INTERNATIONAL MONETARY FUND

Carbon Policy and Stock Returns: Signals from Financial Markets

Martina Hengge, Ugo Panizza, and Richard Varghese

WP/23/13

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2023
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WORKING PAPER

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IMF Working Paper
Strategy, Policy, and Review Department

Carbon Policy and Stock Returns: Signals from Financial Markets
Prepared by Martina Hengge, Ugo Panizza, and Richard Varghese*

Authorized for distribution by Martin Čihák
January 2023

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JEL Classification Numbers:	G12; G14; G18; G32; G38: Q54
Keywords:	Carbon Emissions; Carbon Prices: Climate Change; Transition Risk; Stock Returns
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* We would like to thank Bruno Albuquerque, Patrick Bolton, Ludwig B. Chincarini, Martin Čihák, Torsten Ehlers, Niels-Jakob Hansen, Zeina Hasna, Diego Känzig, Divya Kirti, Alessandro Martinello, Laurent Millischer, Marco Pani, Henk Reinders, Hélène Rey, Fabián Valencia, Wei Xiong, Attilio Zanetti, and conference and seminar participants at the European Commission Joint Research Centre, FTSE Russell World Investment Forum 2023, IMF, LTI-Bank of Italy Workshop on Long-Term Investors' Trends, Riksbank and Sustainable Finance Lab Conference on Climate Change and the Financial System, Swiss Winter Workshop on Macroeconomics and Finance, and University of Zurich for useful comments and suggestions.

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April 2024*

Abstract

This paper uses institutional features of the EU Emissions Trading System (ETS) and high-frequency data on more than 2,000 publicly listed European firms over 2011–21 to study the impact of carbon policy on stock returns. After extracting the surprise component of regulatory actions, we show that events resulting in a higher carbon price lead to negative returns for firms with high emission intensities. This negative relationship is even stronger for firms in sectors which do not participate in the EU ETS. Taken together, our results indicate that investors price in transition risk stemming from the shift towards a low-carbon economy. We conclude that policies which increase carbon prices are effective in raising the cost of capital for emission-intensive firms.

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1 Introduction

A recent survey of the scientific literature found a nearly unanimous consensus on human-caused climate change (Lynas et al., 2021), and a large number of countries have now committed to reducing carbon emissions. The European Union is a pioneer in this effort. In 2005, it set a cap on CO2 emissions and established the EU Emissions Trading System (ETS) which was the world's first international emissions trading scheme. In December 2020, EU leaders committed to a European Green Deal which, among other goals, aims at a 55 percent reduction in greenhouse gas emissions by 2030 and climate neutrality by 2050. In June 2021, the European Council adopted the European Climate Law which legally commits member countries to these goals. Meeting these commitments requires directing financial resources towards the low-carbon economy. Carbon pricing policies such as the EU ETS are therefore more effective if they cause financial markets to price in emission externalities, and ultimately raise the cost of capital for emission-intensive firms with respect to their low-emission counterparts.

In this paper, we provide evidence that carbon policy has the potential to encourage markets to price in transition risk. Specifically, we use a large sample of European firms to study how the impact of carbon policy on stock returns varies with carbon emissions. After accounting for the endogeneity of the relationship between carbon prices and stock returns, we find that EU ETS regulatory events resulting in higher carbon prices lead to negative realized returns. This negative impact increases with a firm's carbon emissions. Thus, we document that EU ETS announcements which tighten carbon policy raise the cost of capital for emission-intensive firms.

We start by sourcing firm-level annual data on carbon emissions for over 2000 listed firms in the EU during 2011–21, and merge them with daily data on stock returns. We then show that emission intensity (i.e., total emissions scaled by revenues) is positively associated with stock returns. Our data thus corroborate existing work that has found that investors demand a carbon premium—compensation for their exposure to carbon transition risk (Bolton and Kacperczyk, 2021, 2022; Busch et al., 2022; Cheema-Fox et al., 2021; Delmas et al., 2015). To illustrate the link between studies exploring the carbon premium hypothesis and the focus of our paper, we also put forward a conceptual framework which describes the heterogeneous impact of carbon policy shocks on firms' value due to different emission characteristics.

Next, we interact firm-level carbon emissions with daily changes in EU ETS carbon prices to study whether carbon emissions affect the relationship between carbon prices and stock returns. Perhaps surprisingly, we find that companies that are more carbon intensive have returns that are positively correlated with carbon prices. This result is robust to controlling for both country-sector-time fixed effects and firm-year-quarter fixed effects. The positive correlation between carbon prices and stock returns for emission-intensive firms is likely to be driven by endogeneity. Consider for instance an exogenous shock, such as unusually warm weather, that reduces the demand for the products of some carbon-intensive companies. Since the shock would lead to lower expected profits for those firms and lower demand for carbon emission allowances, it would generate a positive correlation between carbon prices and stock returns of emission-intensive firms.

A natural question is how to capture shocks which lead to a repricing of carbon risk. We follow Känzig (2022) who constructs a series of carbon policy surprises documenting the change in carbon prices around regulatory events related to the EU ETS. Specifically, we extend his data to 2021 and use 98 regulatory events regarding the supply of EU carbon allowances (EUAs) to identify a daily measure of carbon policy shocks—computed as the percentage change in EUA futures prices on the day of regulatory events. Positive (negative) values of the carbon policy surprise series indicate a tighter-than-anticipated (looser-than-anticipated) policy announcement. Quantifying these carbon policy surprises allows us to move to our main question of interest, and test how carbon policy affects the relationship between stock returns and company-level carbon emissions.

Our findings suggest that carbon policy surprises have a statistically significant negative impact on stock returns. This relationship increases with a firm's carbon intensity. Our point estimates imply that a one standard deviation increase in the price of carbon on regulatory event days (i.e., a positive carbon policy surprise) lowers the return of a firm with median carbon emissions by around 2 percent relative to the average daily return in our sample.[1] The estimated impact is even larger once we adjust for the downward bias in the carbon policy surprise. Thus, we provide novel firm-level evidence in support of the hypothesis that climate policy tightness negatively affects emission-intensive firms. This result is robust to jointly controlling for country-sector-time fixed effects and firm-year-quarter fixed effects, and to a vast battery of robustness checks. Our findings are also in line with those of Berthold et al. (2023), Bolton et al. (2023), and Millischer et al. (2022) who, using different approaches, find that shocks which tighten carbon policies negatively affect brown firms.

There are two possible explanations for the negative impact of tighter carbon policy on stock returns of emission-intensive firms. The first explanation relates to the fact that regulatory events resulting in higher carbon prices lead to an increase in input costs for firms that need to surrender emission allowances under the EU ETS. According to this explanation, there is a direct *input cost channel* linking carbon policy and stock returns of emission-intensive firms. The second explanation pertains to the fact that tighter-than-expected carbon policy might signal policymakers' resolve to reduce carbon emissions. Such a policy surprise, thus, can be taken as an indication that policy tightening will continue in the future, with the ultimate objective of ensuring that that all firms (including firms that do not currently participate in the EU ETS) internalize the externalities which their emissions create. This explanation is consistent with the presence of a *transition risk channel* (see Bolton and Kacperczyk, 2021, 2022) which links carbon policy with stock returns of emission-intensive firms. While the two channels are not mutually exclusive, the fact that our results are stronger when we drop firms in sectors that participate in the EU ETS suggests that carbon transition risk does matter.

We also test for the presence of asymmetries between days when carbon prices increase and

[1] While our key explanatory variable is the daily change in carbon prices, for ease of reading we refer to changes in the carbon price when interpreting the regression results.

days when carbon prices decrease. We find evidence of asymmetries on non-regulatory event days. Specifically, we show that the positive correlation between carbon prices and stock returns for emission-intensive firms is driven by days when carbon prices decreases. On days when carbon prices increase, instead, carbon emissions do not matter. There is no statistically significant asymmetry for our main variable of interest—the carbon policy surprise. However, we do find that the effect is about three times as large in absolute value when a regulatory surprise leads to an increase as opposed to a decrease in carbon prices. This result provides further evidence that a tightening in carbon policy is particularly effective in increasing the cost of equity capital for emission-intensive firms.

Related Literature

Our paper contributes to a growing body of literature on the impact of climate risk and carbon policy on financial markets. Bolton and Kacperczyk (2021, 2022) find that high levels of and growth in carbon emissions lead to higher stock returns in a cross-section of firms. They describe three mechanisms that could lead to a positive link between carbon emissions and stock returns: (i) a carbon risk premium; (ii) disinvestment; and (iii) carbon alpha. According to the carbon risk premium hypothesis, companies with high carbon emissions are exposed to carbon pricing and regulation risk. Hence, forward-looking investors require higher returns to hold stocks that carry these risks. According to the disinvestment hypothesis, instead, companies with high emissions are equivalent to "sin stocks" (Hong and Kacperczyk, 2009): as socially responsible institutional investors turn away from emission-intensive stocks, their prices decrease and, for any given level of profits, their returns increase. According to the carbon alpha hypothesis, markets are inefficient and underprice carbon risk. Bolton and Kacperczyk (2021) conclude that there is no strong evidence in support of the disinvestment and carbon alpha hypotheses, and that their results are in line with the carbon risk premium hypothesis.[2]

One important methodological issue relates to whether researchers should focus on total carbon emission or carbon intensity (for differing views, see Aswani et al., 2023a,b and Bolton and Kacperczyk, 2023). In our view, this choice depends on the question under examination. We focus on emission intensity because this measure is better suited to estimate the relationship between policy shocks and stock returns and, as discussed by Bolton and Kacperczyk (2021, p.519): "emission-intensive firms might well be the first to become unprofitable should the carbon price rise." In addition, as highlighted in Bauer et al. (2022), emission intensity is an industry standard and widely used in finance research to measure the exposure to transition risk. Atilgan et al. (2023) find that both the level of and change in emissions are positively associated with earnings surprises but that this relationship disappears when focusing on emission intensities or disclosed emissions. They suggest that the carbon premium, where it exists, partially reflects an unpriced externality requiring government action.

[2] There is also a large literature which uses portfolio returns (instead of firm-level returns) and finds that green stocks (proxied by low emissions) outperform brown stocks (see Bauer et al., 2022; Garvey et al., 2018; Huij et al., 2022; In et al., 2019).

Another methodological choice relates to whether stock returns should be linked to contemporaneous or lagged carbon emissions. While Bolton and Kacperczyk (2021, 2022) use contemporaneous stock returns, Zhang (2023) suggests that researchers should focus on lagged emissions as this is the information available to investors. Using data on lagged emissions, she finds a negative carbon premium for US firms. She also shows that there is significant cross-country heterogeneity and that the carbon premium is not statistically significant for a joint sample of firms located in advanced and emerging economies. We use lagged carbon emissions for our baseline specification, and also show that our results are robust to alternative lagging strategies.

