Global Spillovers of Climate Policy Shocks*

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Abstract

The slow adoption of climate change policies stems from concerns about their economic impact. The EU has led global carbon pricing through its Emissions Trading Scheme (ETS). This study examines the effect of ETS policy shocks on global stock market returns at the country-industry level using linear and spatial autoregression models. Results show that while markets react negatively to rising carbon prices, the impact is small in magnitude. Global spillovers are limited to sectors linked to EU industries via intermediate goods trade, with no significant effects beyond these supply chain linkages. Overall, the unintended consequences of EU climate policies appear negligible, with minimal effects on targeted industries' stock returns and no spillovers outside supply chain linkages.

Keywords: climate policy, spillovers, supply chain

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1 Introduction

Policies to combat climate change are designed to address a global problem, but are generally implemented at the national level.[1] Thus, national considerations dominate the climate policy debates, and a substantial academic literature investigates domestic effects of such policies.[2] However, the impact of domestic climate policies may spillover internationally given the economic and financial interdependence of the countries. For example, a carbon tax charged to domestic firms' CO_2 emissions resulting from their use of fossil fuels will increase production costs, which firms can offset in the short-run by charging higher prices to their domestic and foreign customers. Furthermore, given the importance of global value chains, the impact of the carbon tax may propagate across multiple layers of cross-border production linkages. Understanding the impact of these international spillovers is paramount as countries continue to adopt policies to combat climate change.

Our paper takes a step in this direction by quantifying the spillover effects of climate policies on forward-looking global asset prices. To do so, we estimate the impact of carbon price shocks in the European ETS market on stock prices across a broad set of country-industry pairs. Thus, we measure how stock markets evaluate the impact of carbon price on the growth and profitability prospects of firms.

We conjecture that a key transmission mechanism through which EU ETS carbon policy shocks may propagate is via cross-country input-output (IO) linkages. Specifically, building on the intuition of a canonical macro-network model, such as Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012), carbon price shocks can be viewed as production cost shocks to firms within the EU ETS that are directly exposed to paying for carbon offsets given emissions generated in production. These higher carbon prices then lead to higher production costs for exposed firms, who may then pass these costs on via higher prices charged to their customer firms, raising those firms' input costs of productions and possibly reducing their

[1] See de Silva and Tenreyro (2021) for the effects of various national policies on emissions.

[2] For the survey of economic effects of climate policies, see Timilsina (2022).

profitability and, in turn, their stock market returns, *ceteris paribus*.[3]

For our analysis, we aggregate monthly firm-level stock return data to the country-sector level over 2005–2019, and merge resulting stock price indexes with the World Input-Output Database (WIOD) country-sector input-output and emissions data.[4] We then combine these data with the monthly growth rates of carbon price permits in the ETS market and Känzig (2023)'s carbon price surprise time series. Känzig's carbon surprises are extracted from changes in carbon price futures around unexpected announcements of changes to EU carbon policy, and can thus be thought of as supply shocks. We use the surprise series to instrument for carbon price growth rates – an approach that is analogous to measuring the impact of monetary policy shocks in the empirical monetary policy literature (e.g., Jarociński and Karadi, 2020). We begin our empirical analysis by estimating fixed effect panel regressions to evaluate the average impact of the carbon price shock on stock returns around the world. We next extend the analysis to allow for heterogeneity at the country-sector level due to upstream (intermediate imports) and downstream (intermediate exports) trade linkages. Finally, we move beyond direct trade linkages, and extend the analysis to a spatial autoregressive regression (SAR) framework, which allows us to quantify the role of the global supply chain network in transmitting carbon price shock to global stock returns.

We find that on average, global stock returns decline by roughly 0.16 of one standard deviation in response to a one-standard deviation carbon price shock. This is a small effect that masks a substantial degree of heterogeneity across country-sectors. We find that most of this heterogeneity is explained by the degree to which a given sector depends on highly emitting EU sectors for its intermediate imports. This finding is consistent with cost shocks being transmitted via production linkages as supplier firms in the EU's highly emitting sectors are the ones directly targeted by the ETS policies. We then quantify the role of the

[3]To generate positive profits, the baseline model would have to move away from perfect competition and CRS production technology as in Acemoglu et al. (2012). Common approaches to do this would be to allow for decreasing returns along fixed costs of production, or some imperfect competition structure, like monopolistic competition. See, for example, Bigio and La'O (2020) or Ozdagli and Weber (2017).

[4]We have to create these custom country-sector stock indexes because most existing industry indexes across countries do match sector classification in the WIOD.

trade network linkages using our SAR framework and find that nearly 90% of the carbon price shock spillovers are due to supply chain linkages. Even within the EU, the share of spillovers that is due to these linkages is 87%. While the distribution of direct effects (those effects orthogonal to trade linkages) across country-sectors is symmetric around zero, most of the network effect distribution is in the negative territory.

Our evidence thus provides strong support for the downstream spillovers of policy-driven carbon price shocks via the global supply chain linkages. In addition, we find some upstream effects that is related to carbon leakage. Specifically, we find a positive response of the stock returns to the carbon price shock for firms outside the EU that export to highly-emitting EU sectors, indicating a shift (or an expected shift) of the most emitting portion of the production processes to these firms away from EU firms. This effect is consistent with other findings on carbon leakage in the literature (e.g., Coster, di Giovanni and Mejean, 2024), but is not the main focus of our paper.

To the best of our knowledge, this is the first paper to study the spillover effects of domestic climate policies on forward-looking asset prices worldwide. Recent work has examined the impact of domestic climate policies on domestic firms' stock prices and found negative impact of increases in carbon prices on stock returns and related variables, generally small in magnitude. For example, Bolton and Kacperczyk (2023) explore how transition risks relating to technological shifts, social norms, and energy policies impact stock price premia for a large cross section of firms across countries. Bolton, Lam and Muûls (2023) estimate how changes in carbon prices in the third phase implementation of the EU ETS affects stock prices of European firms, depending on their emissions allowances.[5] Känzig (2023) uses his carbon price shocks in a VAR framework to examine the macro impact of carbon innovations, including showing a negative impact on an EU stock index given a positive shock. Berthold, Cesa-Bianchi, Di Pace and Haberis (2023) extend Känzig's analysis using firm-level data for

[5] A large number of studies focus on pricing climate transition risks in equity portfolios, usually measured by the importance of fossil fuels or emissions in the production function. For a recent survey, see Campiglio et al. (2023).

EU ETS countries to explore heterogeneous impacts of carbon price shocks on firms.[6] Our results complement these studies in that we show how EU ETS carbon price innovations have an indirect impact on non-EU firms connected via international trade linkages, and particularly those that rely heavily on imports of products from EU firms in high-emission sectors, which are directly affected by changes in EU carbon price innovations.

Our work also relates to the literature that studies the real effects of climate transition risk in the context of production networks (e.g., King, Tarbush and Teytelboym, 2019; Devulder and Lisack, 2020; Aghion, Barrage, Hemous and Liu, 2024). Empirically, recent work by Martin, Muûls and Stoerk (2024) use data on Belgium firm-to-firm input-output relationships to estimate the spillover effects of the ETS on customers and suppliers of regulated firms. The authors study the spillover effects of variables such as value added, employment, or innovation, but confine their study to a closed-economy setting and do not examine the asset price implications of their results.

