CARBON PREMIUM & POLICY UNCERTAINTY

AN ANALYSIS OF CORRELATION BETWEEN CARBON EXPOSURE AND STOCK RETURNS, AND THE IMPACT OF PRESIDENTIAL ELECTIONS ON CARBON RISK

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Bachelor Thesis
Stockholm School of Economics
2022

Carbon Premium & Policy Uncertainty: An Analysis of Correlation Between Carbon Exposure and Stock Returns, and the Impact of Presidential Elections on Carbon Risk.

Abstract

Earth's climate is changing, but the timing and extent of policy responses remain uncertain. This paper aims to test the correlation between firms' carbon emissions and stock returns. The analysis is two-leveled; a general test throughout the period 2012 to 2022, and two separate tests surrounding the last two American presidential elections. The purpose of the latter analysis is to understand if investors are accounting for policy change probabilities as part of their risk compensation. The paper draws inspiration from a forthcoming Journal of Finance paper, *The Pollution Premium*, authored by Hsu et al. (2022). Hsu et al. suggest a micro-founded general equilibrium model, where the possibility of stricter policies induces a negative price of risk for high-polluting firms. We test this relationship and utilise the last two presidential elections as shocks to the probabilities of stricter policies for carbon emissions on the firm level. The data used in the tests are monthly stock returns for New York Stock Exchange listed firms, as well as Refinitive Eikon for emission and firm-level financial data. The result of this paper suggests a significant negative correlation between carbon exposure and stock returns, particularly when measured in emission intensity. The result also supports previous findings of the importance of business sectors. The 2016 Trump election win also has a significant, negative impact on the correlation between firms' emission exposure and their stocks' returns while controlling for sectors. In contrast, the effect of the Biden election is more ambiguous. This result suggests that presidential elections may impact how investors account for carbon risk, but that the impact is likely contingent on factors surrounding such elections.

Keywords

Carbon premium, Stock returns, Carbon, Emissions, Sustainable finance, Trump, Biden, Presidential elections

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Acknowledgments

We want to thank Olga Obizhaeva for the much-needed advice and support of our research concept throughout this process. We also want to thank Michael Klug for his support on statistical methods. Finally, we want to extend our thanks to Sina Behzadifard for his help with data access and support on Refinitive Eikon.

Bachelor Thesis
Bachelor Program in Business & Economics
Stockholm School of Economics

1 Introduction

This paper aims to provide an understanding of the effects of firms' carbon exposure on stock returns, and how this is affected by significant political events - namely the periods following President Trump's and President Biden's respective election wins. As investors are becoming increasingly concerned with climate risk in asset pricing, particularly with climate regulatory risks, it is important to explain if and to what extent investors are accounting for different political environments and their corresponding policy change probabilities (Krueger, Sautner et al. 2020). Examples of policy change with regard to carbon emissions are carbon pricing or taxation, both likely to be varyingly costly for firms depending on their carbon exposure. As investors account for future profitability in current firm valuations, the timing and extent of policy implementations are central. Given the difference in political attitudes towards climate change, the last two presidents' respective election wins provide an interesting backdrop for policy uncertainties. In this paper, the two elections of Trump and Biden will serve as diametral shocks to investor valuations and they will do so for two reasons. Firstly, both election outcomes were uncertain, particularly in 2016 with the odds of Trump winning estimated to be less than 30 per cent (Silver 2016). Secondly, Trump's and Biden's attitudes to climate change and their policy enactments are widely different, with Trump leaving the 2015 Paris agreement and Biden re-entering and subsequently pledging several climate change mitigation initiatives. The variation in their climate change approaches allows for more robust claims on the impact of policy probabilities.

This paper is largely based on the article by Hsu et al. (2022), in which they construct a micro-founded model for asset pricing under political uncertainty concerning policy regime shifts. While Hsu et al. (2022) empirically test for a pollution premium (toxic pollutants), the model is reasonably assumed to be equally applicable to firms' carbon emissions. *The Pollution Premium* Model derives a negative price of risk from the probability of increased policy costs, which consequently lowers valuations for firms with greater exposure. In other terms, it increases expected returns for high-emitting firms as investors must be compensated for this increase in risk. As for *the Pollution Premium*, Hsu et al. (2022) found a significant average annual return of 4.42 per cent for a portfolio investing long high toxic emission stocks and short low toxic emission stocks. This paper will test two different hypotheses;

1. Carbon emissions correlate positively with stock returns (i.e. the carbon premium hypothesis).
2. They do so to a greater extent following the Biden election win than following Trump's, as the probability of a costly policy change is deemed more likely and investors want to be compensated for this risk.

2 Literature Review

The problems caused by climate change grow day by day. Societies and economies all over the world need to work together to mitigate these problems. In order to battle climate change, robust regulatory actions are required. Carbon pricing has been introduced by a number of jurisdictions, for example, the EU and Canada, in order to diminish greenhouse gas emissions and limit the associated risks of a warming planet. Carbon pricing, a price to emit carbon, can influence firms in different ways, but perhaps most importantly through reduced profitability. Consequently, the possibility of carbon pricing should lead to higher expected returns and lower equity prices for carbon-intensive firms. This is to compensate for their additional risk, as a carbon pricing policy would be costlier for firms with greater carbon exposure. The risk is often denoted as carbon risk and its associated risk compensation as carbon premium. This new kind of risk generally includes both negative and positive impacts on firms that come up in the process of transitioning from a brown to a green economy. Measuring carbon risk is thus not limited to carbon emission measures, but a firm's overall strategic and operational exposure to unexpected changes when transitioning to a green economy. The existence of a positive relationship between firms' returns and carbon risk has empirically proven to be uncertain, as several studies have found varying results (Görgen et al., 2020). This literature review will provide a few key perspectives that perhaps can explain an emission-return relationship; behavioural explanations, corporate policies and governance, and existing systematic risks.

Matsumura et al. (2014) examined the carbon emission effects on firm value and the act of voluntarily disclosing carbon emission information. They found that, as carbon emissions increase, firm value decreases, meaning a negative relationship exists between carbon emissions and firm value. The paper also found that companies that disclose their carbon emissions tend to have a lot higher firm value than non-disclosing firms. Their results suggest that all firms get punished for their carbon emissions by the market and that a further penalty is attached to firms that do not disclose their emission information at all. Hamilton (1995) showed that US firms with high pollution levels experienced negative abnormal returns when the Toxic Release Inventory (TRI) first came out with firm-specific emissions data.

A few papers investigate whether investors efficiently price carbon risk, by trying to identify a carbon risk premium in the US market. Similar to Hsu et al. (2022), Bolton and Kacperczyk (2021) analysed stock returns in the cross-section. They found a positive relationship between high carbon dioxide emissions and stock returns. Their results suggest that investors demand compensation for their carbon emission risk exposure. The increasing awareness of carbon risk has also given rise to carbon risk hedging strategies. This has especially benefited long-term passive investors, as some strategies have allowed them to hedge climate risk with no sacrifice in financial returns. When climate change mitigation policies are still pending, the low-carbon index achieves the same return as the benchmark index; but as soon as the carbon dioxide emissions are priced, or expected to be priced, the low-carbon index should start to outperform the benchmark (Andersson et al., 2016).