Two other papers that are closely related to our work are Bolton et al. (2023) and Millischer et al. (2022). One key difference between our work and theirs is that while we use all listed firms for which we have data on carbon emissions, Bolton et al. (2023) and Millischer et al. (2022) focus on firms that participate in the EU ETS and study how carbon prices affect stock returns conditional on the share of firm emissions covered by freely allocated allowances. Bolton et al. (2023) find that for firms that have shortfalls in freely allocated emission allowances, a higher carbon price translates to lower returns, while the opposite is true for firms that have free allowances exceeding their emissions. Exploiting a novel dataset on free and paid emissions, Millischer et al. (2022) find that higher paid carbon intensity leads to significantly lower stock returns when carbon prices increase. These results are consistent with the idea that, within the EU ETS, the cost channel dominates the risk compensation channel. Our findings on firms in non-EU ETS sectors suggest that transition risk also plays a role. Our results are also in line with the findings of Berthold et al. (2023) who show that a brown firm sees its equity price decrease more than a comparable green firm following a carbon pricing shock.

Our paper also connects to the literature which analyzes financial market reactions to major climate policy initiatives. Seltzer et al. (2022) use the Paris Agreement of December 2015 as a natural experiment to show that bonds issued by listed US non-financial companies with poor environmental profiles or high carbon footprints tend to have lower credit ratings and face higher yield spreads, particularly if they have plants in US states with stricter regulatory enforcement. Monasterolo and de Angelis (2020) also focus on the Paris Agreement and, using data on EU, US and global stock indices, show that the agreement has led to an increase in systematic risk and a decrease of the portfolio weights of carbon-intensive indices. Investigating equity price reactions to two events associated with the US Inflation Reduction Act, Bauer et al. (2023) provide evidence that financial markets respond to transition policies whereby brown (green) events lower the stock market value of green (brown) firms and boost the value of brown (green) firms.

Finally, related work has shown that investors monitor and differentiate firms across their perceived exposure to climate-related risks. Based on textual and narrative analysis of climate change related news, Faccini et al. (2023) find that climate risk associated with imminent government interventions is priced in US stocks and that firm exposure to regulatory shocks is negatively associated with valuation changes. Sautner et al. (2021) apply text analysis to earning calls transcripts to build a firm-level time-varying measures of market participants' perception of firm exposures to climate change for firms in 34 countries. They show that exposure to regulatory events has a negative effect on stock valuations. Engle et al. (2020) also rely on text analysis but focus on news and show how to build portfolios that can hedge climate news. Using data for US and global equity markets, Bansal et al. (2016) provide evidence that higher temperatures lower equity valuations. In a survey, Krueger et al. (2020) find that institutional investors worry about climate and regulatory risks but that these risks are not fully reflected in equity valuations.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 presents our empirical strategy with a special focus on how we estimate the causal effect of carbon policy shocks. Section 4 presents our baseline results, together with a set of extensions focusing on potential asymmetries and a battery of robustness checks. Section 5 provides concluding remarks.

2 Data

Our analysis brings together information on firm-level carbon emissions, the EU carbon futures market—which is a cornerstone of the EU's climate change mitigation policy—and firms' stock market performance. Our baseline dataset spans 2,149 firms across 38 sectors in 23 EU countries over January 2011–December 2021.[3]

We obtain annual data on Greenhouse Gas Protocol defined emissions (referred to as carbon emissions in this paper) from Urgentem.[4] The year of our emission variables refers to the reporting year, i.e. the year in which data on companies' emissions was published. The database reports absolute emissions (tCO2e) and emission intensity (tCO2e/$m revenue) for scope 1, scope 2, and scope 3 emissions. Scope 1 emissions are direct emissions by each firm. Scope 2 emissions are indirect emissions from the purchase of electricity, steam, heating, or cooling for own use. Scope 3 emissions are all indirect emissions (not included in scope 2 emissions) that occur in the upstream and downstream value chain of the firm. Due to challenges in establishing scope 3 emissions (see, for example, Kruse et al., 2020), our analysis concentrates on scope 1 and 2 emissions. As highlighted above, we focus on emission intensity which may determine a firm's profitability as carbon prices increase.

Table 1 reports the summary statistics for the firms in our baseline sample. The average firm emits around 170 tCO2e per US$ million revenue. The median emission intensity is considerably smaller, indicating that the distribution of carbon emission intensity is skewed to the right. We observe a decline over time in both the average and median cross-section emission intensities (see Table A.1). As noted in Bolton and Kacperczyk (2021), declining firm-level emissions over time are expected as a result of innovation and energy efficiency gains as well as the increasing reliance

[3]In a robustness check, we also include data for the UK until December 2020 when it ended its participation in the EU ETS. Including the UK increases the sample of firms to 2,502. Our sectoral classification is based on ICB sectors available on Refinitiv Datastream.

[4]Greenhouse Gas Protocol is a non-profit organization convened in 1998 by World Business Council for Sustainable Development (WBCSD) and World Resources Institute (WRI) with the aim of establishing a comprehensive global standardized frameworks to measure and manage greenhouse gas (GHG) emissions. See Greenhouse Gas Protocol.

on renewable energy.

Table 1: Summary Statistics

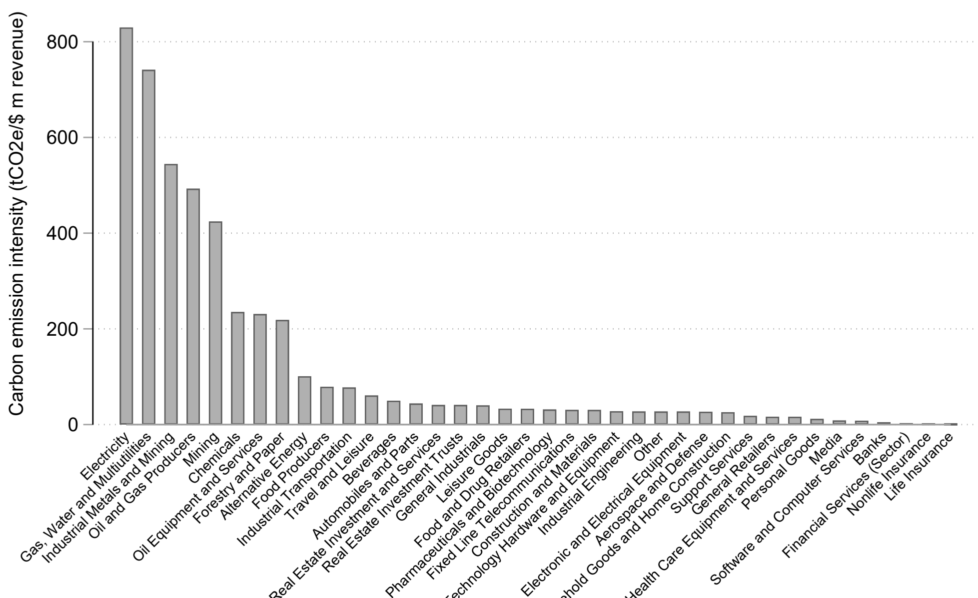
This table reports summary statistics for our baseline sample which consists of 2,149 firms across 38 sectors in 23 EU countries over January 2011–December 2021. The sample excludes observations with daily returns greater than 100%.

	Variable	Mean	Median	SD
Daily stock return (percent)	R	0.048	0.000	2.364
Scope 1 + 2 carbon emissions intensity (tCO2e/$m revenue)	CE	169.24	26.26	503.96
Daily change in EUA futures price (percent)	ΔCP	0.11	0.00	3.21
Daily change in EUA futures price on event days (percent)	$\Delta CP \times EV$	-1.10	-0.70	5.19

Zooming in on emission intensities across sectors shows that energy producers, utilities, and mining are the most carbon-intensive sectors. Firms in these sectors account for 58.4 percent of total emissions and roughly 6 percent of total observations in our sample. Firms in the financial and insurance sector are on the other end of the spectrum, accounting for 0.4 percent of total emissions and about 15 percent of observations (Figure 1).

Figure 1: Carbon Emission Intensity across Sectors

This figure shows the median scope 1 plus scope 2 carbon emission intensity across sectors.



We complement our firm-level dataset with information on the EU ETS carbon market. The EU ETS was launched in 2005 and relies on a cap and trade principle. Firms participating in the scheme need to surrender a quantity of EUAs (carbon allowances) equivalent to their emissions on an annual basis.[5] EUAs are traded on several spot and futures markets. In line with Känzig

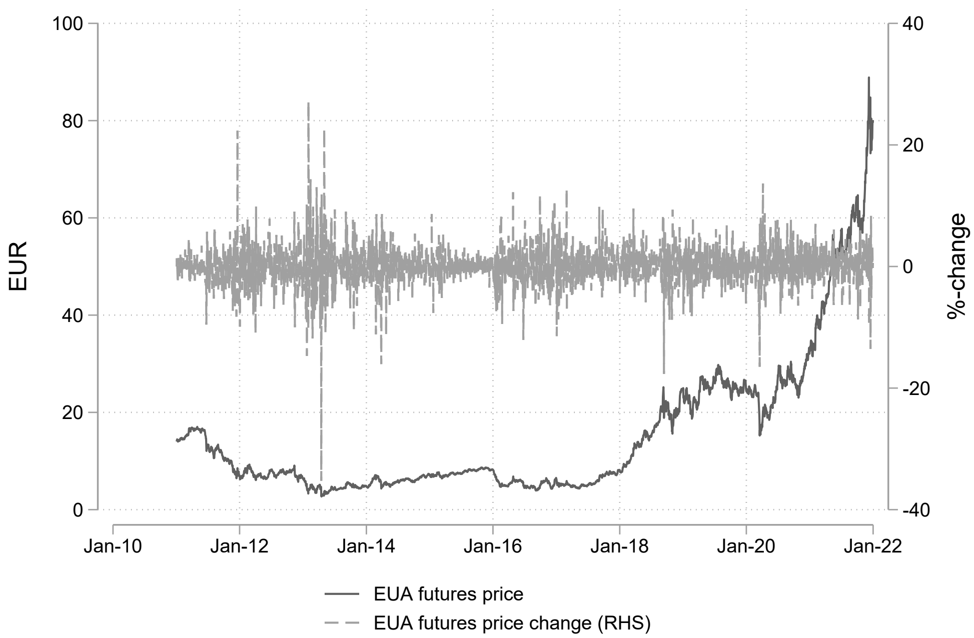
[5]Each EUA entitles the holder to emit one tonne of carbon dioxide or carbon-equivalent greenhouse gas (tCO2e).

(2022), we focus on EUA futures traded on the Intercontinental Exchange (ICE) which dominate the price discovery in the EU ETS.

Figure 2 illustrates the evolution of the EUA futures price over our sample period. The EU carbon price has increased over time, with the average daily change amounting to 0.11 percent between 2011–2021 (Table 1). Demand side factors as well as regulation are key drivers of the EUA price. The substantial increase in the EUA price in 2018 and 2019 is linked to more stringent EU climate policies and to changes to the EU ETS design. In 2021, the price accelerated further partly because of cold weather, which led to higher demand for energy, and also because of legislation which affirmed the role of the EU ETS. Changes to the supply of EUAs also played a role (Ampudia et al., 2022). On average, prices have been particularly volatile over 2020-2021. However, there have also been volatility spikes in 2013 and 2016.

