The Carrot and the Stock: In Search of Stock-Market Incentives for Decarbonization*

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Highlights

- European stock and carbon prices are found to co-move.
- The higher a firm's carbon costs, the lower its stock return when carbon prices rise.
- For a firm with carbon costs of 10% of revenues, a 1% carbon price rise is linked to a stock price drop of 0.04%.
- Free emission allowances are found not to impact the stock/carbon price co-movement.
- This relationship can provide an incentive for firms to decarbonize.

Abstract

Financial markets can support the transition to a low-carbon economy by redirecting funds from highly emissive to clean investments. We study whether European stock markets incorporate carbon prices in company valuations and to what degree they discriminate between firms with different carbon intensities. Using a novel dataset of stock prices and carbon intensities of 338 European publicly traded

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companies between 2013 and 2021, we find a strongly statistically significant relationship between weekly carbon price changes and stock returns. Crucially, this relationship depends on firms' carbon intensity: the higher the carbon costs a firm faces, the poorer its stock performance during the periods of carbon price increases. Emissions that firms cover with free allowances however do not impact this relationship, illustrating how both carbon pricing and disclosures are needed for financial markets to foster climate change mitigation. The relationship we identify can provide an incentive for firms to decarbonize. We argue in favor of more ambitious carbon pricing policies, as this would strengthen the stock-market incentive channel while causing only limited financial stability risk for stocks.

Keywords: European Union Emissions Trading Scheme; Carbon price; Stock price valuation; Climate Finance; Climate Change Mitigation; Multifactor Market Model

JEL classification: G12; G14; Q53; Q54; Q54

1 Introduction

The financial sector has an important role to play in supporting the transition to a low-carbon economy. According to International Energy Agency estimates (IEA, 2021), annual global investment in the energy sector alone will need to triple by 2030 to around $4 trillion in order to reach net zero emissions by 2050. With the aim of achieving this ambitious target, financial markets should be made to increasingly channel funding towards sustainable projects. Funds tend to flow towards those investments that provide the highest return for a given level of risk. Therefore, any policy that either lowers returns of highly emissive ventures with respect to less polluting ones or provides transparency on the higher risks they face, will contribute to a more environmentally desirable allocation of resources.

Two key policies are generally put forward to achieve that goal. First, carbon pricing initiatives (World Bank, 2021), which aim to internalize the costs of greenhouse gas emissions, reduce the relative profitability of highly emissive firms. But polluting firms also face higher *risks* from possible additional regulation that might impact their future profitability. The second kind of proposed policies are transparency initiatives that increase the availability of high-quality, comparable, emissions-related data (NGFS, 2022) that allow financial markets to adjust prices to reflect these risks. These two policies – carbon pricing and data disclosure – are mutually reinforcing in pushing financial markets to support the transition to a low-carbon economy.

The European Union (EU) has considerably advanced on both fronts in recent years. Transparency was greatly enhanced by the publication of the EU taxonomy and of the EU green bond standard. The work on the Corporate Sustainability Reporting Directive (CSRD) addressed the gap in unified reporting standards. Taken together, these instruments have standardized green financing procedures and considerably reduced the room for greenwashing. In parallel, the rising price of carbon within the EU Emissions Trading System (EU ETS) has increased carbon costs for polluting firms. In this paper, we illustrate the mutually reinforcing effect of carbon pricing and increased climate data transparency by analyzing whether stock markets penalize the stock prices of the most carbon intensive companies amid rising carbon costs.

The EU ETS is a carbon pricing mechanism set up in the EU in 2005. Its rules were updated several times[1] and it gradually became a cornerstone of the European climate policy. The EU ETS is a "cap and trade" scheme whereby a limit is set on the total amount of greenhouse gases that can be emitted by the participating installations and the equivalent amount of tradeable allowances are issued. The system covers electricity and heat generation, energy-intensive industries, and partially the aviation sector. Every year, the installations from these sectors need to surrender allowances for the greenhouse gases that they emit. A fraction of these allowances are allocated to the installations for free,[2] while the residual needs to be covered with allowances purchased in public auctions or on the secondary market. In this paper we focus on the years 2013 to 2021, when the system had already matured into a well-functioning emissions market.

The EU ETS is primarily a carbon pricing mechanism that reflects the current and future supply and demand of emissions allowances. At the same time, the reporting on the functioning of the system provides the market with data on the emissions, free allocation of allowances and transactions. This audited and comparable information about firms' carbon intensity is freely accessible to market participants. Thus, the EU ETS serves both as a carbon pricing and as a transparency tool that partially[3] addresses the lack of reliable and comparable climate-related information.

Our paper explores the case of the EU ETS with the aim to measure the implications for the stock market of a higher carbon price and increased availability of climate-related data. Specifically, we assess the extent to which stock markets consider carbon price dynamics and firms' carbon intensities. If stock markets were found to discriminate highly emissive firms, this could imply the existence of a stock market incentive channel for shareholders to decarbonize firms' operations and accelerate the transition to a low-carbon economy. To conduct this analysis, we have compiled a unique dataset on free and paid emissions allowances of 338 publicly traded European companies.

Our results reveal a strongly statistically significant relationship between carbon price changes and stock returns. This relationship is found to depend on firms' carbon intensity: the higher the carbon costs a firm faces, the more an increase of the carbon price is linked to a drop of its market valuation. Importantly, the investors seem to price in the costs of purchased emissions allowances, while the free allowances do not impact the relationship between carbon prices and stock returns. This illustrates the importance of both internalizing the emissions externality via carbon pricing and improving data availability. Taken alone, transparent information about the levels of emissions does not seem to inform how investors consider carbon price changes when valuing stocks. However, financial markets reflect climate policies when these lead to

[1]It went through several "trading phases": a pilot Phase I (2005-2007) to test the system, Phase II (2008-2012) when free allocation of allowances started to decline, Phase III (2013-2020) when auctioning became the default method for allocating allowances, Phase IV (2021-2030) setting more ambitious targets in terms of annual decline in emissions allowances.

[2]This fraction varies from sector to sector and typically increases with the risk of carbon leakage due to international competition. Since 2013 the fraction is very low for the electricity sector.

[3]It addresses the problem only partially because (i) not all sectors and all greenhouse gases are included in the EU ETS and (ii) no forward-looking data on firms' future emission paths is available.

noticeable current or future financial costs for firms. In particular, our estimates show that higher carbon price is associated with stock price declines for companies that spend more than 1.7% of their revenue on emission allowance purchases. In recent years, a 1% carbon price increase is linked to a stock price drop of up to 0.21% for the most polluting companies. The magnitude of the effect varies across different subsamples, but the nature of the relationship stays unchanged.

The paper is organized as follows. Section 2 summarizes the related literature, Section 3 describes the data collection process and the resulting final dataset. Section 4 sets out the econometric framework and the estimates. Section 5 summarizes the results and draws policy conclusions.

2 Literature Review

The first empirical studies on the effect of carbon prices on stock prices were published a few years after the introduction of the European Union Emissions Trading System (EU ETS) in 2005. So far, the literature has not reached a consensus on the direction of this relationship. Results differ depending on the choice of countries, companies, periods, and analytical approaches. At the same time, most papers conclude that the magnitude of the relationship is fairly small (1% change in the carbon price tends to coincide with a stock price change of only a few basis points). Another broadly confirmed result is that the interaction between stock and carbon price changes is not stable over time. This evolution is typically explained by changes in the functioning of the EU ETS, particularly by its transition from Phase I (2005-2007) to Phase II (2007-2012) and eventually to Phase III (from 2013).[4]Another recurring conclusion is on the asymmetric reaction of stock prices to carbon price upward and downward moves. Overall, the literature has broadly followed two econometric approaches: the multifactor market model approach (MMM henceforth) and the capital asset pricing model approach (CAPM). We summarize the results of papers applying both approaches.

Multifactor market model approach

These models essentially estimate the relationship between stock returns and carbon price changes controlling for overall stock market returns and energy price dynamics as measured by oil, gas, and electricity price returns. The period analyzed in these papers was gradually extended from just a few years of the EU ETS existence to its several phases.

Oberndorfer (2009) started by analyzing the data only for 2005-2007 (Phase I of the EU ETS), which corresponds to the period when the allocation of allowances to energy producers was fully free of change. The analysis found a statistically significant positive relationship between the carbon price change and electricity stock returns. A higher carbon price implied a higher value of freely allocated allowances held

[4]The free allocation of allowances dropped from close to 100% in Phase I to 90% in Phase II and was subsequently replaced by auctioning as the default method for allocating allowance in Phase III. The sectoral coverage of the EU ETS was gradually expanding. The system included only power generation and carbon-intensive industries (like oil refineries, cement production, iron and steel) during Phase I, but was expanded to aviation in 2012 and finally to ferrous and non-ferrous metals in Phase III.

on the companies' balance sheet, which is consistent with positive stock market moves. These results were confirmed in Veith et al. (2009) who applied a similar methodology to a sample of 22 European electricity generating firms. Jong et al. (2014) also find similar results via an event study methodology applied to April 2006, when the carbon price dropped sharply due to the overallocation of emission allowances. Firms with higher amounts of carbon allowances on their balance sheet and with lower carbon intensities register the largest increase in share prices.

Mo et al. (2012) and Tian et al. (2016) subsequently extended the analysis by using the data for 2006-2010 and 2005-2012, respectively. This allowed to explore the evolution of the relationship after the transition from Phase I to Phase II, when the proportion of freely allocated allowances fell to around 90%. Mo et al. (2012) concluded that carbon price developments have affected corporate value in the opposite directions: in Phase I (2005-2007), the increase in carbon price tended to be accompanied with corporate value appreciation, while during Phase II (2008-2010), it was more likely to induce depreciation. Mo et al. (2012) link these changes to the adjustment of the allowances allocation policy between Phases I and Phase II. Tian et al. (2016) do not find statistically significant relationship between the carbon price changes and electricity stock returns either during Phase I or Phase II. Tian et al. (2016), however, confirm that the stock market penalizes "dirtier" energy producers. The stock returns of carbon-intensive companies are negatively correlated with carbon price changes, while the opposite is true for less carbon-intensive producers.

Da Silva et al. (2016) and Moreno and da Silva (2016) extended the period under analysis to 2008-2014 and 2008-2015, respectively. The papers focus on the Spanish stock market and base their analysis on 13 and 31 companies, respectively. Longer samples allowed to compare the relationship during Phase II and Phase III, when the free allocation of allowances was gradually replaced by auctioning mechanisms. Both papers find evidence of a positive relationship between carbon price changes and stock returns during Phase II, and either negative or insignificant relationship during Phase III. Positive correlation with the carbon price is found for power companies relying on renewable energy sources. However, it turns negative for nearly all companies relying on non-renewable energy sources. The relationship also differs across sectors depending on the share of allowances allocated for free.

The aforementioned results are confirmed in Zhu et al. (2018) who apply MMM approach and quantile regressions to a dataset of 65 companies covering 2005-2017. The authors find a positive relationship between carbon price returns and stock returns in Phase II and negative relationship during Phase I and III. Similarly to Da Silva et al. (2016), Zhu et al. (2018) show some evidence on the asymmetric reaction of stock returns to carbon price increases and drops, the latter typically being stronger.

Overall, these papers provide some evidence on the fact that the relationship between carbon price changes and corporate stock returns in the electricity sector gradually switched from positive to negative, as the EU ETS evolved towards more market-based allocation of allowances. In addition, the stock returns of companies that are more carbon intensive (or more reliant on non-renewable energy sources) seem to be negatively affected by carbon price increases.

Capital Asset Pricing Model approach

Another strand of the literature tries to quantify the carbon premium (defined as the excess rate of return of dirty companies over otherwise comparable clean ones) by employing the CAPM approach.

Witkowski et al. (2021) apply this theoretical approach to portfolios of dirty and clean companies in energy and energy-intensive sectors from all the EU ETS countries for the period between 2003 and 2019. The authors confirm the presence of a carbon premium but they provide evidence of its unstable nature. The premium was positive – and statistically significant – prior to the introduction of the EU ETS and during 2003-2012, but became negative during 2013-2015 and statistically insignificant starting from 2016. The switch in the sign of the premium may be linked to changes in the rules governing the EU ETS.

Oestreich and Tsiakas (2015) apply CAPM approach to the data for 65 German companies during 2003-2012. They find a highly statistically significant carbon premium in 2003-2009 and also link it to the free allocation of allowances. The carbon premium dissipates after 2009 (one year into Phase II of the EU ETS). Ryszka (2021) employs the CAPM approach to explore the data on 900 European companies but fails to identify a statistically significant carbon premium after controlling for firm-specific characteristics.

Using US firm-level data, Bolton and Kacperczyk (2021) study to what extent carbon emissions and carbon risk affect stock returns and equity prices. Bolton and Kacperczyk (2021) find a positive and statistically significant effect of carbon emissions on returns. This effect is identified as evidence for a "carbon premium" – i.e., investors' demand for higher returns due to the exposure to carbon risk. Bolton and Kacperczyk (2021) argue that the carbon premium is directly related to the total level (and not the intensity) of emissions, which is not ideal given that total emissions are highly dependent on the size of the firm.

Görgen et al. (2020) build a firm "brownness-greenness" indicator and reveal that (i) brown firms outperform green firms, on average (ii) firms becoming "browner" relative to the preceding year experience negative returns. The two effects are found to have similar magnitudes, which reveals the ambiguous effect of carbon risk on stock returns.

While both the MMM and the CAPM approaches investigate corporate stock returns in light of carbon pricing, they do not aim to measure the same effects. The focus of CAPMs is on excess returns of highly-emitting over comparable clean firms. When found, these excess returns are interpreted as additional compensation that investors require to bear an undiversifiable "carbon risk" (such as a possible future tightening of climate policy depressing the valuation of polluting firms). The estimates of this implied premium are highly dependent on the ability to construct portfolios of stocks with very similar firm characteristics (apart from those that are controlled for in the specification) but different carbon intensities. At the same time, the CAPM does not allow to directly link the stock price performance to carbon price changes. The MMM, on the other hand, explicitly measures this *co-movement* – which is also the focus of this paper.

Identifying clean firms

The results of the above-mentioned studies show that carbon price changes affect carbon-intensive and clean companies differently. The authors use various methods and data sources to classify companies by this criterion. For instance, Tian et al. (2016) consider companies that generate 50% or more of their electricity from fossil fuels as carbon-intensive. Da Silva et al. (2016) use corporate information on the use of renewable and non-renewable energy sources. Oestreich and Tsiakas (2015) classify as "dirty" those firms which have received more than one million free allowances (anually) during the initial two phases of the EU ETS. Witkowski et al. (2021) develop their carbon risk exposure ratio calculated as the difference between actual emissions and free allowances normalized by companies' total assets. To the best of our knowledge, carbon intensity classifications based on the EU ETS data have not yet been used in the studies following the MMM approach.

Alternative analysis techniques

Several other studies explored linkages between emission allowance price changes and stock returns using techniques, other than CAPM and MMM described above.

Using VAR-GARCH models, Dutta et al. (2018) find that carbon emissions prices transmit their volatilities into the stock performance of European electricity companies. Wen et al. (2020) recur to non-linear autoregressive distributed lags (NARDL) models to explore the asymmetry between the carbon price and the stock prices moves in China. Wen et al. (2020) find that an increase in the carbon price affects stock prices stronger than a decrease.

More recently, the impact of transition risk on stock returns was also assessed using modern textual analysis techniques that allowed to build text-based metrics of carbon intensity using key words from quarterly earnings conference calls (Sautner et al., 2020). Using these text-based metrics of carbon intensity, Deng et al. (2022) show that until late-2021 the stocks of those US companies that are more vulnerable to a low-carbon economy transition performed better. This result likely reflects investors' expectation of a slowdown in transition policies in the US, while in Europe – where climate policy is found to be more ambitious – the effects were the opposite. Faccini et al. (2021) find that the climate policy factor is priced in the U.S. stock market. In particular, investors tend to demand positive risk premia for those companies exposed to the US climate risk policy.

