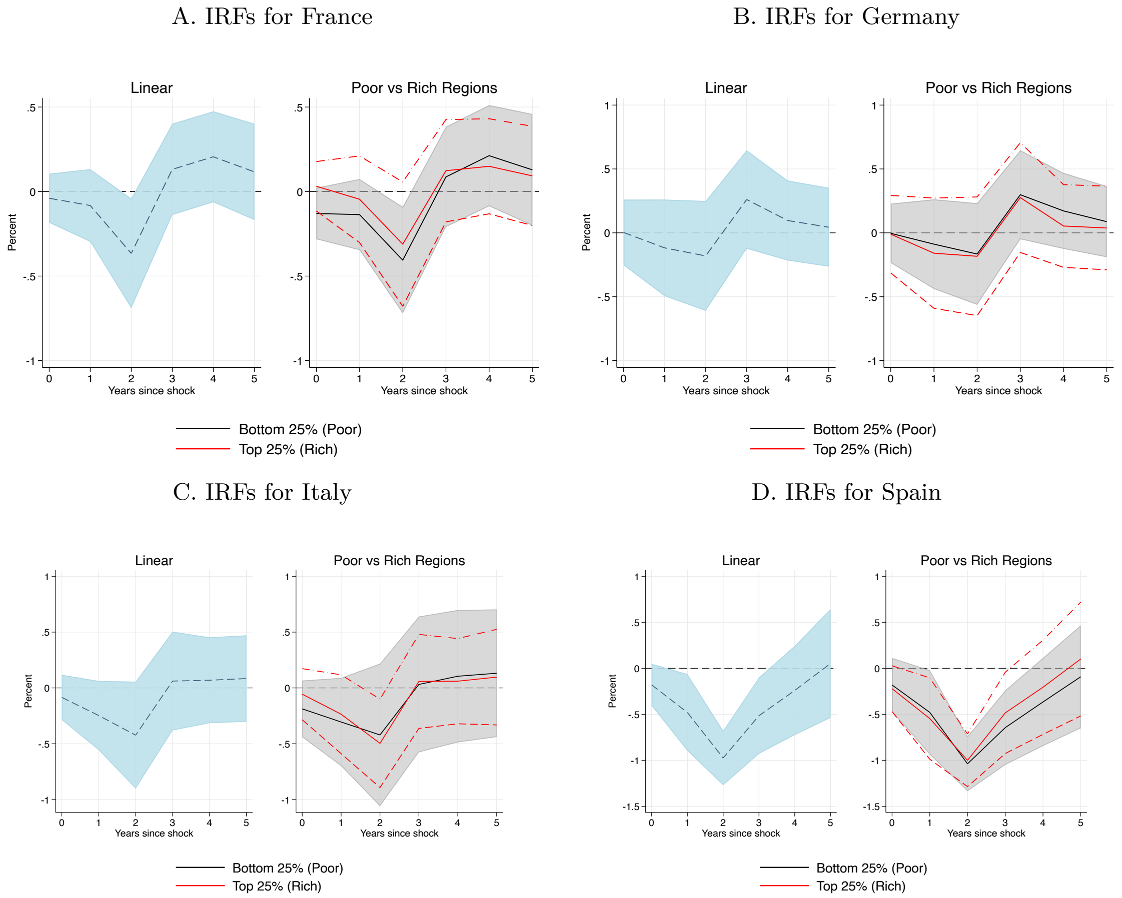


Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA from capital-intensive sectors. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

The same result can be more formally evaluated by considering a different definition of the GVA per capita percentiles. Instead of defining the dummy $D^p_{i,t}$ equal to 1 if the GVA per capita of the region i belongs to the p-th percentile at time t and 0 otherwise, I set it equal to 1 if region i of country c belongs to the p-th percentile at time t of country c and 0 otherwise. In this way, the coefficients β^p_h of equation (6) compare the responses to carbon policy shocks of rich and poor regions *within* the same country.

Figure 11 shows the results of the within-country analysis. There is basically no difference in the responses of the regions at the bottom 25% and the top 25% of GVA per capita once we control for the country to which they belong. This striking result confirms that whether a region is poor or rich does not matter in terms of the sensitivity to carbon policy shocks. What matter is whether the region is part of a rich or poor country.