Figure 2: EU ETS Carbon Price

This figure shows the level of the EUA futures price (in EUR) and its daily change (RHS) over 2011–2021.



To measure firms' stock market returns, we collect data on daily stock prices for active listed firms from Refinitiv Datastream. Table 1 shows that the firms in our sample have an average daily return of 0.05 percent with a standard deviation of 2.36 percent.[6]

3 Conceptual Framework and Empirical Strategy

Several studies explore the relationship between carbon emissions and the firm-level cross section of stock returns, although with ambiguous findings on whether a premium exists (for example, Aswani et al., 2023a; Bolton and Kacperczyk, 2022; Zhang, 2022). To describe the link between

[6]We exclude observations with daily returns greater than 100 percent to limit the impact of outliers.

what we do and existing cross-sectional analyses, it is useful to consider two firms that produce at no cost one asset which will have value C at time T and assume that the firms are identical except for the fact that firm A produces a "green" asset (imagine the patent for a new type of solar panel) and firm B a "brown" asset (for instance, a new oil field).[7] Further assume that at time $t < T$ investors do not know that there is a risk associated with the brown asset produced by firm B (or they do not know that B is brown) and that the required daily (without loss of generality) rate of return for both firms is r. Firm value at time t is then given by:

$$V_t^A = V_t^B = \frac{C}{(1+r)^{T-t}}$$

Let us now assume that at time $t' > t$, the value of the asset produced by firm B is subject to a carbon shock. To fix ideas, consider the following three scenarios for a carbon shock:

1. Investors think that the expected value of the asset produced by firm B is still C. However, this value is no longer certain. This could be because the time t' shock has revealed the "browness" of firm B. Alternatively, the shock might have convinced investors that there is now a risk of future regulatory actions that could affect the value of the asset produced by firm B. If investors are risk averse, B's stocks need to be repriced to reflect the increased risk. If we assume that the relevant risk premium is $\rho > 0$, on day t' the price of stock B will drop from $V_t^B = \frac{C}{(1+r)^{T-t'}}$ to $V_{t'}^B = \frac{C}{(1+r+\rho)^{T-t'}}$. After t', the daily return increases to $r + \rho > r$. In this set up, ρ measures the difference in cross sectional returns after the carbon shock. The black solid line in Figure 3 plots the value of firm B under this scenario (the thick green line plots the value of firm A which does not change across scenarios).

2. Investors think that at time T the asset produced by firm B will be δC (with $\delta < 1$) with certainty. Under this scenario, on day t' the price of stock B drops from $V_t^B = \frac{C}{(1+r)^{T-t'}}$ to $V_{t'}^B = \frac{\delta C}{(1+r)^{T-t'}}$. After t', the daily return goes back to r. The gray solid line plots the value of firm B under this scenario.

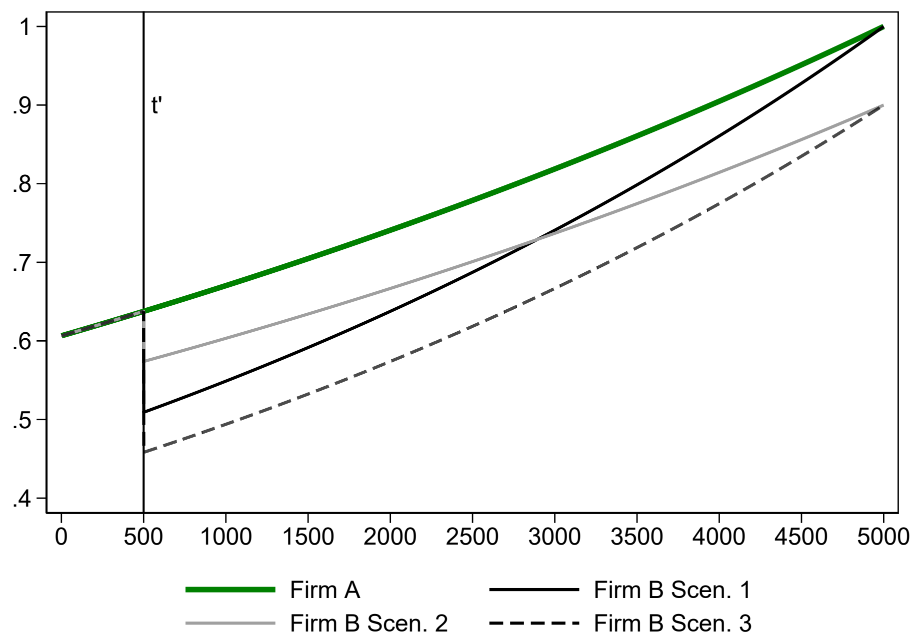
3. Investor think that at time T the asset produced by firm B will have an expected but uncertain value δC (with $\delta < 1$) and want to be compensated for the risk associated with holding B stocks. The relevant risk premium is $\rho > 0$. Under this scenario, on day t' the price of stock B drops from $V_t^B = \frac{C}{(1+r)^{T-t'}}$ to $V_{t'}^B = \frac{\delta C}{(1+r+\rho)^{T-t'}}$. After t', the daily return increases to $r + \rho > r$. The black dashed line plots the value of firm B under this scenario.

In this example, the carbon shock always reduces the firm value on impact and therefore leads to negative returns on day t'. Shocks that increase carbon risk also lead to higher cross-sectional returns. However, this is not the case for the shock under the second scenario. In this case, there is a drop in the value of the firm but no increase in risk because the future value of the asset is now lower with certainty.

[7] Alternatively, we could assume that the "green" asset is produced with low-carbon emitting technologies whereas the production of the "brown" asset is carbon intensive.

Figure 3: Simulation

This figure simulates the evolution of the values of firm A (the thick green line) and firm B under three scenarios: 1. investors think that the expected value of the asset produced by firm B is unchanged but that the value is no longer certain (the black solid line); 2. investors think that the expected value of the asset produced by firm B will be lower with certainty (the gray solid line); and 3. investors think that the expected value of the asset produced by firm B is lower but uncertain (the black dashed line). The simulations assume that $C = 1$, $T = 5000$, $t' = 500$, $r = 0.0001$, $\rho = 0.00005$, and $\delta = 0.9$.



As mentioned, the purpose of the simulation described above is to illustrate the difference between the literature aimed at estimating how carbon emissions affect cross-sectional returns and our objective of estimating how carbon policy affects stock returns on impact. If we only had one shock, we could discriminate among the three scenarios and assess the impact of a carbon shock by estimating the following model:

$$R_{i,t} = CE_i \left(\alpha_1 + \alpha_2 POST_t + \beta SHOCK_t\right) \tag{1}$$

where $R_{i,t}$ measures the daily return for firm i on day t, CE_i is a firm-level measure of carbon emissions, $POST_t$ is a dummy that takes value one after the day of the shock (t' in our simulation above), and $SHOCK_t$ is the carbon shock which takes a nonzero value on t'. Equation (1) and all other equations in the remainder of this section abstract from other control variables and fixed effects.

In Equation (1), α_2 measures the impact of the carbon shock on cross-sectional returns (ρ in our example; as carbon emissions do not affect returns prior to the shock, we expect $\alpha_1 = 0$) and β measures the impact on the day of the shock ($V^B_{t'} - V^B_t$ in our example).

There are two challenges related to estimating Equation (1). The first challenge has to do with the presence of multiple shocks. In our example we only have one shock and the difference in returns before and after the shock is captured by α_2. Keeping track of a large number of shocks would require a model with innumerable interactive dummies. One way to address this issue is to estimate the model without the $CE_i \times POST_t$ interaction:

$$R_{i,t} = CE_i \left(\alpha + \beta SHOCK_t\right) \tag{2}$$

and use α as a measure of the impact of carbon emissions on cross-sectional stock returns. Equation (2) will underestimate the true value of the impact of carbon emissions on stock returns in the post shock period because α is a weighted average of α_1 and α_2. Yet, a positive value of α would still be consistent with the idea that investors price carbon risk and that this leads to higher cross-sectional returns for firms with high carbon emissions.[8]

The second challenge relates to quantifying the carbon shock. While we do not directly observe the policy shock, Känzig (2022) suggests that we can measure it through its effect on the price of carbon allowances. Specifically, he builds a *carbon policy surprise* by interacting percentage changes in carbon prices with EU ETS regulatory events regarding the supply of EUAs. These events may concern the auctioning and allocation of EUAs or the overall EU ETS cap, for example. EU ETS regulatory events occur frequently in our sample period as the EU has continuously adjusted the novel scheme to increase its perimeter and address shortcomings such as market distortions (see Känzig, 2022).

[8] Another advantage of Equation (2) is that we do not need to worry about possible anticipation effects for the t' event. Such anticipation effects are potentially important because if the event that takes place at t' is not a pure shock, forward-looking investors will price carbon risk before t'. In this case, we should find that $\alpha_1 > 0$. In fact, if the event is fully anticipated (i.e., it is not a shock), we would get $\alpha_1 > 0$ and $\alpha_2 = \beta = 0$.

We thus take 83 regulatory events over January 2011–December 2018 from Känzig (2022) and extend his list with 15 events over January 2019–December 2021 (see Table A.2) which we identify based on the European Commission Climate Action news archive.[9] We then compute the carbon policy surprise $CPS_{d(y)}$ on day d in year y as the percentage change in the EUA futures price on the day of regulatory events $EV_{d(y)}$ relative to the previous day:

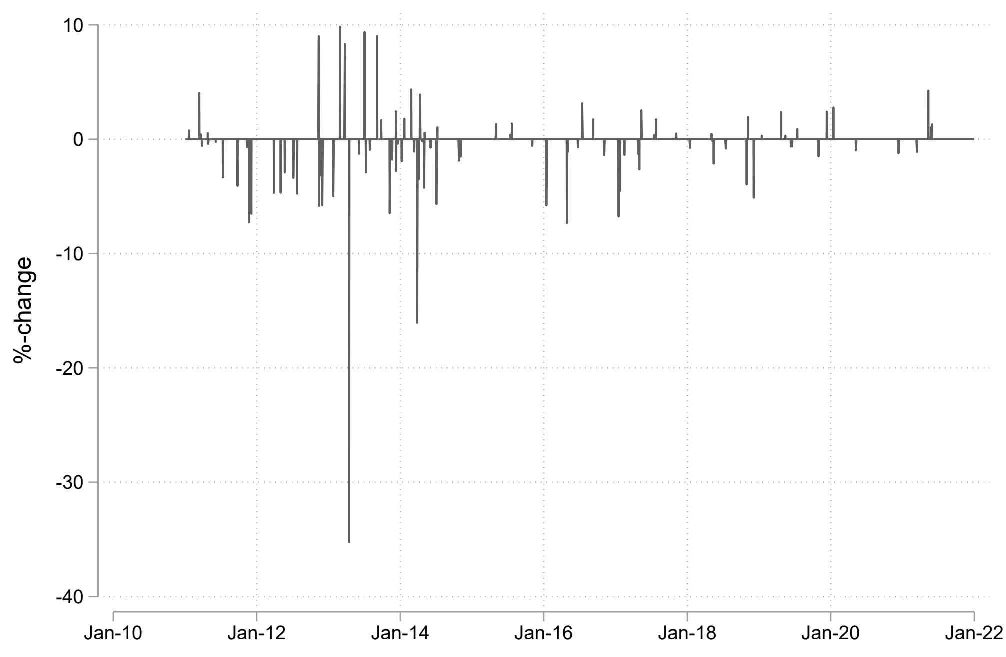
$$CPS_{d(y)} = \underbrace{(F_{d(y)}/F_{d-1(y)} - 1) * 100}_{\Delta CP_{d(y)}} \times EV_{d(y)} \tag{3}$$

where $F_{d(y)}$ is the price of the EUA futures contract and $EV_{d(y)}$ is a dummy that takes value one on days of regulatory events and zero otherwise.