Contribution of this paper

We follow the strand of literature using multifactor market models (Oberndorfer 2009, Veith et al. 2009, Mo et al. 2012, Tian et al. 2016, Da Silva et al. 2016), but we extend the analysis in a number of ways.

First, our research covers Phase III of the EU ETS (2013-2020) and the start of Phase IV (launched in 2021). The previous studies applying the MMM approach were limited to the analysis of data for 2005-2017, a period when free allocation of allowances remained high and allowance prices stayed low. Our study thus contributes to the earlier work on the evolution of the relationship between stock returns and carbon price changes across the EU ETS phases.

Second, we significantly expand the number of companies in the sample and extend the analysis beyond the electricity sector. The previous papers applying MMMs were based on relatively small samples (with a maximum number of companies in Zhu et al. 2018 of 65). Our sample consists of 338 companies whose business is affected by the EU ETS and is not limited to the electricity sector.

Third, we introduce a quantitative measure of the corporate carbon costs based upon the EU ETS data for 2012-2021. In the existing studies applying the MMM approach, the distinction between more and less carbon intensive firms is typically done based on corporate information about energy sources for electricity generation, which might not always be fully transparent, comparable and easily quantifiable. We take advantage of the EU ETS data to construct an indicator reflecting the annual costs related to the purchase of emission allowances. This indicator allows us to differentiate more rigorously between companies that are more and less affected by carbon pricing. Our approach is broadly similar to the one followed by Witkowski et al. (2021) but we use revenue and market capitalization as normalizing variables instead of total assets. We draw from the approach described in Abrell et al. (2021) and Jaraitė et al. (2013) when matching the EU ETS accounts with corporate data from ORBIS database when compiling our dataset.

3 Data

3.1 Dataset

Our analysis focuses on the relationship between the market price of emission allowances and the stock prices of the companies covered by the EU ETS. To conduct this analysis, we have built a database of publicly traded companies that have subsidiaries covered by the EU ETS. The database includes annual data on emission allowances allocated to these publicly traded companies (both for free and via the market), the firms' key financial indicators (notably, revenue and market capitalization) and their stock prices at a weekly frequency converted into EUR if the company is quoted in a different currency.

When collecting the data, we relied heavily on three sources of information. One is the EU ETS data on emissions, emission allowances and transactions between the participants of the system. The second source is Orbis, a set of company databases owned and operated by the commercial data provider Bureau van Dijk. The third source is an open database of financial market indicators provided by Yahoo Finance. We also benefit from earlier work of Abrell et al. (2021), who collected the data from the European Union Transaction Log (EUTL) in a user-friendly format.[5] We have also followed some of the recommendations provided by Jaraitė et al. (2013), who describe an approach to matching the EU ETS accounts with corporate information from the ORBIS database.

Putting together the dataset used in the analysis represented a significant challenge given that the EU ETS data is provided at a disaggregated installation level and is not directly linked to specific publicly

[5] See https://euets.info/ for further reference

traded companies. To collect the data we had to resolve three main tasks: (i) matching the installations with their parent companies,[6] (ii) keeping in the sample only the parent companies that are quoted on the stock exchange, (iii) ensuring that those installations belonging to the same parent company are properly consolidated. Matching the EUTL and Orbis data is at the heart of completing these tasks. A more detailed description of each step in the matching procedure can be found in subsection A.1 of the Annex.

The matching process was complicated given the heterogenous format of company identification numbers within the EUTL. Hence, matching the EUTL data with Orbis data required a substantial amount of manual work. The universe of entities covered by the EU ETS is very large (it included around 10,500 account holders as of 2020), which makes the complete matching highly time-consuming. We managed to unequivocally match almost 5800 account holders within the EU ETS with specific firms from Orbis. Out of these, 2112 are controlled by publicly traded companies. The remaining account holders do not have publicly traded companies in their ownership structure, and hence were excluded from further analysis. Certain account holders were often controlled by a single company. Once we have taken this into account in consolidation procedures, we end up with 634 publicly traded companies in our sample.

We stopped further matching when the quality of results started to decline and unambiguous matching was no longer possible. In particular, this was the case for small installations and companies. Nevertheless, we believe that our sample is sufficiently representative of the companies affected by the carbon pricing via the EU ETS. In any given year since 2013, the 5800 account holders within the EU ETS that we matched with Orbis corporate data accounted for around 95% of purchased emission allowances within the EU ETS (Figure 1). Two thirds of these purchased emission allowances belong to publicly traded companies. The rest was acquired by account holders with no publicly traded parent companies. This high coverage of purchased emission allowances by our sample should not be surprising. The concentration of emission allowances among the key players is quite high. For instance, in 2019, 74% of emission allowances were purchased by only 1% of account holders.

For further analysis, we decided to narrow our sample to the *European* traded companies. This allowed us to concentrate on a more homogeneous sample and to be able to control companies' stock prices for the general stock market trends that can be approximated with Eurostoxx 600 dynamics.[7] Non-European traded companies account only for a small share of emissions allowances allocated within the EU ETS (not more than 2.5% in any given year, see Figure 1). Excluding them does not do much harm to the emissions allowances coverage of our sample. Once we remove the European companies for which some data (either stock prices or revenues used for normalizing carbon costs) is missing, we end up with our final dataset of 338 publicly traded companies.

Earlier studies that applied multifactor market model approach to explore the link between the price of carbon and the stock market prices were conducted based on the data for not more than 22 European

[6]The installations are matched to their current parent companies and it is assumed that the controlling shareholder did not change during the sample period. Given high complexity of a full historical matching and a relatively small share of companies exposed to change in ownership, we do not expect this assumption to significantly alter our results.

[7]Stock index of 600 European stocks, including large, small and mid capitalization companies from 17 European countries

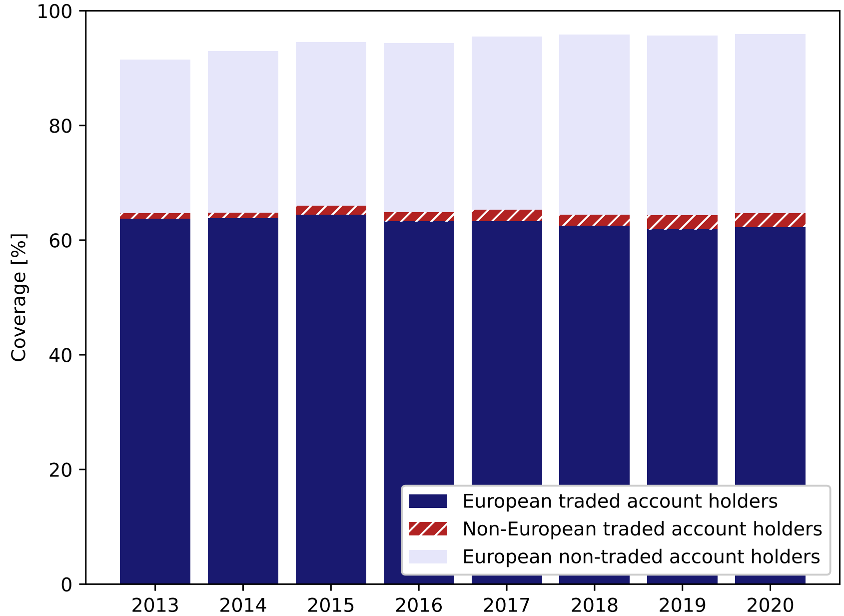

Figure 1: Paid emission allowances covered by the sample

energy companies. Our sample is much broader both in terms of the number of companies and their sectoral profile (see Figure 3). Apart from energy companies (12% of our sample), our dataset includes chemical producers (19%), mining companies (8%), transportation industry (6%) and numerous manufacturers from other sectors.

Our sample includes companies from 24 European countries, with the UK, Germany, France, Poland and Italy having the largest representation and jointly accounting for 55% of companies in the dataset (Figure 2). About a quarter of the companies in the sample are mid-size (have revenue of less than USD 1bn), while the remaining three quarters are represented by large-sized enterprises.

We also collect data on weekly changes of oil, electricity and gas prices converted into EUR which we subsequently introduce as control variables in our regressions (see more in Section 4.2). Specifically, we use Brent price for oil, ICE Dutch TTF one month futures for gas, and German electricity futures prices from Europe Exchange AG for electricity[8].

3.2 Stylized Facts

In recent years, the rising price of emission allowances within the EU ETS (see Figure 4) has attracted a lot of attention. However, there is little evidence on the magnitude of actual carbon costs for firms. Do these costs represent a sizeable share of the overall operating expenses? Can they significantly erode companies' profitability? Or are they negligible and only marginally affect corporate financials? Having matched the

[8]German electricity futures prices from the EEX are typically chosen as a proxy for the European electricity market developments as this market is the biggest in Europe.

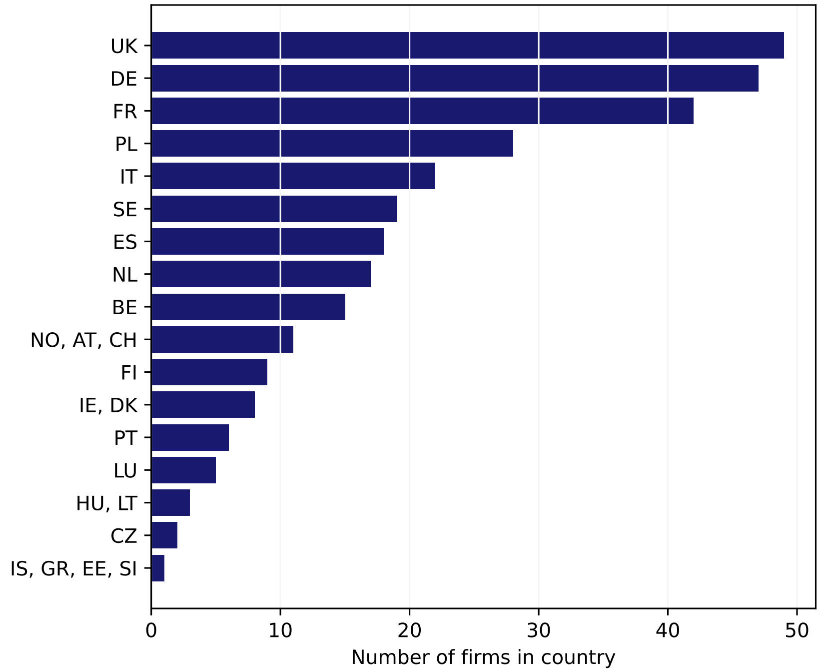

Figure 2: Data sample description: number of firms by country

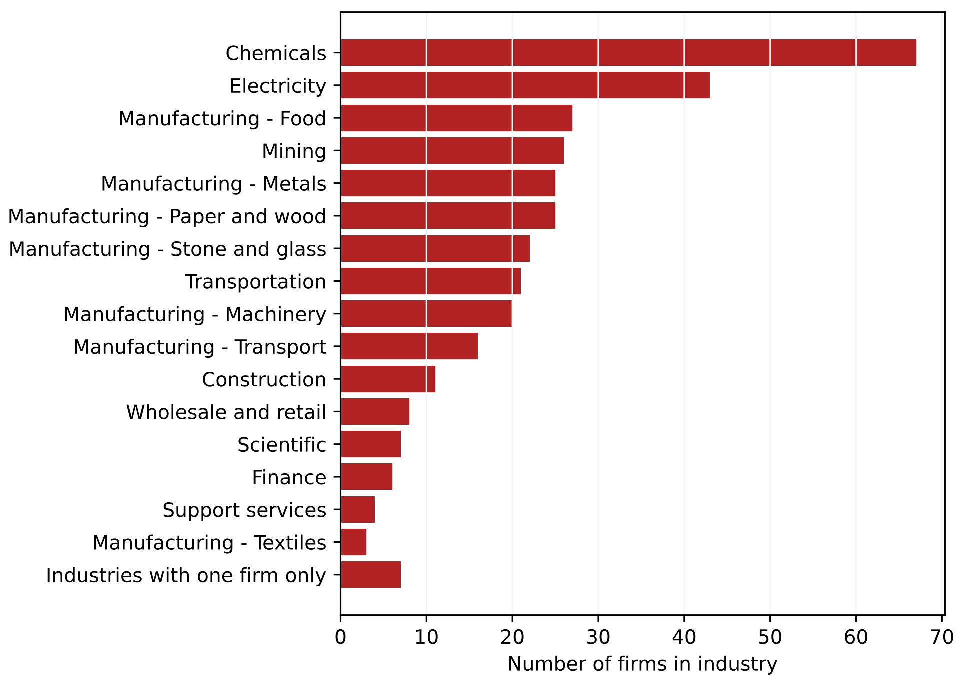

Figure 3: Data sample description: number of firms by industry

EU ETS data on emission allowances with the Orbis corporate finance data, we can provide some insights into these questions. In this section we start with an initial data overview, which we then complement with more rigorous econometric analysis in Section 4.

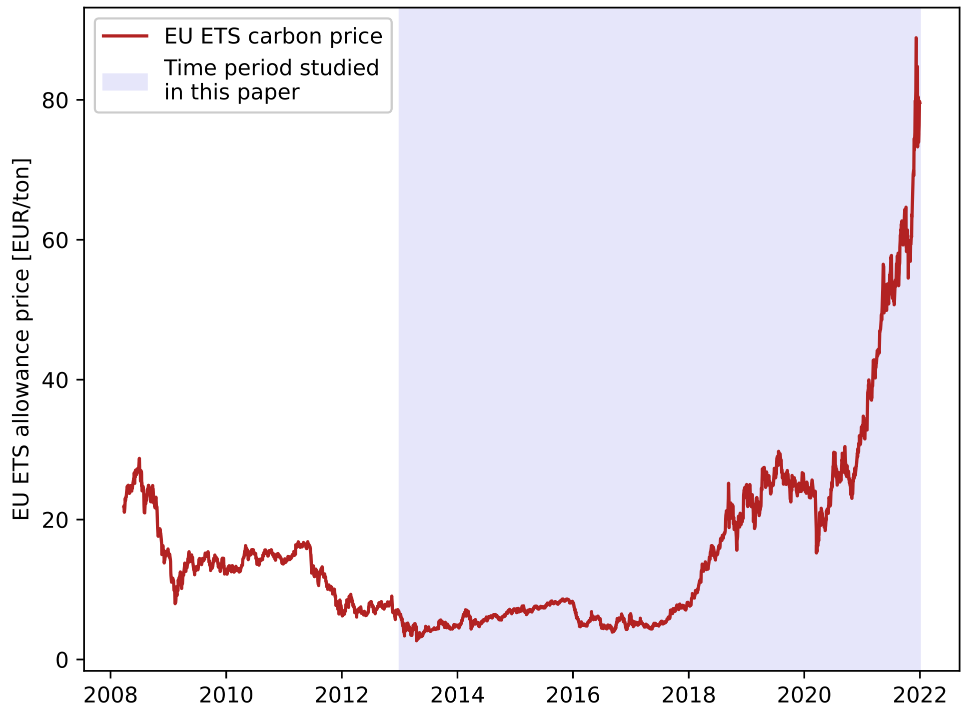

Figure 4: The price of carbon within the EU ETS

Over the latest decade, the companies in our sample, in particular electricity generating ones, managed to decrease their carbon footprint. The volume of their verified emissions was gradually declining (Figure 5). A sharper drop in 2020, particularly pronounced in electricity generation and aviation (included in "Other industries" category), was triggered by the COVID19 pandemic.

To recall, the companies from the industries covered by the EU ETS need to surrender allowances for their verified emissions. The allowances can be distributed either via free allocation or bought (via auctions or on the secondary market). The corresponding volumes are published by the European Commission on an annual basis. The shares of purchased allowances (defined as total emissions minus free allowances) in total allowances differs a lot across industries in our sample (Figure 6). In line with the existing regulation, the free allocation of allowances was gradually phased out for the electricity sector, with the share of purchased allowances exceeding 90% since 2019. In sectors like mining and chemistry, which we also focus on in this paper, the coverage of emissions by purchased allowances is still below 50%. The negative share of purchased allowances in 2012 reflects free allocation of allowances exceeding the volume of actual emissions during Phase II of the EU ETS. This allowed the companies to accumulate a stock of allowances instead of having to purchase them.