A natural question related to unilateral carbon pricing schemes, such as the ETS, is whether it leads to substitution of intermediate inputs away from countries directly affected by rise in carbon prices, so-called "carbon leakage." Our sample precedes the introduction of the EU carbon border adjustment mechanism (CBAM) and thus, theoretically, such leakage is possible. The literature so far found that such substitution in the case of the ETS is either very limited in magnitude (Koch and Basse Mama, 2019) or not detected (Dechezleprêtre, Gennaioli, Martin, Muûls and Stoerk, 2022; Colmer, Martin, Muûls and Wagner, 2024), while Känzig, Marenz and Olbert (2024) find a reduction in emissions of multinationals both in the EU and in unregulated locations. However, recent work by Coster et al. (2024), which exploits granular French import data, presents evidence of leakage as firms adjusted their sourcing of high-emission inputs to non-EU suppliers over time. While not the main focus of our analysis, we find some evidence that is consistent with the presence of carbon leakage from EU ETS policy shocks.

[6] For a review of the climate risks and macroeconomy, see Batten et al. (2020).

Section 2 provides our empirical strategy. Section 3 discusses the different data sources we use and variable construction. Section 4 presents our main empirical results. Section 5 concludes.

2 Empirical Strategy

We begin our analysis by estimating the average effect of a carbon policy shock on global stock returns expressed in U.S. dollars in a fixed-effects panel regression setting. Importantly, to interpret the carbon price shock as a supply or cost shock, we must be sure that the carbon price innovation that we feed into the regression model does not pick up potential demand effects. For this, as we describe in more detail below, we estimate a first-stage regression of carbon price on carbon policy "surprises" identified by Känzig (2023) that capture supply-side effects of announcements regarding regulatory changes in the EU ETS.

To allow for potentially heterogeneous responses of country-sector cells to the innovation in the EU ETS policies, we also estimate a panel mean-group estimator that allows for heterogeneity of the effects at the country-sector level, following di Giovanni and Hale (2022). We then test for the specific trade-related propagation channel using interactions terms of the shock variable with various types of trade linkages, as well as controlling for the emissions content of goods being traded at the industry level. This approach allows for a nuanced understanding of different trade linkages that might be important for the EU ETS shocks propagation.

Finally, we quantify the proportion of the total effect of EU ETS shocks on stock returns globally that could be attributed to input-output linkages within and across borders. To do so, we estimate a spatial autoregression model (SAR) with heterogeneous coefficients following Ozdagli and Weber (2017) and di Giovanni and Hale (2022). We conduct all analysis at the country-sector level at the monthly frequency and control for covariates of the global financial cycle throughout our analysis.

2.1 Panel Fixed Effects Regressions

Our first step is to establish the effect of carbon price shocks on global stock returns. To do so, we estimate panel fixed effects regressions for the full sample, a sample of EU countries, and a sample that excludes EU countries, using the following specification:

$$y_{mi,t} = \alpha_{mi} + \beta\,\Delta\ln CP_{t-1} + \mathbf{Z_t}'\gamma + \varepsilon_{mi,t}, \tag{1}$$

where $y_{mi,t}$ is the monthly log change is of the stock price index of country m sector i month t (denominated in US$), α_{mi} is a set of country×sector fixed effects, and $\Delta\ln CP_t$ is the carbon price growth rate, which we lag one period to allow time for markets to internalize its effects.[7] Since the carbon price shock only varies over time, we cannot include time fixed effects. Instead, we control for the covariates of the Global Financial Cycle (GFC) that affect stock returns worldwide (Miranda-Agrippino and Rey, 2020), $\mathbf{Z_t}$, which include changes in VIX, the Broad U.S. Dollar Index, and the 2-year U.S. Treasury rate.[8] Because our main exogenous variable of interest *only* varies over time, we cluster standard errors $\varepsilon_{mi,t}$ on time as well as at the country-sector level. Given that a positive innovation in $\Delta\ln CP_{t-1}$ is a positive shock to carbon prices, we conjecture that $\beta < 0$ – that is, an increase in the carbon price acts as a negative cost shock that drives down firms' profits in the short-term and may require costly adjustments in supply chains or production technology in the long-term, thus reducing net present value of the firms' future cash flow, and therefore putting downward pressure on stock prices.

We instrument the carbon price growth rate by the Känzig (2023) carbon price surprise series to isolate the policy surprise induced variation of our main regressor. This first-stage relationship is represented by the following regression:

$$\Delta\ln CP_t = \alpha + \eta\,CS_t + e_t, \tag{2}$$

[7] Unlike monetary policy shocks, with effects well understood by financial markets, carbon price shocks' effect on firms profitability may not be immediately obvious because of the lack of reporting of GHG emissions.

[8] We use a 2-year rate instead of the Fed Funds rate because 2-year rate never hit the zero lower bound and is highly correlated with various measures of the shadow Fed Funds rate. Thus, it is a transparent alternative to a shadow policy rate measure.

where the identifying assumption is $\mathrm{E}[e_t\, \varepsilon_{mi,t}] = 0$.[9] The correlation between the growth rate of the carbon price is 0.16 when including all months and increases to 0.51 when dropping observations for months with no surprises in them; see Figure A.1 for a scatter plot of the two series and the corresponding regression estimate. We repeat the panel fixed effect analysis replacing $\Delta \ln CP_t$ with its instrumented version: $\widehat{\Delta \ln CP_t} = \alpha + \eta\, CS_t$.

In addition, since country-sectors may vary in how they are exposed to different shocks, we allow for potential heterogeneity of coefficients for changes in the carbon price and GFC variables across country-sectors. To do so, we estimate a mean-group regression (Pesaran and Smith, 1995), where groups are defined as country-sectors pairs. That is, for each mi we have a separate set of estimates:

$$y_{mi,t} = \alpha_{mi} + \beta_{mi}\, \Delta \widehat{\ln CP}_{t-1} + \mathbf{Z}_t' \gamma_{mi} + \varepsilon_{mi,t}. \tag{3}$$

In this specification, standard errors are group-specific, which means we cannot cluster them on time as we do for the OLS. For this reason, we do not focus on the significance of the coefficients for the mean-group specification, but mainly analyze the heterogeneity of point estimates.

2.2 Panel Regressions with Trade Interactions

We delve deeper into specific sources of heterogeneity in the transmission carbon price shocks by next turning our attention to international production and trade linkages. To do so, we interact the instrumented carbon price change with different measures of intermediate trade between a country-sector mi and the EU. While we are primarily focused on the impact of a change in carbon prices on stock returns via a cost channel and thus via imports, we also include export measures to allow for potential customer effects (e.g., changes in demand

[9] Känzig (2023) estimates a carbon policy shock series using a vector autoregression (VAR), where the surprise series is used as an external instrument to avoid potential measurement error (e.g., the surprise series does not contain all relevant regulatory information). We do not follow this approach given our empirical setup, but instead rely on the predictive power of the surprise series of observed carbon price changes, and also include financial variables in our regressions to absorb potential contaminants that would otherwise invalidate our identification assumptions.

for intermediate goods by EU country-sectors that are directly impacted by a carbon price shock) and potential carbon leakage effects. We do so by estimating different versions of the following specification:

$$\begin{aligned} y_{mi,t} = \alpha_{mi} + \beta_1 \Delta \widehat{\ln CP}_{t-1} + \beta_2 IM_{mi,t-1} + \beta_3 EX_{mi,t-1} + \beta_4 \Delta \widehat{\ln CP}_{t-1} \times IM_{mi,t-1} \\ + \beta_5 \Delta \widehat{\ln CP}_{t-1} \times EX_{mi,t-1} + \mathbf{Z}_t' \gamma + \varepsilon_{mi,t}, \end{aligned} \tag{4}$$

where $IM_{mi,t-1}$ and $EX_{mi,t-1}$ are the annually lagged values of country-sector intermediate imports-to-gross output and exports-to-gross output ratios, respectively. The imports measure is either (i) total intermediate imports, (ii) total intermediate imports from the EU, (iii) high emissions intermediate imports, or high-emission intermediate imports from the EU. The export measure is (i) total intermediate exports, (ii) total intermediate exports to the EU, (iii) high-emissions intermediate exports, or high-emissions intermediate exports to the EU.