Ramelli et al. (2021) investigate stock-price reactions and institutional investors' portfolio adjustments after Donald Trump's election, and his nomination of the climate change sceptic Scott Pruitt to lead the Environmental Protection Agency. The paper found that stocks of carbon-intensive firms benefited from the Trump election, which was expected. More surprisingly, however, is that the authors also found that firms with responsible action plans also did well, despite the lessened urgency of climate change mitigation by the Trump administration. This suggests that, since responsible firms receive a premium, long-horizon investors move into climate-responsible stocks, expecting green policy to reappear post-Trump.

Ilhan et al. (2021) study the impact of policy uncertainty changes on tail risk and show that climate policy uncertainty makes it difficult for investors to quantify the effect of future climate regulations. The paper investigated the options market and found that the option market prices climate policy risk, and higher cost of option protection against downside tail risk was more prominent for firms with more carbon-intensive business models. Furthermore, the article found that the cost is amplified when the overall attention to climate change is high. A drop in the cost of options used to hedge tail risk was also observed, particularly for high emitting firms, when Donald Trump was elected president, indicating a drop in the far-out risk for climate policy changes.

In et al. (2019) look at financial performance, corporate environmental performance, and the relationship between the two. They investigated this relationship by examining the characteristics of carbon-efficient firms and the risk-return relationship of low-carbon investment. Their results suggest that holding a long position in carbon-efficient firms and a short position in carbon-inefficient firms would lead to significant abnormal returns. It was also found that carbon-efficient firms tend to be characterised as "good" regarding financial performance and corporate governance.

Pástor et al. (2022) look at the relationship between green assets and returns and found that green assets have had high returns in recent years. The authors suggest that this performance reflects unexpected increases in environmental concerns, not necessarily higher expected returns. It was also found that U.S. green stocks outperformed brown when climate concerns increased. Consistent with theory, the authors still estimated that green stocks will generate lower expected returns than brown stocks, despite the observed outperformance.

In *the Pollution Premium*, Hsu et al. (2022) list several possible mechanisms that could explain the emission-return relationship. One such mechanism is a behavioural mechanism, namely preferences. Both institutional and retail investors have preferences against firms with poor social image, such as bad CSR scores (Hong, Kacperczyk 2009, among others). Because of these preferences, the prices of firms with such qualities tend to be discounted by the market and offer good dividend yields. If these polluting firms improve their CSR score, their price will increase and result in a positive emission-return relationship. Also, there may exist investors who value high dividend yield stocks over stock reputation. When such investors earn higher yields, they may buy more high-emission stocks and thus push the prices of the stocks upwards. Therefore, the emission-return relation could be driven by investors' preferences on emissions. However, Hsu et al. (2022) found that preferences alone cannot explain the emission-return relationship.

Berk and van Binsbergen (2021) also study preferences and the impact of impact investing. They found that the change in the cost of capital due to divestment can be explained by a simple linear function of three parameters. (1) the fraction of socially conscious capital, (2) the fraction of targeted firms in the economy, and (3) the return correlation between the targeted firms and the rest of the stock market. The paper demonstrates that the influence impact investing has on the cost of capital is minuscule and does not affect real investment decisions meaningfully. As such, the trend of investors omitting high-emission firms from portfolios should in itself drive higher expected returns. Their results also suggest that, to have an impact, socially conscious investors should invest and use their rights of control to change corporate policy, instead of divesting.

Another explanation could be under-reaction to emission reduction. Bernard and Thomas (1990) found that investors might under-react to market news, potentially due to lagged information spread or limited attention. High-polluting firms may be under great pressure from the government or the community and are therefore more likely to decrease their emissions in the following period. If this improvement is underestimated by pro-social investors, it is likely that the stock price still goes up, which would result in a positive emission-return relationship.

The relationship could also be linked to retail investors and behavioural biases. Several articles have found that retail investors are less likely to act rationally and may therefore be subject to behavioural biases (e.g. Daniel et al. 1998). To illustrate, retail investors may act irrationally in regard to firms' emission news and sell all their stocks at large discounts (Krüger 2015). If the overreactions play a role in the relationship between emissions and returns, stocks with an overrepresentation of retail investors as shareholders should expect to see significant drops in returns.

Governance and corporate policies may also affect an emission-return relationship. Masulis and Reza (2015), among others, have found that high-emitting firms may have weaker monitoring and governance. If that is the case, investors who are concerned about risks associated with governance, or alike, will discount stocks. Low prices are likely to attract active investors who want to improve the governance and monitoring of these firms. This increases firms' prices and leads to return predictability. If these channels are responsible for the emission effect, it would be expected that there is no emission-return relationship within firms with strong corporate governance. It could also be, as Liu et al. (2017) showed, that the relationship is related to political connections, meaning that their stock prices and profits are subject to uncertainty with respect to governments. Because future stock returns are positively related to political connections, which, in turn, also is associated with risk premiums (Santa-Clara, Valkanov 2003), the emission-return relation might be reflecting the asset pricing implications of political relations. This suggests that there is no emission-return relation among firms with weak political connections.

Finally, existing systematic risks should also be considered. Current literature suggests four alternative channels of systematic risk that may drive variations in the emission-return relationship. Technology obsolescence (Lin et al. 2019), financial constraints (Lins et al. 2017), economic and political uncertainty (Brogaard, Detzel 2015), and adjustment costs (Kim, Kung 2016). Firms that are high-emitters invest in less advanced capital and adopt more obsolete technology in production. New technology forces these firms to upgrade their capital which makes their cash flows sensitive to a frontier technology shock. As modelled by Hsu et al. 2022, high-emission firms may also be subject to risks linked to financial constraints, due to potential penalties and litigation risks regarding environmental issues. Another issue might be related to risks in macroeconomic- (e.g. trade conflicts or economic downturns) and political uncertainty (e.g. changes in the ruling party). Lastly, high-emitters find it costly to adjust their capital stock, especially during economic downturns, which may be the reason for the higher expected returns.

3 Hypothesis and Research Design

This paper largely derives its hypotheses from the model developed by Hsu et al. (2022). In their paper, *the Pollution Premium*, the authors study asset pricing implications of industrial pollution. They develop a microfounded, general equilibrium asset pricing model that features risk related to environmental policy regime shifts. A key feature of the model is a utility maximisation problem that the government faces. In this problem, the government must maximise the utility of households that are all invested in firms by choosing an environmental policy regime, either a strong or a weak regime. The two scenarios affecting utility are thus either implementing a weak regime and facing the costs of environmental degradation, or implementing a strong regime and facing the costs of mitigating the impact on the environment. Another key feature of the model is that the strong policy regime will negatively affect profits to a greater extent for firms with higher levels of toxic pollutants emission intensity.

Which of these regimes the government decides to implement depends entirely on the true environmental cost. If the environmental cost is higher than a threshold value depending on the two policies (i.e., higher than the abatement costs), the government will implement the stronger policy. The true environmental cost is a variable that is unknown to all agents until time T when regime change is to be implemented. However, signals indicating the true environmental cost can be observed by all agents prior to time T. This gives the agents, i.e. the investors, a perception of the probabilities of the true environmental cost exceeding the threshold value for a strong policy regime implementation. As such, the environmental cost signals consequently indicate the probability of a policy regime shift that will adversely affect profitability, in particular the profitability of high-emission intensity firms. In a more practical sense, this could be translated to investors learning about increasingly severe consequences of climate change in media or scientific reporting, which in turn affects their perception of policy change.