To assess the costs associated with the purchase of allowances, we need to multiply the carbon price by

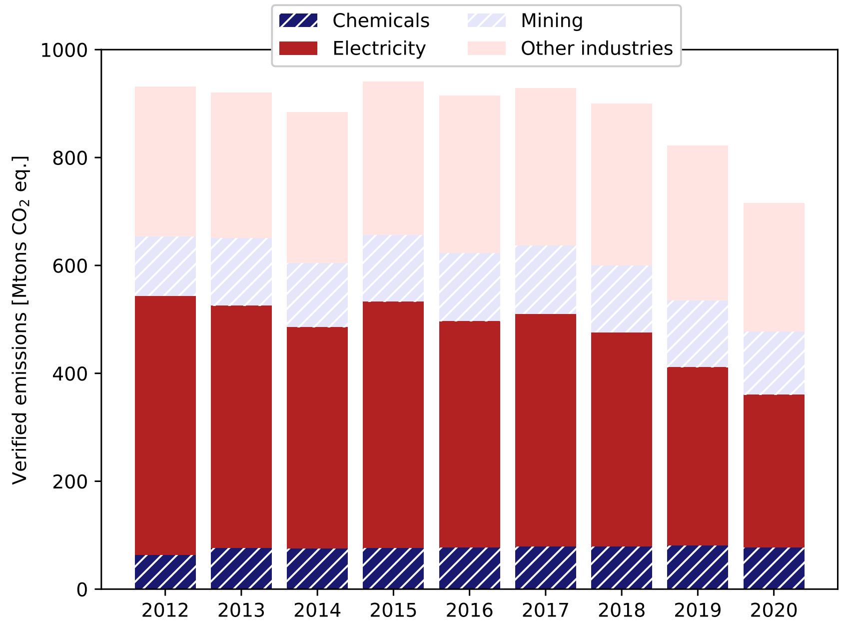

Figure 5: Verified emissions by industry, Mt CO_2 eq.

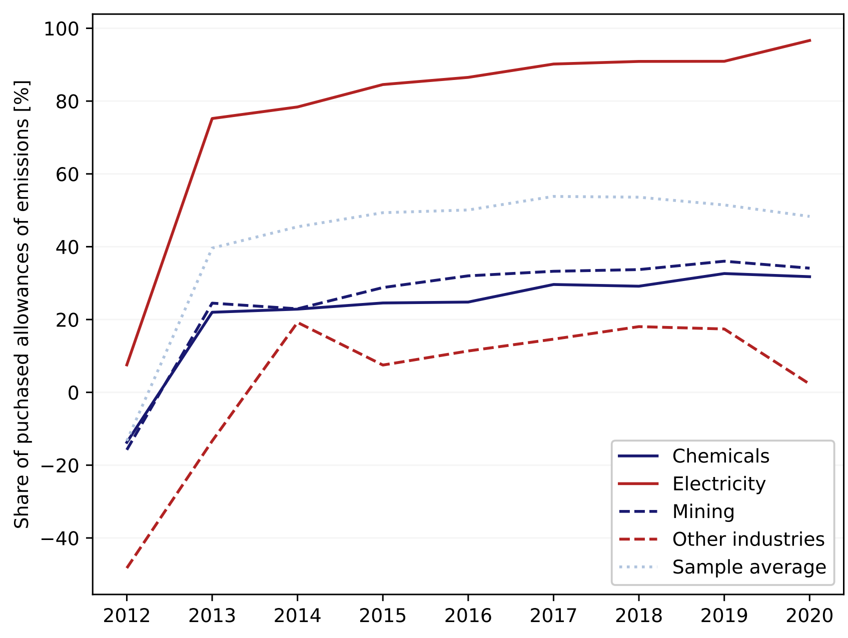

Figure 6: The share of purchased emission allowances in total emission allowances, %

the volume of emissions not covered by free allowances. We make a number of assumptions for that. Given that the EUTL database does not contain specific information on the precise time and price of purchases, we assume that the companies were spreading them evenly throughout the year. Hence, we approximate the actual price of the transactions with a mean annual price.[9] To make carbon costs comparable across firms, we scale them by the firms' yearly revenues.[10] We refer to the obtained indicator as "paid carbon intensity" or "relative carbon costs" (we use these terms interchangeably hereinafter). A similar indicator based on allowances allocated for free is referred to as "free carbon intensity".

For the majority of companies included in our sample the paid carbon intensity roughly tripled in 2019-2021 compared to earlier years. The move reflects a sharp increase of the price of carbon within the EU ETS since 2018. However, even after this increase the costs stayed quite low: the sample mean remained around 0.5% of revenue, the median has not deviated much from zero (see Figure 7 and Table 1). Still, in a few cases carbon costs were sizeable and exceeded 10% of revenue.

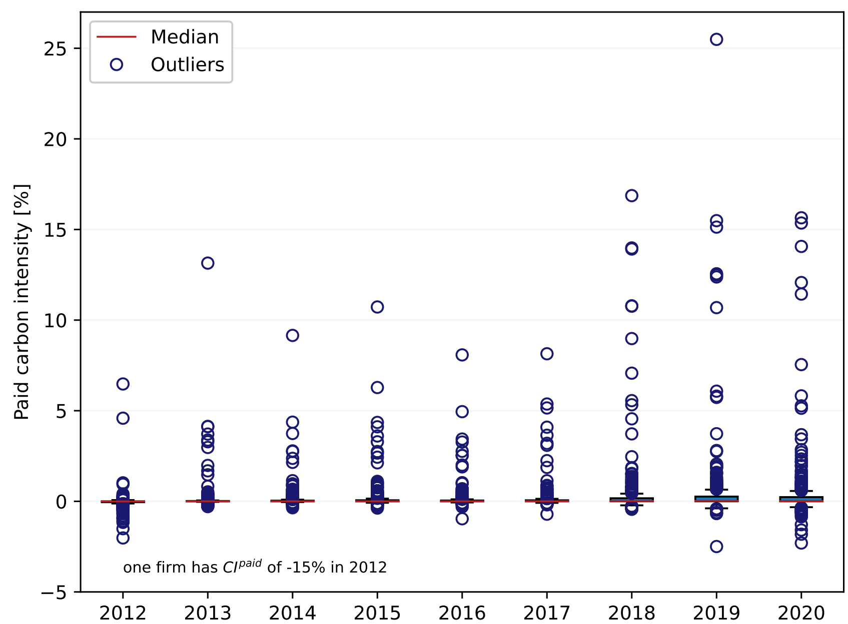

Figure 7: Distribution of the paid carbon intensity of firms through time.

We notice that paid carbon intensity differs significantly across industries (Figure 8). Electricity generating firms face costs above 3% of total revenues on average in 2019-2021 compared to around 1% in the preceding years. To put this number into context, the average profit margin for European electricity generating firms in our sample is around 8%, according to Orbis data. The effects of carbon price increases are hence noticeable in this sector and will likely play a role in stock price dynamics. This is in stark contrast

[9] This, of course, need not be true. Firms could be surrendering allowances they purchased or received for free in previous years. They could also enter into derivative contracts (futures or options) leading to them not paying the spot price. However, public auctions are organised (bi)weekly and therefore our approximation seems valid. For more discussion on the timing of purchases, see section A.4.3

[10] We also use other financial metrics for normalization as a robustness check. See the results in Annex A.4.4

with other industries, where the average paid carbon intensity does not exceed 0.5% of revenue. These sectoral differences are not surprising given that manufacturing industries keep receiving a high share of their emissions allowances for free. The measure is meant to limit "carbon leakage".

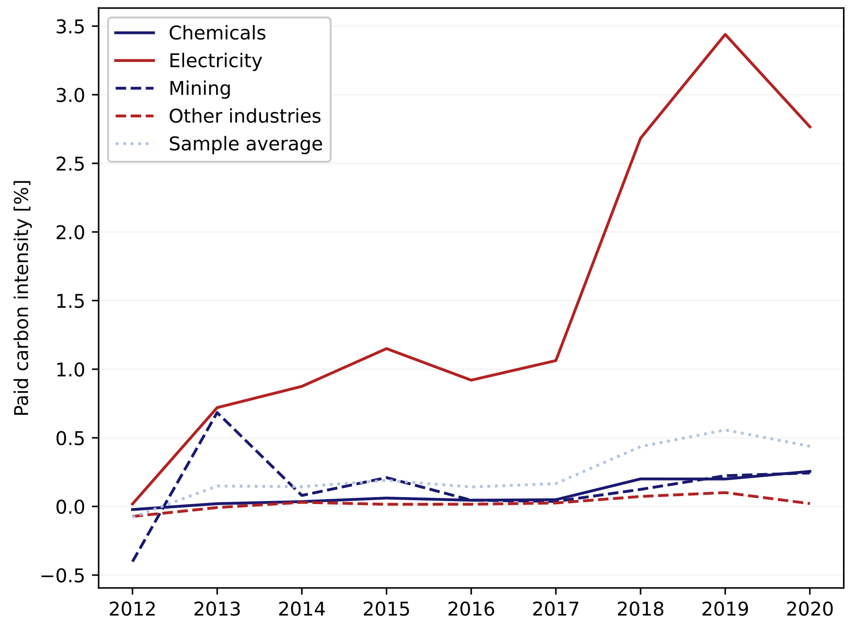

Figure 8: Paid carbon intensity by industry (in % of revenue)

When comparing paid carbon intensity across countries, we notice that on average it stayed below 1% of revenue even at the end of the sample when the price of carbon already significantly increased (Figure 9). The costs are noticeably higher only in three countries: Greece, Poland and Czech Republic. In the particular case of Greece, the results are based on the data for a single company and hence should not be treated as representative of carbon costs level in the country in general. The data on paid carbon intensity rhymes with other relevant environmental indicators. For instance, Poland and Czech Republic are among countries with the lowest GDP per unit of energy-related CO_2 emissions (OECD, 2015).

Low "paid carbon intensity" in the majority of firms suggests that at the current stage this indicator is unlikely to have strong relationship with the stock prices in sectors other than electricity. Indeed, the impact of this indicator of the firms' profitability is low and can be expected to be disregarded by investors. We will test this hypothesis more rigorously in the following sections.

Table 1 presents summary statistics for the main variables of interest. Interestingly, the summary statistics showcase some similarities between commodities markets and the market of emissions allowances. In particular, the carbon and commodities price returns exhibit much higher volatility than the European stock market. Judging by the mean and median weekly returns, during the decade under consideration, the price of carbon was increasing much faster than the price of commodities or stocks, reflecting a rapidly declining supply of emissions allowances.

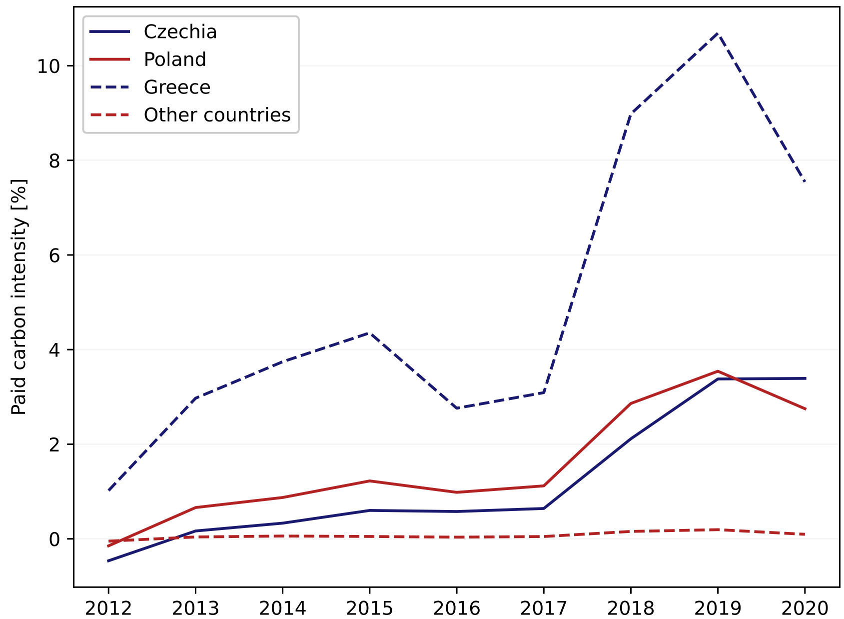

Figure 9: Paid carbon intensity by country (in % of revenues)

	Frequency	N	Mean	Median	Min	Max	Stdev.
Stock Returns	Week-firm	147,171	0.27	0.20	-82.7	212.46	5.18
Eurostoxx Return	Week	470	0.14	0.37	-18.4	7.36	2.25
Carbon Price Return	Week	470	0.77	0.67	-33.5	26.37	6.70
Gas Return	Week	470	0.48	-0.22	-36.3	46.54	7.50
Oil Return	Week	470	0.14	0.46	-26.5	35.90	5.49
Electricity Return	Week	470	0.61	0.16	-47.1	47.51	7.62
CI (paid)	Year-firm	2,844	0.25	0.00	-15.3	25.49	1.38
CI (free)	Year-firm	2,844	0.32	0.05	-0.40	39.41	1.25

Table 1: Summary Statistics (Mean, Median, Min, Max, Standard deviation in %)

4 Econometric Analysis

This section is structured as follows: we start by presenting the theoretical underpinning of our analysis (section 4.1), then state the econometric specification for the empirical analysis (section 4.2), present the estimates on the full dataset (section 4.3), on different sub-samples (section 4.4) and finally present an event study (section 4.6).

4.1 Theory

In this section we aim to understand how carbon price changes can impact a firm's stock price by means of a stylized model. We start by writing the stock price as the sum of discounted future profits:

$$S = \sum_t b^t \pi_t \tag{1}$$

where b^t denotes the discount factor for year t and π_t denotes the firm's profit in year t.

We can then express that profit as a function of the carbon price (following Bushnell et al., 2013):

$$\pi_t = \underbrace{P_t(q_t, q_t^o)q_t}_{\text{revenue}} - \underbrace{C(\omega)q_t}_{\text{costs}} - \underbrace{(r_t q_t - F_t)\tau_t}_{\text{carbon costs}} + \underbrace{A_{t-1}(\tau_t - \tau_{t-1})}_{\text{allowance valuation}} + \underbrace{\delta_t}_{\text{other effects}} \tag{2}$$

where $P_t(q_t, q_t^o)$ is the price given by the demand curve faced by the firm (expressed as a function of the quantities produced by the firm q_t and competing firm q_t^o). We denote the unit cost of the firm by C, which depends on a vector of input prices ω. The exogenous emission rate is given by r_t (in tCO_2e/unit, and determined by the firm's decarbonization path), τ_t denotes the carbon price per tCO_2e at the end of year t, F_t is the amount of free allowances received in year t, and A_{t-1} is the stock of allowances the firm held at the end of year $t-1$.

In the Appendix we derive the impact on the stock price of an exogenous carbon price shock:

$$\frac{dS}{d\tau_0} = \underbrace{\sum_t b^t P_t' \frac{dq_t^{o*}}{d\tau_0} q_t^*}_{[A]} - \underbrace{\sum_t b^t \frac{\partial C}{\partial \omega}\frac{\partial \omega}{\partial \tau_0} q_t^*}_{[B]} + \underbrace{A_{-1}}_{[C]} - \underbrace{\sum_t b^t (r_t q_t^* - F_t)}_{[D]} \tag{3}$$

where π^* and q^* are consistent with profit maximization and τ_0 is today's carbon price.

Each term in equation (3) represents a different (and sometimes opposite) effect of a carbon price change on the stock price. Term [A] shows how revenues can increase if competing firms have reduced output in response to the higher carbon price,[11] term [B] the additional costs faced by firms due to the carbon price impact on inputs, term [C] the valuation gains on the allowance inventory and term [D] the firm's increased carbon costs. This expression suggests that the impact of a carbon price shock on the stock price is dependent on several factors that go beyond the inmediate carbon cost increase, such as: how differently a particular firm reacts compared to its competitors, the input structure (i.e., how sensitive are input prices to carbon prices), and/or the amount of allowances held by the firm.