Figure 10: Age specific parameters



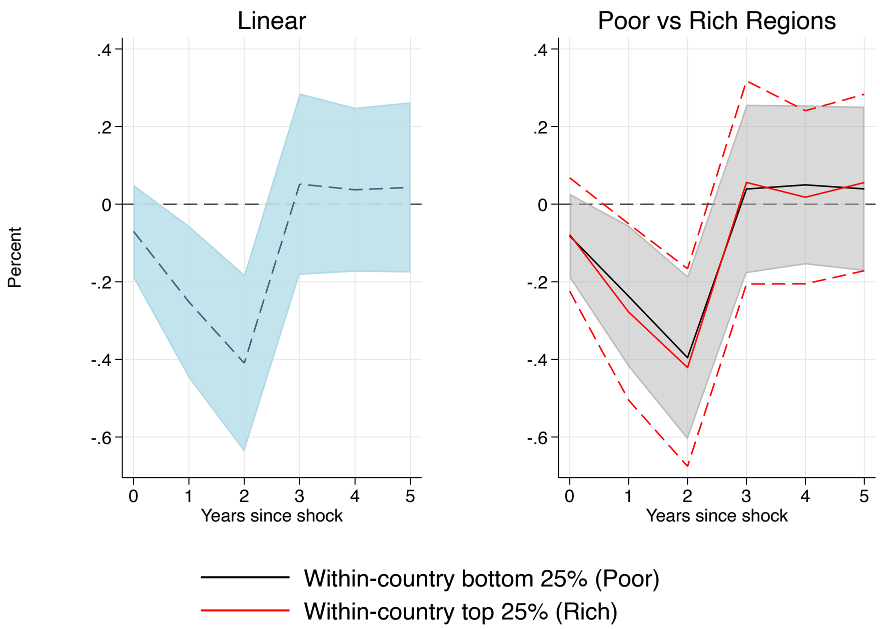
Notes: The left side of each panel plot for different countries the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right side of each panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution. Panel A: The plot shows the responses for France. Panel B: The plot displays the responses for Germany. Panel C: The plot reports the responses for Italy. Panel D: The plot shows the responses for Spain.

4.3 The importance of country characteristics

In the previous section, I show that across-country variation is the main driver behind the heterogeneous sensitivity of regions along the GVA per capita distribution. I now study which country characteristics correlate the most with the responsiveness to carbon policy shocks.

To do so, first I compute the impulse responses of real gross value added to a carbon policy shock for each country in our sample. Second, I define two measures of country responsiveness: The minimum value of the impulse response and the cumulative value to capture the persistency of the response. Third, I relate the responsiveness measures to country characteristics commonly studied in the literature.

Figure 11: Impact of climate policy shocks on log real GVA, within-country percentiles