From this, the model derives a stochastic discount factor contingent on the environmental cost signals as investors learn about the true environmental costs. The state price of density, i.e. the sources of risk, in the stochastic discount factor include the risk of fundamental shocks and the risk for uncertainty shocks, i.e. the risk for signals indicating a policy regime shift. The latter of the two risks is dependent on the marginal utility in variation to the observed cost signal, which is in itself dependent on the level of exposure to the regime shift, something the model assumes to be proportional to firms' emission intensity. They prove that this exposure carries a negative price of risk. To compensate for this increased risk, i.e. the risk that the probability of a costly policy change will increase, investors must be compensated with greater returns in order to invest in firms with higher emission intensities.

From this, the first testable hypothesis can be derived:

I. Firms' carbon emissions correlate positively with stock returns.

We will test this relationship by regressing monthly stock returns on emissions, both intensity, and total. The timespan is 2012 to 2022. With this time horizon, we can observe the overall relationship between returns and carbon emissions.

$$Returns = \beta_0 + \beta_1 * Emissions + Controls_i + \epsilon_i \tag{1}$$

The emissions variable refers to both emission intensity and total emissions. Emission intensity is defined as emissions normalised by revenue (TON CO2 / Dollar Millions in Revenue). A normalised measure is generally preferred over a total emission variable, as this would otherwise risk generating a size bias, and is utilised by both Hsu et al. (2022) and Ilhan et al. (2021). However, a significant correlation between returns and total emissions was identified by Bolton, Kacperczyk (2021), and as such, that relationship will also be tested here. As firms report emissions for a certain year the following year, emission variables will be lagged by one year. That is, returns for time t will be regressed emissions reported in time t-1. The controls are Market Capitalization (ME), Book-to-market-ratio (B/M), Investment Rate (I/K), Return on Assets (ROA), Return on Equity (ROE), Tangibility (TANT), and Leverage, the same controls as used by Hsu et al. (2022). As high-emitting firms tend to cluster in industries (energy, industrials, etc.), fixed effects will also be included on an industry level to control for this effect.

The first testable hypothesis is thus;

$$H_0 : \beta_1 \leq 0$$
$$H_1 : \beta_1 > 0$$

Cost signals in the *Pollution Premium* model can in a practical sense be defined as a wide range of variables. As mentioned, signals can be news in the media reporting on the effects of climate change, as studied by Engle et al. (2020). Hsu et al. (2022), used the aggregate growth in civil penalties against polluting firms in their empirical tests as a proxy for cost signals. Regardless, the two last presidents of the United States can be assumed to have observed distinctively different levels of cost signals. To quote President Trump -*"I don't think there's a hoax. I do think there's probably a difference. But I don't know that it's man-made... I don't wanna give trillions and trillions of dollars."* (Cheung 2020). Whether or not this is true, the likelihood of President Trump and President Biden implementing strong policies to mitigate climate change were and are distinctively different, which in turn is equal to observing different cost signals within the *Pollution Premium* equilibrium model.

A few days into his presidency, President Trump announced Scott Pruitt, an environmental sceptic, as the head of the Environmental Protection Agency (Ramelli, et al. 2021). Another six months in, President Trump announced that the US was to exit the 2015 Paris Agreement (The White House 2017). President Biden, on the other hand, has taken a diametrically different stance - *"And when it comes to fighting the climate change — climate change, I will not take no for an answer. I will do everything in my power to clean our air and water, protect our people's health, to win the clean energy future."* (Biden 2022). As far back as 2013, Biden commented specifically on the importance of carbon legislation, *"You should be attacking the carbon emissions, period, and whether it's cap-and-trade or carbon tax or whatever, that's the realm in which we should be playing"* (Brinkley 2013). The Biden Climate Plan, the climate agenda that President Biden campaigned with prior to the election, included, among many other pledges, a pledge to rejoin the Paris Agreement and to ensure a 100 per cent clean energy economy with net-zero emissions by 2050 (Biden 2019). As such, the two presidential election wins serve as two opposite shocks to the probability of a regime shift, or in other words, as two opposite environmental signal shocks. The Pollution Premium model would suggest that the Trump election win would serve as a *negative* signal shock, thereby reducing the relative stochastic discount factor and reducing the expected returns for high-emission firms. The Biden election win would serve as a *positive* signal shock, increasing the relative stochastic discount factor for high-emission firms and increasing the expected returns for high-emission firms. This gives us our second hypothesis:

II. Firms' carbon emissions correlate positively with stock returns to a greater degree following the Biden presidential election win compared to following the Trump presidential election win.

This hypothesis is partially supported by Ilhan et al. (2021), as they found reduced costs of hedging against carbon tail risk following the Trump election win. This relationship will be tested by regressing monthly stock returns on emission intensity and total emissions separately while using the respective presidents as dummy variables. The timespan for both regressions is one year prior and one year following each presidential election win. This time horizon allows for observations of the overall relationship between returns and carbon emissions while utilising Trump and Biden as special events. The interaction coefficient will determine whether there is indeed a change in whether or not investors account for shocks to probabilities of regime shifts. The regression is split into two parts, one period covering the transition from Obama to Trump, and one covering the transition from Trump to Biden.

$$\begin{split} Returns = \beta_0 + \beta_1 * Emissions + \beta_2 * President + \\ \beta_3 * Emissions * President + Controls_i + \epsilon_i \end{split} \tag{2}$$

Emission variables, control variables, and fixed effect variables are defined as in hypothesis one. The president variable values for Trump are set to 0 from November 9th, 2015, and 1 from November 9th, 2016 to November 9th, 2017. The Biden dummy is set to 0 from November 3rd, 2019, and 1 from November 3rd, 2020 to November 3rd, 2021.

The second testable hypothesis is thus:

$$H_0 : \beta_3\,(Biden) \leq 0$$
$$H_1 : \beta_3\,(Biden) > 0$$
$$H_0 : \beta_3\,(Trump) \geq 0$$
$$H_1 : \beta_3\,(Trump) < 0$$