[11] $P(q)$ being the demand curve, $P_t' < 0$, if competing firms reduce output then $dq_t^{o*}/d\tau_0 < 0$ and term [A] is positive. If demand is inelastic then P_t' is highly negative and carbon prices can be passed on to consumers.

4.2 Specification for the empirical analysis

We now aim to capture the co-movements of stock returns and changes in the carbon price, in line with the multifactor market model approach presented in the Literature Review, regressing stock returns on carbon price returns and a number of controls. To do this, we estimate the following ordinary least squares (OLS) regression:

$$r_{i,t}^{stock} = \beta_1 r_t^{index} + \left[\beta_2 + \beta_3 CI_{i,Y}\right] r_{i,t}^{carbon} + \beta_4 r_t^{comm} + FE_{i,t} + \varepsilon_{i,t} \tag{4}$$

Where $r_{i,t}^{stock}$ is the stock return of firm i in week t; r_t^{index} is the stock index (Eurostoxx) return in week t controlling for the overall market dynamics; r_t^{carbon} is the return of the carbon price in week t; $CI_{i,Y}$ is the carbon intensity of firm i in year Y-1,[12] for which we use different metrics, all capturing emissions relative to firm size (see Section 4.3); r_t^{comm} is a vector of commodity weekly returns (gas, oil, electricity) used as controls - this is in line with the multifactor market model literature and accounts for the relationship of energy prices with both stock and carbon prices; and finally $FE_{i,t}$ are the industry and country × month fixed effects.

The main econometric innovation with respect to the literature is the modelling of the relationship between stock returns and carbon price returns. Thanks to the significant data collection effort, we are able to not only capture the co-movements with one term $\left(\beta_2 r_t^{carbon}\right)$ but also allow the relationship to vary with the carbon-intensity of each firm $\left(\beta_3 CI_{i,Y} \times r_{i,t}^{carbon}\right)$. For any firm i in year Y, the sensitivity of the stock return to the carbon price return is therefore given by:

$$\frac{\partial r^{stock}}{\partial r^{carbon}} = \beta_2 + CI_{i,Y} \times \beta_3. \tag{5}$$

In this setup, β_2 captures the co-movement of stock returns and carbon price changes for a company with a carbon intensity of zero. Throughout the remainder of this section, we will focus on β_3 as it captures the degree to which stock markets treat firms with different carbon intensities differently.

Relating the specification for the empirical analysis to the stylized model in the previous section, β_2 would capture the combined effect on the stock price of changed revenue, higher costs and allowance stock valuation gains – terms [A], [B] and [C] in Equation (3) – while β_3 would reflect the sensitivity to the paid carbon intensity ($r_t q_t^* - F_t$ in term [D]). Having no information about firms' market power and cost structure, we cannot explicitly account for the inter-firm variability of terms [A], [B][13] and [C].[14]

We chose to include country-month interacted fixed effects to account for country-specific business cycles as well as industry fixed effects to account for average heterogeneity across sectors. We further believe that

[12] Data for year Y are only published in year Y+1. In order to avoid using information that is not yet available to market participants, we plug the latest known statistics into the regression, i.e. those of year Y-1. For instance, emissions and free allocations for the year 2021 were published in April 2022, revenues for 2021 in early 2022. Throughout 2021 therefore, the latest information on firms' carbon intensity available to market participants is that of 2020.

[13] Term B should not be confused with the vector of commodity controls in Equation (4). They are included into the specification to address potential endogeneity between the carbon price and commodity prices and not as the price of inputs in the production process.

[14] In Appendix A.4.5 we show that estimating firms' allowance inventories - term [C] in Equation 3 is not possible with the data in the EU ETS database.

the errors should be clustered at the firm level as treatment exposure (i.e. factors affecting how stock prices react to carbon price changes) differs from one firm to another (the firm's country, industry, size, etc. might affect the relationship).

4.3 Full sample estimates

As discussed in Section 3.1, different metrics of "carbon intensity" ($CI_{i,Y}$) can be constructed based on the data published by the European Commission.

Total carbon intensity

We start by estimating equation (4) using the "total carbon intensity", computed as a firm's total ETS emissions[15] multiplied by the average annual carbon price and divided by the firm revenue.

$$CI_{i,Y}^{total} = \frac{E_{i,Y}^{total} \times \hat{P}_Y}{R_{i,Y}} \tag{6}$$

where $E_{i,Y}^{total}$ are firm i's verified ETS emissions in year $Y-1$, $\hat{P}_Y$ is the mean price of carbon in year $Y-1$ and $R_{i,Y}$ is the total revenue of firm i in year $Y-1$ (in EUR), used to normalize the carbon costs (the carbon intensity $CI_{i,Y}$ can then be compared across firms).[16]

The results of the regression on the full sample of 338 publicly traded firms over 9 years are shown in Table 2 column (1). Individual stock returns are found to co-move with the stock price index in a highly statistically-significant way ($\beta_1 = 0.914$). An increase of the Eurostoxx index of 1% is found to coincide on average with an increase of individual stock prices of 0.914%. Oil and electricity price returns have no significant impact on stock returns, while gas prices correlate positively.[17] We attribute these differences in coefficient signs for commodities to the heterogeneous nature of our sample. While the emissions allowances clearly represent an input for all firms, the commodities can in fact be even an output as well (for example, electricity price for electricity generating companies, oil price for mining). Moreover, the actual prices paid for commodities by the firm may deviate quite a lot from a single benchmark price of gas and electricity used in the specification. However, including commodity price controls into the specification is a standard practice in the papers following MMM approach. This is typically done to control for the potential endogenous relationship between the carbon price and commodity prices. In the absence of these controls, a statistically significant relationship with carbon returns could partially be attributed to the effect from resource or electricity price developments.

[15]The sum of all the verified emissions under the EU ETS. To see which economic activities and greenhouse gases are covered, see the European Commission website.

[16]$CI_{i,Y}$ can be seen as the total cost of carbon relative to revenues a firm would have to pay if there were no free allowances in the EU ETS.

[17]This is broadly in line with the findings of earlier publications applying multifactor market model approach. Most of them do not find any clear evidence on the direction of the relationship between stock returns and oil, gas, and electricity price changes.

Turning to the key relationship analyzed in this paper, an increase in the carbon price is found to coincide on average with a minuscule but highly statistically significant increase in stock prices ($\beta_2 = 0.009$). This implies that a weekly increase in carbon prices of 1% is associated with an increase in stock prices of 0.009%. Furthermore, this relationship is found to depend on the emission intensity of the firm ($\beta_3 < 0$): the higher the carbon intensity, the lower the stock price return for a given increase in carbon prices.[18]

[18] It should be noted however, that β_3 is not significantly different from 0 in some alternative standard error clustering approaches, see Appendix A.4.2.

	(1) Full Sample	(2) Full Sample	(3) Electricity	(4) Chemicals	(5) Mining	(6) Others	(7) 2013-2017	(8) 2018-2021	(9) High CC	(10) Low CC
r^{carbon} (β_2)	0.011***	0.010***	0.031***	0.005	0.002	0.008*	0.016***	-0.002	0.012***	0.008*
	(0.002)	(0.002)	(0.008)	(0.006)	(0.008)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
$CI^{total} \times r^{carbon}$ (β_3)	-0.309*									
	(0.120)									
$CI^{paid} \times r^{carbon}$ (β_3^{paid})		-0.566***	-0.549**	1.177	0.172	0.135	0.192	-0.860***	-0.586***	-0.241
		(0.170)	(0.192)	(1.261)	(0.215)	(2.156)	(0.209)	(0.169)	(0.172)	(1.191)
$CI^{free} \times r^{carbon}$ (β_3^{free})		-0.044	-0.151	-0.931	-0.030	0.390	0.091	-0.070	-0.073	0.217
		(0.097)	(0.087)	(1.528)	(0.162)	(0.582)	(0.089)	(0.206)	(0.082)	(0.596)
Eurostoxx Return	0.911***	0.911***	0.706***	0.930***	0.973***	0.941***	0.809***	0.990***	0.920***	0.901***
	(0.021)	(0.021)	(0.055)	(0.039)	(0.059)	(0.029)	(0.022)	(0.024)	(0.030)	(0.029)
Gas Return	0.016***	0.016***	0.009	0.017*	0.008	0.019***	-0.013**	0.021***	0.016***	0.017***
	(0.003)	(0.003)	(0.006)	(0.007)	(0.009)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Oil Return	-0.003	-0.003	-0.008	0.002	0.146***	-0.023***	0.006	-0.002	-0.005	0.000
	(0.006)	(0.006)	(0.009)	(0.008)	(0.038)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)
Electricity Return	-0.001	-0.001	-0.006	-0.002	0.024*	-0.002	-0.007	0.004	0.002	-0.004
	(0.003)	(0.003)	(0.006)	(0.005)	(0.011)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
N	147,171	147,171	19,000	29,208	11,665	87,298	79,218	67,953	78,677	68,494
Industry FE	✓	✓	–	–	–	✓	✓	✓	✓	✓
Country/Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.202	0.202	0.230	0.296	0.291	0.198	0.156	0.238	0.179	0.237
Adj. R^2	0.188	0.188	0.168	0.250	0.202	0.177	0.140	0.225	0.171	0.216

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Regression results, estimation of equations (4) and (7). Columns correspond to different sub-samples.

Free and paid carbon intensity

The sensitivity of stock prices to carbon prices is found not to robustly depend on the total carbon intensity of a firm. We therefore split the total carbon intensity $CI_{i,Y}^{total}$ in its free and paid components (respectively the parts of emissions covered by allowances allocated for free and allowances that needed to be purchased):

$$CI_{i,Y}^{total} = \frac{(E_{i,Y}^{free} + E_{i,Y}^{paid}) \times \hat{P}_Y}{R_{i,Y}} = \underbrace{\frac{E_{i,Y}^{free} \times \hat{P}_Y}{R_{i,Y}}}_{CI_{i,Y}^{free}} + \underbrace{\frac{E_{i,Y}^{paid} \times \hat{P}_Y}{R_{i,Y}}}_{CI_{i,Y}^{paid}} \tag{7}$$

where $E_{i,Y}^{free}$ (the number of free allowances received by firm i in year $Y-1$) can be retrieved from the EU ETS database and $E_{i,Y}^{paid}$ is computed as the complement to $E_{i,Y}^{total}$[19]. Equation (4) therefore becomes:

$$r_{i,t}^{stock} = \beta_1 r_t^{index} + \left[\beta_2 + \beta_3^{free} CI_{i,Y}^{free} + \beta_3^{paid} CI_{i,Y}^{paid}\right] r_{i,t}^{carbon} + \beta_4 r_t^{comm} + FE_{i,t} + \varepsilon_{i,t} \tag{8}$$

The results of this specification for the full sample are shown in Table 2 column (2). The co-movements of individual stock prices with the stock index, oil, electricity and gas prices are identical in value and significance to the regression using the total carbon intensity, as is that of carbon price changes (β_2).

The major difference appears in the sensitivity to firms' carbon intensities (β_3^{free} and β_3^{paid}), with a higher *paid* carbon intensity leading to significantly lower stock returns in the face of a carbon price increase, while the *free* carbon intensity has no impact at all. Indeed β_3^{paid} is negative and statistically significant whereas β_3^{free} is not significantly different from zero.

Using Equation (5), we can represent the sensitivity of stock prices on a 1% increase in carbon prices (Figure 10). We can see that for firms with a paid carbon intensity above 1.7% (facing carbon costs higher than 1.7% of revenues, represented by the dashed red line on the plot) an increase in carbon prices is associated with a drop in stock price[20]. Stated differently, for a firm with a paid carbon intensity of 10%, a carbon price increase of 1% will coincide with a stock price drop of 0.04% (represented by the dotted red line on the plot), all else equal.[21]

To summarise, the results imply that stock markets do take carbon prices into account when valuing firms' stocks. Not only do stock prices and European carbon prices co-move, but they do so differently depending on the actual carbon costs a firm faces: the higher the carbon costs, the bigger the lower the stock return when carbon prices increase. However, stock markets do not seem to take the emissions into account beyond the part that firms need to pay for within the EU ETS. Free emissions do not change the stock price sensitivity to carbon price returns.

[19] Every year each firm needs to surrender an amount of ETS allowances equivalent to its yearly emissions. The fraction of allowances not received for free needs to be purchased in an auction or on the secondary market. Hence $E_{i,Y}^{total} = E_{i,Y}^{free} + E_{i,Y}^{paid}$.

[20] We also compute a significance test for the ratio $\beta_2 / -\beta_3^{paid}$ and find that the non-linear transformation of the coefficients yields significant results - results available upon request

[21] The width of the uncertainty band on Figure 10 is not constant but depends on the square of the carbon intensity. This can be derived from equation (5): $\delta = \sqrt{\mathrm{Var}(\partial r^{stock} / \partial r^{carbon})} = \sqrt{\mathrm{Var}\beta_2 + CI^2 \times \mathrm{Var}\beta_3 + 2CI \times \mathrm{Covar}(\beta_2, \beta_3)}$

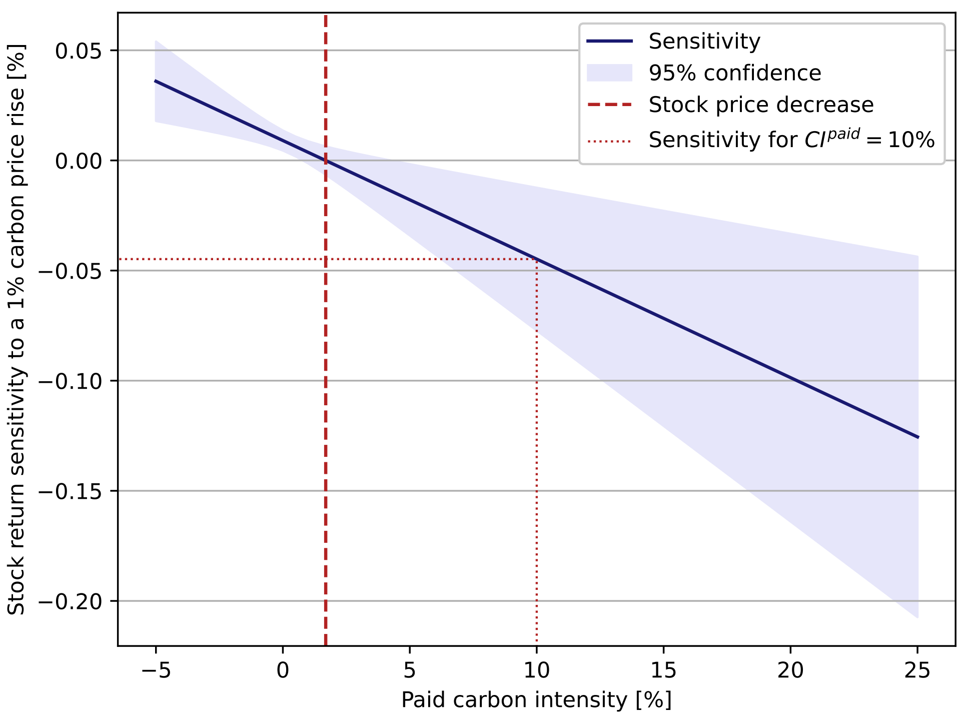

Figure 10: Sensitivity of the stock return to a 1% increase in carbon price as a function of the paid carbon intensity. Firms with an intensity above 1.7% (to the right of the dashed red line) will see their stock price decline if carbon prices increase. A firm with CI^{paid} = 10% will see its stock price drop by 0.04% (dotted red line).

Reverting to the stylized model in section 4.1 in which we represent the stock price as the sum of discounted future profits, it becomes apparent that the sensitivity of stock price returns to carbon price changes depends not simply on the contemporaneous carbon intensity but the entire future path of paid carbon intensities. In equation (3) the carbon intensity depends on the unit emissions rate representing the firm's decarbonization path (r_t for all future t) as well as the path of allocated free allowances (F_t). Firms' future carbon intensities might differ from the observed yearly values.

