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Carbon Policy Surprises and Stock Returns: Signals from Financial Markets

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January 2023

ABSTRACT: Understanding the impact of climate mitigation policies is key to designing effective carbon pricing tools. We use 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 policies on stock returns. After extracting the surprise component of regulatory actions, we show that events resulting in higher carbon prices lead to negative abnormal returns which increase with a firm's carbon intensity. This negative relationship is even stronger for firms in sectors which do not participate in the EU ETS suggesting 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.

JEL Classification Numbers:	G12; G14; G18; G32; G38: Q54
Keywords:	Carbon Emissions; Carbon Prices: Climate Change; Transition Risk; Stock Returns

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Abstract

Understanding the impact of climate mitigation policies is key to designing effective carbon pricing tools. We use 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 policies on stock returns. After extracting the surprise component of regulatory actions, we show that events resulting in higher carbon prices lead to negative abnormal returns which increase with a firm's carbon intensity. This negative relationship is even stronger for firms in sectors which do not participate in the EU ETS suggesting 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 100% 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 things, aims at a 55% 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.

Reaching these objectives will require redirecting financial resources towards sustainable projects and activities. Policy actions aimed at diverting capital to support climate change mitigation are only effective if they raise the cost of capital for firms with high carbon emissions with respect to their greener counterparts. In this paper, we show that this is the case: we document that policies that increase carbon prices have an impact on stock prices and raise the cost of equity capital for firms with high carbon emissions.

We use firm-level data for a large sample of European companies to study how the impact of carbon policy on stock returns varies with company-level carbon emissions. After accounting for the endogeneity of the relationship between carbon prices and stock returns, we find that regulatory actions which result in positive carbon policy surprises (i.e., higher carbon prices) lead to negative abnormal returns which increase with carbon emissions. We explore whether our findings are driven by increased carbon risk or by the effect of an increase in the cost of carbon for firms that need to surrender carbon emission allowances under the EU ETS. The fact that our results are robust to dropping firms that participate in the Trading System suggests that carbon transition risk does matter. We conclude that regulation is effective in increasing the cost of equity capital for high-emission companies. Our results are thus consistent with existing work that has found that investors demand compensation for their exposure to carbon transition risk (Bolton and Kacperczyk, 2021b, 2022)—and even more so when tighter policies lead to higher carbon prices.

Our paper also contributes to identifying events that lead to a repricing of carbon risk (Känzig, 2022) and provides a test for the role of a key potential driver of this risk. Specifically, we provide firm-level evidence for the hypothesis that climate policy tightness is an important driver of carbon transition risk. This result is in line with the findings of Bolton and Kacperczyk (2022) who, using a different approach, find that domestic policy tightening is a driver of the relationship between stock returns and firm-level carbon emissions.

We start by sourcing firm-year level data on carbon emissions from Urgentem for 2,149 listed firms in the EU over 2011–21 and merge them with daily data on stock returns. We then show that our data corroborate existing evidence that carbon emissions are associated with a higher cost of capital. Instead, our results are not in line with studies that find that low carbon emission intensity is associated with higher returns, such as In et al. (2019) and Garveya et al. (2018). Note, however, that these studies use a smaller sample of companies and focus on portfolios instead of firm-level returns.

While our results on the link between carbon emissions and average returns are similar to those of Bolton and Kacperczyk (2021b, 2022), there are two notable differences between their empirical approach and ours. First, we focus on emission intensity (i.e., total emissions scaled by revenues). We do this because our ultimate objective is to estimate the relationship between policy shocks and stock returns and, as discussed by Bolton and Kacperczyk (2021b, p.519): "emission-intensive firms might well be the first to become unprofitable should the carbon price rise." Second, we use daily stock returns. Again, this choice is linked to our objective of estimating the effect of carbon policy surprises which are defined at daily frequency.[1]

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 abnormal 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 high-emission 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 high-emission firms.

Finally, we move to our main question of interest and test how carbon policy affects the relationship between stock returns and company-level carbon emissions. To quantify the policy shock, we follow Känzig (2022) and use a measure of carbon policy surprises. 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 the EUA futures prices on the day of regulatory events. We find that carbon policy surprises have a statistically significant negative impact on stock returns which increases with a firm's carbon intensity. 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 point estimates imply that a one standard deviation increase in the carbon price on regulatory event days (the carbon policy surprise) lowers an average firm's daily return by around 7%.

We also test for the presence of asymmetries between days when carbon prices increase and days when carbon prices decrease. We find strong evidence of asymmetries on non-regulatory event days. Specifically, we show that the the positive correlation between carbon prices and stock returns for high-emission firms is driven by days when carbon prices decrease. Carbon emissions, instead, do not matter (the coefficient is basically zero) on days when carbon prices increase. While there is no statistically significant asymmetry for our main variable of interest—the carbon policy surprise

[1] We use the term "carbon policy" to refer to policy conducted in the EU through its ETS which aims at reducing greenhouse gas emissions.

—we do find that the effect is quantitatively larger in absolute value when a regulatory surprise leads to an increase in carbon prices (the difference is about 25%). This result provides further evidence that regulatory surprises which result in an increase in carbon prices are particularly effective in increasing the cost of equity capital for carbon-intensive firms.