Figure 4 depicts the daily carbon policy surprise series. Carbon policy surprises are relatively frequent and take both positive and negative values (Table 1 shows that the mean of the carbon policy surprise series is -1.1 percent). Regulatory news resulting in large carbon policy surprises relate, for example, to a vote by the European Parliament against an EUA back-loading proposal (April 2013) and a decision on industrial free allocations (September 2013). During the period for which we extended the series, events that had a sizeable impact were the decision on free EUA allocations from the New Entrants' Reserve (July 2019) and updated information on the use of international credits (May 2021), among others.

Figure 4: Carbon Policy Surprises

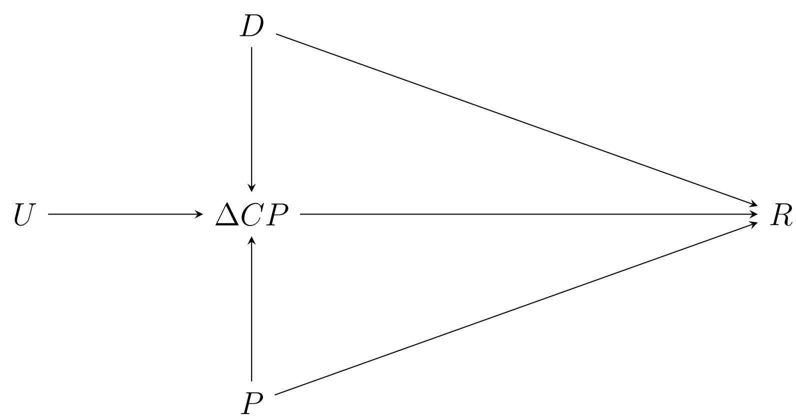
This figure shows the daily series of carbon policy surprises for the EU ETS.



[9]We identified 16 events over 2019–21. However, since two events occurred on the same day, we classified them as one event.

Figure 5: Endogeneity Associated with an Unobserved Demand Shock

This figure shows a Directed Acyclic Graph that illustrates how an unobserved demand shock D leads to an endogeneity bias by directly affecting carbon prices ΔCP and stock returns R. The policy shock P also has a direct effect on carbon prices and on stock returns.



Having identified a proxy for regulatory shocks, we could replace $SHOCK_t$ in Equation (2) with the daily carbon policy surprise CPS_t and estimate the following model:

$$R_{i,t} = CE_i \left(\alpha + \beta CPS_t\right) \tag{4}$$

However, our proxy for the carbon policy surprise CPS is potentially contaminated by other shocks because it is built using carbon prices data. Formally, let us assume that the change in the price of carbon depends on three uncorrelated shocks: $\Delta CP = f(D, P, U)$, where D is a demand shock,[10] P is the policy shock we care about, and U is a residual shock. The Directed Acyclic Graph (DAG) of Figure 5 illustrates the role of these shocks.

If we could observe the three shocks, we could estimate the causal effect of the policy shock (i.e., the sum of the direct link $P \rightarrow R$ and the indirect link $P \rightarrow \Delta CP \rightarrow R$) by regressing stock returns on these three shocks without controlling for ΔCP (controlling for ΔCP would lead to "collider bias", see Pearl, 2009 and VanderWeele, 2014).

$$R_t = CE_i(a + bD_t + cU_t + gP_t) + \varepsilon_t \tag{5}$$

The problem is that we do not observe P but only a proxy that also includes D and U. Nevertheless, we can achieve our objective of estimating the total effect of carbon policy on stock returns

[10] Assume that, for exogenous reasons, there is an increase in the demand for goods produced by carbon-intensive companies (perhaps a particularly cold winter or high demand for certain chemical products). Such a shock is likely to increase the profits of emission-intensive companies that produce these goods while also increasing the prices of carbon emission allowances because these companies (or their suppliers) need to buy allowances to scale up production. This mechanism can lead to a positive correlation between carbon prices and firms' profits which, in turn, results in a downward bias (in absolute magnitude) in the estimate of β.

(i.e., the sum of the direct and indirect effects) by estimating a model that includes both carbon prices and the carbon policy shock, and adjusting for the resulting bias.

As CPS is equal to the change in carbon prices on event days, we start by estimating the following interactive model:

$$R_{i,t} = CE_i \left(\alpha + \beta_1 \Delta CP_t + EV_t(\beta_2 + \beta_3 \Delta CP_t)\right) \tag{6}$$

where EV is a dummy that takes value 1 on regulatory event days.

In the set-up of Equation (6), for a given level of carbon emissions, β_3 measures the difference between the correlation of ΔCP and R on event days and the correlation of ΔCP and R on non-event days. While β_3 does not measure the causal effect of a regulatory policy surprise on stock returns (i.e., parameter g in Equation (5)), we can recover the impact, g, from the parameters of Equation (6). Specifically, as shown in Appendix B:

$$g = \hat{\beta}_1 + \hat{\beta}_3 \frac{k}{k-1} \tag{7}$$

where $k \geq 1$ is the ratio between the variance of ΔCP_t on event days and the variance of ΔCP_t on non-event days. Equation (7) implies that $\hat{\beta}_3$ is a downward (in absolute value) biased estimate of $\hat{g}$ as long as $\hat{\beta}_1(k-1) < -\hat{\beta}_3$.

4 Results

In this section, we test whether carbon policy has an impact on the cost of equity capital and whether this relationship depends on carbon intensity.

4.1 Baseline Estimations

Before moving to our main result, we test whether carbon emissions affect stock returns in our daily sample of European firms. Formally, we start by estimating the following model:

$$R_{i,d(y)} = \alpha CE_{i,y-1} + \phi_i + \tau_{d(y)} + \varepsilon_{i,d(y)} \tag{8}$$

where $R_{i,d(y)}$ measures the stock return of company i on day d in year y, $CE_{i,y-1}$ measures carbon intensity (defined as scope 1 plus scope 2 carbon emissions over revenues) of company i published in year $y-1$, ϕ_i are firm fixed effects, $\tau_{d(y)}$ are time fixed effects which implicitly control for market returns plus all possible factors and shocks that may affect daily returns, and $\varepsilon_{i,d(y)}$ is the error term. Our variable of interest is α.

Column 1 of Table 2 shows that there is a positive and statistically significant relationship between carbon emissions and stock returns. This result is robust to replacing the time fixed effects with country-sector-time fixed effects $\tau_{c,s,d(y)}$ (column 2), however, it does not hold when we drop the firm fixed effects. Controlling for firm fixed effects and for all possible shocks that are specific to a given sector in a given country on a given day, we find that a one standard deviation increase in carbon intensity is associated with a 0.6 basis point increase in daily returns, or 1.5 percent compounded at the annual frequency (column 3). This finding suggests that investors in European stocks demand a carbon risk premium.

Table 2: Baseline Estimations

This table reports a set of regressions where the dependent variable is daily stock returns (scaled by 10^5) and the explanatory variables are: firm-year carbon emission intensity (CE); the interaction between CE and percentage change in the EUA futures price (ΔCP); the interaction between CE and a dummy that takes value one on key regulatory event days (EV); and the interaction between CE and a carbon policy surprise obtained by interacting ΔCP and EV. Column 1 controls for firm and time fixed effects and columns 2-6 control for firm and country-sector-time fixed effects (time fixed effects absorb the main effects of ΔCP and EV). All regressions are estimated with robust standard errors double clustered at the firm and day level. The standard errors immediately below the value of $\hat{\beta}_1 + \hat{\beta}_3 \times \frac{k}{k-1}$ consider k as non-stochastic; the following line uses the bootstrapped value of k. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)	(5)	(6)
CE	2.27***	1.27**	1.17**	1.36***	1.27**	1.25**
	[0.606]	[0.501]	[0.507]	[0.504]	[0.502]	[0.510]
CE × ΔCP			0.58***			0.63***
			[0.213]			[0.220]
CE × EV				-3.71*		-3.96*
				[2.212]		[2.198]
CE × ΔCP × EV					-1.08*	-1.81***
					[0.621]	[0.645]
$\hat{g} = \hat{\beta}_1 + \hat{\beta}_3 \times \frac{k}{k-1}$						-2.20**
						[0.969]
						[1.088]
Observations	1,247,870	1,247,870	1,247,870	1,247,870	1,247,870	1,247,870
R-squared	0.16	0.4	0.4	0.4	0.4	0.4
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No	No	No
Country-Sector-Time FE	No	Yes	Yes	Yes	Yes	Yes

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

We now study how emission intensity affects the relationship between stock returns and carbon prices in the EU futures market by estimating the following model:

$$R_{i,d(y)} = CE_{i,y-1}\left(\alpha + \beta_1 \Delta CP_{d(y)}\right) + \phi_i + \tau_{c,s,d(y)} + \varepsilon_{i,d(y)} \tag{9}$$

where $\Delta CP_{d(y)}$ measures the daily change in carbon prices in the EU futures market and all other variables are defined as in Equation (8).[11]

In the set up of Equation (9), α measures the correlation between emission intensity and stock returns on days when carbon prices do not change ($\Delta CP_{d(y)} = 0$) and β_1 measures how carbon emission intensity affects the relationship between carbon prices and stock returns. Column 3

[11] As our main variable of interest (the interaction between the day-level carbon price and firm-year level carbon intensity) varies at the firm and day level, we double cluster our standard errors at the firm and day level. Our results are robust to alternative clustering strategies.

of Table 2 shows that carbon-intensive companies tend to have higher returns when the price of carbon increases. The point estimate (β_1) indicates that when the price of carbon increases by one standard deviation, the daily return of a company with a median carbon emission intensity will be about 1 percent above the average daily return in our sample.[12]

There are two possible explanations for this result. The first has to do with the fact that firms that receive free allowances within the EU ETS could benefit from the increased value of these allowances associated with a higher carbon price. However, this is an unlikely explanation for two reasons. First, the share of free allowances has been decreasing over time and we find a positive correlation between carbon prices and stock returns for emission-intensive firms also when we focus on post phase 2 of the EU ETS. Second, our sample includes a large number of firms that do not receive free allowances. In fact, this result is robust to dropping firms in sectors that participate in the EU ETS as we further elaborate on below.