However, the fact that β_3^{paid} is negative and statistically significant is consistent with stock markets considering today's carbon intensities as a good proxy for future CI. If that were not the case (and the firm with highest CI were widely expected to decarbonize fastest) then β_3^{paid} would carry no significance in the estimation. Savvy investors can be expected to consider future emission paths when valuing firms. In the absence of high quality comparable data on future emission paths, we investigated whether the crude proxy of research and development (R&D) expenditures allowed us to explain further cross-sectional variability, i.e. whether firm with high R&D expenditure are less affected by increasing carbon prices. However, as shown in section A.4.6 in the appendix, we find no statistically significant relationship.

In order to examine the robustness of our estimates, we provide alternative specifications in the Appendix. The results are found to be robust to all possible clusterings of standard errors and different combinations of fixed effects as depicted in Table 6[22]. The choice for the normalization factor (i.e., revenues or market capitalization) is also found to not alter the conclusions. In the Appendix we further study the timing of purchases and the build-up of allowance inventories by firms, and the effect of firm's research and development costs.

4.4 Sub-sample estimates

In order to better understand the stock price-carbon price relationship identified in the previous section, we complement the results on the full sample with studies on sub-samples (slicing the data by industry, by time periods and by country groups). As we show below, in all three sampling approaches the interaction between carbon price and stock prices is particularly strong when carbon intensity is high. Concretely, we reveal statistically significant relationships in the electricity sector, during the recent period of a rapid carbon price increase, and in the countries with the highest carbon costs. We now describe the results for each sub-sample in more detail.

Results by industry

We have explored the relationship between the carbon price and the stock price performance for companies from the electricity, mining and chemicals sectors separately. We chose these three sectors because they

[22]Note: the choice of controlling at the monthly level is based on the fact that controlling at a lower frequency (i.e., at the weekly level) does not allow to provide estimates (and hence control) for the Eurostoxx nor the commodities returns (see Table 6. This is due to the fact that both the Eurostoxx and the commodities return vary at the weekly level and hence controlling for weekly fixed effects creates evident multicollinearity problems

are covered by the EU ETS and our dataset provides sufficient data for their in-depth analysis (top three industries by number of firms, see Figure 3). We are particularly interested in the results for the electricity companies, because they are most exposed to the carbon pricing (see Figure 8). Our electricity sector subsample is based on the information on 43 electricity companies, which is twice larger than the samples in similar existing publications. Our chemicals sector subsample encompasses the data on 67 companies, many of which are cement producers. The mining sector subsample is comprised of 26 companies. The remaining 202 companies are grouped into the category called "Other industries".

Among the industries that we examine in greater detail, companies from the electricity sector have the highest carbon costs. They were close to 3% of revenues in 2019-2021 when calculated for the whole sector. For companies from the mining and chemicals sectors, the carbon costs remain relatively low so far and on average do not exceed 0.5% of revenues.

We find (see column 3 of Table 2) that, in the electricity sector, carbon price increases are linked to positive and statistically significant stock returns ($\beta_2 > 0$). Similar to the results for the full sample we see that the relationship between the stock price performance and the carbon price varies depending on the firm's carbon intensity, in particular its paid part ($\beta_3^{paid} < 0$). Concretely, the calibrated coefficients imply that, on average, stock prices of firms with carbon costs above 5.5% of revenues decrease when the price of carbon increases - as described in Equation (5). Similarly to the full sample results, the emissions covered by free allowances do not change this relationship.

The coefficients establishing the relationship between carbon price changes and stock performance for chemicals, mining or other industries are non-significant (see columns 4 to 6 in Table 2).

Results by sub-periods

As a next step, we run our regression on the data covering different periods with the aim to analyze the evolution of the identified relationship over time. As our sample almost fully overlaps with Phase III of the EU ETS (2013-2020), we cannot explore the changes in the relationship across different EU ETS trading phases. We decided to divide our initial sample into two sub-periods (2013-2017 and 2018-2021) that differ significantly in carbon price dynamics. The price remained low and relatively stable over the first sub-period but started to increase rapidly during the second sub-period (see Figure 4) on the back of a lower supply of allowances and the approval of more ambitious EU climate goals.[23]

We run our main regression specification on the two sub-periods (see columns 7 and 8 in Table 2). First, we can note that the ETS price changes positively co-move with stock returns (very small effect) during 2013-2017. The difference between the magnitude of this relationship across firms depending on their carbon intensity (either its free or paid component) was not statistically significant. However, the relationship changed fundamentally in the more recent period. The coefficient next to carbon price interacted with the

[23]The so-called "Market Stability Reserve" (a mechanism that automatically reduces the amounts of auctioned allowances if the stock of outstanding allowances reaches a threshold) was decided upon in 2018 and started in January 2019. The increased goal of cutting emissions by 55% by 2030 (instead of the previous 40%) was proposed in 2020 and adopted in June 2021.

paid component of carbon intensity (β_3^{paid}) becomes negative and highly statistically significant between 2018 and 2021. The free allocation of allowances does not change the nature of this relationship (β_3^{free} is not statistically significant).

These results imply that the relationship between the carbon price and stock performance that we found for the full sample is likely driven by the developments in the last few years. Interestingly, the magnitude of the coefficients[24] suggests that during this period the carbon price becomes inversely correlated with carbon price returns fro all the companies that have to buy emissions allowances (in other words have a positive paid component of carbon intensity). This is in contrast with the results for the full sample where the negative effect is observed only for the companies exceeding 1.7% carbon intensity threshold.

We also re-estimate regressions over sub-periods separately for each industry from our dataset. We find a similar pattern for the electricity sector (see Table 5 in Appendix A.3) which is most exposed to carbon pricing. When it come to chemicals, mining or other sectors the relationship between the carbon price changes and stock performance is positive and statistically significant in the first sub-period but it is not affected by firm's carbon intensity. We find almost no statistically significant relationships in the second sub-period for these industries.

This analysis contributes to the earlier results published by Mo et al. (2012) who provided evidence on the switch in relationship between carbon price and corporate valuation from positive in Phase I to negative in Phase II of the EU ETS. We focus on Phase III and show that the relationship was positive in the first half of the period but turned negative in the second half (with the magnitude changing with the firms' carbon intensity). During 2018-2021, amid a sustained increase in the price of emissions allowances, a weekly increase in carbon prices of 1% was associated with a drop in stock prices of 0.08% for a firm with paid carbon intensity of 10%.

Figure 11 shows the stock returns of *actual* firms in our sample associated with a 1% increase in carbon prices. The light blue distribution shows the firms in the full period (2,894 firm-years). The dark blue distribution shows the firms in the most recent sub-period (1,335 firm-years) of 2018-2021: the sensitivity for the firm with highest paid carbon intensity reaches 0.21%. Two effects explain why the latter distribution is shifted and more spread out. First, the estimated coefficients in the second sub-period ($\beta_2 = 0$, $\beta_3^{paid} = -0.830$) point to a higher sensitivity of stock returns to carbon price returns than in the overall period ($\beta_2 = 0.009$, $\beta_3^{paid} = -0.538$). Second, firms in the second sub-period tend to have higher carbon intensities (0.4% vs. 0.2% in the overall sample) as shown in Figure 7.

Results by country groups

We further explore the link between carbon prices and stock performance by checking whether it differs across country groups. With this exercise we contribute to earlier work done by Oberndorfer (2009) who also explored country-specific market effects of carbon price dynamics. The paper found a positive relationship between carbon prices and stock performance in most EU countries with the exception of Spain in 2005-2007.

[24] β_2 is not statistically different from zero.

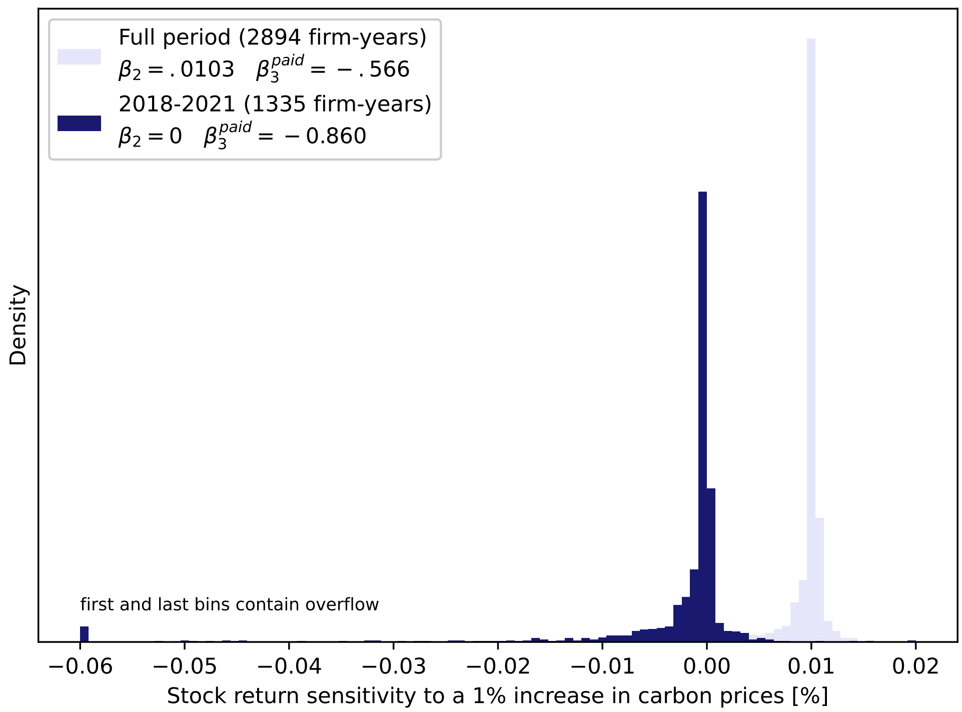

Figure 11: Stock returns associated with a 1% increase in carbon prices for firms in our sample. The light blue distribution shows the 2,894 firm-years of the full period. The dark blue distribution shows the 1,335 firm-years of the most recent sub-period (2018-2021) which have higher paid carbon intensities and a higher estimated dependency on carbon intensities (see β_3^{paid} in Table 2).

Back then, the carbon price was still low and electricity companies benefited from an over-allocation of free emission allowances. We use a different time period and methodology for the analysis, hence our results differ.

We divide our dataset into sub-samples of firms headquartered in countries with high and low relative carbon costs. We classify a country into the high carbon cost category if at least one company from this country incurred carbon costs exceeding 3% of revenue in at least one year over the full period.

The high carbon cost sub-sample comprises companies from seven countries (Poland, Czechia, Great Britain, Germany, France, Greece and Norway). High carbon intensities of firms from some of these countries are linked to a higher than EU average share of coal in their primary energy consumption during 2013-2021 (BP, 2021). Some of these countries are also among those with the lowest CO_2 productivity in the EU, measured as GDP per unit of energy-related CO_2 emissions (OECD, 2015).

Our core findings hold in the high carbon cost sub-sample (see columns 7 and 8 in Table 2). The relationship between carbon price and stock performance is statistically significant and carbon intensity dependent. As in other samples, it is the paid rather than the free component of the carbon intensity that is being priced in by the market. The magnitude of the effect is similar to the one observed for the full sample: a carbon price increase is associated with a stock price decline for the companies with relative carbon costs above 2% of revenue. At the same time we find no statistically significant relationship in the low carbon cost sub-sample.

4.5 Permanence of the effect

With the purpose of shedding light on the permanence of the effect of interest, we re-estimate the main regression by adding lags of certain independent variables. In particular, we include up to four lags of the carbon price return, both without interaction and interacted with the paid and free carbon firm intensity. The results depicted in Table 3 reveal three main findings. First, the carbon price (up to the second lag) is found to have a positive association with the stock returns. We find further that only the *contemporaneous* carbon price return interacted with the paid carbon intensity is significantly correlated with the stock returns, with the same sign as the results shown in previous sections. Finally, and in line with the previous estimates, the carbon price return is not significantly associated with stock returns at any lag. Overall, these results suggest that the effect of carbon price as a function of the carbon intensity associated to the firm's paid allowances is permanent.

4.6 Event study using regulatory updates

Data with daily frequency

As a robustness check, we estimated equation (8) using daily data instead of weekly data (Table 4). The results confirm those obtained when running the regression on weekly data: individual stock returns are found to positively co-move with the Eurostoxx index in a highly statistically-significant way ($\beta_1 = 0.874$).

	(1)
$r_t^{carbon}(\beta_2)$	0.013^{***}
	(0.003)
r_{t-1}^{carbon}	0.007^{***}
	(0.002)
r_{t-2}^{carbon}	0.007^{**}
	(0.002)
r_{t-3}^{carbon}	0.002
	(0.002)
r_{t-4}^{carbon}	0.001
	(0.002)
$CI_t^{paid} \times r_t^{carbon}$	-0.596^{***}
	(0.163)
$CI_t^{paid} \times r_{t-1}^{carbon}$	0.221
	(0.142)
$CI_t^{paid} \times r_{t-2}^{carbon}$	-0.086
	(0.139)
$CI_t^{paid} \times r_{t-3}^{carbon}$	-0.178
	(0.206)
$CI_t^{paid} \times r_{t-4}^{carbon}$	-0.156
	(0.246)
$CI_t^{free} \times r_t^{carbon}$	-0.064
	(0.110)
$CI_t^{free} \times r_{t-1}^{carbon}$	0.228
	(0.206)
$CI_t^{free} \times r_{t-2}^{carbon}$	-0.188
	(0.105)
$CI_t^{free} \times r_{t-3}^{carbon}$	-0.117
	(0.158)
$CI_t^{free} \times r_{t-4}^{carbon}$	-0.003
	(0.157)
Eurostoxx Return	0.941^{***}
	(0.020)
Gas Return	0.016^{***}
	(0.003)
Oil Return	0.000
	(0.006)
Electricity Return	0.001
	(0.003)
N	139,744
Industry FE	✓
Country/Month FE	✓
Clustered SE	Firm
R^2	0.223
Adj. R^2	0.209

Standard errors in parentheses
Independent variable is the stock return in all cases
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Permanence of the effect

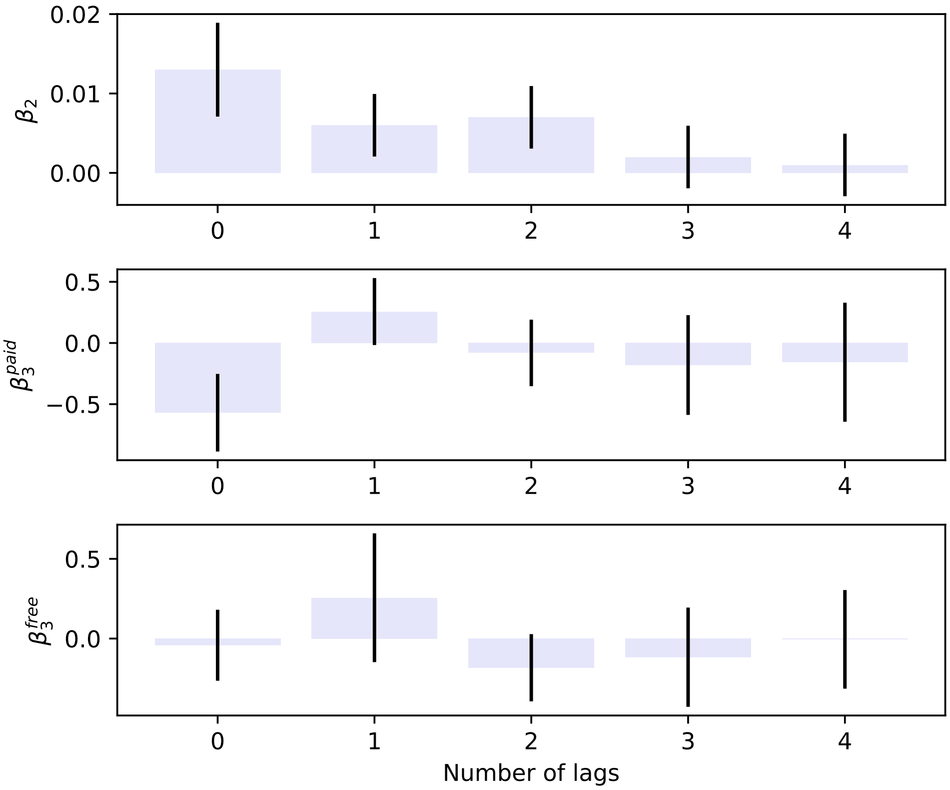

Figure 12: Significance of lagged variables

Only the parameters for oil, gas and electricity price returns differ. Concerning the role of carbon prices, an increase in the carbon price is found to coincide on average with a small but highly statistically significant increase in stock prices ($\beta_2 = 0.007$). On daily data too the stock price-carbon price relationship is found to negatively depend on the *paid* carbon intensity of the firm ($\beta_3^{paid} < 0$) while the free carbon intensity has no statistically significant impact.