Related Literature

This paper contributes to a growing body of literature that studies the impact of climate risk and policy on financial markets. As mentioned, Bolton and Kacperczyk (2021b, 2022) show that company-level carbon emissions lead to higher stock returns in a cross-section of firms. They describe two mechanisms that could lead to a positive link between carbon emissions and stock returns: (i) carbon risk premium and (ii) disinvestment.[2] According to the carbon risk premium hypothesis, companies with high carbon emissions are exposed to carbon pricing and carbon regulation risk. Hence, forward-looking investors will 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 high-emission stocks, their prices decrease and, for any given level of profits, their returns increase. Bolton and Kacperczyk (2021b) conclude that there is no strong evidence in support of the disinvestment hypothesis and that their results are in line with the carbon risk premium hypothesis. In this paper, we provide further evidence in this direction.

Two other papers that are closely related to our work are Bolton et al. (2022) 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. (2022) 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. For instance, Bolton et al. (2022) find that for firms that have shortfalls in freely allocated emission allowances, higher carbon prices translate to lower returns, while the opposite is true for firms that have free allowances that exceed their emissions. They also find that firms with a shortfall of allowances tend to reduce emissions within the EU but not globally. These results are consistent with the idea that, within the EU ETS, the cost channel dominates the risk compensation channel.

However, the cost channel should not be at play for firms that do not participate in the EU ETS. Given that our sample is dominated by firms that do not participate in the ETS, our finding of a negative relationship between stock returns and policy shocks that increase carbon prices for high-emission firms suggests that carbon transition risk also plays a role. In fact, we find that when we exclude firms that participate in the EU ETS our results become stronger.

Related work also includes Hsu et al. (2022) who show that the cross-sectional variation in stock returns is linked to industrial pollution and Faccini et al. (2021) who find that climate risk associated with 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

[2]They also discuss a third possible mechanism (carbon alpha). However, this mechanism is not consistent with the observed positive cross-sectional correlation between carbon emissions and stock returns.

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 find that exposure to regulatory events has a negative effect on stock valuations. Engle et al. (2020) also use text analysis but focus on news and show how to build portfolios that can hedge climate news.

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 and that this is particularly the case 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 of systematic risk and a decrease of the portfolio weights of carbon-intensive indices. In a survey of institutional investors, Krueger et al. (2020) find that these investors worry about climate and regulatory risks but that these risks are not fully reflected in equity valuations.

Other relevant papers include Veith et al. (2009) and Jong et al. (2014) who found a positive correlation between stock returns of electricity producers and carbon prices. The main explanation for this finding is that these authors used data for the first phase of the EU ETS (2005-07), a period in which emission allowances were freely allocated. Studies that focus on the second phase of the EU ETS tend to find either a negative or not statistically significant relationship between carbon prices and stock returns of electricity producers (da Silva et al., 2016; Mo et al., 2012; Tian et al., 2016). Focusing on Germany, Oestreich and Tsiakas (2015) find a premium before 2009 and no significant relationship between stock returns and carbon prices in more recent years. Using data on European companies, Ryszka and Rösler (2020) also find no significant relationship between carbon emissions and stock prices, but Dutta et al. (2018) find that carbon emissions increase the volatility of European electricity producers. Witkowski et al. (2021) also emphasize the time-varying nature of the relationship between carbon prices and stock returns in energy and energy-intensive sectors. They find that the carbon premium in energy-intensive sectors relative to greener firms was positive and statistically significant before the introduction of the EU ETS, then turned negative, and surprisingly became insignificant after 2016.

Focusing on US firms, Matsumura et al. (2014) find that carbon emissions reduce firm value but that there is a mitigating effect of voluntary disclosure. Along similar lines, Chava (2014) finds that stocks excluded by environmental screens have a higher implied cost of capital and face higher interest rates with respect to firms that do not face such environmental concerns. Likewise, Bolton and Kacperczyk (2021a) show that voluntary disclosure of carbon emissions lowers the cost of capital for firms in 77 countries.

There is also a literature that focuses on climate events and climate news. Bansal et al. (2016) use data for US and global equity markets and find that higher temperature lowers equity valuations. Along similar lines, Painter (2020) find that US counties that are more likely to be affected by climate change face higher interest and underwriting costs when they issue municipal bonds.

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 concludes.

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 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 we are interested in the response of stock returns to carbon policy shocks, we focus on emission intensity.

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 that both the average and median cross-section emission intensity have declined over time (see Table A.1). As noted in Bolton and Kacperczyk (2021b), declining firm-level emissions over time are expected as a result of innovations and energy efficiency gains as well as the increasing reliance on renewable energy.

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% of total emissions and roughly 6% 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% of total emissions and about 15% of observations (Figure 1).

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

[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.