A more likely explanation for the positive correlation between carbon prices and stock returns for carbon-intensive companies has to do with the presence of an unobserved demand shock (see the discussion in Section 3). Consider, for instance, the case of an exogenous increase in the demand for electricity. Such exogenous shock is likely to increase both the profit (and hence the returns) of electricity generation companies and the production of electricity. The increase in electricity production will, in turn, lead to a higher demand for emission allowances and a higher carbon price. In this example, and as illustrated in Figure 5, the positive correlation between carbon prices and stock returns of carbon-intensive companies is caused by an unobserved third variable.

To estimate how the causal effect of carbon policy on stock returns varies with company-level carbon emissions, we need a proxy for the shock. As discussed in Section 3, we follow Känzig (2022) who builds a series of carbon policy surprises by interacting the change in carbon prices with a dummy variables that takes value one during EU ETS regulatory events.

Formally, we estimate the following model:

$$R_{i,d(y)} = CE_{i,y-1}\left(\alpha + \beta_1 \Delta CP_{d(y)} + \beta_2 EV_{d(y)} + \beta_3 \Delta CP_{d(y)} \times EV_{d(y)}\right) + \phi_i + \tau_{c,s,d(y)} + \varepsilon_{i,d(y)} \quad (10)$$

where $EV_{d(y)}$ is a dummy variable that takes value one on days of the regulatory events identified by Känzig (2022) and extended in this paper. All other variables are defined as in Equation (9).

Equation (10) implies that:

$$\frac{\partial R}{\partial(\Delta CP)} = CE(\beta_1 + \beta_3 EV)$$

Hence, β_1 measures how the correlation between carbon prices and stock returns varies with carbon intensity on non-regulatory event days and β_3 measures the difference in this correlation between event and non-event days. Thus, $\beta_1 + \beta_3$ measures how the correlation between carbon prices and

[12] An increase in carbon prices by one standard deviation results in a 0.05 basis points increase in daily returns for a firm with a median carbon emissions intensity, equivalent to about 1 percent of the average daily return of 0.048 percent in our sample.

stock return varies with carbon intensity on regulatory event days. A negative and statistically significant value of $\beta_1 + \beta_3$ would indicate that on days of regulatory actions, there is a negative correlation between carbon prices and stock returns which increases with carbon intensity. Note that we used the word "correlation" because, as discussed in Section 3, our estimate of β_1 cannot be interpreted as the causal effect of carbon prices on stock returns of carbon-intensive firms. Hence, $\beta_1 + \beta_3$ does not measure a causal effect, either.

When we estimate Equation (10), we continue to find a positive correlation between carbon prices and stock returns on non-regulatory event days which increases with a firm's carbon intensity (β_1). The coefficient on the interaction between emission intensity and the carbon policy surprise (β_3) suggests that this correlation is negative on regulatory event days. The point estimates imply that, for a firm with a median carbon emission intensity, a one standard deviation increase in the carbon price is associated with a daily return which is 1.1 percent above average on non-regulatory event days and 2.1 percent below average on regulatory event days.

Figure 6 shows the correlation between stock returns and carbon prices at different levels of emission intensity for both event and non-event days. The slope of the line in the upper part of the graph depicts β_1. It visually confirms the results of column 6 of Table 2 by showing that there is a positive and statistically significant relationship, which increases in carbon emission intensity, between stock returns and carbon prices on non-event days. The figure also shows that there is a negative and statistically significant relationship between carbon prices and stock returns on event days. Moreover, this negative relationship strengthens with increases in the carbon emission intensity. The slope of the relationship between stock prices and the change in carbon prices on event days ($\beta_1 + \beta_3$) is negative and about twice (in absolute value) the slope on non-event days.

To estimate the causal effect of carbon policy on stock returns, we adjust for the downward bias in the coefficient on the carbon policy surprise (β_3) as derived in Section 3. Our estimate of the total effect of the carbon policy surprise on stock returns, $\hat{g}$, implies that the unbiased coefficient is roughly twice as large in absolute value (Table 2, column 6).[13] Note that the standard errors reported below $\hat{g}$ assume that k is non-stochastic. In the table, we also report standard errors obtained by bootstrapping k and find that the coefficient remains statistically significant at the 5 percent confidence level.[14]

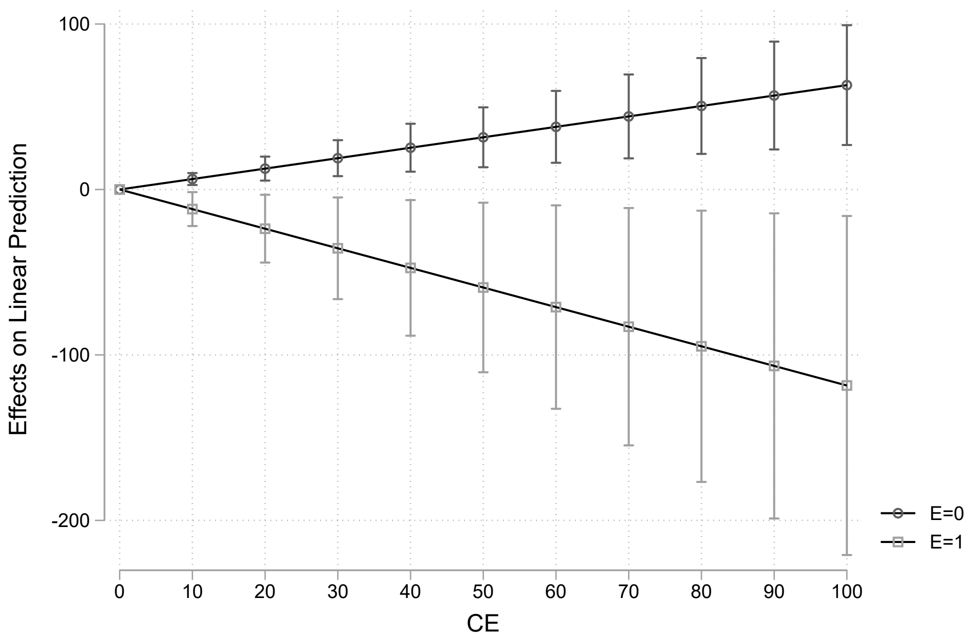
In addition, we control for all components of the triple interaction separately. We find that the interaction between carbon emissions and the regulatory event dummy is negative and statistically significant (this is also the case in column 4 of Table 2, where the event dummy is the only variable interacted with carbon emission intensity). The triple interaction is negative and statistically significant even when we do not include its components (column 5). Note that a model which only

[13]The total impact is $\hat{g} = -2.20$ compared with $\hat{\beta}_1 + \hat{\beta}_3 = -1.19$. $k = 26.96/9.65 = 2.79$.

[14]The bootstrapped standard errors are based on 500 draws. Let $K = \frac{k}{k-1}$ (with $\bar{K} = 1.55$), σ_K^2 its bootstrapped variance, and se_{β_1} and se_{β_3} the standard errors of β_1 and β_3. Then, the adjusted standard errors of g are: $se_g = \left[se_{\beta_1}^2 + se_{\beta_3}^2 \bar{K}^2 + 2cov(\beta_1, \beta_3)\bar{K} + se_{\beta_3}^2 \sigma_K^2 + \sigma_K^2 \beta_3^2\right]^{0.5}$, where the last two elements allow for K to be stochastic (we are assuming that $cov(\beta_3, K) = 0$). Note that K becomes very large when k approaches one. Thus, we bound our bootstrapping exercise so that $max(K) \leq 1.5\bar{K}$; the results hold, but are only statistically significant at the 10 percent confidence level if we set $max(K) \leq 2\bar{K}$.

Figure 6: Carbon Price and Stock Returns

This figure plots the marginal effect of a change in carbon prices on stock returns at various levels of emission intensity during non-regulatory event days (the upper line) and regulatory event days (the upper plus the lower line). The figure is based on the estimation in column 6 of Table 2.



includes the triple interaction and does not control for the main effect of carbon prices implicitly assumes that on regulatory event days the endogenous component of carbon prices (D in $\Delta CP = f(D, U, P)$) is either zero or very small compared to the policy shock P. The fact that the coefficient on the triple interaction in column 5 is about 60 percent (-1.08 versus -1.81) that of column 6 suggests that this assumption might not hold.

While the regressions of Table 2 control for firm fixed effects, they do not control for time-varying firm characteristics such as size, profitability, book-to-market value, leverage, plant property and equipment, sales growth, and a host of other variables which are likely to be correlated with stock returns. Rather than controlling for these variables individually, we re-estimate Equation (10) by including firm-year-quarter fixed effects. This set of fixed effects controls for all possible firm-specific shocks at the quarterly frequency (we use quarterly fixed effects as they coincide with the highest frequency at which firms report financial information). The inclusion of firm-year-quarter fixed effects does not allow estimating the main effect of emission intensity which only varies at the annual frequency. However, it does allow us to estimate our coefficients of interest. When we estimate Equations (9) and (10) with firm-year-quarter fixed effects, the results are essentially identical to those of our baseline regressions (compare columns 3 and 6 of Table 2 with columns 1 and 4 of Table 3). This finding confirms that the baseline results in Table 2 are not driven by time-varying firm-level unobserved heterogeneity.

One important question is whether our results are driven by the direct effect of the price of

Table 3: Baseline with Firm-Year-Quarter Fixed Effects

This table reports a set of regressions where the dependent variable is daily stock returns (scaled by 10^5) and the explanatory variables are: the interaction between firm-year carbon emission intensity (CE) and percentage change in the EUA futures price (ΔCP); the interaction between CE and a dummy that takes value one on key regulatory event days (EV); and the interaction between CE and a carbon policy surprise obtained by interacting ΔCP and EV. All regressions control for country-sector-time fixed effects (which absorb the main effects of ΔCP and EV) and firm-year-quarter fixed effects (which absorb the main effect of CE). All regressions are estimated with robust standard errors double clustered at the firm and day level. The standard errors immediately below the value of $\hat{\beta}_1 + \hat{\beta}_3 \times \frac{k}{k-1}$ consider k as non-stochastic; the following line uses the bootstrapped value of k. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)
CE $\times$ ΔCP	0.58***			0.63***
	[0.210]			[0.217]
CE $\times$ EV		-3.64*		-3.88*
		[2.171]		[2.199]
CE $\times$ ΔCP $\times$ EV			-1.06*	-1.80***
			[0.560]	[0.589]
$\hat{g} = \hat{\beta}_1 + \hat{\beta}_3 \times \frac{k}{k-1}$				-2.174**
				[0.880]
				[1.001]
Observations	1,247,870	1,247,870	1,247,870	1,247,870
R-squared	0.41	0.41	0.41	0.41
Country-Sector-Time FE	Yes	Yes	Yes	Yes
Firm-Year-Quarter FE	Yes	Yes	Yes	Yes

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

carbon emission allowances on firm profitability or by an increase in the risk premium associated with transition risk. Focusing on a sample of firms that participate in the EU ETS, Bolton et al. (2023) find strong evidence in support of the idea that the increase in the cost of carbon is the dominant element for firms that need to buy carbon allowances. The fact that we find an effect of carbon policy on stock returns in our sample dominated by companies that do not participate in the EU ETS suggests that transition risk might also play a role.