4 Data

4.1 Sample

Data has been sampled from Yahoo Finance as well as Refinitive Eikon. Data on stock returns were gathered through Yahoo Finance using the *yfinance* package in Python, which uses Yahoo Finance's open API to collect data. While data to calculate stock returns are available through Refinitive Eikon, it does not include adjusted closing prices, which would provide incorrect stock prices for dividend-paying firms or any firm conducting a stock split. Firms in the two data sets were matched on tickers. Emission data and other financial data for control variables were collected from Refinitive Eikon. Inflation data, used to adjust market capitalisations, was collected from the Federal Reserve Economic Data database (Fred (2022)). For regressions 1 and 2, emission information is gathered on an annual basis from 2012 to 2022, while returns are collected on a monthly basis. Analysing monthly returns data and annual emission data is common in previous literature, for example, Bolton, Kacperczyk (2021). In total, the data set for regression 1 contain 16,084 observations, and the data set for regression 2 contain 3,175 (Trump) and 3,227 (Biden) observations respectively The time frame for regressions 1 and 2 is motivated by the fact that prior to 2012, few firms were reporting on carbon emissions, and as such the sample universe is quite small. The sample of firms is exclusively New York Stock Exchange-listed firms, as investors of American firms are deemed to be incorporating US policy probabilities to a greater and more meaningful extent. Non-American firms also have less predictable profitability implications of a potential policy regime shift. Control variables are also sampled from Refintive Eikon, including industries. The industry definition used in the analysis is The Refinitive Business Classification (TRBC, previously Thomson Reuters Business Classification) scheme, in which the levels of granularity used are the business sectors. In total, there are 28 business sectors, of which 23 are included in the sample (meaning they have firms reporting from 2012 and onwards). Similar to Hsu et al., all independent variables other than emissions variables are normalised to a mean of zero and a 1 standard deviation after being winsorized at the 1st and 99th percentile. Returns are also winsorized at the 1st and 99th percentile, but not normalised. By winsorizing, outlier values greater than the 99th and 1st percentile are replaced by the 1st and 99th percentile values, reducing their effect on coefficients and variance.

The number of firms reporting emissions in the sample is illustrated in figure 1. For regression 1, only firms reporting throughout the entire period, i.e. from 2012 and onwards, are included.

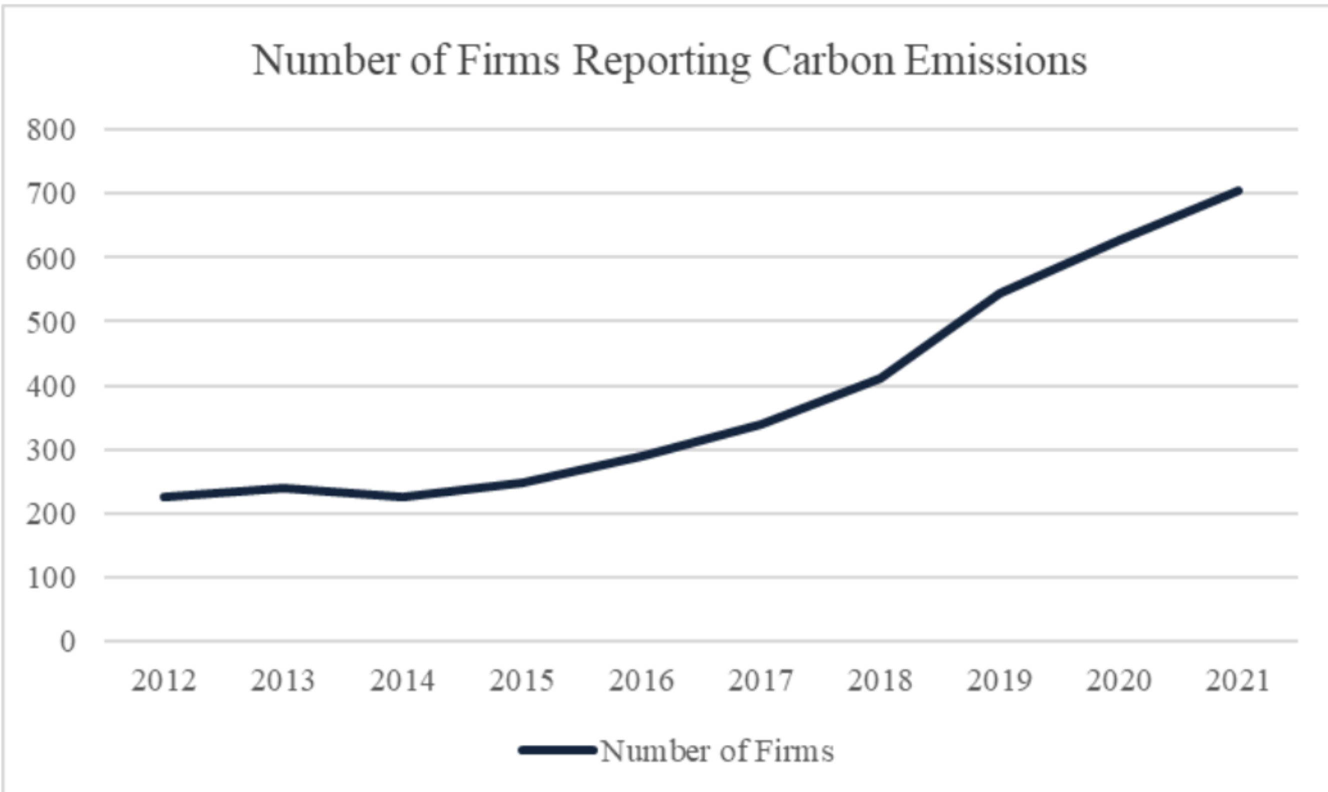

Figure 1: The chart illustrates the number of firms included in the sample reporting carbon emissions by year 2012-2021.

Table I presents the TRBC sectors included in the sample. The largest business sector, in terms of the number of firms included, is Food and Beverages, while the smallest is Industrial and Commercial Services. As might be expected, Utilities, Chemicals, and Energy are at top of the bracket in terms of intensity.

Note that the sample total of the number of firms is 130. Of a total set of 2332 firms initially available, only 130 have reported continuously throughout 2012-2022 in Refinitive Eikon's database. The size of the sample will be discussed further in the discussion section of this paper.

Table I

This table presents the number of firms included in the sample by TRBC business sector, as well as the mean, minimum, and maximum values of carbon emission intensities, ranked by mean.

Business Sector	Number of Firms	Mean	Min	Max
Utilities	8	1495.1	136.1	4718.2
Chemicals	7	864.3	28.7	3508.3
Energy - Fossil Fuels	9	808.0	45.7	5257.7
Mineral Resources	5	444.8	195.8	1058.7
Transportation	6	391.3	89.5	2249.3
Applied Resources	3	384.6	66.0	718.5
Cyclical Consumer Products	2	262.4	27.8	929.3
Cyclical Consumer Services	7	249.9	0.0	2291.2
Consumer Goods Conglomerates	2	144.6	34.0	265.9
Personal Household Products Services	3	118.7	34.9	263.6
Real Estate	5	95.6	1.2	533.7
Food Beverages	13	84.1	11.9	230.8
Telecommunications Services	2	79.7	36.2	131.4
Automobiles Auto Parts	3	40.2	24.9	57.5
Industrial Goods	7	39.5	11.5	255.3
Technology Equipment	6	30.5	3.9	78.1
Pharmaceuticals Medical Research	4	30.2	6.0	80.5
Retailers	5	29.0	7.5	46.7
Industrial Commercial Services	1	27.3	10.2	45.8
Healthcare Services Equipment	10	23.7	0.6	91.0
Software IT Services	7	13.4	0.6	41.8
Banking Investment Services	10	12.6	2.6	36.9
Insurance	5	2.4	0.4	5.9
Sample Total	130	2.4	195.8	5257.7

4.2 Returns

Returns are defined as percentages based on stock prices, adjusted for dividends. As the sample firms are all domiciled in the United States, risk-free rates are not accounted for. Returns are all denoted in the same currency, US dollars.