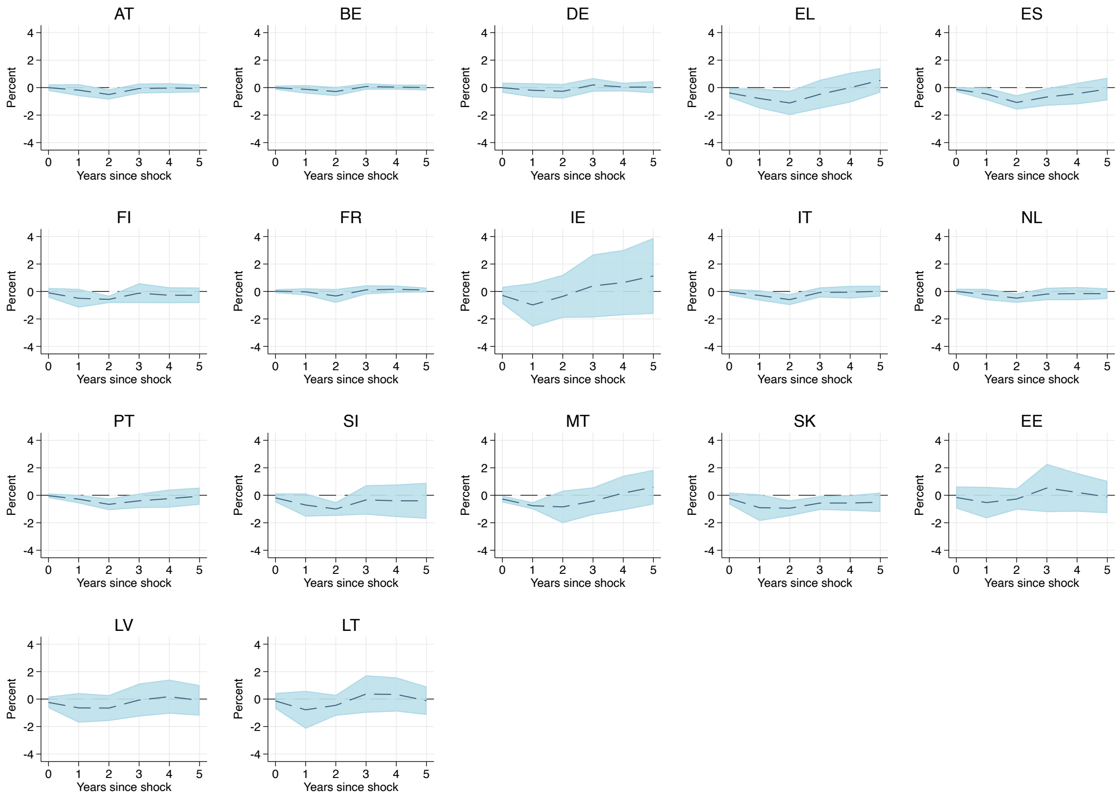


Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The middle right reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

Figure 12 presents impulse responses of real gross value added for each country. On the one hand, the estimated impulse response functions reveal that carbon policy shocks lead to a significant decrease in output for all countries. On the other hand, the shape and the magnitude of the responses considerably differ across countries, both in minimum value and cumulative effect.

As in Gallegos et al. (2022), I gather country-level data on variables that are likely to be relevant for the sensitivity to carbon policy shocks. Subsequently, for each variable, I investigate whether (i) it is correlated with the minimum value as well as the cumulative responses, (ii) it is correlated with the gross value added per capita, and (iii) whether after controlling for the variable, the gross value added per capita still explains a significant part of the output responses we observe. The variables I consider are the gross value added per capita (*GVA per capita*), the ratio of output in the capital-intensive sectors over the output in the labor-intensive sectors (*Industry Ratio*), the ratio between gross available energy and GDP (*Energy intensity*), the share of natural gas in gross available energy (*Gas Share in Energy*), the share of oil and petroleum product in gross available energy (*Petroleum Share in*

Figure 12: Impact of climate policy shocks on log real GVA at country-level



Notes: Each panel plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the log of real GVA at the country level. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months.

Energy), the amount of CO2 emission per capita (*CO2 Emiss.*), the share of Hand-to-Mouth households (*HtM*), the share of wealthy Hand-to-Mouth households (*Wealthy HtM*), the share of poor Hand-to-Mouth households (*Poor HtM*), the average age of household heads *Age*, a measure of trade openness defined as the sum of imports and exports as a share of GDP (*Trade openess*), a measure of how regulated labor markets (*ROL*) are and the house price growth (*HP Growth*). See Section 2 for a description of the source of the data and how the variables are computed.

All results are summarized in Table 1. The first and second columns in the table present raw correlations between the two responsiveness measures and the different variables. In the third column, I report the correlations between the gross value added per capita and the variables that vary across the rows.

Table 1: Correlations table

X	(1) ρ(Min., X)	(2) ρ(Cum. IRF, X)	(3) ρ(GVA pc, X)	(4) ρ(Min., GVA pc - X)	(5) ρ(Cum. IRF, GVA pc - X)
GVA per capita	0.472*	0.639***	1	NA	NA
Industry Ratio	-0.243	-0.110	-0.00312	0.470*	0.639***
Energy Intensity	0.0588	-0.247	-0.430*	0.550**	0.590**
Petroleum Share in Energy	-0.179	0.0246	0.169	0.509**	0.644***
Gas Share in Energy	0.183	0.196	0.155	0.448*	0.616***
CO2 Emiss.	0.204	0.229	0.507**	0.427*	0.607***
HtM	-0.615**	-0.589**	-0.585**	0.164	0.513**
Wealthy HtM	-0.658***	-0.745***	-0.747***	0.002	0.307*
Poor HtM	-0.209	0.131	0.149	0.529**	0.750***
Age	-0.0301	-0.251	-0.374	0.519**	0.719***
Trade Openess	-0.354	-0.218	-0.159	0.420*	0.612***
ROL	0.163	-0.0919	-0.352	0.534*	0.650**
HP Growth	-0.0298	-0.150	-0.385	0.406*	0.631**

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The first column shows the correlation coefficients between estimated min values of the IRFs and the country characteristics. The second column shows the correlation coefficients between the cumulative IRFs and the country characteristics. The third column reports the correlation coefficients between the GVA per capita and the country's characteristics. The fourth and fifth columns report the semipartial correlations. See the main text for information about the source and construction of the variables.