To probe further, we re-estimate our baseline models by dropping all firms that belong to sectors covered by the EU ETS. Specifically, we exclude the following sectors: (i) Chemicals; (ii) Construction and Materials; (iii) Electricity, Gas, Water and Multiutilities; (iv) Industrial Metals and Mining; (v) Mining, Oil and Gas Producers; and (vi) Travel and Leisure.[15] When we exclude companies in sectors that participate in the EU ETS our results become stronger. The point estimate of our key coefficient of interest (β_3) changes from approximately -1.8 to -2.4 (compare column 6 of Table 2 and column 4 of Table 3 with columns 4 and 5 of Table 4). The interaction between the regulatory event dummy and emission intensity also becomes larger in (absolute)

[15] The EU ETS covers the following gases: (i) carbon dioxide (CO2) from electricity and heat generation, energy-intensive industry sectors including oil refineries, steel works, and production of iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals, commercial aviation within the European Economic Area; (ii) nitrous oxide (N2O) from production of nitric, adipic and glyoxylic acids and glyoxal; and (iii) perfluorocarbons (PFCs) from production of aluminium. We do not exclude "General Industrial." While this sector includes "glass" which is one of the industries covered by the EU ETS, it also includes several industries not covered by the ETS. Our results are robust to also excluding this sector.

magnitude. This finding is in line with the results of Bolton et al. (2023) who find that for EU ETS firms, the relationship between carbon prices and stock returns depends on whether firms are long or short in carbon allowances.

Table 4: Excluding EU ETS Sectors

This table reports the models of columns 3-6 in Table 2 and column 4 of Table 3 by dropping the stocks of firms in sectors that participate in the EU ETS. The dependent variable is daily stock returns (scaled by 10^5) and the explanatory variables are: firm-year carbon emission intensity (CE); the interaction between CE and percentage change in the EUA futures price (ΔCP); the interaction between CE and a dummy that takes value one on key regulatory event days (EV); and the interaction between CE and a carbon policy surprise obtained by interacting ΔCP and EV. Columns 1-4 control for firm and country-sector-time fixed effects (which absorb the main effects of ΔCP and EV). Column 5 controls for country-sector-time fixed effects and firm-year-quarter fixed effects (which absorb the main effect of CE). All regressions are estimated with robust standard errors double clustered at the firm and day level. The standard errors immediately below the value of $\hat{\beta}_1 + \hat{\beta}_3 \times \frac{k}{k-1}$ consider k as non-stochastic; the following line uses the bootstrapped value of k. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)	(5)
CE	0.86	1.02	0.90	0.94	
	[0.744]	[0.735]	[0.724]	[0.747]	
CE × ΔCP	0.36			0.44*	0.45*
	[0.236]			[0.246]	[0.249]
CE × EV		-4.57**		-5.43***	-5.37***
		[2.001]		[1.878]	[1.856]
CE × ΔCP × EV			-1.76**	-2.39***	-2.41***
			[0.829]	[0.833]	[0.772]
$\hat{g} = \hat{\beta}_1 + \hat{\beta}_3 \times \frac{k}{k-1}$					-3.30***
					[1.215]
					[1.301]
Observations	1,025,509	1,025,509	1,025,509	1,025,509	1,025,509
R-squared	0.38	0.38	0.38	0.38	0.39
Firm FE	Yes	Yes	Yes	Yes	No
Country-Sector-Time FE	Yes	Yes	Yes	Yes	Yes
Firm-Year-Quarter FE	No	No	No	No	Yes

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

4.2 Asymmetries

It is possible that positive and negative carbon price changes have different effects on stock returns of emission-intensive companies. We test for the presence of such asymmetries by allowing our coefficients of interest to vary between days on which carbon prices increases and days on which carbon prices decreases. Formally, we estimate the following equation:

$$\begin{aligned} R_{i,d(y)} = CE_{i,y-1} \left(\alpha + \beta_1 \Delta CP_{d(y)} + \beta_2 EV_{d(y)} + \beta_3 \Delta CP_{d(y)} \times EV_{d(y)}\right) + \\ + CE_{i,y-1} \times \Delta CP_{d(y)} \times D_{d(y)} \left(\beta_4 + \beta_5 EV_{d(y)}\right) + \phi_i + \tau_{c,s,d(y)} + \varepsilon_{i,d(y)} \end{aligned} \quad (11)$$

where $D_{d(y)}$ is a dummy variable that takes value one when $\Delta CP_{d(y)} > 0$ and all other variables are defined as in Equation 10.

Equation (11) implies that:

$$\frac{\partial R}{\partial(\Delta CP)} = CE\left(\beta_1 + \beta_3 EV + D(\beta_4 + \beta_5 EV)\right)$$

Hence, β_1 measures how the correlation between carbon prices and stock returns varies with carbon intensity on non-regulatory event days when $\Delta CP_{d(y)} < 0$; $\beta_1 + \beta_3$ measures how the correlation between carbon prices and stock return varies with carbon intensity on regulatory event days when $CP_{d(y)} < 0$; $\beta_1 + \beta_4$ measures how the correlation between carbon prices and stock return varies with carbon intensity on non-regulatory event days when $\Delta CP_{d(y)} > 0$; and $\beta_1 + \beta_3 + \beta_4 + \beta_5$ measures how the correlation between carbon prices and stock return varies with carbon intensity on regulatory event days when $\Delta CP_{d(y)} > 0$.

We estimate Equation (11) on our baseline sample to test for the presence of asymmetries. Table 5 reports the results providing the coefficients from estimations with firm fixed effects and country-sector-time fixed effects (column 1) and firm-year-quarter fixed effects and country-sector-time fixed effects (column 2). These two specifications yield almost identical results.

Focusing on non-event days, we find that β_1 is positive and statistically significant while β_4 is negative and statistically significant with approximately the same magnitude of β_1 (in absolute value; thus, $\beta_1 + \beta_4 \approx 0$). Our baseline result of a positive correlation between carbon prices and stock returns for emission-intensive firms on non-event days is thus driven by days when carbon prices decreases.[16] In contrast, on non-event days characterized by an increase in carbon prices, there is no significant correlation between carbon prices and stock returns. Therefore, there are substantial asymmetries in the relationship between carbon prices and stock returns on non-event days.

There are instead no significant asymmetries during regulatory event days; both $\beta_1 + \beta_3$ and $\beta_1+\beta_3+\beta_4+\beta_5$ are negative and β_5 is not statistically significant. Carbon policy surprises lead to a negative correlation between carbon prices and stock returns of emission-intensive firms regardless of whether there is a policy tightening or loosening. Nevertheless, we find that the effect is about three times as large for policy surprises that lead to an increase in carbon prices as opposed to a decrease in carbon prices. Regulatory surprises which lead to a tightening in policy, i.e. an increase in carbon prices, are therefore especially effective in raising the equity cost of capital for carbon-intensive firms.

[16] Days characterized by a decrease in carbon prices are associated with lower returns for more carbon-intensive companies.

Table 5: Testing for Asymmetries

This table reports a set of regressions where the dependent variable is daily stock returns (scaled by 10^5) and the explanatory variables are: firm-year carbon emission intensity (CE), the interaction between (CE) and and percentage change in the EUA futures price (ΔCP); the interaction between CE and a dummy that takes value one on key regulatory event days (EV); the interaction between CE and a carbon policy surprise obtained by interacting ΔCP and EV; the interaction between CE, ΔCP, and a dummy variable D that takes value one on days on which ΔCP>0; and the interaction between CE, the carbon policy surprise, and D. Column 1 controls for firm fixed effects and country-sector-time fixed effects (which absorb the main effects of ΔCP, EV, and D) and column 2 controls for country-sector-time fixed effects and firm-year-quarter fixed effects (which absorb the main effect of CE). All regressions are estimated with robust standard errors double clustered at the firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)
CE	2.39***	
	[0.697]	
CE $\times$ ΔCP	1.19***	1.23***
	[0.396]	[0.415]
CE $\times$ EV	-3.79	-3.57
	[3.482]	[3.559]
CE $\times$ ΔCP $\times$ EV	-1.98**	-1.92**
	[0.920]	[0.851]
CE $\times$ ΔCP $\times$ D	-1.10**	-1.17*
	[0.552]	[0.603]
CE $\times$ ΔCP $\times$ EV $\times$ D	-0.16	-0.26
	[2.392]	[2.400]
Observations	1,247,870	1,247,870
R-squared	0.40	0.41
Firm FE	Yes	No
Country-Sector-Time FE	Yes	Yes
Firm-Year-Quarter FE	No	Yes

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

4.3 Robustness Checks

We now subject our results to a battery of robustness checks.

Our carbon policy surprise series relies on daily event windows as we are unable to use intraday windows due to lack of information on the exact announcement time of our events. A longer event window, however, might be contaminated by confounding news. Therefore, as a first robustness check, we implement a standard placebo test to mitigate concerns about background noise within our daily event window.[17] Specifically, we rerun our baseline specification in Equation (8) with an alternative series of carbon policy surprises generated from 500 random draws. Figure C.1 plots our main coefficient of interest, β_3, for these simulations together with 95 percent confidence intervals. As expected, the estimated coefficients based on the simulated carbon policy surprise series are not significant, except for the extremes of the distribution of β.[18] This suggests that background noise

[17] To a large extent, we tackle the presence of other drivers of carbon prices on event days by adjusting for the downward bias in our main coefficient of interest. Nevertheless, for completeness, we report the results of a placebo test, a standard application in event studies since Brown and Warner (1985).

[18] A draw from a normal distribution with a mean of zero and a standard deviation of one has a 5 percent likelihood to obtain values which are 1.96 standard deviations above or below the true mean. Therefore, even when the true coefficient is zero, we expect that some coefficients are statistically significant.

is unlikely to have a major impact on our results.

We also examine the window around events. Specifically, we estimate the following specification, including lags and leads of our explanatory variables:

$$
\begin{aligned}
R_{i,d(y)} = \sum_{h=-2}^{2} \Big[& CE_{i,y-1} \left(\alpha + \beta_1^h \Delta CP_{d(y+h)} + \beta_2^h EV_{d(y+h)} + \beta_3^h \Delta CP_{d(y+h)} \times EV_{d(y+h)} \right) \Big] \\
& + \phi_i + \tau_{c,s,d(y)} + \varepsilon_{i,d(y)}
\end{aligned}
\tag{12}
$$

where h takes discrete values from -2 to 2. All other variables are defined as in Equation (10). Figure C.2 plots β_3^h at various horizons together with 95 percent confidence intervals. The estimated coefficients are not statistically significant, except for the announcement day (i.e., the coefficient at h = 0). This result shows that our estimations do not capture the effect of events that happen around policy days and that carbon prices reflect a true policy surprise which happens on the day on which a new policy is announced.