In addition to providing information on the importance of trade linkages in transmitting shocks across borders, comparing the non-interacted coefficients β_1 in equation (4) with the main effect, β in our baseline regression (1), will also be informative on whether innovations to ETS carbon policy has an average effect on global stock markets in general, regardless of trade linkages. Further, by using different measures of a country-sector's reliance on trade will allow us to be more precise on whether the general openness to trade matters or whether the direct link to the EU or the relative emissions of products being trade impacts is key for the transmission of ETS carbon price shocks on the country-sector's stock return. This specification also provides a natural bridge between the main effects estimated of (1) and the spatial autoregression framework that we introduce in the next section.

2.3 Spatial Autoregressive Regression

The SAR specification follows from a model in which intermediate inputs are traded internationally. The model predicts that the spillover of the carbon price shock from country-sector mi to country-sector nj is proportional to the coefficients in the Leontief inverse of the world input-output matrix ($\mathbf{W}$), which provides input-output coefficients for N countries and J sectors.

The following equation is an empirical specification of the potential spillover effects via the global production network using a spatial autoregressive regression:

$$y_{mi,t} = \boldsymbol{\beta}\,\Delta\,\widehat{\ln CP}_{t-1} + \boldsymbol{\rho}\,\mathbf{W}'\boldsymbol{y}_t + \varepsilon_{mi,t}, \tag{5}$$

where for each t, $\mathbf{W}$ is the input-output matrix and $\boldsymbol{y}$ is the $(N \times J) \times 1$ vector of stock market returns. $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ are $(N \times J) \times 1$ vectors of the parameters we estimate, one for each country-sector cell. We are able to identify all these coefficients due to the time dimension in the panel structure of our data. As in our OLS specifications, we further control for the GFC covariates and instrument the carbon price growth rate with the carbon price surprise series. We estimate (5) using the methodology proposed by Aquaro, Bailey and Pesaran (2021).

We follow the approach in Acemoglu, Akcigit and Kerr (2016) to decompose the total effect of the shocks into the proportion due to input-output linkages and the remaining effect, which in this specification shows up as a direct effect **de**, simply defined as:

$$\mathbf{de} = \boldsymbol{\beta}.$$

The total effect that includes both direct and indirect (network) effects, is computed as

$$\mathbf{te} = (\mathbf{I} - \mathbf{W}'\boldsymbol{\rho})^{-1}\boldsymbol{\beta},$$

and the network effect is then the difference between total and direct effects:

$$\mathbf{ne} = \mathbf{te} - \mathbf{de}.$$

Since our analysis includes heterogeneous estimates for β and ρ, we report direct, total, and network effects averaged across the country-sector estimates:

$$ade = \frac{1}{NJ}\sum_m \sum_i de_{mi}, \quad ate = \frac{1}{NJ}\sum_m \sum_i te_{mi}, \quad ane = ate - ade.$$

Finally, we are concerned that the analytical standard errors proposed by Aquaro et al. (2021) are unreliable in our setting given a short and wide panel. As discussed in di Giovanni and Hale (2022), for our model, the best approach is a wild bootstrap, in which random perturbations are added to the dependent variable by multiplying residuals by a random variable drawn from a specific distribution.[10] In contrast with analytical standard errors, which would need to be corrected for the use of an instrumented explanatory variable, bootstrapped standard errors account for this additional complexity.

We compute standard errors using the wild bootstrap procedure with a continuous distribution proposed by Mammen (1993). We allow for cross-sectional correlation in the errors by implementing a cluster version of this procedure; i.e., we draw random variables for the size T vector and repeat the same perturbation for all country-sector cells within a given time period. We bootstrap standard errors for each element of $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, $\mathbf{de}$, and $\mathbf{ne}$. To do so, for each iteration z of the 500 repetitions, we replace our dependent variable with a synthetic one that is equal to the fitted values from the main estimation plus a random perturbation $\nu_{mi,t}$ of the residuals for each 500 iterations of z:

$$\nu^z_{mi,t} = \frac{\xi^z_t}{\sqrt{2}} + \frac{1}{2}\left[(v^z_t)^2 - 1\right], \quad \forall m\,\forall i,$$

where ξ and v are drawn from independent standard normal distributions. We then estimate our SAR model replacing the true dependent variable with a synthetic one and retain estimation results. The standard deviations of each estimated parameter across 500 repetitions are reported as bootstrapped standard errors.[11]

[10] In contrast with the standard residual bootstrap, a wild bootstrap allows for heteroschedasticity (Davidson and Flachaire, 2008) and is frequently used in heteroschedastic models as well as models with multiple equations.

[11] We also need to correct standard errors for the use of an instrumented shock variable. However, when we repeat the second stage of the instrumental variables regression in Table 1 column (2) without correcting for the use of the instrument, the standard error actually increases, suggesting that the correction will reduce the standard errors we report by a factor 0.78. We thus report uncorrected, more conservative, values for the standard errors.

3 Data

Our dataset consists of a monthly EU ETS carbon price series and a carbon policy surprise series (Känzig, 2023), firm-level stocks returns data from Refinitiv, and information on global production linkages from the World Input-Output Database (WIOD, Timmer et al., 2015). We use the WIOD environmental accounts (Corsatea et al., 2019) to classify WIOD country-sectors as "highly emitting" (HE).

3.1 Carbon Prices and Surprises

To assess the effect of an increasing carbon price in the EU on global stock returns, it is not sufficient to simply use the observed carbon price in each period, since this price is determined by a host of factors that are not the *direct* result of changes in the carbon pricing regime. We thus use the EU ETS carbon policy "surprise" series from Känzig (2023), which gets around the aforementioned endogeneity issue by leveraging high-frequency movements of carbon futures prices around 126 regulatory announcements concerning future supply of carbon emissions allowances over the 2005–2019 period.

The series is constructed by observing the percentage change in the futures price for EU carbon credits between the previous day and the day of a regulatory announcement. Identification of the pure exogenous element of the price change is based on the assumption that other determinants of the future carbon price are already known during this one-day period. Consequently, the observed price changes reflect only the effect of the regulatory event on the implied path of carbon prices, rather than other potential determining factors such as political and macroeconomic conditions.