Both measures of responsiveness are positively and significantly correlated with the GVA per capita in line with the findings of the previous sections. This confirms that the poorer the country the more negative and more persistent the response to carbon policy shocks. Most of the other coefficients are close to zero and not significant. The only exceptions are the shares of Hand-to-Mouth and wealthy Hand-to-Mouth households which negatively correlate with the minimum value, the cumulative responses as well as the GVA per capita. The relationship implies that the higher the share of financially constrained households the stronger the output response.

The importance of the share of HtM households for the responsiveness of output to shocks is well established in the theoretical literature (see, among others, Bilbiie, 2008, Auclert, 2019 and Bilbiie, 2020). As shown by Bilbiie (2019), the output response to shocks is amplified if the income elasticity of constrained agents with respect to aggregate income is larger than one and a larger fraction of constrained agents amplifies this channel. Gallegos et al. (2022) document empirically the relationship between financially constrained households and output responsiveness by focusing on monetary policy shocks. I extend their result by showing that the share of HtM households is an important determinant of the country's sensitivity to carbon policy shocks as well.

It is important to assess whether the strong correlation between GVA per capita and output responsiveness disappears once we control for these other variables. To get a sense of whether this could be the case, I calculate semipartial correlations between the minimum value, the cumulative responses, and the GVA per capita. The semipartial correlation measures the strength of the linear relationship between the responsiveness measure and GVA per capita holding a third variable, varying across the rows in the table, constant for the GVA per capita. The semipartial correlations are reported in the fourth and fifth columns of Table 1. The size and the significance of the correlation coefficients are not remarkably affected by controlling for a third variable.

5 Robustness

In this section, I perform some robustness checks to strengthen the validity of the main results. First, I consider an alternative measure for the carbon policy surprises. Second, I use total employment as a measure of economic activity instead of the gross value added. Third, I extend the sample to more countries that are part of the EU ETS. Fourth, I repeat the empirical analysis using geographical data at NUTS1 and NUTS2 level of aggregation. The plots are reported in Appendix A.

5.1 Alternative measure of carbon policy surprise series

Since in some periods the EUA futures price series has values close to zero, taking the percentage change as a carbon policy surprise might overestimate the importance of some regulatory events. As an alternative measure of carbon price surprises I then also consider the simple change in futures price around the events. The monthly series is reported in Figure 2.

Figure 13 shows the Proxy-VAR responses to a carbon policy shock once I use this alternative measure as an instrument. As it can be noticed, the confidence intervals are larger than the baseline but the main results still hold, inflation increases whereas GHG emission and industrial production decrease.

From the residuals of the Proxy-VAR, I can then extract a new series for the carbon policy shocks. Figure 14 shows that using this series in the panel local projections does not affect the main findings. Regions at the bottom of the GVA per capita distribution are significantly more exposed to carbon policy shocks than those at the top. Finally, Figure 15 confirms that even the responses across sectors previously documented are not affected by the measure of surprises used.

5.2 Employment

As an alternative measure of economic activity to gross value added I use total employment. The European Regional Database provides data on total employment at the NUTS3 level at aggregate as well as sectoral levels. I then compute the same regional impulse responses to carbon policy shocks using employment as dependent variable.

Figure 16 reports the aggregate response (left panel) as well as the responses for the regions at the top and bottom 25% of the GVA per capita distribution (right panel). Aggregate employment strongly decreases following the shock down to 0.25% after 2 years.

The response of the poorer regions is stronger than those of the rich ones. After 2 years, poor regions observe a decreases in the employment of 0.4% whereas rich regions only 0.15%.

Figure 17 shows the sectoral responses of employment. Similarly to the baseline specification with gross value added, employment in the capital-intensive sectors responds slightly more than employment in the labor-intensive sectors. The difference in the responses across sectors is not statistically significant. In conclusion, using gross value added or employment as a measure of economic activity delivers similar results.

5.3 Extra countries

In the baseline analysis, the sample includes the EA-19 member states to be consistent with the macroeconomic evidence. However, there are more countries that are part of the EU Emissions Trading System and for which the geographical data from the European Regional Database are available. Therefore, I extend the sample by including the NUTS3 regions of Bulgaria, Croatia, the Czech Republic, Denmark, Hungary, Iceland, Liechtenstein, Norway, Poland, Romania, and Sweden.