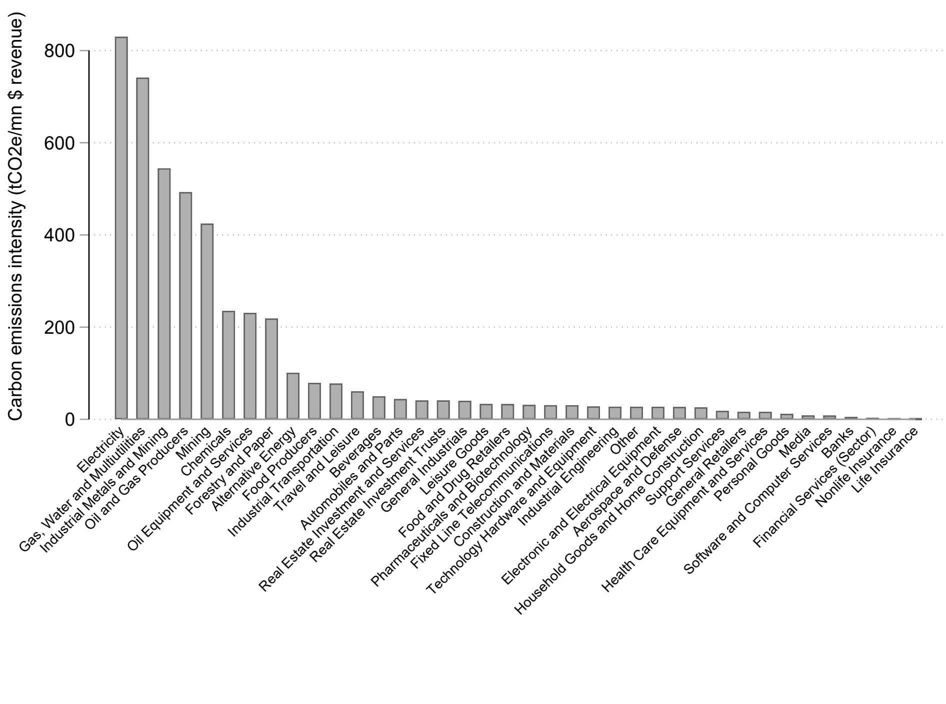
Table 1: Summary Statistics

This table reports summary statistics for our baseline sample which consists of 2,149 firms across 38 sectors in 23 EU countries over the period from 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	0.24	0.28	2.97
Daily change in EUA futures price on event days (percent)	$\Delta CP \times EV$	-0.01	0.00	0.67

Figure 1: Carbon emission intensity across sectors

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

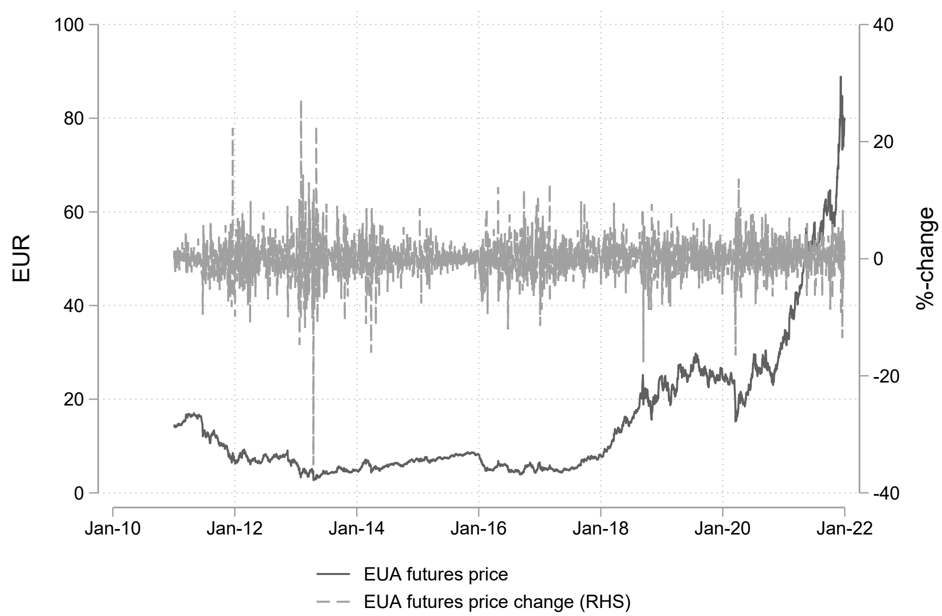


on an annual basis.[5] EUAs are traded on several spot and futures markets. In line with Känzig (2022), we focus on EUA futures data from the Intercontinental Exchange (ICE) which dominate the price discovery in the EU ETS.

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 0.24% between 2011–21 (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 but also because of legislation which affirmed the role of the EU ETS and changes to the supply of EUAs (Ampudia et al., 2022). The figure also shows that, on average, prices have been particularly volatile over 2020-21, but that there have also been volatility spikes in 2013 and 2016.

Figure 2: EU ETS carbon price

This figure shows the evolution of the EUA futures price and daily price change (RHS) over 2011–21.



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% with a standard deviation of 2.36%.[6]

[5] Each EUA entitles the holder to emit one tonne of carbon dioxide or carbon-equivalent greenhouse gas (tCO2e).
[6] We exclude observations with daily returns greater than 100% to limit the impact of outliers.

3 Conceptual Framework and Empirical Strategy

There is evidence that carbon emissions affect the cross section of stock returns both in the US and globally (Bolton and Kacperczyk, 2021b, 2022). To describe the link between what we do and existing cross-sectional analyses it us 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 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 $t' > t$ there is a policy shock that reveals that the value of the asset produced by firm B is subject to carbon risk. 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).