We aggregate the surprise series to a monthly frequency (with announcement-free months taking a zero value) and then use it as an external instrument for observed carbon price changes.[12] Figure 1 plots the time series of the carbon price series along with the surprise instrument, with vertical lines dividing the different phases of the EU ETS over time. Figure 1

[12]Note that the carbon price series does not exist for the first quarter of 2005, so we end up with a time series of log changes for 2005m5–2019m12.

shows that there were substantial fluctuations in the carbon price over time (panel (a)), part of which was driven by changes in regulation (e.g., changing the number of free allowances for firms) as well as macroeconomic shocks such as the Great Financial Crisis. Panel (b) reveals that there were in fact policy-driven carbon price surprises during the three phases of the ETS and that these varied in size.

3.2 Stock Returns

Stock returns data are sourced from Refinitiv at the firm level, which we aggregate into country-sector indexes based on WIOD sector classifications to allow us to combine stock returns data with information on global production linkages.

Our merged data set covers 26 countries that both have active stock markets and are covered in the WIOD input-output tables. The sample period is 2005–2019, the pre-COVID EU ETS time frame, for which the Känzig (2023) series also exists. We pull information from Refinitiv on each given stock's end-of-month price and market capitalization, as well as its North American Industrial Classification System (NAICS) 2022 code. Using the combination of the NAICS 2022–NAICS 2007 concordance provided by the U.S. Census Bureau and the NAICS 2007–International Standard Industrial Classification (ISIC) Revision 4 concordance established in di Giovanni and Hale (2022), we are then able to assign each stock to a WIOD sector.

We include a stock in our sample if it is present in its country's Refinitiv index on a given date. A country-sector returns index is then constructed by taking a log change of the weighted average of prices for in-sample stocks, where weights are determined by market capitalization. This returns index is then adjusted for exchange rate fluctuations vis-à-vis the U.S. dollar and winsorized at the 1% level. Our return indices ultimately include 932 out of the 1,456 country-sectors our data could cover (56 WIOD sectors $\times$ 26 countries).[13]

[13] 54 of the 56 WIOD sectors are covered in our data. The two exceptions are sectors without corresponding stock prices: "T" (*Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use*) and "U" (*Activities of extraterritorial organizations and bodies*). Neither of these sectors are well-connected to the rest of the WIOD network (di Giovanni and Hale, 2022) and

3.3 Supply Chain Linkages

We use the 2016 release of the WIOD input-output tables to construct trade ratios for the interaction terms and to run the SAR. These IO tables provide bilateral intermediate transaction information for 56 sectors and 43 countries along with a rest-of-the-world aggregate, indicating total U.S. dollar input purchases and sales for any sector by any other. We construct our various trade ratios by first eliminating all intra-country transactions, then aggregating intermediate imports from a specific set of source country-sectors for each destination country-sector. These total intermediate trade measures are then divided by sectors' gross output (also given in the WIOD tables). While an input-output table exists for each year in the WIOD 2016 coverage period (2000–2014), we abstract from year-to-year variation in production linkages and instead only use information from the 2000 table to eliminate concerns about endogenous reallocation of input purchases or sales in response to the carbon shocks. We also use the intermediate trade and gross output data to construct the direct requirements table, $\mathbf{W}$, for the SAR estimation.

3.4 WIOD Environmental Accounts Data

The WIOD Environmental Accounts provide information on country-sector carbon emissions over 2000–2016.[14] Emissions data account for both Scope 1 emissions (i.e., those directly associated with firms' production processes) and Scope 2 emissions (i.e., those associated with energy purchases by firms over the course of their production process).

We compute each country-sector's emissions-to-gross output ratio for each year across the 2000–2016 period of coverage for the Environmental Accounts, we then take an average of those ratios over time. These averages then provide a distribution of emissions intensities across country-sectors which forms the basis of our definition of high emission sectors. Fig-

therefore their exclusion is unlikely to affect any results.

[14] All but one of our 26 countries are included in these data, with the exception of the Netherlands. We interpolate Netherlands' emissions data by applying average EU emissions intensities by sector to their Dutch counterparts. For instance, in order to estimate the emissions intensity of the Netherlands' mining sector ("B" in the WIOD classifications), we take the average emissions intensity across all "B" sectors in EU and apply this average to the Netherlands' sector "B".

ure A.2 shows the cumulative distribution function of the average emissions intensities across all WIOD sectors, demonstrating the high kurtosis of the distribution. As a consequence of this fat right tail, the natural cutoff point we choose to classify country-sectors as high emission is the 90th percentile.[15] Note that this classification is based on the entire set of WIOD sectors, rather than only those in our sample of stock returns. Figure A.3 indicates the classification of country-sectors by their emissions' status as well as whether they are part of our sample of stock returns.

3.5 Controls

Our regressions include controls that proxy for the global financial cycle. These include the VIX, the two-year U.S. treasury rate, and the broad U.S. dollar index. The VIX is sourced from Federal Reserve Economic Data (FRED); we employ the end-of-month value in our regressions. The two-year U.S. treasury rate and the broad U.S. dollar index are both sourced from the Board of Governors of the Federal Reserve. The two-year U.S. treasury rate is series H.15, while the broad U.S. dollar index is series H.10.

4 Results

We first present our benchmark results and then turn to the spillovers through trade linkages, first by using interaction terms in the panel fixed effects setting and then turning the SAR framework.

4.1 Benchmark Results and Heterogeneity

We begin our analysis by estimating panel regressions of stock returns on contemporaneous carbon shock. We estimate three main specifications: (i) panel country-sector fixed effects regression with raw change in carbon prices as an explanatory variable, (ii) instrumental

[15] We additionally experimented with using the 75th percentile of average emissions intensity as the cutoff separating dirty and clean sectors. Results are generally less strong than the results using the 90th percentile definition. In particular, we ran specifications of our various interaction regressions separating trade with sectors above the 90th percentile and trade with sectors between the 75th and 90th percentiles, finding that all of the shock transmission could be attributed to the former.

variable (2SLS) regressions with country-sector fixed effects, and (iii) a mean group estimator (Pesaran and Smith, 1995) in which we use the instrumented carbon price growth that provides separate coefficients for each country-sector cell. All regressions include controls for the correlates of the global financial cycle: VIX, Broad USD Index, and 2-year Treasury Rate. Standard errors are clustered at the time and country-sector levels for the fixed effects regressions, while they are group-specific for the mean group estimates.

Table 1 provides our baseline estimates for the full sample of country-sector cells, a sample of EU countries, and a sample of non-EU countries. We provide panel fixed effects (OLS) estimates in columns 1, 3, and 5, and the corresponding IV estimates in columns 2, 4, and 6, respectively. The estimated average impact of changes in carbon prices on global stock returns is negative in all specifications, confirming our conjecture. Furthermore, the point estimates are similar across the three samples (full, EU, non-EU). Comparing the OLS and IV estimates, it is interesting to note that the IV estimates of β are larger in absolute value. This is due to the measurement error reduction that IV estimates provide, in particular, two periods of extreme carbon price growth in our sample around the GFC. However, the significance level of the estimated IV coefficients fall across the three samples.[16]

In terms of magnitude, the overall effect is as follows: a one standard deviation increase in the log change of carbon prices (which is 64.5 basis points in our regression sample) reduces stock returns by about 16 percent of standard deviation (1.6 basis points) in the IV specification and half that amount in the OLS specification.[17] This modest average effect masks a sufficient degree of heterogeneity as the plot of mean-group regression coefficients demonstrates in Figure A.4. We now turn to exploring the role of global production linkages in explaining this heterogeneity.