Regulatory update events

We further conduct an event study using the EU ETS regulatory update series identified by Känzig (2022), which we extend up until end-2021. Only "regulatory update events that were specifically about changes to the supply of emission allowances in the European carbon market and do not include broader events such as outcomes of Conference of the Parties (COP) meetings or other international conferences" are included in that time series.[25] It is further shown to have no serial correlation and that macroeconomic and financial variables have no power in forecasting the series. We perform this event study because, as Känzig (2022) writes, "reverse causality of the state of the economy can be plausibly ruled out because it is known and priced prior to the decision and unlikely to change within the tight window."

In order to see whether the relationship described in section 4.3 is also observed on dates with regulatory update events, we estimate the specification of equation (9) below:

$$r_{i,t}^{stock} = \beta_1 r_t^{index} + \left[\beta_2 + \beta_3^{free} CI_{i,Y}^{free} + \beta_3^{paid} CI_{i,Y}^{paid}\right] r_{i,t}^{carbon} \times s_t + +... \tag{9}$$

where s_t is a dummy variable indicating whether on day t a regulatory update took place. The estimates are reported in Table 4 and show that the relationship holds on regulatory update days. Specifically, on those days, a carbon price increase is found to coincide on average with a small but highly statistically significant decrease in stock prices ($\beta_2 = -0.012$) and the relationship is also found to negatively depend on the *paid* carbon intensity of the firm ($\beta_3^{paid} = -0.752$). The *free* carbon intensity still has no statistically significant impact.

Finally, we disentangle the nature of the regulatory update events and examine whether the type of regulatory change matters when it comes to the carbon price-stock price relationship. For that we estimate equation (10) below:

$$r_{i,t}^{stock} = \beta_1 r_t^{index} + \beta_2 \times r_{i,t}^{carbon} \times s_t + \left[\beta_3^{free} CI_{i,Y}^{free} + \beta_3^{paid} CI_{i,Y}^{paid}\right] r_{i,t}^{carbon} \times s_t^{type} + ... \tag{10}$$

here s_t^{type} is a dummy variable that can take three values: "no update", "free" (when the regulatory update on that day concerns the allocation of free allowances) and "price" (when the regulatory update has an impact on the supply and demand of auctioned allowances[26]).

The estimates are reported in Table 4. The carbon price-stock price relationship is found to depend on the *paid* carbon intensity of firms on days with no regulatory update ($\beta_3^{paid} = -0.271$) and even more so on

[25] We collect 89 update events covering the years 2013-2021.

[26] All regulatory updates on auctions, caps and the Market Stability Reserve are subsumed under this category.

days with regulatory updates impacting the allowance price ($\beta_3^{paid} = -0.687$). What is remarkable is that – for the first time in all the regressions presented in this paper – the *free* carbon intensity impacts the carbon price-stock price relationship, but only on days with regulatory updates concerning free allowances ($\beta_3^{free} = -0.912$). On these days, if a regulatory update amounts to a reduction in free allowances, the carbon price is expected to rise on the back of higher demand in the auctions. Firms with high *free* carbon intensities are expected to have to purchase more allowances and therefore face higher costs. It is therefore intuitive to see their stock prices decline overproportionally.

These results are consistent with stock markets incorporating regulatory news in firm valuations in a very sophisticated manner.

5 Discussion

5.1 Conclusions

Using a novel dataset of stock prices and carbon intensities of 338 European companies between 2013 and 2021, we demonstrate a strongly statistically significant relationship between carbon price changes and stock returns. Crucially, this relationship depends on firms' *paid* carbon intensity: the higher the carbon costs a firm faces, the poorer its stock performance during the periods of carbon price increases. Firms' total emissions however do not matter beyond the paid carbon intensity.

Taking a closer look at the sensitivity of the carbon price-stock price relationship to firm's carbon intensity, we find that a firm facing carbon costs of 10% of its revenue would see its stock price decline by 0.04% on average when carbon prices rise by 1%. Over the entire observation period, stocks of firms with paid carbon intensities exceeding 1.7% decline on average when the price of carbon increases. Conversely, firms paying less than 1.7% of their revenue for carbon allowances would see their stock price rise. The fact that the carbon price positively correlates with the stock price of a firm with zero carbon intensity might seem surprising at first. Indeed, as the firm faces no carbon costs, one could expect it not to be impacted by carbon prices at all, neither positively nor negatively. However, in markets with inelastic demand, where companies can pass on carbon costs to consumers (see, e.g. Fabra and Reguant, 2014 and Sijm et al., 2006 on electricity markets), an increase in carbon costs will result in a higher market price and therefore a windfall profit for low-carbon firms. This is consistent with a stock price increase of these firms. Other authors, such as Bushnell et al. (2013) draw similar conclusions. The stylized model presented in section 4.1 captures this effect in term [A] of equation (3).

When studying the relationship between stock prices and carbon prices on sub-samples of our dataset, we find that it is driven by those segments in which firms face high carbon costs. When considering industries, the relationship is found in the electricity sector (where free allowances were phased out in 2013 and paid carbon intensities are correspondingly high) but not in other industries where carbon intensities are much lower. When considering sub-periods, we can confirm the relationship in recent years (carbon prices have taken off in 2018) but not in the previous period in which low carbon prices led to lower paid carbon

	(1) Full Sample	(2) Update dates	(3) Update Dummy
r^{carbon} (β_2)	0.007***		
	(0.001)		
$noupdate \times r^{carbon}$($\beta_2$ for $s_t = 0$)		0.009***	0.009***
		(0.001)	(0.001)
$update \times r^{carbon}$(β_2 for $s_t = 1$)		-0.012***	-0.012***
		(0.002)	(0.002)
$CI^{paid} \times r^{carbon}$ (β_3^{paid})	-0.288**		
	(0.099)		
$noupdate \times CI^{paid} \times r^{carbon}$($\beta_3^{paid}$ for $s_t = 0$)		-0.273*	-0.273*
		(0.109)	(0.109)
$update \times CI^{paid} \times r^{carbon}$($\beta_3^{paid}$ for $s_t = 1$)		-0.756***	
		(0.199)	
$freealloc \times CI^{paid} \times r^{carbon}$($\beta_3^{paid}$ for $s_t =$ free)			-1.181
			(0.904)
$price \times CI^{paid} \times r^{carbon}$($\beta_3^{paid}$ for $s_t =$ price)			-0.695***
			(0.204)
$CI^{free} \times r^{carbon}$ (β_3^{free})	-0.116		
	(0.077)		
$noupdate \times CI^{free} \times r^{carbon}$($\beta_3^{free}$ for $s_t = 0$)		-0.119	-0.119
		(0.091)	(0.091)
$update \times CI^{free} \times r^{carbon}$($\beta_3^{free}$ for $s_t = 1$)		-0.163	
		(0.094)	
$freealloc \times CI^{free} \times r^{carbon}$($\beta_3^{free}$ for $s_t =$ free)			-0.909*
			(0.413)
$noupdate \times CI^{free} \times r^{carbon}$($\beta_3^{free}$ for $s_t = 0$)			-0.119
			(0.091)
$price \times CI^{free} \times r^{carbon}$($\beta_3^{free}$ for $s_t =$ price)			-0.059
			(0.086)
Eurostoxx Return	0.872***	0.871***	0.871***
	(0.018)	(0.018)	(0.018)
Gas Return	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Oil Return	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Electricity Return	0.004**	0.004**	0.004**
	(0.001)	(0.001)	(0.001)
N	679,295	679,295	679,295
Industry FE	✓	✓	✓
Country/Month FE	✓	✓	✓
Clustered SE	Firm	Firm	Firm
R^2	0.144	0.144	0.144
Adj. R^2	0.141	0.141	0.141

Standard errors in parentheses
Independent variable is the stock return in all cases
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Results on daily data

intensities. Finally, the relationship is confirmed only in the group of countries with high paid carbon intensities (including Poland, Greece, Czechia and Germany).

Several reasons can explain why the relationship is not observable in all sub-samples. First, carbon costs of companies from most industries are still relatively low as a share of companies' revenues (the median in our sample remained close to 0% even in 2018-2021 when the price of carbon increased significantly). Hence, at this stage, investors and analysts may simply disregard corporate carbon costs for most firms. Second, even for those firms for which carbon costs are not entirely negligible, the information about the actual corporate carbon costs is published at a yearly frequency with a significant time lag and is not straightforward to compile. It might therefore not be available to most market participants. Third, our estimates of carbon costs are subject to some uncertainty. This is driven on the one hand by the lack of information on the exact timing of allowances purchases as well as on firms' hedging strategies against carbon price fluctuations via derivatives. On the other hand some uncertainty stems from the fact that we only take direct carbon costs into account as our dataset does not capture costs from firms' purchased inputs, such as electricity.[27]

Finally we also studied the impact of free emissions (those covered by free allowances) and find that they nearly never affect the relationship between stock prices and carbon prices. One could have expected stock markets to also consider free emissions, for instance in anticipation of their future inclusion in the EU ETS. Within the setting studied in this paper however, only taxed emissions play a role in how stock prices react to carbon prices. There is only one instance where the free carbon intensity was found to significantly change the explored relationship, namely on the days of regulatory updates affecting the free allocation of allowances. Should the gradual phasing out of free allocation continue together with broadening of the sectors covered by the EU ETS, more frequent regulatory updates regarding free allocation could lead to the free carbon intensity becoming a more important variable for investors.

The carrot and the stock

We have shown that – controlling for the overall stock market, energy prices, industries and country-specific business cycles – stocks of firms with high carbon costs under-perform in weeks where carbon price increases.

While this result does not establish a causal relationship, there is theoretical ground to assume that it is changes in the carbon price that drive the carbon cost-dependent under-performance of stock prices and not the relative performance of stock prices in our sample impacting the European carbon price or firm's carbon intensity.[28] The results of the event study using regulatory updates point at a stronger and

[27]ETS allowances need to be purchased for the so-called "Scope 1" emissions only, i.e. those that are physically emitted by the firms' activities. "Scope 2" (energy-related) and "Scope 3" (induced) emissions are not considered. However an increase in carbon prices is expected to also trigger an increase in costs of purchased products (such as electricity) and thus depress a firm's value.

[28]Investors taking carbon costs into account when valuing stocks would entail $r^{carbon} \Rightarrow r^{stock}$. Once the overall stock market, energy prices, industries and country-specific business cycles are controlled for, $r^{stock} \Rightarrow r^{carbon}$ seems implausible. Finally, there is no reason why $r^{stock} \Rightarrow CI^{paid}$. The number of controls and the robustness of the result under different specifications reduce the likelihood of a common driver of r^{stock} and r^{carbon}.

more statistically significant relationship between the stock performance and carbon returns on days of ETS regulatory changes. This evidence gives us additional ground to view carbon price changes as one of the factors influencing stock performance and not the other way around. By assuming that carbon returns affect stock returns and do so differently depending on the paid carbon intensity of the firms, stock markets can be considered to discriminate carbon-intensive firms in the face of a carbon price increase.

This would provide for a quantifiable incentive channel for shareholders and management to decarbonize firms' operations, a mechanism via which high-emitters are punished and low-emitters rewarded in terms of stock price changes – a carrot and a stick. Indeed, under any assumed path of increasing carbon prices, lowering carbon costs by reducing greenhouse gas emissions would result in a measurable financial upside for shareholders which can be weighed against the cost of decarbonization. This would also apply to firms' management team, whose remuneration package is often indexed on their employer's stock price performance.

5.2 Policy implications

We argue that, from the perspective of the stock-market incentive channel, there is room for more stringent carbon pricing in the European Union. Higher carbon costs for firms would strengthen the incentive to decarbonize and increase the EU ETS's impact as a climate change mitigation tool, while not endangering financial stability.

Strengthening the decarbonization incentive

Our results indicate that stock price performance serves as an incentive channel for shareholders of highly polluting companies to decarbonize their firms' operations. Any policy leading to higher carbon costs for emitting firms will tend to strengthen this incentive.

Higher carbon costs for firms within the EU ETS can be achieved in three ways. First, by making sure the price of allowances continues to rise. While in a cap-and-trade system direct price control is impossible, strengthening the Market Stability Reserve for instance or introducing an explicit price floor (Ohlendorf et al., 2022) would have such an effect. Second, by phasing out free allowances. This could be done quickly for domestic air travel without impact on competitiveness and gradually for the manufacturing sector alongside the introduction of a carbon border adjustment. Third, by including further sectors in the EU ETS: currently heating, transport, agriculture and waste management are largely excluded from the scheme.Higher carbon prices are expected to play a bigger role than the phase-out of free allowances. Indeed, if the volume of emissions and the price of carbon stay at their current level while the free allocation of allowances drops to zero, the relative carbon costs in industries like mining and chemicals will remain below 1% of revenue, which might be insufficient for the stock market channel to become much stronger.

If the carbon-related costs rise across sectors, we expect this factor to be viewed as increasingly important by investors. Our analysis shows that the impact of carbon prices on stock performance was most pronounced where carbon costs were highest. This could strengthen the incentive channel in a non-linear way.[29]

[29] By increasing both CI and $|\beta_3|$ in equation (5).

Mitigation: transparency vs. carbon pricing

This paper illustrates the fact that high-quality, reliable and comparable data on firms' carbon intensity is not always sufficient to ensure that financial markets contribute to climate change mitigation. Indeed the EU ETS provides an exceptional setting in which firms' audited emissions and carbon costs are published since 2005.

However, we show that in most cases stock markets do not consider firms' *total* emissions when determining the impact of carbon price changes on stock prices: only those emissions for which firms need to *pay* do matter [30]. In this setting, stock markets can contribute to channeling private investments to lower emitting firms using high-quality emissions data, but only in conjunction with a carbon pricing scheme.

Financial stability

Finally, given the magnitude of the carbon-price impact on stock prices, we argue that the aggregated financial stability risk for stocks from higher carbon prices appears to be limited at this stage.

Indeed, when considering the entire studied period, most firms' stock prices *increase* when carbon prices rise. For a firm with carbon costs representing 10% of revenues, an increase in carbon prices of 1% is linked with a stock price decrease of 0.04%. While this impact is robust and, when accrued over time, can lead to share prices diverging (carbon prices have increased by over 300% in 2020-2021), barring a tipping point or major non-linearity, this relationship does not seem to indicate that a further increase in carbon costs will trigger a widespread stock market crash. Indeed, in recent years, according to the estimated model, the average impact of a 1% rise in carbon prices on stocks of firms in our sample would be no more than -0.003%.[31]

The results presented in this paper are also applicable for the assessment of carbon price-related transition risk, i.e. the risks to financial institutions "related to the process of adjustment towards a low-carbon economy" (BCBS, 2021). The specifications and estimates presented in this paper can be used when modeling the impact of rising carbon prices on stock portfolios, for instance in climate stress tests.

[30] The only exception to this pattern can be observed on the days of regulatory changes with regard to free allocation of allowances. On these few occasions free carbon intensity makes the relationship between stock price and carbon price changes more negative.