The responses of regional real gross value added to a climate policy shock are reported in Figure 18. The inclusion of 11 extra countries does not affect either the magnitude or the shape of the responses. Following a carbon policy shock, the gross value added significantly decreases, and the response of the "rich" regions (top 25%) is remarkably more muted than the response of the "poor" regions.

5.4 Regional data at NUTS1 and NUTS2 level

The baseline sample consists of 964 NUTS3 regions. I repeat the same analysis using data at NUTS1 (80 regions) as well as NUTS2 (188 regions) level. The results are reported in Figure 19 and Figure 20 respectively.

The responses to a climate policy shock are extremely similar across the three NUTS levels of aggregation. This is not surprising since I have shown that most of the heterogeneity in exposure to the shocks comes from across-country rather than across-region variations.

6 Conclusion

Climate change cannot be solved by a single country or by implementing a specific policy. Only through coordination across countries and by adopting an appropriate policy mix we can hope to reduce its negative effects on the environment. Assessing the economic impact that these policies can have is crucial for the design of complementary fiscal policies targeted at mitigating the potential negative spillovers.

In this paper, I study the heterogeneous effects of carbon pricing across regions. This is done by combining the carbon policy shocks developed by Känzig (2022) with regional-level data for Europe. I document that the regions in poorer countries are significantly more exposed to these shocks. Following a tightening carbon policy shock, the gross value added of regions at the bottom quartile of the GVA per capita distribution decreases more than twice as much relative to the regions at the top quartile.

I show that different sectoral compositions or within-country variations do not explain this result. The main driver of the heterogeneous responses along the GVA per capita distribution is the across-country variation.

Since no single country can solve climate change by itself, no country should bear the economic costs of climate policies alone. The empirical findings I provide suggest that countries are heterogeneously impacted by variations in carbon price due to changes in regulation with poorer countries significantly more affected. Therefore, I believe more coordination is necessary among European governments to effectively allocate the burden of carbon pricing across countries.

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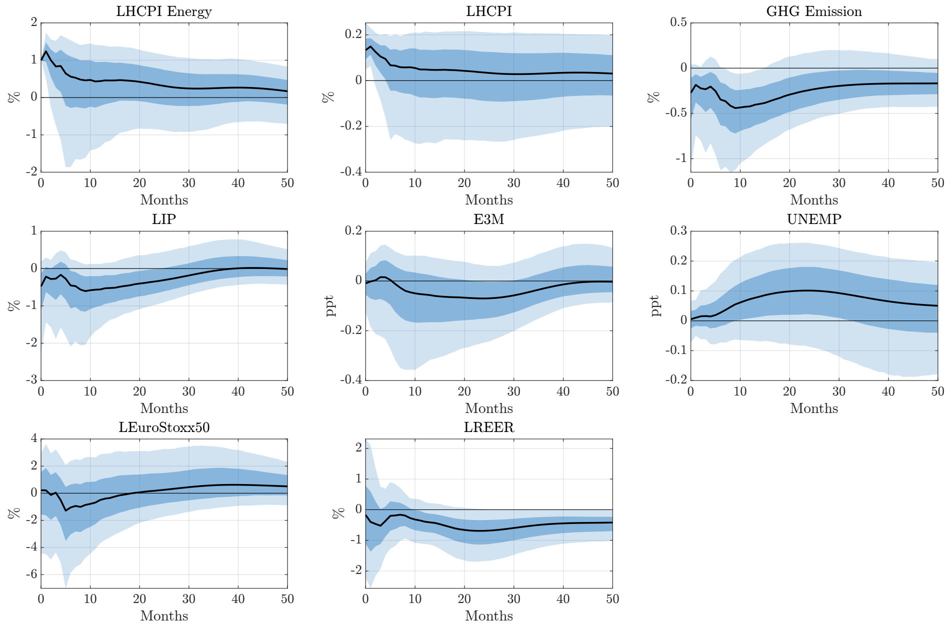
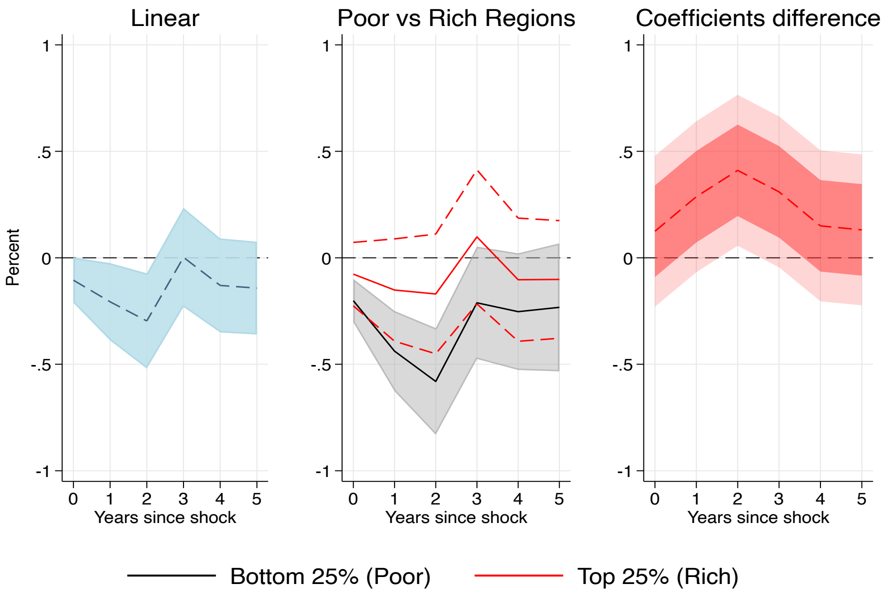
A Additional figures and tables