Table 2 reports the results of a panel regression in which the instrumented log change of the carbon price is interacted with each country-sector's imports of intermediate inputs

[16]The first-stage F-statistic is 14.20, 14.08, and 14.32 for the full, EU, and non-EU samples, respectively. These values fall between the Stock-Yogo weak ID test critical values at the 10% (16.38) and 15% (8.96) maximal values.

[17]See Table A.1 for the moments of the distributions of variables in our analysis.

and with each country-sector's intermediate goods' exports. We create four categories of these interaction terms to estimate the effects: 1) total intermediate imports and exports as a share of total output, 2) intermediate imports from and exports to EU country-sectors, 3) intermediate imports from and export to high-emission (HE) sectors, and 4) intermediate imports from and export to EU HE sectors.

We find that once we include these interaction terms, the main (non-interacted) effects of a carbon shock are smaller in magnitude than the average effects reported in Table 1 and are no longer significant, indicating that spillovers through channels other than intermediate goods trade are not different from zero on average. All intermediate import interactions coefficients are statistically significant in the full and EU samples. The effects for non-EU subsample are less precisely estimated with only interaction with imports from HE sectors statistically significant for the non-EU subsample. Export interactions only play a significant *positive* role in non-EU subsample when restricted exports to EU HE sectors. This result likely reflects carbon leakages, where firms outside the EU benefit from increased demand for their output by EU HE sectors that may now offshore some of their most highly emitting production.[18]

To get a sense of the magnitudes of the interaction effects reported in Table 2, we calculate the differences between the effect of the shock on country-sectors in the 90th percentile of the interaction variable and those in the 10th percentile. The results are reported in Figure 2 with the bar outlines reflecting statistical significance of the regression coefficients. For instance, the effect of a one standard deviation increase in the log change of the carbon price (64.5 basis points) would lead to the stock price decline for firms in the sectors with high reliance on imports from HE sectors that is 1 basis point larger in absolute value than the decline for firms with low reliance on imports from HE sectors. Given the average impact of 1.6 basis points reported in Table 1, this suggests that a substantial part of dispersion of the effects is driven by the spillovers of the shock via intermediate inputs' usage. Interestingly,

[18]Importantly, our sample ends before the introduction of the carbon border adjustment mechanism.

with the exception of non-EU imports from the EU, all effects are similar in magnitudes across sub-samples and import share aggregates.

4.2 SAR Regression

The results of the SAR regression with heterogeneous coefficients (equation (5)) are reported in Table 3 with panel A reporting average regression coefficients across country-sectors and panel B reporting direct, network, and total effects as well as the share of the network effect.[19] As expected given the results of our analysis of the interaction effects, the direct effect, that is transmission of the carbon price shock that is orthogonal to the trade linkages, is nearly zero, and most of the effect, nearly 90%, goes through the global production network. Moreover, as expected, the direct effect is slightly larger in magnitude for the EU sample of stock returns, although even in our EU subsample the share of the network effect is 87%. Figure A.5 shows that the direct effect estimates are distributed nearly symmetrically around zero while most of the mass of the distribution of the network effect is below zero.

5 Conclusion

We find that the average effect of carbon price shocks on stock returns worldwide is negative but quite small in magnitude, with the effects observed almost entirely in the sectors that are related to the EU highly-emitting sectors via trade.

Our tests consistently demonstrate that spillovers of the EU ETS policy shocks that are reflected in carbon prices are limited to the supply chain channels. While we do not test explicitly for other channels, once we control for supply chain linkages, whether through interaction terms or in the SAR, there is very little effect that remains unexplained. In fact, our SAR estimates suggest that nearly 90% of the shock is due to network linkages. This

[19] These total effects are slightly larger than total effects obtained by our IV specification in Table 1. This result is partly due to the left-skewed distribution of the heterogeneous effects. When we estimate a standard SAR with coefficients restricted to be the same across all country-sectors, total effects are the same as in panel IV regressions. Also note that since we needed to balance the data at the annual level, we drop observations from 2005 for the SAR estimation, which explains the fall in observations relative to the panel regressions reported in Table 1.

is in contrast with the effect of demand shocks, such as the impact of U.S. monetary policy shock, for which di Giovanni and Hale (2022) find less than 70% share of spillovers are due to global production linkages. Moreover, the spillover effects are also quite small in magnitude, which is consistent with the literature that finds small, if any, damages from the EU carbon policies (Metcalf and Stock, 2023; Colmer, Martin, Muûls and Wagner, 2024).

Thus, while the concern about a negative impact of carbon pricing is shared by markets worldwide, the magnitude and spillovers of this effect from shocks to the EU ETS has thus far been quite limited, and foreign firms that are not linked to targeted sectors through production linkages are not affected. This finding supports the view that erring on the side of a carbon tax that might be too high is likely be less harmful than failing to mitigate greenhouse gas emissions (Hassler, Krusell and Olovsson, 2021). In addition, given that our results are based on the measure of changes in the EU ETS carbon policies, the fact that we only find a small reaction of stock prices also alleviates concerns related to the carbon price volatility effect compared to direct carbon taxation (Bilal and Stock, 2025).

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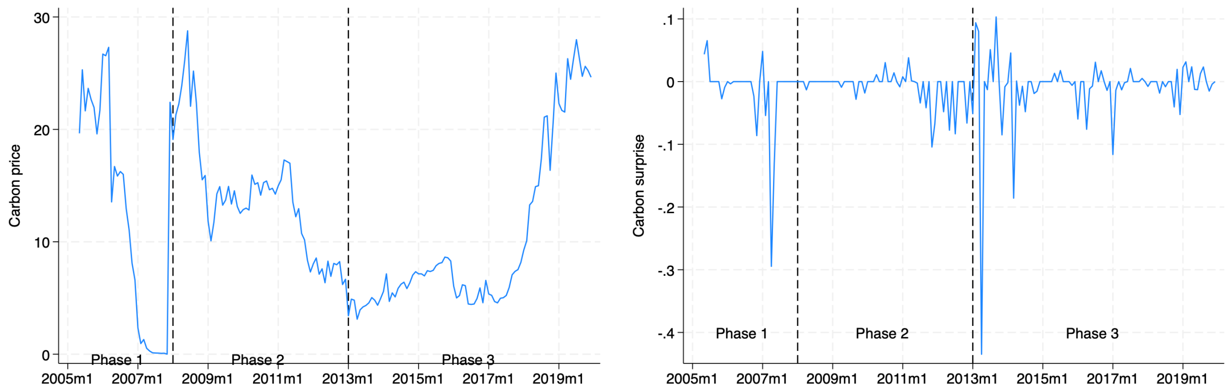
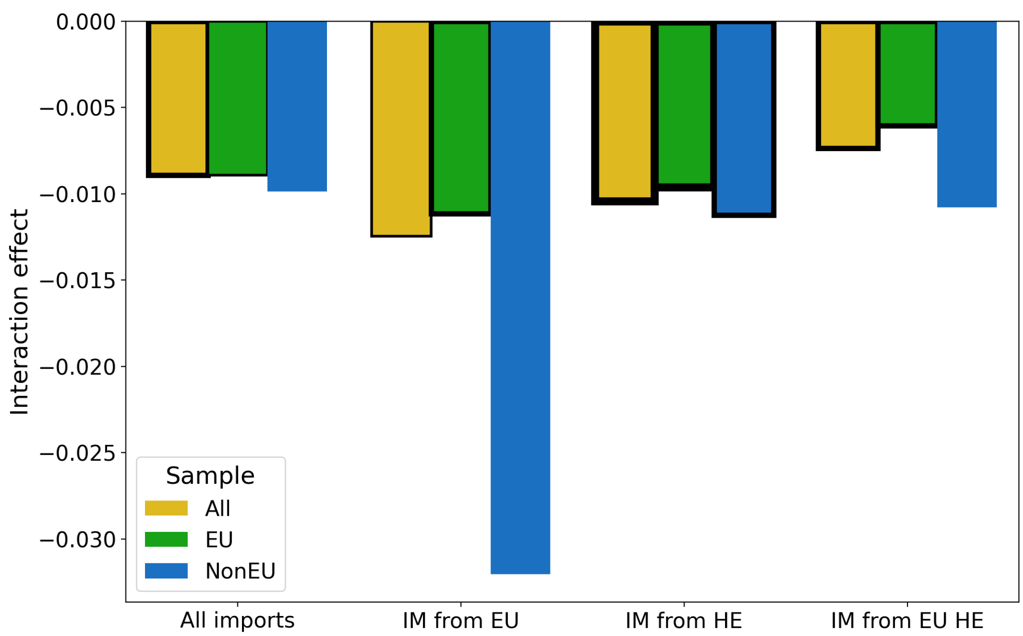
6 Main Figures and Tables