4.3 Emissions

Refinitiv Eikon collects self-reported emissions data from companies or other publicly available data (Carbon Disclosure Project, for example). Even with publicly available data, such data is self-reported by companies, which raises the risk of a biased selection. High-emitting firms may not be reporting carbon emissions for reputational reasons. Still, self-reported data is used widely in practice and remains the best alternative for this paper's purpose. The scope of emissions data in the sample is scope 1 and 2. The emissions scopes are defined by the Greenhouse Gas Protocol's corporate standard (2015), which is a global standard for corporate emissions reporting. Scope 1 is defined as the emissions occurring from sources directly owned or controlled by the company (for example, furnaces, vehicles, production equipment, etc.). Scope 2 is defined as indirect emissions, i.e. the emissions arising from energy purchased and consumed by the company. The protocol has defined a third scope, scope 3, which is other indirect emissions, such as emissions arising from the transportation of purchased materials. Few firms report on scope 3 emissions, and given its vague definition and difficulty to measure or monitor, the data risks being inaccurate. For this reason, scope 3 is omitted from the sample. Each of the regressions will test both of the emission variables, total and intensity.

Summary statistics for all variables included in regressions testing hypotheses 1 and 2 are presented in table II.

Table II

This table presents a summary of variables included in all regressions. The table includes the number of observations, mean, standard deviation, median, the minimum and maximum values of all variables. A full explanation of variable definitions and sources is included in the appendix.

	CO2Total	EmissionIntensity	MEadj	PriceOverBook	IK	ROA	ROE	TANT	Leverage
Observations	19649	19648	19649	18723	17226	19283	19427	17643	17009
Mean	5345424.232	305.913	53133578230	5.721	0.082	7.381	24.304	0.596	20807268308
sd	14339717.525	673.509	68615426174	11.286	0.042	5.267	44.850	0.423	28559552393
Median	877835	47.861	24833387384	2.592	0.072	6.542	15.700	0.476	11078143000
Min	5815	0.366	2341331876	0.567	0.020	-3.238	-115.400	0.011	1073100000
Max	143000000	5257.685	3.32769E+11	84.675	0.268	23.120	298.169	1.682	1.70981E+11

5 Results

5.1 Regression 1 - General Emission Return Relationship 2012-2022

The results suggest that a 10 per cent increase in emission intensity leads to a significant decrease of 1.07 per cent in annual returns, controlling for year-fixed effects and robust standard errors. While controlling also for sector fixed effects, a 10 per cent increase in emission intensity correlates with a significant decrease of 0.41 per cent in annual returns. When using total emissions instead of emission intensity the results suggest that a 10 per cent increase in total emissions correlates with a significant decrease of 0.52 per cent in annual returns, controlling for year-fixed effects and robust standard errors. When also controlling for sector fixed effects, the results suggest that a 10 per cent increase in total emissions leads to an insignificant increase of 0.06 per cent in annual returns. All regression coefficients are reported in table III.

Table III

This table presents regression coefficients and standard errors for regressions testing hypothesis 1, i.e. the correlation between emissions and returns throughout the entire sample period 2012-2022. Dependent variable is monthly returns annualised, explanations for all independent variables are included in table VI in the appendix. The table includes results for regressions for both emission intensity and total emission, as well as with and without sector-fixed effects.

	Dependent Variable: Monthly Returns (Annualised)			
	(1)	(2)	(3)	(4)
log(EmissionIntensity)	-0.107^{***}	-0.041^{**}		
	(0.017)	(0.021)		
log(Scope1ANDScope2)			-0.052^{***}	0.006
			(0.015)	(0.018)
IK	0.038	-0.002	0.273	0.109
	(0.408)	(0.496)	(0.406)	(0.494)
TANT	0.554^{***}	0.307^{***}	0.436^{***}	0.207^{**}
	(0.066)	(0.099)	(0.068)	(0.096)
Leverage	-0.008	0.061	0.220	0.096
	(0.174)	(0.204)	(0.171)	(0.204)
log(MEadj)	-0.055^{**}	-0.105^{***}	-0.013	-0.112^{***}
	(0.023)	(0.027)	(0.025)	(0.031)

log(BookToMarket)	0.191***	0.251***	0.160***	0.259***
	(0.043)	(0.046)	(0.044)	(0.048)
ROA	−0.047***	−0.050***	−0.041***	−0.047***
	(0.005)	(0.006)	(0.005)	(0.006)
ROE	−0.001**	−0.001**	−0.001**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.142***	2.711***	1.340**	2.578***
	(0.572)	(0.670)	(0.563)	(0.680)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	No	Yes	No	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01

The results of the regressions suggest that the overall relationship between emissions and returns is negative, which supports the findings of previous literature. The relationship is particularly significant when the emission intensity measure is used as a proxy for carbon exposure. Further, the results indicate that a lot of the variation in the data indeed can be explained by sector-fixed effects. When using emissions intensity and controlling for sector-fixed effects, the relationship becomes smaller and less significant, and when using total the relationship loses all statistical significance and the coefficient changes sign. Regardless of what measure is used, the result also implies that H0 of hypothesis 1 cannot be rejected.

5.2 Regression 2 - Trump and Biden Election Wins

The second test intends to use the election wins of President Trump and President Biden as policy shock proxies and to test these shocks' effects on returns. Given the significance of sector fixed effects, they are included in all of regression 2's tests. Following Trump's election win, the regression suggests a significant, negative impact on returns for high-emitting firms when carbon exposure is measured in intensity. When measured in total emissions, the significance level and the magnitude of the correlation decrease. Notably, the overall emission intensity-return relationship is significantly positive throughout the period prior to and following the Trump election win. The election, however, seems to shift this relationship negatively which is in line with the theory proposed by Hsu et al. (2022) regarding policy probability shocks. Following the Trump election win, a 10 per cent increase in emissions is correlated with a decrease of 1.35 per cent in annual returns. The Biden election seems to have the opposite correlation - a positive, albeit small, effect. However, in both cases of measures, the effects are insignificant. Altogether, this implies that H0 (Trump) can be rejected, while H0 (Biden) cannot. All regression coefficients are reported in table IV.

Table IV

This table presents regression coefficients and standard errors for regressions testing hypothesis 2, i.e. the effect of president Trump and President Biden's election wins on the correlation between emissions and returns. Sample periods are one year prior and one year following the elections. Dependent variable is monthly returns annualised, explanations for all independent variables are included in table VI in the appendix. Table includes results for regressions for both emission intensity and total emission, for both the Trump election regression and the Biden election regression. All regressions include both year and sector-fixed effects.