Figure 13: Impulse responses to a carbon policy shock



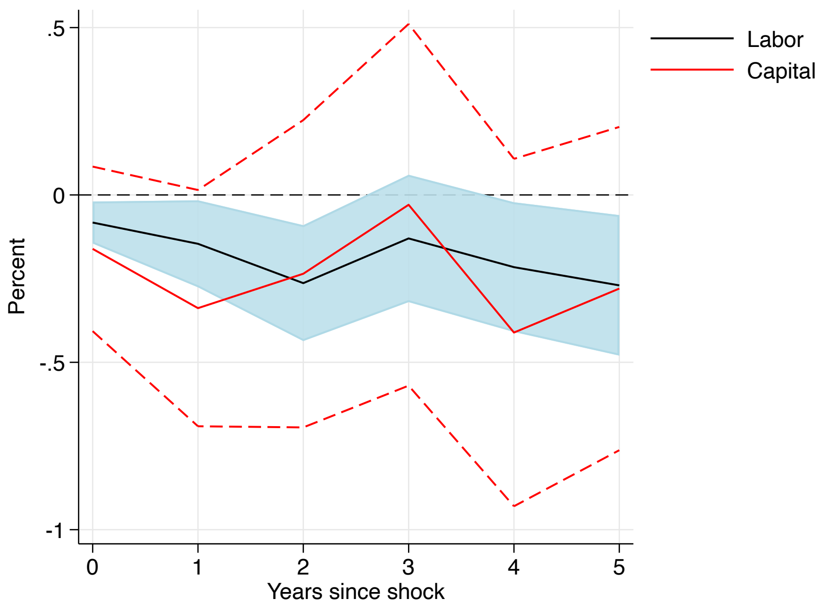
Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid lines are the point estimate and the dark and light-shaded areas are 68 and 90 percent confidence bands, respectively. The change of the EUA futures price is used as an instrument.

Figure 14: Impact of climate policy shocks on log real GVA, Proxy-VAR IV: Change of the EUA futures price



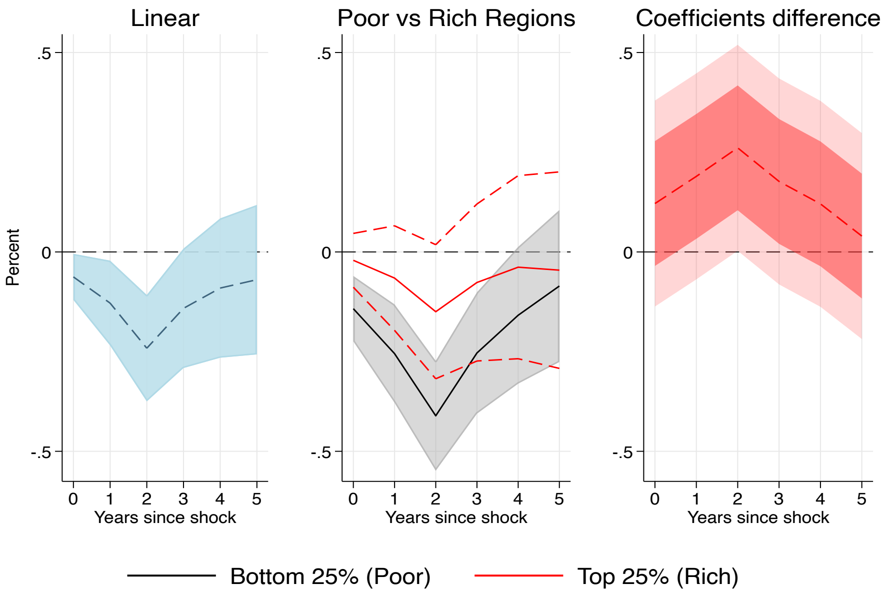
Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