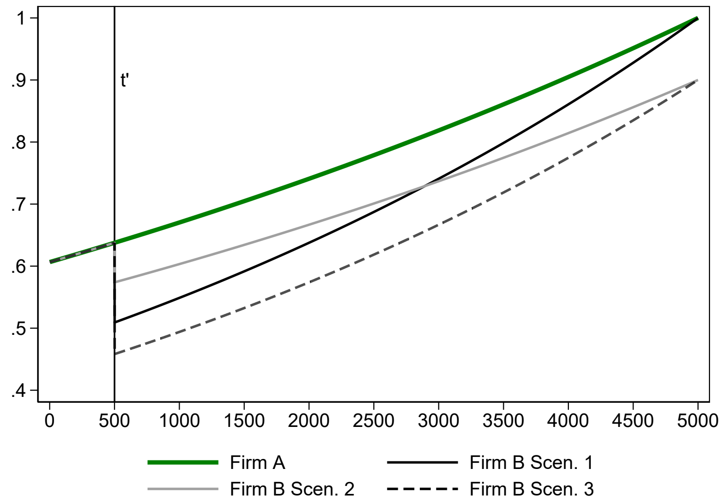
2. Investors think that at time T the asset produced by firm B will be δC (with $\delta < 1$) with certainty. Under this scenario, on day t' the price of stock B drops from $V_t^B = \frac{C}{(1+r)^{T-t'}}$ to $V_{t'}^B = \frac{\delta C}{(1+r)^{T-t'}}$. After t', the daily return goes back to r. The gray solid line in Figure 3 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.

[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 $\delta = 0.9$.



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 but not uncertain. Our empirical strategy uses multiple shocks and therefore does not allow to directly test the three scenarios described above. However, the fact that there was no significant carbon premium prior to the Paris Agreement of December 2015 (Bolton and Kacperczyk, 2022) does not seem consistent with the second scenario.[8]

In our sample of European listed firms, a policy shock that increases carbon prices could have a direct effect on firm profitability for companies that participate in the EU ETS. As highlighted by Bolton et al. (2022), this effect will be positive for firms that are long in emission allowances and negative for firms that are short in emission allowances. There could also be an indirect effect through transition risk. The relevant scenario for these firms would thus either be one one in which $\delta \neq 1$ and $\rho = 0$ or one in which $\delta \neq 1$ and $\rho > 0$.

However, for firms that do not participate in the EU ETS there should be no direct effect on profitability and changes in cross-sectional returns should be driven by ρ. Finding that high-emission firms have higher average returns and negative abnormal returns on impact when there is a policy action that leads to higher carbon prices would be consistent with the joint hypothesis

[8]The fact that the premium increased after the Paris Agreement is also inconsistent with a fourth possible scenario in which a policy shock reduces uncertainty about future policies and thus leads to lower cross sectional stock returns.

that investors price in carbon risk and that policy tightenings are a key driver of carbon risk. The objective of our empirical strategy is to test this joint hypothesis.

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 daily returns 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 abstracts 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 in our example carbon emissions do not affect returns before 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 (again, we abstract from other control variables and fixed effects). 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.[9]

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

[9] 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 $\alpha_2 = \beta = 0$.

novel scheme to increase its perimeter and address shortcomings, such as market distortions (see Känzig, 2022).

We thus take 81 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.[10] 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. Based on the assumption that risk premia do not vary over the one-day event window and that regulatory actions are not correlated with other shocks at daily frequency, this high-frequency series represents carbon policy surprises caused by EU ETS regulatory events.[11]

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 -0.01%). 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.

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:

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

However, our proxy for the 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,[12]

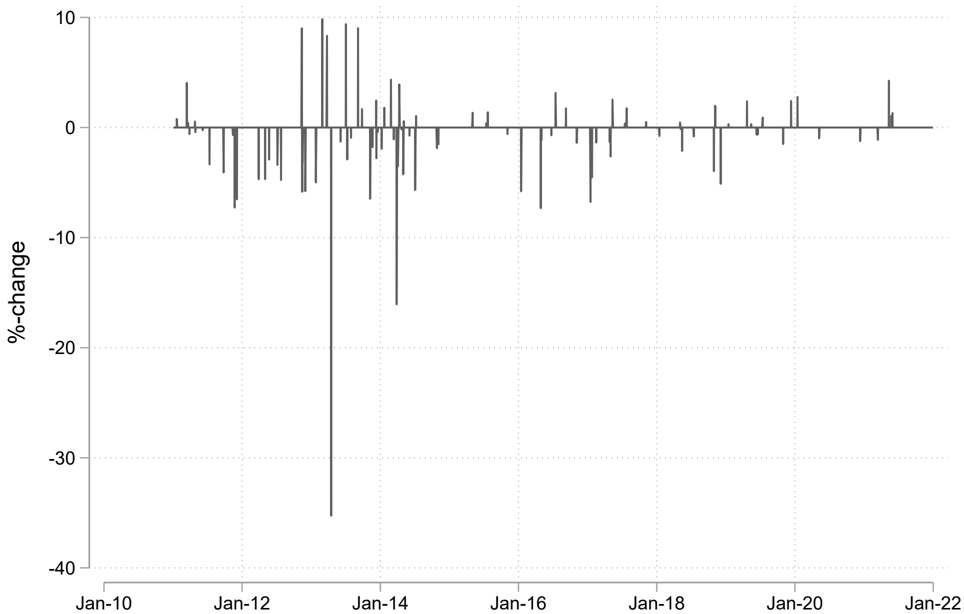
[10] We identified 16 events over 2019–21. However, since two events occurred on the same day, we classified them as one event.