	Dependent Variable: Monthly Returns (Annualised)			
	(1)	(2)	(3)	(4)
log(EmissionIntensity)	0.177***		−0.222***	
	(0.057)		(0.072)	
log(Scope1ANDScope2)		0.029		−0.143**
		(0.034)		(0.057)
IK	1.607*	1.047	3.044*	3.185*
	(0.952)	(0.923)	(1.804)	(1.816)
log(BookToMarket)	0.125	0.064	0.277***	0.262**
	(0.154)	(0.158)	(0.105)	(0.105)
TANT	0.110	0.352**	0.872***	0.609**
	(0.192)	(0.167)	(0.311)	(0.282)
Leverage	0.435	0.457	−0.416	−0.259
	(0.460)	(0.461)	(0.592)	(0.584)
log(MEadj)	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	−0.025*	−0.027*	−0.167***	−0.162***
	(0.014)	(0.014)	(0.021)	(0.021)
ROE	−0.001	−0.001	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
TrumpDummy	0.844***	1.022**		
	(0.210)	(0.411)		
TrumpDummy * log(EmissionIntensity)	−0.135***			
	(0.042)			

TrumpDummy * log(Scope1ANDScope2)		-0.056^{**} (0.027)		
BidenDummy			1.559^{***} (0.313)	0.599 (0.744)
BidenDummy * log(EmissionIntensity)			0.008 (0.052)	
BidenDummy * log(Scope1ANDScope2)				0.070 (0.052)
Constant	-1.265^{***} (0.399)	-0.822 (0.547)	1.594^{***} (0.530)	2.531^{***} (0.883)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01	

6 Robustness

6.1 Variable Biasedness

A few biases related to emission levels are inherently controlled for in the model. Firstly, a potential size bias is controlled for by using a normalised emission measure, intensity, by dividing by revenue. Secondly, industry effects are also controlled for by including fixed effects variables for each of the business sectors included in the sample. Likewise, all regressions include year-fixed effects. Following the methodology of Hsu et al. (2022), all independent variables, excluding emission variables, are winsorized at the 1st and the 99th percentile, and then normalised to a mean of zero and a 1 standard deviation to reduce the effect of outliers.

6.2 Gauss-Markov Assumptions

Testing the Gauss-Markov assumptions of linear regressions, requires testing for heteroskedasticity and autocorrelation. Testing for heteroskedasticity using a Breusch-Pagan test showed that none of the regressions are likely suffering from heteroskedasticity. Additionally, a Durbin Watson (DW) test was performed to test for autocorrelation among error terms. If a model's error terms are positively correlated, the more common case in economic modelling, the true variance of the estimator will be underestimated, which in turn will overestimate the t-statistic of the estimator (Wooldridge 2018). Essentially, the estimator will be perceived as more precise than it actually is. The test statistics show that autocorrelation indeed is prevalent (t-value below 2) across all tests. The DW test statistics are reported in table VII in the appendix. To test the effects of autocorrelation, all regressions were tested with Newey-West standard errors (Newey, West 1987). The impact is seemingly minimal on the magnitude of the coefficients, but small a effect can be found on the significance levels of the coefficients. This effect, however, is not large enough to alter any conclusion of the results. The results of the regressions with Newey-West robust standard errors are reported in tables VIII and IX in the appendix.

6.3 Sample Size and Period Selection Robustness

The sample consisting of firms reporting continuously throughout the sample period 2012-2022 is limited to 130 firms. This selection of firms risks introducing a potentially material selection bias. Given the potential scrutiny a firm that reports relatively high emissions would face, firms that reported as early as 2012 may have been generally low-emitting. Combined with the findings of In, Park, et al. (2017) that carbon-efficient firms tend to be categorised as good in terms of financial performance, this selection would tilt the relationship negatively. To mitigate this specific selection bias, the same relationship was tested with all firms that reported during 2012-2022, i.e. not just firms that reported throughout the entire period but also firms that started reporting in 2016 or 2018, for example. While this unfortunately introduces a new bias regarding the type of firms that are choosing to report later on in the time period, it mitigates the specific 2012 selection bias. The result of the regression for the entire available sample of reporting firms is reported in Table V.

Table V

This table presents regression coefficients and standard errors for regressions testing hypothesis 1, i.e. the correlation between emissions and returns throughout the entire sample period 2012-2022. The sample is not limited to firms reporting continuously throughout the entire sample period. Dependent variable is monthly returns annualised, explanations for all independent variables are included in table VI in the appendix. Table includes results for regressions for both emission intensity and total emissions, as well as with and without sector-fixed effects.

	Dependent Variable: Monthly Returns (Annualised)			
	(1)	(2)	(3)	(4)
log(EmissionIntensity)	-0.067^{***}	0.009		

	(0.016)	(0.019)		
log(Scope1ANDScope2)			-0.029^{*}	0.005
			(0.016)	(0.018)
IK	1.214^{***}	1.075^{**}	1.257^{***}	1.076^{**}
	(0.428)	(0.465)	(0.432)	(0.464)
TANT	0.806^{***}	0.491^{***}	0.697^{***}	0.500^{***}
	(0.082)	(0.110)	(0.083)	(0.108)
Leverage	0.398^{**}	0.594^{***}	0.498^{***}	0.580^{***}
	(0.192)	(0.204)	(0.191)	(0.203)
log(MEadj)	-0.158^{***}	-0.171^{***}	-0.147^{***}	-0.174^{***}
	(0.028)	(0.029)	(0.031)	(0.033)
log(BookToMarket)	0.030	0.178^{***}	0.025	0.180^{***}
	(0.049)	(0.049)	(0.050)	(0.051)
ROA	-0.034^{***}	-0.056^{***}	-0.032^{***}	-0.057^{***}
	(0.006)	(0.007)	(0.006)	(0.007)
ROE	-0.002^{*}	-0.002^{**}	-0.002^{*}	-0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	4.183^{***}	6.913^{***}	4.039^{***}	6.946^{***}
	(0.672)	(2.636)	(0.688)	(2.643)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	No	Yes	No	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01	

This regression intends to test the robustness of the captured relationship between emissions and returns during our sample period, 2012-2022. The results suggest that a 10 per cent increase in emission intensity leads to a significant decrease of 0.67 per cent in annual returns, controlling for year-fixed effects and robust standard errors. When also controlling for sector fixed effects, the results suggest that a 10 per cent increase in emission intensity leads to an insignificant increase of 0.09 per cent in annual returns. Using total emissions instead of emission intensity, the results suggest that a 10 per cent increase in total emissions leads to an insignificant decrease of 0.29 per cent, controlling for year-fixed effects and robust standard errors. When also controlling for sector fixed effects, the results suggest that a 10 per cent increase in total emissions leads to an insignificant increase of 0.05 per cent in annual returns.

The regression somewhat supports the findings from the main tests. The relationship is significant when controlling for robust standard errors and year-fixed effects, with coefficients of similar magnitude and sign. However, they become insignificant and smaller in magnitude when controlling for sector-fixed effects. The similarity of the results would suggest that the results in the initial regression are unlikely to be entirely a consequence of the sample selection in 2012. However, as mentioned in section 4, firms reporting on carbon emissions are still doing so voluntarily, which could potentially introduce a self-selection bias, regardless of when firms are starting to report.