Figure 1. Carbon price and Känzig (2023) carbon price surprise series



(a) Carbon price **(b)** Carbon surprise

Figure 2. Magnitude of the interaction effect



Notes: This table reports the product of the coefficient on the interaction effect reported in Table 2 with the difference in the interaction variable's 90th and 10th percentiles. The effect is then multiplied by 0.645, a one standard deviation of the log change in the carbon price, for convenience of interpretation. The thickness of the line outlining the bars corresponds to the statistical significance of the interaction effect: thickest line: significant at 1%; medium line: significant at 5% ; thin line: significant at 10%; no outline means not statistically significant.

Table 1. Baseline regression estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Full	Full	EU	EU	non-EU	non-EU
Specification	OLS	IV	OLS	IV	OLS	IV
$\Delta \ln(\text{Carbon price})_{t-1}$	-0.012***	-0.024*	-0.011***	-0.027	-0.013***	-0.022
	(0.002)	(0.014)	(0.003)	(0.019)	(0.002)	(0.016)
$\Delta \ln \text{VIX}_t$	-0.128***	-0.126***	-0.129***	-0.126***	-0.127***	-0.126***
	(0.018)	(0.019)	(0.020)	(0.021)	(0.019)	(0.019)
$\Delta(\text{Broad USD})_t$	-2.220***	-2.250***	-2.442***	-2.485***	-2.060***	-2.080***
	(0.284)	(0.292)	(0.287)	(0.300)	(0.314)	(0.319)
$\Delta(\text{2-yr Treasury})_t$	0.019	0.010	0.025	0.013	0.014	0.008
	(0.019)	(0.024)	(0.020)	(0.028)	(0.020)	(0.025)
Observations	134,006	134,006	55,765	55,765	78,239	78,239
R-squared	0.203	0.197	0.232	0.222	0.183	0.180

Notes: This table reports coefficients from linear regressions in which the dependent variable is the U.S.dollar country-sector monthly stock return, over 2005 to 2019, and the independent variables include the lagged monthly growth rate of the carbon price in the EU's ETS market, and contemporaneous values of the log-change in VIX, of the changes in the broad USD index and 2-yr US Treasury bond rate. The IV specifications instrument carbon price growth by Känzig (2023)'s carbon price surprise series. All specifications include country×sector fixed effects. Columns (1)-(2) are run for all countries, columns (3)-(4) for the sub-sample of EU countries, and columns (5)-(6) for the sub-sample of non-EU countries. Standard errors (in parentheses) are clustered at the country×sector and time levels, with *** significant at 1%, ** significant at 5% and * significant at 10%. The first-stage F-statistic is 14.20, 14.08, and 14.32 for the full, EU, and non-EU samples, respectively. These values fall between the Stock-Yogo weak ID test critical values at the 10% (16.38) and 15% (8.96) maximal values.

Table 2. Trade interaction coefficients for IV regressions

	ALL (1)	EU (2)	non-EU (3)
Main effect of $\Delta \widehat{\ln CP}_{t-1}$	-0.016	-0.019	-0.014
	(0.015)	(0.021)	(0.018)
Interaction 1			
$(\text{Imports/Output})_{t-1}$	-0.054***	-0.041	-0.066*
	(0.021)	(0.028)	(0.036)
$(\text{Exports/Output})_{t-1}$	-0.015	-0.012	-0.017
	(0.019)	(0.018)	(0.026)
Main effect of $\Delta \widehat{\ln CP}_{t-1}$	-0.018	-0.017	-0.018
	(0.015)	(0.021)	(0.017)
Interaction 2			
$(\text{Imports from EU/Output})_{t-1}$	-0.142	-0.120*	-0.338
	(0.093)	(0.064)	(0.290)
$(\text{Exports to EU/Output})_{t-1}$	0.008	-0.006	0.081
	(0.015)	(0.019)	(0.087)
Main effect of $\Delta \widehat{\ln CP}_{t-1}$	-0.019	-0.022	-0.017
	(0.014)	(0.019)	(0.016)
Interaction 3			
$(\text{HE Imports/Output})_{t-1}$	-0.294***	-0.243**	-0.346***
	(0.086)	(0.118)	(0.123)
$(\text{HE Exports/Output})_{t-1}$	0.045	0.009	0.063
	(0.103)	(0.145)	(0.130)
Main effect of $\Delta \widehat{\ln CP}_{t-1}$	-0.021	-0.022	-0.021
	(0.014)	(0.019)	(0.016)
Interaction 4			
$(\text{HE Imports from EU/Output})_{t-1}$	-0.817**	-0.670***	-1.146
	(0.365)	(0.257)	(1.080)
$(\text{HE Exports to EU/Output})_{t-1}$	0.207	0.092	0.618***
	(0.145)	(0.225)	(0.193)

Notes: This table reports coefficients from four linear regression specifications in which the dependent variable is the U.S.dollar country-sector monthly stock return, over 2005 to 2019, and the independent variables are the same as those in Table 1 (omitted) along with the instrumented monthly growth rate of the carbon price in the EU's ETS market interacted with country×sector import and export ratios, along with the ratios themselves (also omitted). All specifications include country×sector fixed effects. Interactions 1-4 report the coefficients for the interacted terms using a country-sector's (i) total imports (exports) to output ratio, (ii) imports from (exports to) the EU to output ratio, (iii) total *high emission* sectors (HE) imports (exports) to output ratio, and (iv) imports from (exports to) the HE sectors in the EU to output ratio, respectively. A sector is defined to be HE if its emissions-to-value added is in the upper decile of the world's sectoral emissions distribution. The number of observations are in 128,991, 55,356, and 73, 635 in the full, EU, and non-EU samples, respectively. Standard errors (in parentheses) are clustered at the country×sector and time levels, with *** significant at 1%, ** significant at 5% and * significant at 10%.