[31] Average of the light blue distribution (2018-2021) on Figure 11

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A Appendix

A.1 Orbis and EU ETS data matching

We were completing the following steps when matching the EU ETS data on emissions allowances with the data from corporate financials in Orbis:

I. Matching the installations with specific companies. Prior to the actual matching exercise, we have taken several steps in aggregating the raw EUTL data. Each installation within the EU ETS is represented by an operator holding account. For each account the EUTL provides a name of a firm which we here refer to as account holder. An account holder can be related to several installations. The first step in dealing with disaggregated EUTL data was to merge installations by account holder and thus aggregate the data on emission allowances at account holder level. Account holders were subsequently matched with specific companies via Orbis using account holder name, company identification number and address. The outcome of the first step is thus a database including the EUTL data on allocated and surrendered emission allowances and the key financial data from Orbis for each account holder.

II. Identifying publicly quoted parent companies. As a second step we identify publicly quoted companies controlling the account holders from our database. We rely on Orbis database in completing this task. In many cases the ownership structure of the account holders from our list did not include publicly traded companies. Such account holders were excluded from the final sample as there are no stock prices for them to be used as a dependent variable in further analysis. In a few cases account holders from our list were linked to more than one quoted company. In such cases, we used for further analysis the quoted company that was the nearest to the account holder in the ownership chain. We refer to such quoted companies as "lowest traded owners" (LTO). We decided to focus on the lowest and not the highest traded owner because the carbon costs are more likely to affect stock prices of companies more directly related to the specific installations generating CO2 emissions. These lowest traded owners constitute the companies included in our sample. The stock prices of these companies were collected using Yahoo Finance.

III. Consolidating account holders belonging to the same parent company. Since in our regression analysis we use lowest traded owners' stock price as a dependent variable, the EUTL data on purchased emission allowances was aggregated at the lowest traded owner level. This eventually allowed to obtain a proxy for the total amount of purchased emission allowances for each lowest traded owner.

These steps can be summarized in Figure 13.

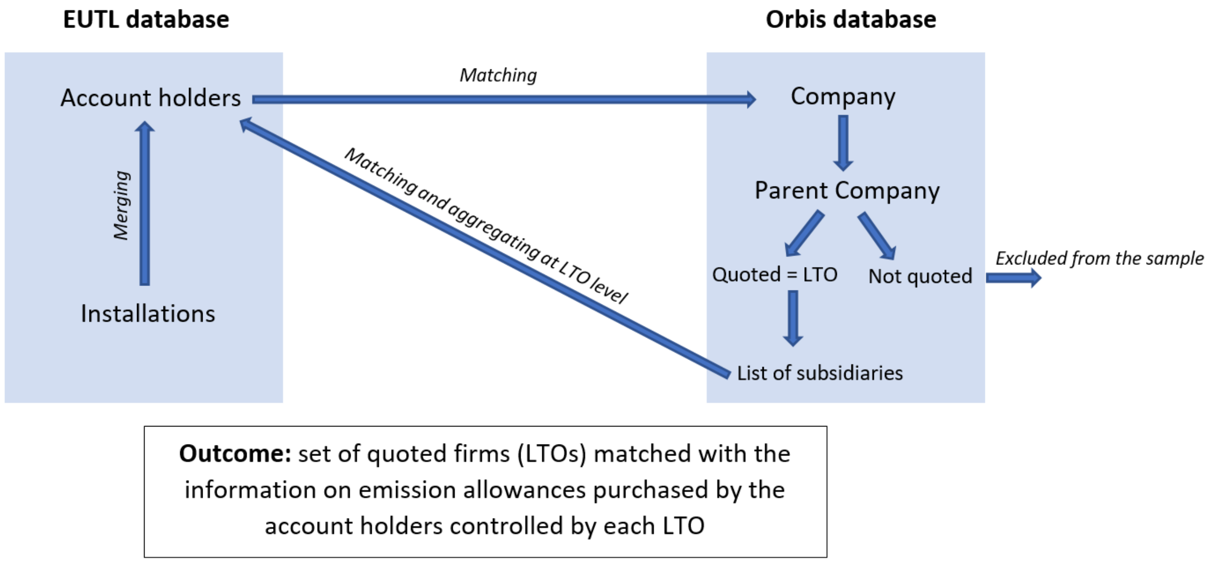

Figure 13: Data gathering scheme

A.2 Theory derivation

Starting from the profits,

$$\pi_t = \underbrace{P_t(q_t, q_t^o)q_t}_{\text{revenue}} - \underbrace{C(\omega)q_t}_{\text{costs}} - \underbrace{(r_t q_t - F_t)\tau_t}_{\text{carbon costs}} + \underbrace{A_{t-1}(\tau_t - \tau_{t-1})}_{\text{allowance valuation}} + \underbrace{\delta_t}_{\text{other effects}} \tag{2}$$

we start by computing the derivative with respect to the carbon price:

$$\begin{aligned}
\frac{d\pi_t}{d\tau_0} &= P_t(q_t, q_t^o)\frac{dq_t}{d\tau_0} + P_t'\left[\frac{dq_t}{d\tau_0} + \frac{dq_t^o}{d\tau_0}\right]q_t - \frac{\partial C}{\partial \omega}\frac{\partial \omega}{\partial \tau_0}q_t - C(\omega)\frac{dq_t}{d\tau_0} \\
&\quad - r_t\frac{dq_t}{d\tau_0}\tau_t - (r_t q_t - F_t)\frac{d\tau_t}{d\tau_0} + A_{t-1}\left[\frac{d\tau_t}{d\tau_0} - \frac{d\tau_{t-1}}{d\tau_0}\right] + \frac{d\delta_t}{d\tau_0} \\
&= \left[P_t(q_t, q_t^o) + P_t' q_t - C(\omega) - r_t\tau_t\right]\frac{dq_t}{d\tau_0} + A_{t-1}\left[\frac{d\tau_t}{d\tau_0} - \frac{d\tau_{t-1}}{d\tau_0}\right] \\
&\quad + P_t'(q_t, q_t^o)\frac{dq_t^o}{d\tau_0}q_t - \frac{\partial C}{\partial \omega}\frac{\partial \omega}{\partial \tau_0}q_t - (r_t q_t - F_t)\frac{d\tau_t}{d\tau_0} + \frac{d\delta_t}{d\tau_0}
\end{aligned} \tag{11}$$

We take the above equation at the profit-maximizing equilibrium, where:

$$\frac{\partial \pi_t^*}{\partial q_t} = P_t + P_t' q_t^* - C(\omega) - r_t\tau_t = 0. \tag{12}$$

Inserting equation (12), the first term in (11) is equal to zero. Further assuming that a change in carbon prices today leads to a parallel shift in the carbon futures curve ($d\tau_t/d\tau_0 = 1$), the second term is also equal to zero. Finally, assuming that other effects do not depend on the carbon price ($d\delta_t/d\tau_0 = 0$), we obtain:

$$\frac{d\pi_t^*}{d\tau_0} = P_t'\frac{dq_t^{o*}}{d\tau_0}q_t^* - \frac{\partial C}{\partial \omega}\frac{\partial \omega}{\partial \tau_0}q_t^* - (r_t q_t^* - F_t) \tag{13}$$

where π^* and q^* are consistent with profit maximization.

Finally, the impact of an exogenous carbon price shock on the stock price is given by:

$$\begin{aligned}\frac{dS}{d\tau_0} &= \sum_t b^t \frac{d\pi_t^*}{d\tau_0} \\ &= \sum_t b^t P_t' \frac{dq_t^{o*}}{d\tau_0} q_t^* - \sum_t b^t \frac{\partial C}{\partial \omega} \frac{\partial \omega}{\partial \tau_0} q_t^* - \sum_t b^t (r_t q_t^* - F_t)\end{aligned}$$

A.3 Industry-subperiod estimates

We report here the estimates of our standard regression specifications for two sub-periods separately for each industry. The results obtained for the full sample are confirmed for the electricity sector. We see that the relationship between carbon price and electricity companies' stock performance becomes carbon intensity dependent in the second sub-period ($\beta_3^{paid} < 0$). When it come to chemicals, mining or other sectors the relationship between the carbon price changes and stock performance is positive and statistically significant in the first sub-period but it is not affected by firm's carbon intensity. We find almost no statistically significant relationships in the second sub-period for these industries.

	(1) 2013-2017 (Electricity)	(2) 2018-2021 (Electricity)	(3) 2013-2017 (Chemical)	(4) 2018-2021 (Chemical)	(5) 2013-2017 (Mining)	(6) 2018-2021 (Mining)	(7) 2013-2017 (Other)	(8) 2018-2021 (Other)
r^{carbon} (β_2)	0.032^{***}	0.017	0.016^{*}	-0.011	0.032^{***}	-0.039	0.013^{***}	-0.002
	(0.007)	(0.015)	(0.007)	(0.010)	(0.008)	(0.022)	(0.004)	(0.006)
$CI^{paid} \times r^{carbon}$ (β_3^{paid})	0.032	-0.615^{**}	3.124	0.938	0.263	-2.134	-5.655	0.711
	(0.508)	(0.214)	(2.814)	(1.535)	(0.142)	(10.760)	(3.546)	(2.850)
$CI^{free} \times r^{carbon}$ (β_3^{free})	-0.226	-0.134	-3.521^{**}	-0.494	0.061	-1.123	-1.142	0.320
	(0.287)	(0.081)	(1.289)	(1.710)	(0.087)	(0.920)	(1.081)	(0.700)
Eurostoxx Return	0.619^{***}	0.773^{***}	0.851^{***}	0.992^{***}	0.846^{***}	1.104^{***}	0.832^{***}	1.022^{***}
	(0.060)	(0.057)	(0.038)	(0.048)	(0.075)	(0.061)	(0.030)	(0.034)
Gas Return	-0.005	0.014	-0.011	0.022^{**}	-0.020	0.007	-0.015^{*}	0.024^{***}
	(0.012)	(0.009)	(0.009)	(0.008)	(0.013)	(0.011)	(0.006)	(0.005)
Oil Return	-0.003	-0.005	0.003	0.007	0.152^{**}	0.150^{***}	-0.011	-0.024^{**}
	(0.012)	(0.013)	(0.014)	(0.011)	(0.041)	(0.039)	(0.007)	(0.008)
Electricity Return	0.007	-0.009	-0.006	0.001	-0.015	0.047^{***}	-0.009	0.003
	(0.010)	(0.009)	(0.008)	(0.007)	(0.024)	(0.011)	(0.005)	(0.006)
N	10,283	8,717	15,515	13,693	6,428	5,237	46,992	40,306
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Country/Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.199	0.258	0.256	0.331	0.249	0.330	0.152	0.232
Adj. R^2	0.132	0.200	0.205	0.289	0.154	0.247	0.129	0.212

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Results by subperiods and industry

A.4 Robustness checks

A.4.1 Controls Selection

We check further the robustness of our estimates to the choice of different controls that may vary at the industry, country, firm and monthly level (see Table 6).

A.4.2 Clustering of standard errors

The results are found to be robust to all possible clusterings of standard errors (i.e., at the industry, firm, country level, see Tables 7, 8, 9).[32]

[32]Note: whenever the standard errors are clustered at the industry level, estimates for the individual industries cannot be obtained.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
r^{carbon} (β_2)	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.023
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.012)
$CI^{paid} \times r^{carbon}$ (β_3^{paid})	-0.517**	-0.566***	-0.385*	-0.458*	-0.424**	-0.372	-0.574***
	(0.163)	(0.170)	(0.167)	(0.187)	(0.163)	(0.224)	(0.161)
$CI^{free} \times r^{carbon}$ (β_3^{free})	-0.015	-0.044	-0.010	-0.016	0.018	0.007	-0.030
	(0.098)	(0.097)	(0.100)	(0.097)	(0.107)	(0.147)	(0.100)
Eurostoxx Return	0.911***	0.911***	0.911***	0.913***	0.935***	0.915***	0.000
	(0.021)	(0.021)	(0.021)	(0.022)	(0.020)	(0.023)	(.)
Gas Return	0.016***	0.016***	0.016***	0.016***	0.006**	0.017***	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(.)
Oil Return	-0.003	-0.003	-0.003	-0.003	0.016**	-0.004	0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)	(.)
Electricity Return	-0.001	-0.001	-0.001	-0.001	0.006*	-0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.008)
N	147,171	147,171	147,171	147,171	147,171	147,171	147,171
Industry FE	✓	✓	✗	✗	✗	✗	✓
Country FE	✓	✗	✓	✗	✗	✗	✓
Month FE	✓	✗	✗	✗	✗	✗	✗
Country/Month FE	✗	✓	✗	✗	✗	✗	✗
Industry/Month FE	✗	✗	✓	✗	✗	✗	✗
Country/Industry/Month FE	✗	✗	✗	✓	✗	✗	✗
Firm FE	✗	✗	✗	✗	✓	✗	✗
Firm/Month FE	✗	✗	✗	✗	✗	✓	✗
Week FE	✗	✗	✗	✗	✗	✗	✓
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.182	0.202	0.202	0.283	0.177	0.360	0.195
Adj. R^2		0.188	0.189	0.194	0.175	0.165	0.193

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Regression results (multiple FE specifications)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full Sample	Full Sample	Electricity	Chemicals	Mining	Others	2013-2017	2018-2021	High CC	Low CC
r^{carbon} (β_2)	0.011***	0.010***	0.031**	0.005	0.002	0.008***	0.016**	-0.002	0.012**	0.008*
	(0.002)	(0.002)	(0.007)	(0.006)	(0.008)	(0.002)	(0.004)	(0.006)	(0.003)	(0.003)
$CI^{total} \times r^{carbon}$ (β_3)	-0.309									
	(0.168)									
$CI^{paid} \times r^{carbon}$ (β_3^{paid})		-0.566*	-0.549***	1.177	0.172	0.135	0.192	-0.860***	-0.586*	-0.241
		(0.213)	(0.109)	(1.214)	(0.215)	(1.823)	(0.257)	(0.114)	(0.205)	(1.122)
$CI^{free} \times r^{carbon}$ (β_3^{free})		-0.044	-0.151	-0.931	-0.030	0.390	0.091	-0.070	-0.073	0.217
		(0.061)	(0.092)	(1.717)	(0.162)	(0.629)	(0.114)	(0.127)	(0.041)	(0.567)
Eurostoxx Return	0.911***	0.911***	0.706***	0.930***	0.973***	0.941***	0.809***	0.990***	0.920***	0.901***
	(0.028)	(0.028)	(0.073)	(0.049)	(0.059)	(0.029)	(0.039)	(0.025)	(0.036)	(0.044)
Gas Return	0.016***	0.016***	0.009	0.017*	0.008	0.019**	-0.013*	0.021***	0.016*	0.017**
	(0.004)	(0.004)	(0.006)	(0.006)	(0.009)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
Oil Return	-0.003	-0.003	-0.008	0.002	0.146***	-0.023**	0.006	-0.002	-0.005	0.000
	(0.008)	(0.008)	(0.006)	(0.008)	(0.038)	(0.007)	(0.010)	(0.010)	(0.015)	(0.005)
Electricity Return	-0.001	-0.001	-0.006	-0.002	0.024*	-0.002	-0.007	0.004	0.002	-0.004
	(0.005)	(0.005)	(0.009)	(0.005)	(0.011)	(0.005)	(0.006)	(0.005)	(0.008)	(0.003)
N	147,171	147,171	19,000	29,208	11,665	87,298	79,218	67,953	78,677	68,494
Industry FE	✓	✓	–	–	–	✓	✓	✓	✓	✓
Country/Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered SE	Country	Country	Country	Country	Firm	Country	Country	Country	Country	Country
R^2	0.202	0.202	0.230	0.296	0.291	0.198	0.156	0.238	0.179	0.237
Adj. R^2	0.188	0.188	0.168	0.250	0.202	0.177	0.140	0.225	0.171	0.216

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Regression results, estimation of equations (4) and (7). Columns correspond to different sub-samples.