7 Discussion

7.1 Regression 1 - General Emission Return Relationship

Testing the general emission return relationship throughout the sample period 2012 to 2022, emissions seem to correlate negatively with returns, both when measured in intensity and total emissions. Controlling for year-fixed effects, both measures have a significant correlation with returns. However, when including sector-fixed effects, the relationship becomes strikingly weaker. This indicates that large parts of the seemingly negative relationship can be explained through business sector preferences, rather than emission levels. Existing literature is somewhat conflicting regarding the emission return relationship, with Bolton, Kacperczyk (2021) finding a positive relationship while several studies in varying settings finding a negative relationship (e.g. In et al. (2017), Pástor et al. (2022) or Matsumura et al. (2013)). However, as many of these studies, including The Pollution Premium by Hsu et al. (2022) conclude, risk-return theory would suggest a positive relationship to compensate for the additional risk.

In contrast to theory, existing literature has found several possible explanations for the empirical negative relationship. For example, In, Park, et al. (2017) find that carbon-efficient firms tend to be good in terms of financial performance, i.e. the doing good by doing well theory. This would imply that the better performance of low carbon exposure stocks is not a result of investors carbon specific risk preferences, but rather a result of overall more financially healthy companies. Pástor et al. (2022), who indeed find a "greenium", i.e. higher returns for green stocks compared to non-green, hypothesise that this could be explained by unexpected increasing climate concerns. While a theoretical explanation, it is particularly relevant with regard to *The Pollution Premium*-model. An increase in climate concerns with investors could theoretically be interpreted as a positive environmental signal shock that would increase the perceived possibility of strong policy. If this would happen continuously throughout the time period, the need for emission risk compensation would increase as climate concerns would increase. In turn, this puts negative pressure on prices, inducing a negative emission return relationship. As Pástor et al. assert, this is a reflection of realised returns, not necessarily lower expected returns for high-emission firms.

7.2 Regression 2 - Presidential Election Signal Shocks

This paper's second set of regressions aimed at testing how a shift of policy change probabilities affects stock returns depending on carbon exposure. As in *The Pollution Premium*, this paper has focused on the impact of the last two presidential elections, 2016 and 2020 as shocks to policy change probabilities. When controlling for year-fixed effects and sector-fixed effects, the Trump election has a significant, negative effect on the correlation between carbon emission intensity and stock returns. This is in line with what The Pollution Premium theory would suggest. As described in section 3, Trump can be interpreted to have observed a lower climate change cost signal, and so, by winning the election, he introduces a negative shock to the probability of a strong policy implementation. This reduces the risk of a costly event, to which investors would demand a lower risk compensation. Assuming efficient markets, this should instantly push prices up for heavily carbon-exposed firms, who, in the subsequent period, should earn lower returns. This regression included data over a two-year timespan, and the expected effect of the election that should dominate is indeed the subsequent lower returns, not the initial surge. Such a surge was documented by Ramelli et al (2021), where heavily carbon-exposed firms outperformed low-exposed firms in the month following the election. The result is also in line with the finding of Ilhan et al. (2021), where the cost to hedge against carbon tail risk was reduced following the Trump election win, indicating a reduced risk for a possible future policy change. By reducing the tail risk, investors should demand lower returns for high-exposure firms following the election, as indicated by the results of this test.

The Biden election, however, seems to lack the clear effect of the Trump election. Although positive, which is in line with the hypothesis, the significance levels of the correlation coefficients imply that a zero-correlation relationship cannot be discarded. This effect can potentially be explained by several reasons. Relative to Trump, the Biden election is more of a statistically blunt tool. Biden was the favoured candidate throughout the year before the election, it was only on the election day and the following days that the election became truly uncertain in outcome. By using monthly data, the tests are unlikely to capture this momentary uncertainty. Rather, any potential shocks to policy change probabilities could potentially have been accounted for by the forward-looking investors prior to the election, which would render the effects of the election weaker compared to those of the Trump election. Furthermore, as studied by Ramelli et al. (2021), carbon-responsible firms also fared well following the Trump election, which the authors hypothesised as investors betting on a policy rebound following Trump's tenure. In other words, following the period of lax regulation during Trump, investors expected the next President to compensate with stricter policies. This, again, would mean that the effect of Biden's election win was already accounted for by investors prior to the election, weakening the election shock to policy change probabilities compared to the Trump election.

Another viable criticism against using presidential elections is the fact that the president is not the single legislative power. Prior to both elections, the party of the winning candidate had a majority in the house of congress (History, Art and Archives - United States House of Representatives 2021). This risks reducing the extent of the shock, as the previous president may have faced difficulties implementing policy changes, be they relaxed or restrictive. As such, the attitude towards climate change of the winning candidate may already have been in place through congress majority, although the effect of this is highly uncertain.

7.3 Study Limitations

The most important limitation of this study is the restricted sample, as discussed in section 6.3. Only firms from the New York Stock Exchange reporting on carbon emissions every year for the period 2012-2022 were included in the sample. Another limitation is the lack of a standardised metric to measure carbon emissions and in consequence capture carbon exposure. Using revenue to normalise emissions is perhaps the most common way to normalise emissions and the measure most readily available to investors. However, as with any normalisation through firm characteristics, this risks capturing the relationship between the firm characteristic rather than through emissions. As such, there is a tradeoff between reliable and precise measures and the ability to study how investors view such information.

7.4 Further Research

The model suggested by Hsu et al. (2022) is, in our modest opinion, an intuitive and appealing way to model how policy probabilities affect risk compensation and stock returns. Extensions of this paper's study would naturally be a larger sample or other geographical areas. The use of other geographical restrictions would also allow for a greater variation in political shocks to policy probabilities. While the difficulties of using the presidential elections as shocks have been highlighted above, under the right conditions they can still prove to be viable statistically as indicated by Hsu et al. (2022) and the result of this paper. Another extension could be to use ratings provided by external parties, such as MSCI, which do not necessarily require firms to be self-reporting their sustainability measures. This could potentially mitigate the selection bias discussed in sections 4.1 and 6.3, while perhaps providing a more realistic measure of how investors view policy exposure. Such measures are not without limitations either, often being estimates whose accuracy can be questioned (Bolton, Halem, et al. 2022). To eliminate the issues with normalisation, as discussed in section 7.3, a possible method could be to use changes in emissions, rather than emissions in absolute terms, as done by In et al. (2019). In their empirical studies, Hsu et al. (2022), use a novel and innovative measure as a proxy for signal costs, and in extension policy change probabilities, namely, the aggregate growth in civil penalties against polluting firms in their empirical tests. Finding similar proxies within the realm of carbon exposure would also be interesting extensions in studying how policy change probabilities affect risk compensation and stock returns.