The emission intensity variable we use in our estimations measures carbon intensity published in year $y-1$ and realized in $y-2$ (see Equation (8)). We opt for this set-up because for part of year y (the year of our stock returns data) the emission intensity data published in y are not available to investors. To acknowledge that emissions are published sometime during year y (not at the end of y) and become available to investors, we implement two alternative lagging strategies. First, we regress stock returns in year y on emissions published in year $y-1$ for quarters 1 and 2 and emissions published in year y for quarters 3 and 4. Second, we regress stock returns in year y on emissions published in year $y-1$ for quarter 1 and emissions published in year y for quarters 2, 3 and 4. Our key results are robust to these alternative lagging strategies (columns 2 and 3 of Table C.3).

Next, we test whether our results are driven by a specific country. We estimate our baseline model dropping one country at a time. Appendix Figure C.3 plots β_3 with its 90 percent confidence interval. It shows that our main result remains significant and is not driven by any individual country.

We also explore whether there are differences between Advanced and Emerging Europe.[19] Column 2 of Table C.4 shows that our results are robust to limiting the sample to Advanced Europe, while our results no longer hold if we concentrate on Emerging Europe (column 3). It is, however, worth noting that Emerging Europe represents only around 10 percent of our sample (216 firms over a total of 2,149).

Our baseline sample does not include the UK as the country ended its participation in the EU ETS in December 2020, and its exit from the ETS was already anticipated by the time of the Brexit referendum in June 2016. However, we have data for 353 UK firms, increasing the sample of firms to 2,502—a total of nearly 500,000 observations at daily frequency. We thus test whether

[19] Advanced Europe includes: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia, Spain,and Sweden. Emerging Europe includes Bulgaria, Croatia, Hungary, Poland, and Romania.

our findings are robust to including UK companies for the period during which they were part of the EU ETS. We find that there is essentially no difference between our sample of EU companies and a sample that also includes UK companies (columns 1 and 4 of Table C.4).

As a final robustness check, we estimate our baseline regressions by dropping financial institutions. Table C.5 shows that the results are unchanged. All of the robustness exercises discussed above hold when we include firm-year-quarter fixed effects.

5 Conclusions

There is now near unanimity on human-caused climate change and a large number of countries are implementing policies aimed at promoting the transition to a low-carbon economy. The European Union has been at the forefront of this effort with the creation of the EU ETS in 2005. This "cap and trade" scheme places a limit on the right to emit greenhouse gases and allows companies to trade emission allowances. The EU has also implemented a series of actions aimed at directing investment toward green activities.

In this paper, we test if such initiatives have the potential to affect the cost of equity of emission-intensive companies. After accounting for the endogeneity of the relationship between carbon prices and stock returns, we show that regulatory surprises that result in an increase in carbon prices have a negative and statistically significant impact on stock returns which increases with a firm's carbon intensity. This negative relationship becomes even stronger when we drop firms in sectors which participate in the EU ETS, suggesting that investors price in transition risk stemming from the shift towards a low-carbon economy.

Our findings support the view that regulation which increases the cost of carbon has an important role to play in the transition towards a low-carbon economy. As investors demand compensation for their exposure to transition risk, EU ETS regulatory events might also affect stock returns for firms in third countries to the extent that tighter EU climate mitigation policy is a driver of transition risk globally. Exploring global spillovers of EU ETS regulatory actions to non-European firms' stock performance could be an interesting avenue for future research. With the proliferation of carbon pricing schemes in recent years, studying their impact on the cost of capital for firms, could provide further evidence on whether carbon policy has the potential to encourage markets to price in transition risk.[20]

[20] International Carbon Action Partnership estimates that as of 2023, there are 28 (national, sub-national, and supra-national) ETS in force and more under different stages of development and consideration.

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Appendix to Carbon Policy Surprises and Stock Returns

A Data

Table A.1: Carbon Emission Intensity over Time

This table reports the cross-sectional average and median of scope 1 plus 2 carbon emission intensity published over the period 2010–20 which we use in our baseline regressions.

	Mean	Median
2010	174.99	37.26
2011	172.34	33.24
2012	123.76	30.37
2013	130.89	27.44
2014	188.78	28.66
2015	162.14	25.96
2016	168.20	25.44
2017	181.51	27.66
2018	164.92	23.19
2019	160.43	26.01
2020	108.25	27.43

Table A.2: Regulatory Events

This table lists the events we identified over 2019–2021 to extend the carbon policy surprise series by Känzig (2022).

	Date	Event	Type
1	Jan 15, 2019	Commission publishes status update for New Entrants' Reserve	Free alloc.
2	April 23, 2019	EU Emissions Trading System: Iceland, Liechtenstein and Norway to start auctions on the common auction platform soon	Auction
3	May 15, 2019	ETS Market Stability Reserve to reduce auction volume by almost 400 million allowances between September 2019 and August 2020	Auction
4	June 12, 2019	Poland's 2020 auction volume to include allowances not used for power sector modernisation	Auction
5	June 19, 2019	Updated information on exchange and international credit use in the EU ETS	Intl. credits
6	July 15, 2019	Commission publishes status update for New Entrants' Reserve	Free alloc.
7	October 31, 2019	Adoption of the Regulation on adjustments to free allocation of emission allowances due to activity level changes	Free alloc.
8	December 12, 2019	The start of auctioning for the Innovation Fund slightly postponed but no delay to the launch of the Innovation Fund	Auction
9	January 15, 2020	Commission publishes status update for New Entrants' Reserve	Free alloc.
10a	May 8, 2020	Updated information on exchange and international credit use in the EU ETS	Intl. credits
10b	May 8, 2020	ETS Market Stability Reserve to reduce auction volume by over 330 million allowances between September 2020 and August 2021	Auction
11	December 11, 2020	Further information on the start of phase 4 of the EU ETS in 2021: emission allowances to be issued for aircraft operators and the Market Stability Reserve	Cap
12	March 15, 2021	Adoption of the Regulation determining benchmark values for free allocation for the period 2021-2025	Free alloc.
13	May 12, 2021	ETS Market Stability Reserve to reduce auction volume by over 378 million allowances between September 2021 and August 2022	Auction
14	May 25, 2021	Updated information on exchange and international credits' use in the EU ETS	Intl. credits
15	May 31, 2021	Commission adopts the uniform cross-sectoral correction factor to be applied to free allocation for 2021 to 2025 in EU ETS	Free alloc.

B Derivation of Bias

Without loss of generality, assume that $CE_i = 1$ for all firms. Then, if we could observe D and U, we could estimate the effect of a change in carbon prices on non-regulatory event days with the following equation:

$$R_t = a_1 + bD_t + cU_t + \varepsilon_t \tag{13}$$

where b is the effect of the demand shock and c is the effect of a carbon price shock on stock returns. Note that b is the *total* effect of the demand shock on returns. This the sum of the direct effect ($D \to R$) and the indirect effect through carbon price ($D \to \Delta CP \to R$). Instead, c measures the effect on returns of an independent shock U to carbon price.

As we do not observe D and U, we cannot separately estimate b and c. However, we observe $\Delta CP = D + U$ and can estimate the following model:

$$R_t = a_2 + m_1 \Delta CP_t + \varepsilon_t \tag{14}$$

where $\hat{m}_1$ is a weighted average of b and c. Specifically, $\hat{m}_1 = b\frac{cov(D,\Delta CP_t)}{V(\Delta CP_t)} + c\frac{cov(U,\Delta CP_t)}{V(\Delta CP_t)}$. As D and U are uncorrelated: $V(\Delta CP_t) = V(D) + V(U)$; $cov(D, \Delta CP_t) = V(D)$; and $cov(U, \Delta CP_t) = V(U)$. Hence:

$$\hat{m}_1 = b\frac{V(D)}{V(D)+V(U)} + c\frac{V(U)}{V(D)+V(U)} \tag{15}$$

Let us now consider regulatory event days. If we observed D, U and P, we could estimate:

$$R_t = a_3 + bD_t + cU_t + gP_t + \varepsilon_t \tag{16}$$

As before, b is the total effect of the demand shock on returns ($D \to R$ plus $D \to \Delta CP \to R$). Similarly, g is the total effect of the policy surprise on returns ($P \to R$ plus $P \to \Delta CP \to R$). Finally, c is the effect of U on returns (not the total effect of carbon price on returns). Given that we observe $\Delta CP_t = D_t + U_t + P_t$, we estimate:

$$R_t = a_4 + m_2 \Delta CP_t + \varepsilon_t \tag{17}$$

In this case, $\hat{m}_2$ is a weighted average of b, c, and g, with:

$$\hat{m}_2 = b\frac{V(D)}{V(D)+V(U)+V(P)} + c\frac{V(U)}{V(D)+V(U)+V(P)} + g\frac{V(P)}{V(D)+V(U)+V(P)} \tag{18}$$

While we do not observe $V(D)$ and $V(U)$ separately, we do observe $V(\Delta CP_{\tilde{E}}) = V(D) + V(U)$ and $V(\Delta CP_E) = V(D) + V(U) + V(P)$. The former is the variance of ΔCP on non-event days and the latter is the variance of ΔCP on event days. Let us write $V(\Delta CP_E) = kV(\Delta CP_{\tilde{E}})$, with $k > 1$ if $V(P) > 0$. Using the fact that $V(P) = V(\Delta CP_{\tilde{E}})(k-1)$, we can write Equation (18) as:

$$\hat{m_2} = \left(b\frac{V(D)}{V(\Delta CP_{\tilde{E}})} + c\frac{V(U)}{V(\Delta CP_{\tilde{E}})} \right) \frac{1}{k} + g\frac{k-1}{k} \tag{19}$$

Substituting Equation (15) into Equation (19), we get $\hat{m_2} = \frac{\hat{m_1}}{k} + g\frac{k-1}{k}$. Solving for g, we obtain:

$$g = \frac{\hat{m_2}k - \hat{m_1}}{k-1} \tag{20}$$

Given that we can estimate $\hat{m_1}$, $\hat{m_2}$, and we know k, we can recover g. In the set up of Equation (6), $\hat{m_1} = \hat{\beta}_1$ and $\hat{m_2} = \hat{\beta}_1 + \hat{\beta}_3$. Substituting into Equation (20), we can compute the total effect of P on R:

$$g = \frac{(\hat{\beta}_1 + \hat{\beta}_3)k - \hat{\beta}_1}{k-1} = \hat{\beta}_1 + \hat{\beta}_3\frac{k}{k-1} \tag{21}$$

C Robustness Checks

Figure C.1: Placebo Test

This figure plots our main coefficient of interest, β_3, from our baseline specification in Equation (8) together with 95 percent confidence intervals for 500 randomly simulated carbon policy surprise series.