Figure 15: Impact of climate policy shocks on output across industries, Proxy-VAR IV: Change of the EUA futures price



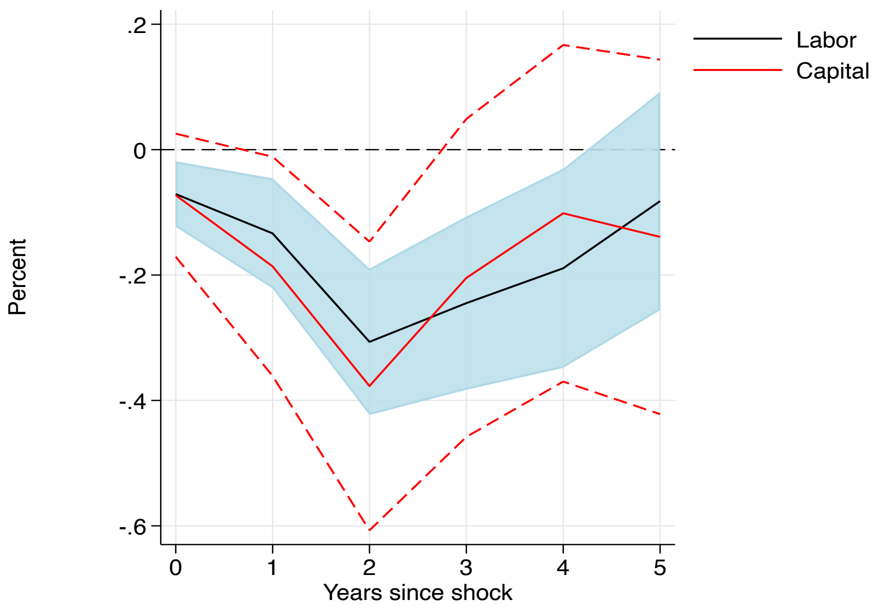
Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region level log real GVA from the capital-, labor-intensive sectors and the construction sector. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

Figure 16: Impact of climate policy shocks on log employment



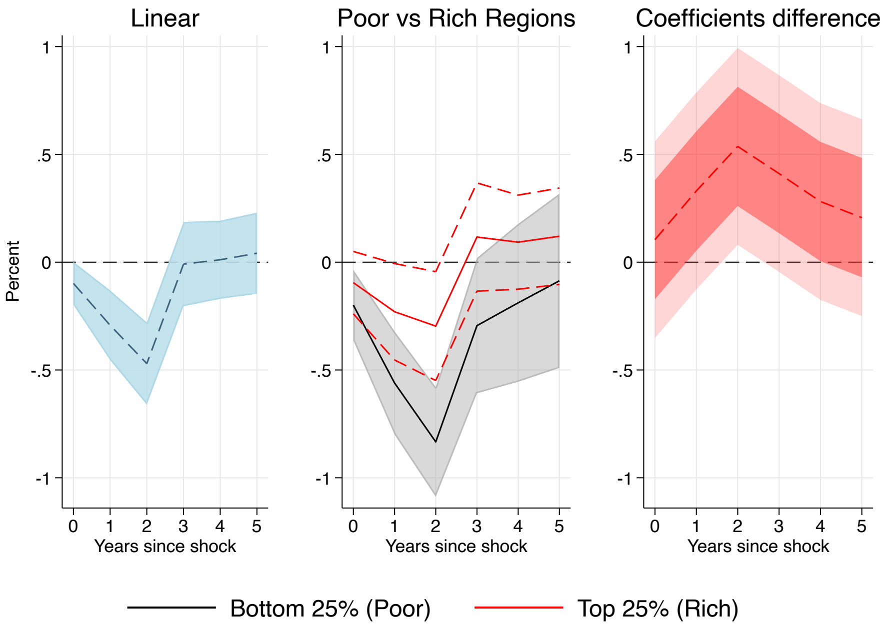
Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log employment. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