	(1) Full Sample	(2) Full Sample	(3) Electricity	(4) Chemicals	(5) Mining	(6) Others	(7) 2013-2017
r^{carbon} (β_2)	0.011*	0.010*	0.008	0.016**	-0.002	0.012*	0.008
	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)
$CI^{total} \times r^{carbon}$ (β_3)	-0.309						
	(0.150)						
$CI^{paid} \times r^{carbon}$ (β_3^{paid})		-0.566**	0.135	0.192**	-0.860***	-0.586**	-0.241
		(0.169)	(1.909)	(0.056)	(0.104)	(0.163)	(1.021)
$CI^{free} \times r^{carbon}$ (β_3^{free})		-0.044	0.390	0.091	-0.070	-0.073	0.217
		(0.091)	(0.634)	(0.074)	(0.170)	(0.066)	(0.678)
Eurostoxx Return	0.911***	0.911***	0.941***	0.809***	0.990***	0.920***	0.901***
	(0.048)	(0.048)	(0.066)	(0.042)	(0.055)	(0.055)	(0.047)
Gas Return	0.016***	0.016***	0.019***	-0.013*	0.021***	0.016***	0.017**
	(0.003)	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)
Oil Return	-0.003	-0.003	-0.023	0.006	-0.002	-0.005	0.000
	(0.015)	(0.015)	(0.013)	(0.015)	(0.015)	(0.018)	(0.011)
Electricity Return	-0.001	-0.001	-0.002	-0.007	0.004	0.002	-0.004
	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)	(0.004)	(0.003)
N	147,171	147,171	87,298	79,218	67,953	78,677	68,494
Industry FE	✓	✓	✓	✓	✓	✓	✓
Country/Month FE	✓	✓	✓	✓	✓	✓	✓
Clustered SE	Industry	Industry	Industry	Industry	Industry	Industry	Country
R^2	0.202	0.202	0.198	0.156	0.238	0.179	0.237
Adj. R^2	0.188	0.188	0.177	0.140	0.225	0.171	0.216

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Regression results, estimation of equations (4) and (7). Columns correspond to different sub-samples.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full Sample	Full Sample	Electricity	Chemicals	Mining	Others	2013-2017	2018-2021	High CC	Low CC
r^{carbon} (β_2)	0.009***	0.009***	0.030***	0.004	0.001	0.006	0.014***	-0.003	0.011***	0.006
	(0.002)	(0.002)	(0.006)	(0.005)	(0.008)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
$CI^{total} \times r^{carbon}$ (β_3)	-0.282									
	(0.146)									
$CI^{paid} \times r^{carbon}$ (β_3^{paid})		-0.538*	-0.548*	1.194	0.178	0.328	0.205	-0.830**	-0.563*	-0.124
		(0.217)	(0.264)	(1.585)	(0.476)	(1.861)	(0.273)	(0.280)	(0.221)	(1.106)
$CI^{free} \times r^{carbon}$ (β_3^{free})		-0.018	-0.150	-0.879	-0.019	0.499	0.117	-0.051	-0.053	0.284
		(0.158)	(0.213)	(1.677)	(0.297)	(0.497)	(0.188)	(0.254)	(0.168)	(0.444)
Eurostoxx Return	0.914***	0.914***	0.706***	0.930***	0.974***	0.946***	0.809***	0.993***	0.924***	0.902***
	(0.009)	(0.009)	(0.022)	(0.017)	(0.035)	(0.012)	(0.009)	(0.013)	(0.013)	(0.011)
Gas Return	0.016***	0.016***	0.009	0.017***	0.007	0.019***	-0.012**	0.021***	0.016***	0.017***
	(0.003)	(0.003)	(0.006)	(0.005)	(0.010)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Oil Return	-0.002	-0.002	-0.007	0.003	0.146***	-0.022***	0.006	0.000	-0.004	0.001
	(0.004)	(0.004)	(0.008)	(0.008)	(0.015)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)
Electricity Return	-0.001	-0.001	-0.006	-0.001	0.025*	-0.003	-0.006	0.004	0.002	-0.003
	(0.003)	(0.003)	(0.006)	(0.005)	(0.011)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	144,164	144,164	18,950	28,698	11,509	85,007	76,755	67,409	76,746	67,418
Industry FE	✓	✓	–	–	–	✓	✓	✓	✓	✓
Country/Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
R^2	0.208	0.208	0.230	0.295	0.292	0.206	0.161	0.243	0.184	0.246
Adj. R^2	0.194	0.194	0.169	0.249	0.201	0.184	0.146	0.230	0.175	0.226

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Regression results, estimation of equations (4) and (7). Columns correspond to different sub-samples.

A.4.3 Timing of purchases

When computing the carbon intensity of firms (see sections 3.2 and 4.3), we multiply the number of allowances a firm purchases (or receives for free) by the average carbon price of that year. We then normalize the obtained carbon cost by the firm's revenue to obtain the carbon intensity, a metric which can be used to compare firms. By using the average carbon price, we implicitly assume that all firms spread out their purchases evenly throughout the year.

This assumption is grounded in the fact that the main channel for allowance purchases are public allowance auctions. These auctions happen every week throughout the year with equal volumes.[33] Neither all firms regularly participate in all auctions, nor do they necessarily purchase the allowances on the spot markets, many of them purchase allowances using futures, the most traded of which being the December expiry contract (see ESMA, 2022).

The list of all physical allowance transactions which we can access via the EU ETS database (see section A.4.5) confirms the high share of non-administrative[34] transactions taking place in December, corresponding to the delivery of future contracts, as shown on Figure 14. Given the dominance of the futures market, we cannot identify firm-specific purchase patterns using the EU ETS database.

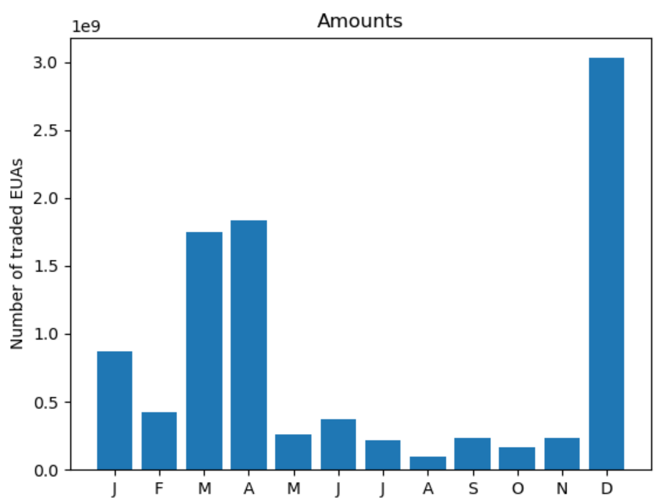

Figure 14: Market-based transactions happen disproportionally often in December, confirming that firms purchase allowances using the futures rather than the spot market.

A.4.4 Normalisation variables

In this subsection, we examine the robustness of our estimates to the use of different normalization variables in carbon intensity calculation. Throughout the paper we used revenue as a normalization factor for

[33]The auction calendar including volumes is published on the website of EEX the European Energy Exchange in charge of running the auctions.

[34]We exclude the allocation of free allowances and the surrendering of allowances.

equations (6) and (7). Being less affected by the differences in accounting standards than profit, it is a less biased proxy for the firm size. We now reproduce our core results using market capitalization for scaling (Table 10).

The significance and the sign of the coefficients next to commodities returns, Eurostoxx return and carbon price return are found to be invariant to the normalization factor selection. The magnitude of the coefficients is different though. As a result the estimated threshold of carbon intensity above which carbon price increases penalize the stock price are much higher in this specification than in the main regression (7.3% of market capitalization versus 1.7% of revenue in the main specification).

We are able to confirm the presence of a statistically significant link between carbon price returns and stock price dynamics. The magnitude of this link depends on the carbon intensity of the firm, in particular, its paid component, while free allocation of allowances is disregarded by investors. The result is robust to the normalization factor.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full Sample	Full Sample	Electricity	Chemicals	Mining	Others	2013-2017	2018-2021	High CC	Low CC
r^{carbon} (β_2)	0.009***	0.009***	0.029***	0.003	0.004	0.008**	0.016***	-0.005	0.012***	0.006
	(0.002)	(0.002)	(0.008)	(0.006)	(0.008)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
$CI^{total} \times r^{carbon}$ (β_3)	-0.104**									
	(0.033)									
$CI^{paid} \times r^{carbon}$ (β_3^{paid})		-0.422*	-0.430	0.883	0.163	0.128	0.185	-0.731***	-0.439*	-0.229
		(0.189)	(0.237)	(1.705)	(0.151)	(2.079)	(0.220)	(0.205)	(0.198)	(1.126)
$CI^{free} \times r^{carbon}$ (β_3^{free})		-0.039	-0.148	-0.143	-0.336	-0.018	-0.186*	0.011	-0.103	-0.016
		(0.047)	(0.083)	(0.643)	(0.233)	(0.059)	(0.090)	(0.071)	(0.139)	(0.046)
Eurostoxx Return	0.921***	0.921***	0.727***	0.920***	0.975***	0.957***	0.817***	0.999***	0.932***	0.908***
	(0.020)	(0.020)	(0.053)	(0.038)	(0.063)	(0.028)	(0.022)	(0.023)	(0.029)	(0.029)
Gas Return	0.016***	0.016***	0.012	0.015*	0.009	0.018***	-0.014**	0.021***	0.016***	0.016***
	(0.003)	(0.003)	(0.006)	(0.007)	(0.009)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Oil Return	-0.003	-0.003	-0.009	0.001	0.141**	-0.022**	0.004	-0.000	-0.006	0.001
	(0.006)	(0.006)	(0.009)	(0.008)	(0.039)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)
Electricity Return	-0.000	-0.000	-0.008	-0.001	0.024	-0.001	-0.004	0.003	0.002	-0.002
	(0.003)	(0.003)	(0.006)	(0.005)	(0.012)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
N	139,532	139,532	18,429	28,110	11,041	81,952	73,979	65,553	74,160	65,372
Industry FE	✓	✓	–	–	–	✓	✓	✓	✓	✓
Country/Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
R^2	0.218	0.218	0.240	0.292	0.289	0.220	0.169	0.254	0.195	0.251
Adj. R^2	0.203	0.203	0.177	0.247	0.194	0.199	0.153	0.241	0.187	0.230

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Main regression results, carbon costs normalized by market capitalization

A.4.5 Allowance inventories

The estimates presented in section 4.3 show that the higher a firm's yearly carbon bill, the more severely its stock price is affected by an increase in carbon prices. This is consistent with the view that stock markets take a firms' (carbon) costs into account when determining its market value. Fluctuation of a firm's carbon costs lead to fluctuations of its valuation.

However, firms could hedge themselves against carbon price fluctuations, either by using derivatives or by building up inventories of emission allowances to cover their expected emissions over some time horizon. Anecdotal evidence exists of some firms engaging in the latter (such as the German utility group RWE, see Flauger and Witsch, 2021). We do not have access to firms' position in ETS options and futures but - using the list of all transactions in the EU ETS database - we could in theory reconstruct all firms' allowance inventories up to April 2019.[35]

Unfortunately, the data quality of the transaction log is poor (for a detailed description see Mahringer, 2021), with the transferring or receiving account of a transaction often missing. In particular, some of the free allocation transactions cannot be linked to firms, which results in meaningless (negative) inventories. We can therefore not use the inventory figures in the regression.

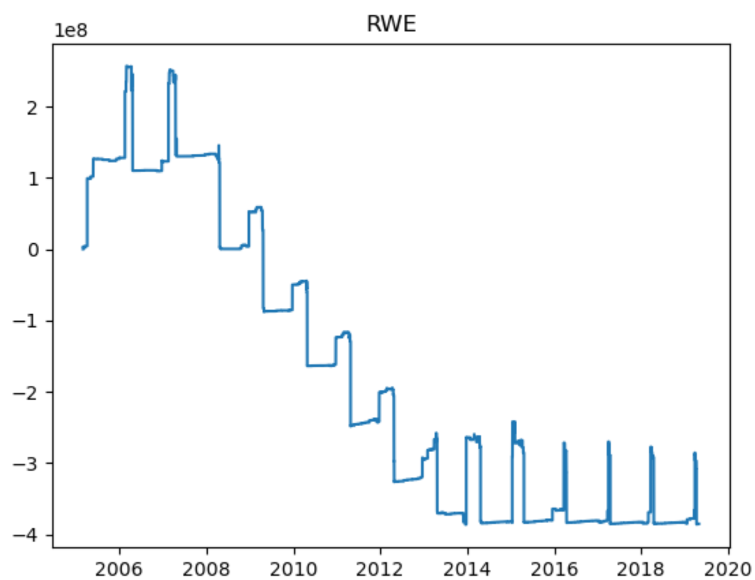

Figure 15: Reconstructed allowance inventory of German utility RWE. Missing data leads to (meaningless) negative inventory figures.

[35] The EU transaction log publishes all transactions of physical allowances (that is free allocations, auction and secondary-market purchases, sales and regulatory surrendering of allowances) with a delay of three years. Derivative transactions do appear only if they lead to the actual delivery of allowances (and are not settled in cash), the time logged would be that of the allowance delivery not of the derivative trade.

A.4.6 R&D expenditure

As another robustness check we also reproduce our estimates conditional on the R&D expenditures of each firm (Table 11). Our objective is to examine whether the discovered relationship between carbon price return and stock price performance holds for highly innovative firms. Firms with higher R&D spending might be viewed by investors as better able to withstand transition risks. Hence one could assume that rising carbon costs have a less negative impact on stock performance of carbon intensive firms that are active in R&D. Essentially, we use R&D spending as a proxy for a firm's innovative capabilities and its readiness to adjust to the changing environment.

We collect the data on annual R&D expenditure in percent of revenues for the companies included in our sample using the Orbis database. Unfortunately, the data availability is poor. Only about 44% of the companies in our sample report positive R&D expenditure, a third have zero R&D expenditure, while the remaining firms do not report this data at all.

We estimate our core specification on several sub-samples: firms that have R&D equal to zero (column 1 in Table 11), firms with positive R&D (column 2), and (conditional on observing positive R&D) firms with R&D expenditure above or below the median (columns 3 and 4). We do not find any statistically significant result beyond the positive association between stock returns and the Eurostoxx and gas returns. The carbon price no longer has a statistically significant relationship with the stock prices of firms (regardless of their carbon intensity) in either of these sub-samples. We attribute this result to the changes in the sample used for the estimates. Only 12 electricity companies and only half of the companies headquartered in high carbon intensity countries report positive R&D and can hence be included into the estimates. It is highly likely that we no longer see statistically significant results because the relationship was particularly strong for highly carbon intensive firms (see 4.4) that are now less well represented in the dataset augmented with R&D expenditure .

	(1) R&D = 0	(2) Positive R&D	(3) R&D below median	(4) R&D above median
r^{carbon} (β_2)	0.004	0.008*	0.013*	-0.000
	(0.004)	(0.004)	(0.006)	(0.005)
$CI^{paid} \times r^{carbon}$ (β_3^{paid})	-0.596	0.480	1.529	-0.820
	(0.355)	(0.735)	(2.643)	(0.605)
$CI^{free} \times r^{carbon}$ (β_3^{free})	0.025	2.290	1.552	8.984
	(0.265)	(1.387)	(1.507)	(7.081)
Eurostoxx Return	0.840***	1.018***	1.007***	1.029***
	(0.032)	(0.026)	(0.036)	(0.035)
Gas Return	0.015**	0.017***	0.019*	0.015**
	(0.005)	(0.004)	(0.008)	(0.005)
Oil Return	-0.015	0.003	0.017	-0.011
	(0.011)	(0.008)	(0.012)	(0.010)
Electricity Return	0.003	-0.002	-0.009	0.004
	(0.006)	(0.005)	(0.008)	(0.005)
N	49,015	63,751	31,925	31,826
Industry FE	✓	✓	✓	✓
Country/Month FE	✓	✓	✓	✓
Clustered SE	Firm	Firm	Firm	Firm
R^2	0.190	0.287	0.271	0.337
Adj. R^2	0.158	0.270	0.236	0.311

Standard errors in parentheses

Independent variable is the stock return in all cases

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Results (R&D)