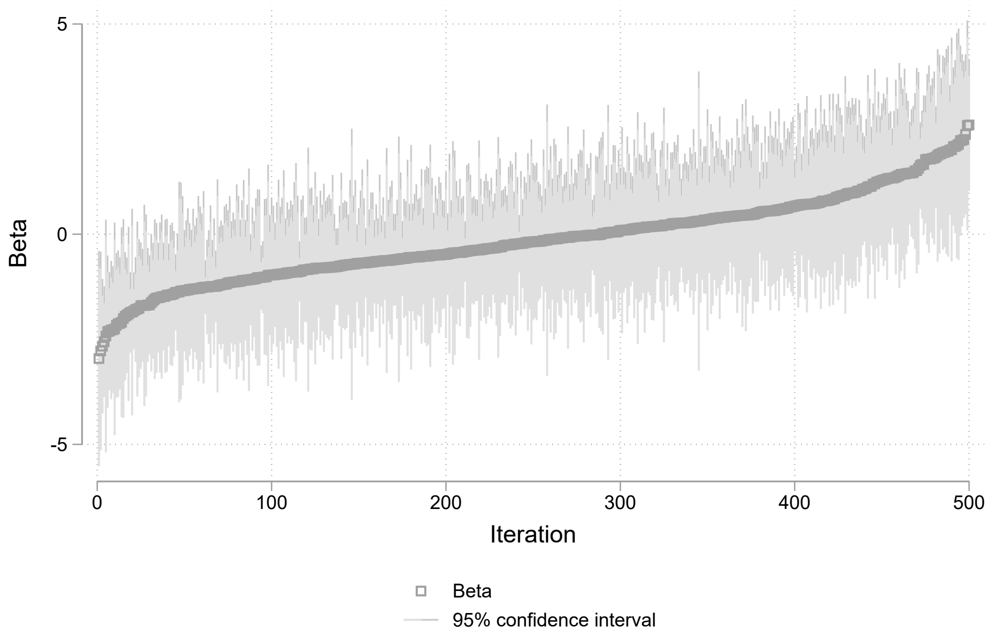

Figure C.2: Windows around Events

This figure plots our main coefficient of interest, β_3^h, at different horizons for the specification in Equation (12) together with 95 percent confidence intervals.

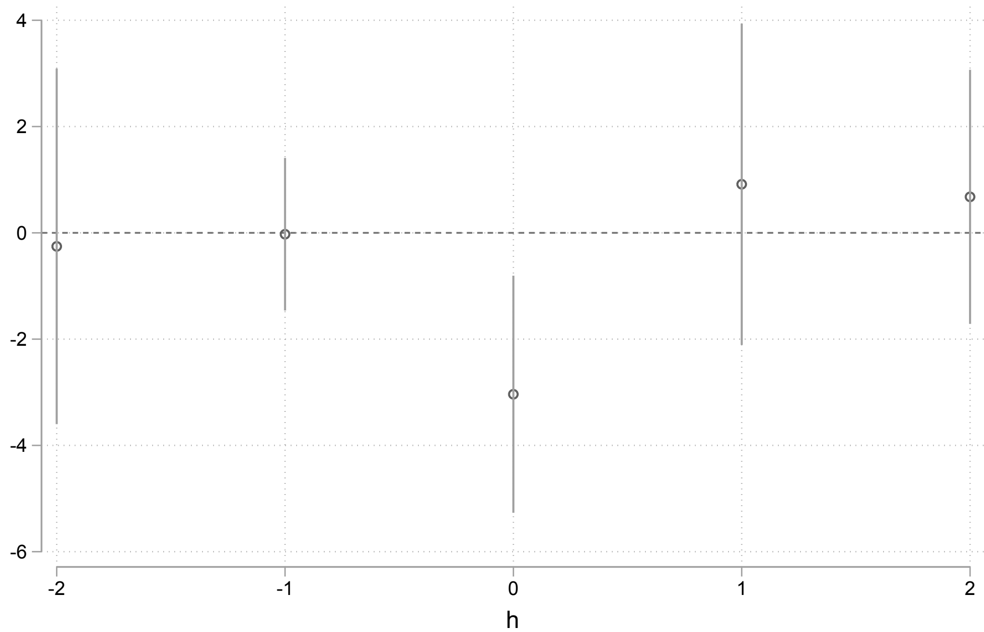

Figure C.3: Dropping one Country at a Time

This figure plots our main coefficient of interest, β_3 for the specification in Equation (10) together with 90 percent confidence intervals. The regressions drop one country at a time from the estimation sample (the column to the right specifies the dropped country).

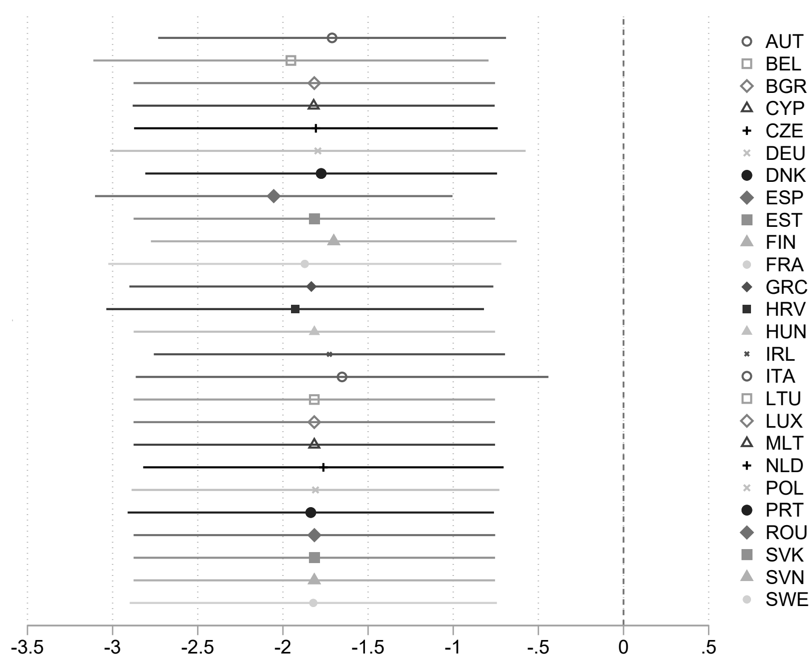

Table C.3: Alternative Lagging of Carbon Emissions

This table reports the model of column 6 in Table 2 for different lags of carbon emission intensity. Column 2 shows the results for a specification in which returns are regressed on carbon emissions published in the previous year for observations in Q1 and Q2 and on carbon emissions published in the same year for observations in Q3 and Q4. Column 3 shows the results for a specification in which returns are regressed on carbon emissions published in the previous year for observations in Q1 and on carbon emissions published in the same year for observations in Q2, Q3, and Q4. For convenience, column 1 reproduces the estimations of column 6 in Table 2 in which returns are regressed on carbon emissions published in the previous year for observations in all quarters. The dependent variable is daily stock returns (scaled by 10^5) and the explanatory variables are: firm-year carbon emission intensity (CE); the interaction between CE and percentage change in the EUA futures price (ΔCP); the interaction between CE and a dummy that takes value one on key regulatory event days (EV); and the interaction between CE and a carbon policy surprise obtained by interacting ΔCP and EV. All regressions control for firm and country-sector-time fixed effects (which absorb the main effects of ΔCP and EV) and are estimated with robust standard errors double clustered at the firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)
CE	1.25**	1.27**	0.56
	[0.510]	[0.568]	[0.629]
CE × ΔCP	0.63***	0.86***	1.08***
	[0.220]	[0.246]	[0.267]
CE × EV	-3.96*	-4.98*	-1.85
	[2.198]	[2.874]	[2.876]
CE × ΔCP × EV	-1.82***	-1.50**	-2.77***
	[0.645]	[0.700]	[0.924]
Observations	1,247,870	1,246,917	1,245,577
R-squared	0.4	0.39	0.38
Firm FE	Yes	Yes	Yes
Country-Sector-Time FE	Yes	Yes	Yes

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table C.4: Heterogeneity across Regions

This table reports the model of column 6 in Table 2 for regional subsamples and the baseline sample plus the UK. Column 2 shows results for a subsample of advanced European economies; column 3 focuses on economies in emerging Europe; and column 4 uses all EU countries plus the UK. For convenience, column 1 reproduces the estimations of column 6 in Table 2. The dependent variable is daily stock returns (scaled by 10^5) and the explanatory variables are: firm-year carbon emission intensity (CE); the interaction between CE and percentage change in the EUA futures price (ΔCP); the interaction between CE and a dummy that takes value one on key regulatory event days (EV); and the interaction between CE and a carbon policy surprise obtained by interacting ΔCP and EV. All regressions control for firm and country-sector-time fixed effects (which absorb the main effects of ΔCP and EV) and are estimated with robust standard errors double clustered at the firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)
CE	1.25**	1.29**	0.93	0.78
	[0.510]	[0.526]	[2.477]	[0.597]
CE × ΔCP	0.63***	0.65***	-0.12	0.65***
	[0.220]	[0.222]	[1.211]	[0.192]
CE × EV	-3.96*	-3.57	-14.72	-3.04
	[2.198]	[2.250]	[12.623]	[2.048]
CE × ΔCP × EV	-1.82***	-1.92***	4.27	-1.86***
	[0.645]	[0.683]	[8.043]	[0.477]
Observations	1,247,870	1,172,947	74,923	1,745,630
R-squared	0.4	0.41	0.34	0.39
Firm FE	Yes	Yes	Yes	Yes
Country-Sector-Time FE	Yes	Yes	Yes	Yes
Sample	All	AEs	EMs	All + UK

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

Table C.5: Excluding Financial Institutions

This table estimate the models of columns 3-6 in Table 2 by dropping the stocks of financial institutions. The dependent variable is daily stock returns (scaled by 10^5) and the explanatory variables are: firm-year carbon emission intensity (CE); the interaction between CE and percentage change in the EUA futures price (ΔCP); the interaction between CE and a dummy that takes value one on key regulatory event days (EV); and the interaction between CE and a carbon policy surprise obtained by interacting ΔCP and EV. All regressions control for firm and country-sector-time fixed effects (which absorb the main effects of ΔCP and EV) and are estimated with robust standard errors double clustered at the firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)
CE	1.20**	1.39***	1.30***	1.28**
	[0.510]	[0.507]	[0.505]	[0.513]
CE × ΔCP	0.60***			0.65***
	[0.216]			[0.224]
CE × EV		-3.70*		-3.95*
		[2.199]		[2.186]
CE × ΔCP × EV			-1.06*	-1.82***
			[0.619]	[0.644]
Observations	1,056,020	1,056,020	1,056,020	1,056,020
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Country-Sector-Time FE	Yes	Yes	Yes	Yes

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

PUBLICATIONS

Carbon Policy and Stock Returns: Signals from Financial Markets

Working Paper No. WP/23/13