Table 3. Heterogeneous Spatial Autoregression Panel Estimation

Panel A. Coefficient Estimates

	(1) Average β	(2) Average ρ	(3) Observations
Full sample	-0.003	0.821	101,136
	(0.041)	(0.242)	
EU	-0.004	0.769	39,984
	(0.099)	(0.240)	
non-EU	-0.003	0.856	61,152
	(0.012)	(0.245)	

Panel B. Total Effects Decomposition

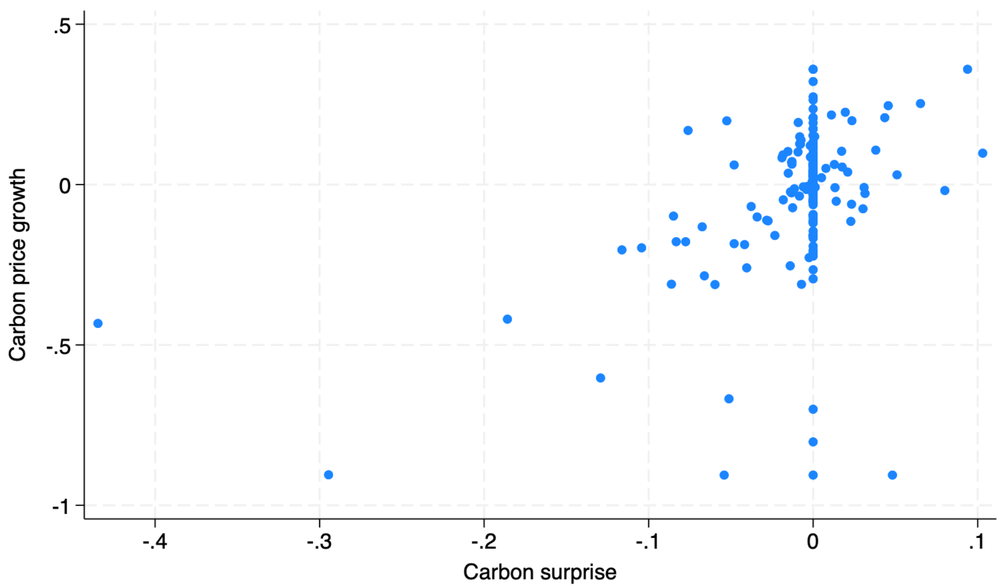
	Avg. **Direct**	Avg. **Network**	Avg. **Total**	**Network/Total**
Full sample	-0.003	-0.025	-0.028	0.882
	(0.041)	(0.012)		
EU	-0.004	-0.028	-0.032	0.874
	(0.099)	(0.016)		
non-EU	-0.003	-0.023	-0.026	0.888
	(0.012)	(0.013)		

Notes: This table reports results from heterogeneous coefficient panel SARs (equation (5)) in which the dependent variable is the U.S.dollar country-sector monthly stock return over 2006 to 2019, and the independent variable is the lagged value of the log change of carbon price changes in the EU ETS, which is instrumented by the carbon price surprise series of Känzig (2023). Regressions control for country×sector fixed effects and contemporaneous values of the log-change in VIX, of the changes in the broad USD index and 2-yr US Treasury bond rate. The direct and network effects are calculated following Acemoglu et al. (2016). Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions, with *** significant at 1%, ** significant at 5% and * significant at 10%.

Appendix

A Appendix Tables and Figures

Figure A.1. Carbon price growth and Känzig (2023) carbon surprise



Notes: This figures plots the growth rate of carbon surprises against the carbon price surprise series from Känzig (2023). Using monthly data over 2005m5–2019m12, the estimated first-stage regression, $\Delta \ln CP_t = \alpha + \eta CS_t + + e_t$ (equation (2) in the main text), yields $\alpha = 0.023$ and $\eta = 2.001$, with robust standard errors of 0.050 and 0.537, respectively; and an R-squared of 0.025.

Figure A.2. Cumulative distribution function of average emissions intensities (kilotons of CO2 per million dollars of output) across all WIOD country-sectors

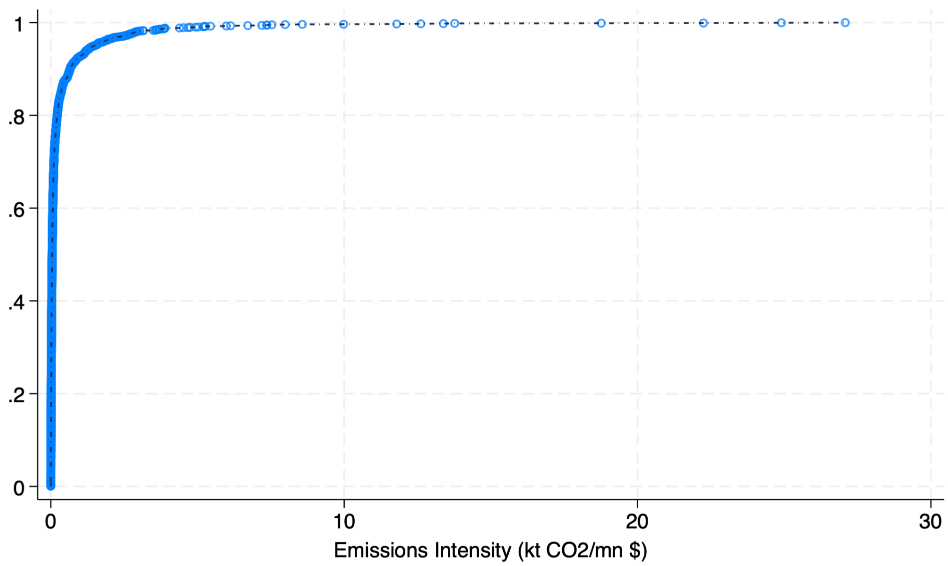


Figure A.3. High-emissions vs. low-emissions and in-sample vs. out-of-sample classifications of all WIOD country-sector cells