[11] Känzig (2022) explains that risk premia of futures prices vary primarily at lower frequencies and that focusing on the front contract mitigates potential concerns about variation in risk premia. To further affirm the exogeneity of the carbon policy surprises, he shows that the series is not correlated with other structural shocks and that it is not autocorrelated or forecastable.

[12] 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 high-carbon emission 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 firm profits which, in turn, results in an upward bias in the estimate of β.

Figure 4: Carbon policy surprises

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



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 directly control for the demand shock (D) and for the policy shock (P), we could estimate the causal effect of the policy shock (i.e., the link of $P \to R$) by simply regressing stock returns on these two shocks without controlling for ΔCP (controlling for ΔCP would lead to "collider bias", see Pearl, 2009 and VanderWeele, 2014). In fact, if we could observe P we could estimate the causal effect of the policy shock even if we did not observe the demand shock, by simply regressing returns on P (this is because we are assuming that P is uncorrelated with the demand shock and the exogenous residual shock). 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 effect of carbon policy on stock returns (i.e., the causal link $P \to R$) by estimating a model that includes both carbon prices and the carbon policy shock:

$$R_{i,t} = CE_i(\alpha + \beta_a \Delta CP_t + \beta_b CPS_t) \tag{5}$$

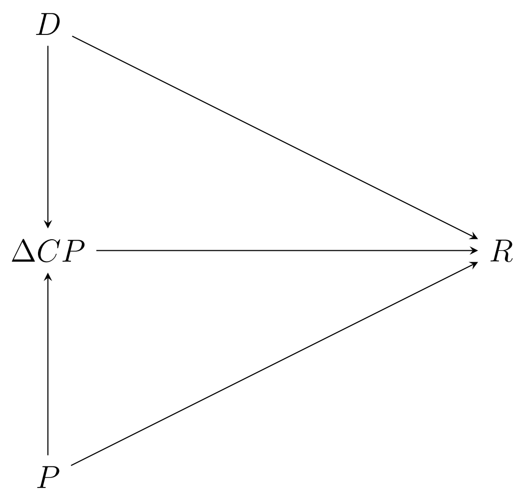
As CPS is equal to the change in carbon price on event days, this is equivalent to estimating the following interactive model:

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

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

Figure 5: Endogeneity Associated with an Unobserved Demand Shock

This figure shows two Directed Acyclic Graphs (DAGs) that illustrate how an unobserved demand shock D leads to an endogeneity bias by directly affecting the carbon price ΔCP and stock returns R (top panel). The policy shock P also has a direct effect on carbon price and on stock returns.



In the set-up of equation 6, β_3 measures the difference between the correlation between ΔCP and R on event days and the correlation between ΔCP and R on non-event days. If we assume that both (i) the effect of the demand shock on carbon prices ($D \rightarrow \Delta CP$) and stock returns ($D \rightarrow R$) and (ii) the effect of carbon price on stock returns ($\Delta CP \rightarrow R$) are not influenced by the presence of a regulatory event, then β_3 will measure the effect of the policy shock on stock returns ($P \rightarrow R$). This is exactly what we want to estimate. Note, however, that β_1 *does not* measure the causal effect of carbon prices on stock returns as we cannot separate $D \rightarrow R$ from $\Delta CP \rightarrow R$ because we do not observe D. Also note that our estimation strategy only allows to estimate the direct effect of the policy shock on stock returns ($P \rightarrow R$). Figure 5 shows that there is also an indirect effect that goes through carbon prices ($P \rightarrow \Delta CP \rightarrow R$). However, we cannot estimate this indirect effect because, as mentioned, we cannot estimate the causal effect of carbon prices on stock returns.

Finally, while we control for the regulatory event dummy, we only do so for completeness. We do not have a prior for its effect on stock returns because regulatory events have an ambiguous effect on carbon prices as shown by the direction of carbon policy surprises (see Figure 4). Moreover, regulatory events that do not affect carbon prices cannot be considered as a surprise. Therefore they should not affect stock returns.

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 follow Bolton and Kacperczyk (2021b, 2022) and test whether carbon emissions affect the cross section of stock returns in our daily sample of European firms. Formally, we start by estimating the following model:

$$R_{i,d(y)} = \alpha CE_{i,y-1} + \phi_i + \tau_{d(y)} + \varepsilon_{i,d(y)} \tag{7}$$

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 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 effect 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). 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 3.9% compounded at the annual frequency. This suggests that investors in European stocks demand a carbon risk premium and confirms the findings in Bolton and Kacperczyk (2021b, 2022).