Figure 17: Impact of climate policy shocks on employment across industries



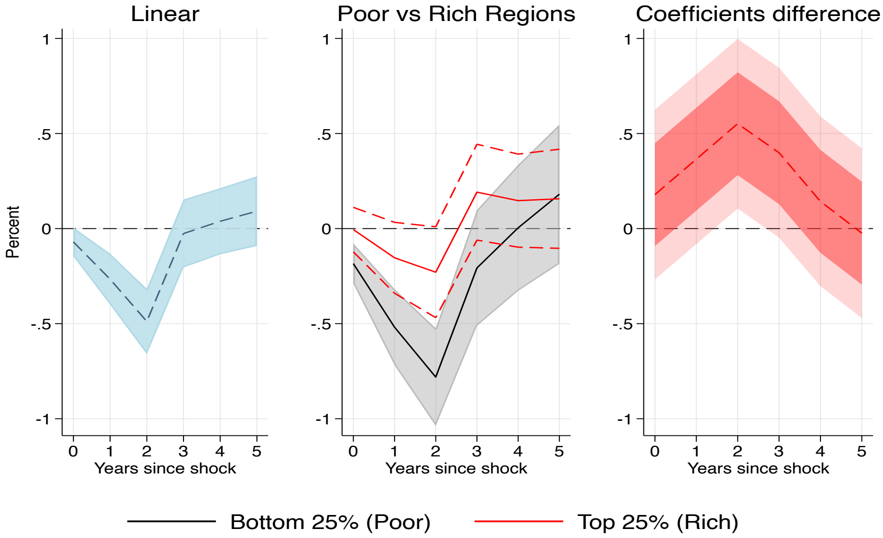
Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region level log employment from the capital-, labor-intensive sectors and the construction sector. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The right panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution.

Figure 18: Impact of climate policy shocks on log real GVA, extra countries



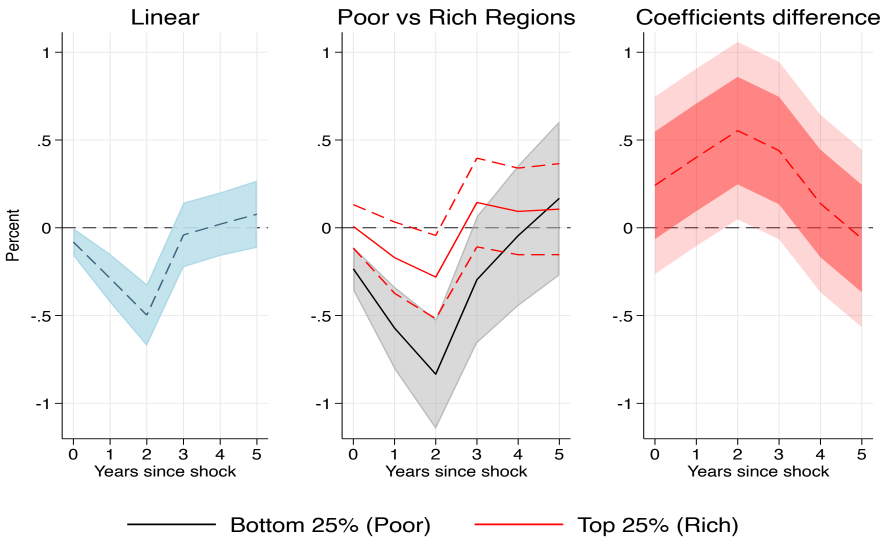
Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The middle panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution. The right panel performs a t-test on the difference between the coefficients of the responses of poor and rich regions. The red-shaded areas are the 68 and 90 percent confidence bands.

Figure 19: Impact of climate policy shocks on log real GVA, NUTS1



Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The middle panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution. The right panel performs a t-test on the difference between the coefficients of the responses of poor and rich regions. The red-shaded areas are the 68 and 90 percent confidence bands.

Figure 20: Impact of climate policy shocks on log real GVA, NUTS2



Notes: The left panel of the figure plots the response to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact, for the region-level log of real GVA. The solid lines are the point estimate and the shaded areas are the 90 percent confidence bands, respectively. The horizontal axis is in months. The middle panel reports the interaction coefficients between the climate policy shock and the dummies identifying the bottom 25% and top 25% of the real GVA per capita distribution. The right panel performs a t-test on the difference between the coefficients of the responses of poor and rich regions. The red-shaded areas are the 68 and 90 percent confidence bands.