8 Conclusion

This paper aims to provide further research on the existence of a so-called carbon premium, the existence of a positive relationship between firms' carbon emissions and their stock returns. Further, this paper extends research and focuses on the impact of presidential elections, used as proxies for policy regime shift probability shocks, as modelled by Hsu et al. (2022). The result of this paper indicates that there is a negative relationship between firms' emissions and their stock returns. When controlling for sector-fixed effects, the relationship becomes less significant, implying that a large part of the variation in the data is explained by sector characteristics, rather than by emissions solely. When testing the relationship a year prior to and following the last two presidential elections, the effects of elections depend on the election in question. In the case of the 2016 Trump election win, the effect is a greater negative relationship between emissions and returns compared to the final year of President Obama's tenure. This is in line with the Pollution Premium model, where the lower possibility of a stricter carbon policy should induce a lower risk compensation for high-emitting firms. The effect of the Trump election is significant even when controlling for sector-fixed effects. In comparison, the Biden election has a less evident effect. Being a relatively more expected win, the Biden election win may have served as a less potent shock to policy shift probabilities. As indicated by Ramelli et al. (2021), some investors may also have already speculated on the return of stauncher carbon policies following Trump to compensate for his more lax approach. The paper's tests also reveal the difficulties of testing the relationship between firms' carbon emissions and stock returns. Data availability is somewhat restricted over a longer time period, and when available, it is generally reliant on self-reporting. As discussed throughout the paper, this may induce self-selection bias. While this is the same data that is available to investors, the bias may restrict the full variation of how investors view firms' emissions and their relation to firm-specific risk. Given the intuitive and comprehensive model suggested by Hsu et al. (2022), one key opportunity for further research is how to model signal shocks to policy change probabilities. Not directly observable, the challenge lies in finding novel proxies for how these probabilities may be observed by investors. Hsu et al. used corporate penalties to gauge the probability of stauncher pollution policies, finding similar proxies for carbon emissions could provide valuable insight into how policy uncertainties are accounted for by investors.

Although several of this paper's tests proved inconclusive or inconsistent with hypotheses, we want to emphasise that these are not inherently negative results. The results indeed contrast with the idea of a tradeoff between returns and carbon emissions. If high-emitting firms continuously provide lower returns, pressure from investors might be expected to accelerate the transition to greener technologies.

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A Appendix

Table VI

This table presents the variables included in the regressions testing hypothesis 1 and 2. The table includes variable names, their definitions, and their sources.

Variable	Definition	Source
Annual_RET	Monthly Returns based on adjusted stock prices, annualised	Yahoo Finance
EmissionIntensity	Emissions normalised by revenue (TON CO2 / Millions $ in Revenue)	Refinitive Eikon
Scope1ANDScope2	Total emissions, scope 1 + scope 2	Refinitive Eikon
IK	Capital expenditure / property, plant, and equipment	Refinitive Eikon
TANT	Property, plant, and equipment / Total assets	Refinitive Eikon
Leverage	(Current liabilities + Long term debt) / Total assets	Refinitive Eikon
MEadj	Market capitalization deflated by CPI	Refinitive Eikon Federal Reserve Economic Data
BookToMarket	The ratio of book equity to market capitalization	Refinitive Eikon
ROA	Return on assets (ROA) is operating income after depreciation scaled by total assets.	Refinitive Eikon
ROE	Return on equity (ROE) is operating income after depreciation scaled by total assets.	Refinitive Eikon
TrumpDummy	Equals 1 on the 9th of November 2016 (the day Trump was elected) and onwards and 0 before	
BidenDummy	Equals 1 on the 3rd of November 2020 (the day Biden was elected president) and onwards and 0 otherwise	

Table VII

This table presents results of the Durbin-Watson tests for autocorrelation of the papers' eight regressions, grouped by carbon emission measure, fixed effects, and election.

Regression		D-W	P-Value	Autocorrelation
Intensity	Year and Fixed	1.583	0	Yes
	Year and Sector Fixed	1.598	0	Yes
Total	Year Fixed	1.578	0	Yes
	Year and Sector Fixed	1.598	0	Yes
Intensity	Trump	1.424	0	Yes
	Biden	1.669	0	Yes
Total	Trump	1.427	0	Yes
	Biden	1.666	0	Yes

Table VIII

This table presents regression coefficients and Newey-West standard errors for regressions testing hypothesis 1, i.e. the correlation between emissions and returns throughout the entire sample period 2012-2022. Dependent variable is monthly returns annualised, explanations for all independent variables are included in table VI in the appendix. Table includes results for regressions for both emission intensity and total emissions, as well as with and without sector-fixed effects.

	Dependent Variable: Monthly Returns (Annualised)			
	(1)	(2)	(3)	(4)
log(EmissionIntensity)	-0.107^{***}	-0.041^{*}		
	(0.020)	(0.025)		
log(Scope1ANDScope2)			-0.052^{***}	0.006
			(0.019)	(0.021)
IK	0.038	-0.002	0.273	0.109
	(0.468)	(0.561)	(0.469)	(0.564)
TANT	0.554^{***}	0.307^{***}	0.436^{***}	0.207^{**}
	(0.085)	(0.122)	(0.088)	(0.115)
Leverage	-0.008	0.061	0.220	0.096
	(0.215)	((0.241)	(0.212)	(0.242)
log(MEadj)	-0.055^{**}	-0.105^{***}	-0.013	-0.112^{***}
	(0.027)	(0.032)	(0.030)	(0.037)
log(BookToMarket)	0.191^{***}	0.251^{***}	0.160^{***}	0.259^{***}
	(0.053)	(0.057)	(0.054)	(0.060)
ROA	-0.047^{***}	-0.050^{***}	-0.041^{***}	-0.047^{***}
	(0.006)	(0.007)	(0.006)	(0.007)

ROE	−0.001**	−0.001**	−0.001**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.142***	2.711***	1.340**	2.578***
	(0.700)	(0.791)	(0.691)	(0.815)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	No	Yes	No	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01

Table IX

This table presents regression coefficients and Newey-West standard errors for regressions testing hypothesis 2, i.e. the effect of president Trump and President Biden's election wins on the correlation between emissions and returns. Sample periods are one year prior and one year following the elections. Dependent variable is monthly returns annualised, explanations for all independent variables are included in table VI in the appendix. Table includes results for regressions for both emission intensity and total emission, for both the Trump election regression and the Biden election regression. All regressions include both year and sector-fixed effects.

	Dependent Variable: Monthly Returns (Annualised)			
	(1)	(2)	(3)	(4)
log(EmissionIntensity)	0.177**		−0.222***	
	(0.079)		(0.069)	
log(Scope1ANDScope2)		0.029		−0.143**
		(0.039)		(0.057)
IK	1.607	1.047	3.044*	3.185*
	(1.051)	(1.039)	(1.828)	(1.842)
log(BookToMarket)	0.125	0.064	0.277***	0.262**
	(0.199)	(0.213)	(0.107)	(0.107)
TANT	0.110	0.352	0.872***	0.609**
	(0.258)	(0.224)	(0.312)	(0.274)
Leverage	0.435	0.457	−0.416	−0.259
	(0.581)	(0.591)	(0.561)	(0.547)
log(MEadj)	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	−0.025	−0.027*	−0.167***	−0.162***
	(0.016)	(0.016)	(0.021)	(0.021)
ROE	−0.001	−0.001	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
TrumpDummy	0.844***	1.022**		

	(0.249)	(0.440)		
TrumpDummy * log(EmissionIntensity)	-0.135^{**}			
	(0.053)			
TrumpDummy * log(Scope1ANDScope2)		-0.056^{*}		
		(0.029)		
BidenDummy			1.559^{***}	0.599
			(0.335)	(0.878)
BidenDummy * log(EmissionIntensity)			0.008	
			(0.054)	
BidenDummy * log(Scope1ANDScope2)				0.070
				(0.062)
Constant	-1.265^{**}	-0.822	1.594^{***}	2.531^{***}
	(0.522)	(0.606)	(0.487)	(0.884)
Year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01	