Having corroborated the existing evidence that support the presence of a carbon premium in the cross section of stock returns, we now study how carbon emission intensity affects the relationship between stock returns and carbon prices in the EU futures market by estimating the following model:

$$R_{i,d(y)} = CE_{i,y-1}\left(\alpha + \beta_1 \Delta CP_{d(y)}\right) + \phi_i + \tau_{c,s,d(y)} + \varepsilon_{i,d(y)} \tag{8}$$

where $\Delta CP_{d(y)}$ measures the daily change in the carbon price in the EU futures market and all other variables are defined as in Equation 7.[13]

In the set up of Equation 8, α measures the correlation between carbon emission intensity and stock returns on days when the carbon price does 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

[13] As our main variable of interest (the interaction between day-level carbon prices 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.

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 1 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 clustered at firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)	(5)	(6)
CE	2.27***	1.27**	1.17**	1.35***	1.27**	1.24**
	[0.606]	[0.501]	[0.507]	[0.505]	[0.502]	[0.512]
CE × ΔCP			0.58***			0.63***
			[0.213]			[0.220]
CE × EV				-3.36		-3.61
				[2.224]		[2.207]
CE × ΔCP × EV					-1.08*	-1.81***
					[0.621]	[0.647]
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

3 of Table 2 shows that β_1 is *positive* and statistically significant: carbon-intensive companies tend to have *higher* returns when the price of carbon increases. The point estimates suggest that when the price of carbon increases by one standard deviation, the daily return of a company with an average carbon emission intensity will be about 4.2% above average.[14]

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 higher carbon prices. However, this is an unlikely explanation for two reasons. First, the share of free allowances has been decreasing with time and we find a positive correlation between carbon prices and stock returns for high-emission 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 that participate in the EU ETS as further elaborated on below.

A more likely explanation for the positive correlation between carbon prices and stock returns for high-carbon intensity 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 of 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 of emission allowances and a higher

[14] An increase of carbon prices by one standard deviation results in a 0.2 basis points increase in daily returns, equivalent to about 4.2% of the average daily return of 0.048% in our sample.

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.

Next, to estimate how the causal effect of carbon policy on stock returns varies with company-level carbon emissions, we need an exogenous shock. As discussed in Section 3, we follow Känzig (2022) who suggests to build a series of carbon policy surprises by interacting the change in carbon price with a set of dummy variables that take the value one during EU ETS regulatory events.

Formally, we estimate the following model:

$$R_{i,d(y)} = CE_{i,y-1}\left(\alpha + \beta_1 \Delta CP_{d(y)} + \beta_2 EV_{d(y)} + \beta_3 \Delta CP_{d(y)} \times EV_{d(y)}\right) + \phi_i + \tau_{c,s,d(y)} + \varepsilon_{i,d(y)} \quad (9)$$

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 as in Equation 8.

Equation 9 implies that:

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

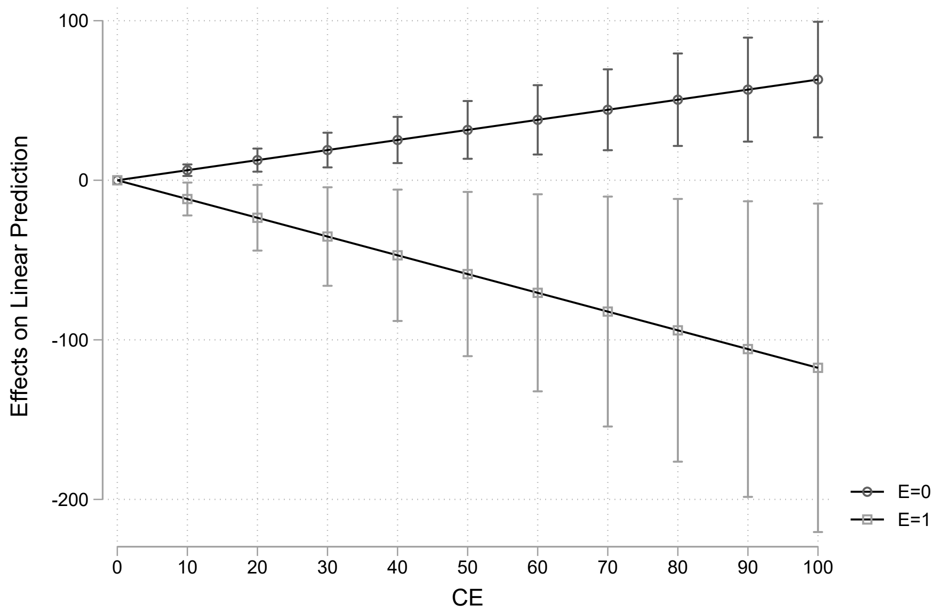
Hence, β_1 measures how the correlation between carbon prices and stock returns varies with carbon intensity on non-regulatory event days and β_3 measures the difference in this correlation between event and non-event days. Thus, $\beta_1 + \beta_3$ measures how the correlation between carbon prices and 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 which result in positive carbon policy surprises there is a negative correlation between the carbon price 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 price on stock returns of carbon-intensive firms. Hence, $\beta_1 + \beta_3$ does not measure a causal effect, either. However, if the assumptions of Section 3 hold, β_3 is the direct causal effect of the carbon policy shock on stock returns of carbon-intensive firms.

When we estimate Equation 9, we find that β_1 remains positive and statistically significant and that the carbon policy surprise has a negative coefficient which is about three times (in absolute value) β_1 (column 6 of Table 2). The point estimates imply that, for a firm with an average carbon emission intensity, a one standard deviation increase in the carbon price is associated with a daily return which is 4.2% above average on non-regulatory event day and 7.3% below average on regulatory event days.