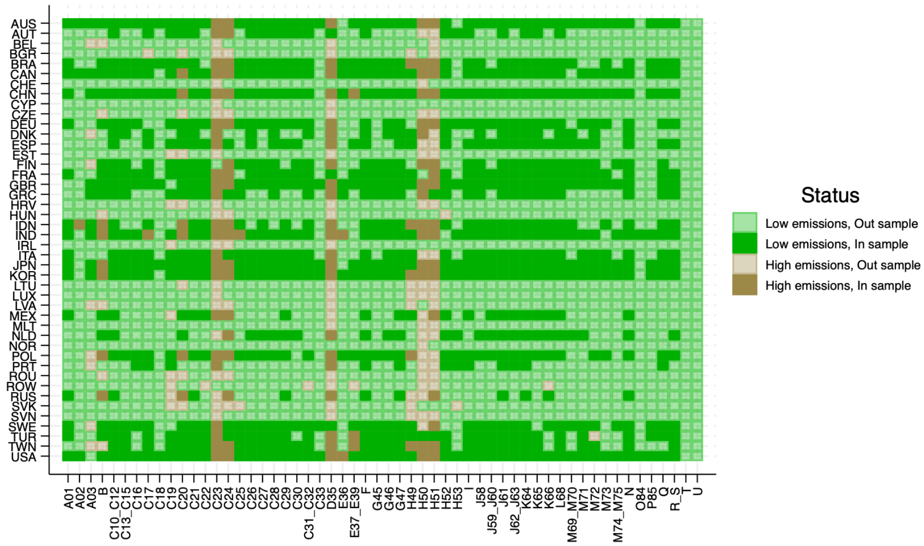
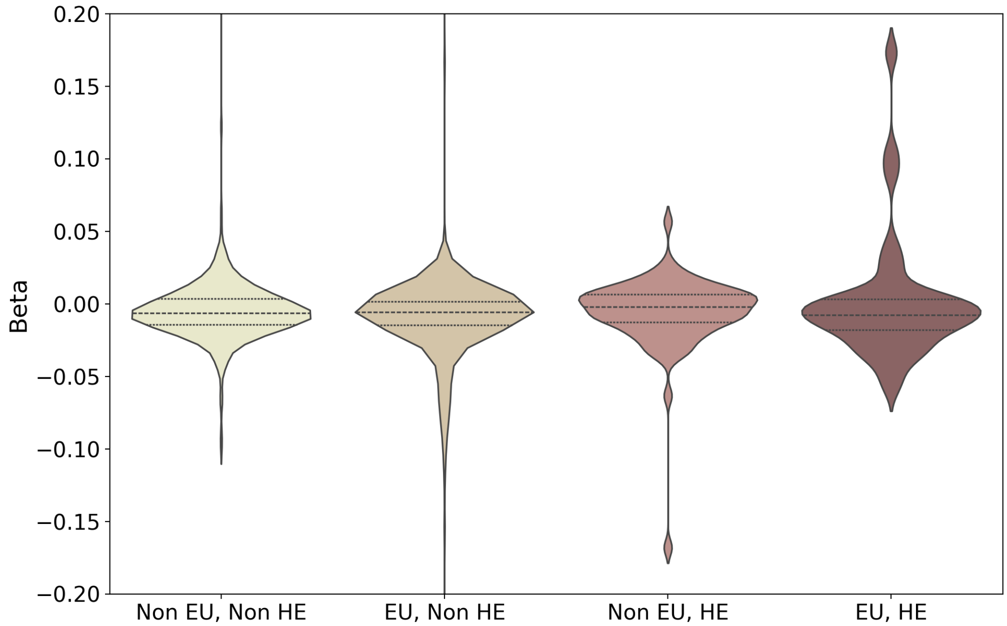
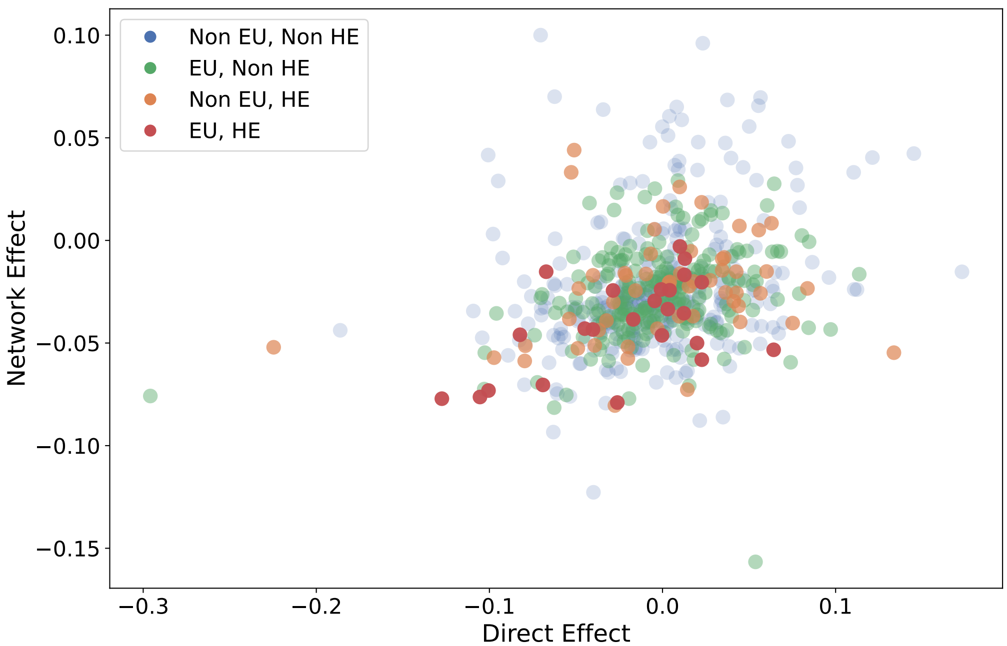


Figure A.4. Distribution of mean group estimates of a carbon shock on stock returns



Notes: The distribution of the coefficients for Mean-Group (MG) estimator regression of stock returns on growth rate of carbon prices The (MG) estimator allows coefficients to be different for each group, in our case, each country-industry cell. EU stands for countries that are in the EU, HE stands for sectors that are high emitters, i.e. in the top 10 percent of emissions-to-output ratio distribution.

Figure A.5. Distribution of the SAR's direct and network effects of a carbon shock on stock returns



Notes: Distributions of direct and network effects from the spatial autoregression (5). This is the distribution corresponding to the average values reported in Table 3.

Table A.1. Summary statistics for returns, shocks, trade, and control variables

	Obs.	Mean	SD	p10	p25	p50	p75	p90	Min	Max
Vary over time and across country-sectors										
USD Returns	134,006	0.003	0.096	-0.100	-0.041	0.007	0.053	0.101	-1.000	1.000
Vary over time										
$\Delta\ln(\text{Carbon price})$	175	0.003	0.645	-0.253	-0.101	0.009	0.086	0.192	-2.197	7.715
$\Delta\ln(\widehat{\text{Carbon}}\text{ price})$	175	0.003	0.102	-0.074	0.006	0.023	0.023	0.058	-0.851	0.230
Carbon surprise	175	-0.010	0.051	-0.048	-0.008	0.000	0.000	0.018	-0.435	0.103
$\Delta\ln$ VIX	175	0.000	0.178	-0.199	-0.112	-0.019	0.072	0.199	-0.373	0.708
Δ(Broad USD)	175	0.001	0.013	-0.014	-0.008	0.000	0.009	0.017	-0.030	0.055
Δ(2-yr Treasury)	175	-0.012	0.165	-0.183	-0.075	0.002	0.078	0.155	-0.641	0.430
Vary across country-sectors										
Imports/Output	932	0.115	0.109	0.023	0.042	0.077	0.154	0.261	0.000	0.782
Exports/Output	932	0.131	0.161	0.002	0.018	0.067	0.192	0.361	0.000	0.936
Imports from EU/Output	932	0.046	0.061	0.004	0.007	0.022	0.057	0.132	0.000	0.461
Exports to EU/Output	932	0.051	0.090	0.000	0.002	0.014	0.053	0.160	0.000	0.738
HE Imports/Output	932	0.017	0.027	0.001	0.003	0.007	0.020	0.044	0.000	0.317
HE Exports/Output	932	0.014	0.031	0.000	0.001	0.003	0.013	0.035	0.000	0.299
HE Imports from EU/Output	932	0.005	0.012	0.000	0.000	0.001	0.004	0.014	0.000	0.149
HE Exports to EU/Output	932	0.005	0.014	0.000	0.000	0.000	0.002	0.010	0.000	0.171

Notes: This table presents summary statistics of all variables used in the regressions for the sample period considered, 2005–2019. Note that the carbon price series only begins in the second quarter of 2005 so that regression sample begins in month five of 2005 as we are using log changes of the carbon price. Summary statistics for $\Delta\ln(\widehat{\text{Carbon}}\text{ price})$ is based on estimates from the first-stage regression (2).