Figure 6 shows the correlation between stock returns and carbon prices at different levels of the distribution of carbon emission intensity for regulatory event days 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 is increasing 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 carbon emission intensity. The slope of the relationship between carbon emissions and policy surprises on event days ($\beta_1 + \beta_3$) is negative and about twice (in absolute value) the slope on non-event days.

Figure 6: Carbon Price and Stock Returns

This figure plots the marginal effect of carbon prices on stock returns at various levels of the distribution of carbon 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 in Table 2.



While our main variable of interest is β_3, we also control for the components of the triple interaction separately. We find that the interaction between carbon emissions and the regulatory event dummy is negative but not 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). This is not surprising given that this dummy does not capture the intensity of regulatory actions and does not separate between measures that tighten and measures that relax environmental standards. The triple interaction is instead negative and statistically significant even when do not include its components (column 5). Note that a model that only includes the triple interaction and does not control for the main effect of carbon price implicitly assumes that on regulatory event days the endogenous component of the carbon price (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 of the triple interaction in column 5 is about 60% (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 9 by including firm-year-quarter fixed effects. This set of fixed effects controls for all possible firm-

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 1 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 clustered at firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)
CE × ΔCP	0.58***			0.63***
	[0.210]			[0.217]
CE × EV		-3.29		-3.54
		[2.184]		[2.209]
CE × ΔCP × EV			-1.06*	-1.79***
			[0.560]	[0.591]
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

specific shocks at quarterly frequency (we use quarterly fixed effects as this coincides with the highest frequency at which firms report financial information). While the inclusion of firm-year-quarter fixed effects does not allow estimating the main effect of carbon emission intensity which only varies at annual frequency, it does allow us to estimate our parameters of interest β_1 and β_3.

When we estimate Equations 8 and 9 with firm-year-quarter fixed effects, we obtain results that are essentially identical to those of our baseline regressions (compare column 3 and 6 of Table 2 with columns 1 and 4 of Table 3). This result confirms that our baseline results of 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 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. (2022) find strong evidence in support of the idea that the increase in the cost of carbon for firms that need to buy carbon allowances is the dominant element. However, the fact that we find an effect 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 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]

[15] The EU ETS covers the following gases: (i) carbon dioxide (CO_2) 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 (N_2O) from production of nitric, adipic and glyoxylic acids and glyoxal;

When we exclude companies that participate in the EU ETS our results become stronger. The point estimate of our coefficient of interest (the triple interaction CE $\times$ ΔCP $\times$ EV) increases from approximately 1.8 to about 2.4 (compare column 4 of Tables 2 and Table 3 with columns 4 and 5 of Table 4) and the interaction between the regulatory event dummy and carbon emissions is now statistically significant.

The fact that excluding sectors that participate in the EU ETS strengthens the negative relationship between carbon prices and stock returns for high-emission firms, is in line with the results of Bolton et al. (2022) 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 1 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 clustered at firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)	(5)
CE	0.86	1.02	0.90	0.93	
	[0.744]	[0.738]	[0.724]	[0.750]	
CE $\times$ ΔCP	0.36			0.44*	0.45*
	[0.236]			[0.246]	[0.249]
CE $\times$ EV		-4.22**		-5.09***	-5.05***
		[2.047]		[1.953]	[1.950]
CE $\times$ ΔCP $\times$ EV			-1.76**	-2.37***	-2.40***
			[0.829]	[0.840]	[0.778]
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 surprises have different effects on stock returns of carbon emission intensive companies.

We test for the possible presence of such asymmetries by allowing our coefficients of interest to vary between days in which carbon prices increase and days when carbon prices decrease. Formally,

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.

we estimate the following equation:

$$R_{i,d(y)} = CE_{i,y-1}\left(\alpha + \beta_1 \Delta CP_{d(y)} + \beta_2 EV_{d(y)} + \beta_3 \Delta CP_{d(y)} \times EV_{d(y)}\right) + \\ + CE_{i,y-1} \times \Delta CP_{d(y)} \times D_{d(y)}\left(\beta_4 + \beta_5 EV_{d(y)}\right) + \phi_i + \tau_{c,s,d(y)} + \varepsilon_{i,d(y)} \tag{10}$$

where $D_{d(y)}$ is a dummy variable that takes value one when $\Delta CP_{d(y)} > 0$ and all other variables are as in Equation 9.

Equation 10 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 10 with firm fixed effects and country-sector-time fixed effects (column 1 of Table 5) and with firm-year-quarter fixed effects and country-sector-time fixed effects (column 2 of Table 5) and obtain almost identical results. We find that β_1 is positive and statistically significant and β_4 is negative and statistically significant with approximately the same magnitude (in absolute value) of β_1 (thus, $\beta_1 + \beta_4 \approx 0$). There are thus substantial asymmetries in the relationship between carbon prices and stock returns on non-regulatory event days. Our baseline result of a positive correlation between carbon price and stock returns for high-carbon emission firms on non-event days is driven by days when the carbon price decreases.[16] On non-event days characterized by increases in carbon prices, carbon emissions do not affect the correlation between carbon prices and stock returns.

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. This results is consistent with the idea that policy surprises lead to a negative correlation between carbon prices and stock returns of more carbon-intensive firms. However, while the difference is not statistically significant, we find that the effect is about three times as large for policy surprises that lead to an increase in carbon prices than for policy surprises that lead to a decrease in carbon prices. This result indicates that regulatory surprises which lead to an increase in carbon prices are 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 1 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 clustered at firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)
CE	2.37***	
	[0.696]	
CE × ΔCP	1.19***	1.23***
	[0.395]	[0.414]
CE × EV	-3.13	-2.92
	[3.590]	[3.668]
CE × ΔCP × EV	-1.88**	-1.82**
	[0.932]	[0.866]
CE × ΔCP × D	-1.09**	-1.16*
	[0.550]	[0.601]
CE × ΔCP × EV × D	-0.44	-0.54
	[2.432]	[2.441]
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.

As a first step, we test whether our results are driven by a specific country by estimating our model dropping one country at a time. Appendix Figure B.1 plots the coefficient of our main variable of interest (β_3) with its 90% confidence interval. It shows that our results are not driven by any particular country and that when we drop one country at a time we obtain coefficients that range between -1.7 and -2.1 (in our baseline estimates of Table 2 we find that $\beta_3 = -1.8$) and are always statistically significant.

Next, we test whether there are differences between Advanced and Emerging Europe.[17] Column 2 of Appendix Table B.3 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 less than 10% of our sample (216 firms over a total of 2,149).

[17]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 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 of 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 our results 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 (column 1 of Appendix Table B.3) and a sample that also includes UK companies (column 4).

As a final robustness check, we estimate our baseline regressions by dropping financial institutions. Appendix Table B.4 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 Emissions Trading System (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 of affecting the cost of equity of high-emission companies. Once we account 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.

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Appendix to Carbon Policy Surprises and Stock Returns

A Data

Table A.1: Carbon emissions intensity over time

This table reports the cross-sectional average and median of scope 1 + 2 carbon emissions intensity over the period 2010–2020 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 Robustness Checks

Figure B.1: The Effect of the Carbon Policy Shock by Dropping one Country at a Time

This figure plots the β_3 coefficient with its 90% confidence interval of from Equation 9 obtained by estimating the model of Table 2 column 6 by dropping one country at a time (the column on the right reports the ISO code of the dropped country).

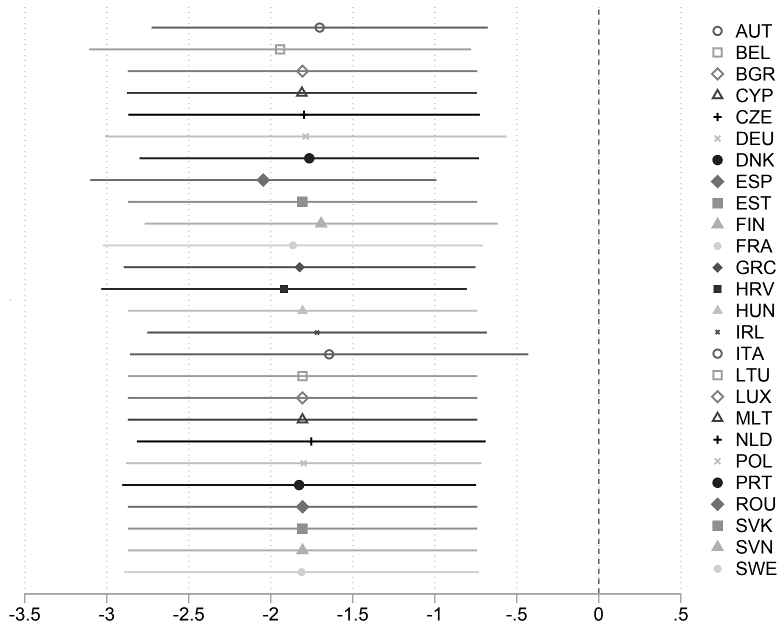

Table B.3: Heterogeneity across Regions

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 sub sample of advanced European economies; column 3 focuses on economies in emerging Europe; and column 4 uses all EU countries plus the UK (column 4). 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 1 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 clustered at firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)
CE	1.24**	1.29**	0.93	0.77
	[0.512]	[0.528]	[2.477]	[0.597]
CE × ΔCP	0.63***	0.65***	-0.12	0.65***
	[0.220]	[0.222]	[1.211]	[0.192]
CE × EV	-3.61	-3.20	-14.72	-2.81
	[2.207]	[2.257]	[12.623]	[2.060]
CE × ΔCP × EV	-1.81***	-1.91***	4.27	-1.85***
	[0.647]	[0.687]	[8.043]	[0.479]
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 B.4: 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 1 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 clustered at firm and day level. Regression results exclude observations with daily returns greater than 100%.

	(1)	(2)	(3)	(4)
CE	1.20**	1.38***	1.30***	1.27**
	[0.510]	[0.509]	[0.505]	[0.515]
CE × ΔCP	0.60***			0.65***
	[0.216]			[0.224]
CE × EV		-3.35		-3.59
		[2.210]		[2.195]
CE × ΔCP × EV			-1.06*	-1.82***
			[0.619]	[0.647]
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

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