BIDDING ON BROWN WHILE ASKING FOR GREEN

AN EVENT STUDY OF THE IMPACT OF CARBON EMISSIONS ON STOCK RETURNS FOLLOWING THE 2016 U.S. PRESIDENTIAL ELECTION

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Abstract

The election of Donald J. Trump as the U.S. president in 2016 shifted people's expectations drastically. Hillary Clinton was expected to win, according to betting polls, with asset prices mainly reflecting such an outcome. In a world where stocks of firms with higher levels of carbon dioxide emissions are more exposed to the risks associated with climate regulations, the victory of climate-sceptic Trump would be beneficial to firms emitting higher levels of carbon emissions. This paper investigates the impact of carbon emissions on U.S. stock returns following the election with the aim to understand how investors price risk associated with expected changes in climate regulations. We conclude that, when including relevant controls for firm characteristics, investors rewarded firms emitting higher levels of carbon emissions following the election.

Keywords

Event study; Market efficiency; Policy shifts; Climate change; Climate regulatory risk

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1. Introduction

1.1. Background

The latest report from the Intergovernmental Panel on Climate Change (IPCC), released on February 28, 2022, emphasizes that the world - governments, corporates and individuals - are not doing enough to mitigate climate change (IPCC, 2022).

In recent years, the world has seen an increasing amount of corporate initiatives aiming to contribute to a more sustainable economy. The financial sector, including banks and investors, try to contribute to the mitigation of climate change, by reallocating capital (Wall Street Journal, 2021). More than 2000 global institutional investors have signed the United Nations supported principles for responsible investment that incorporate ESG aspects into investment practice (Principles for Responsible Investment, 2022). Governments are trying to do their part, pledging to follow the Paris Agreement, signed in November 2016. Their ambitions have further been raised since the latest UN's Climate Change Conference, COP26, held in October 2021. The role of governments in the transition to a more sustainable environment is essential, encouraging businesses to align their activities and investments with climate goals through laws and regulations. (EY, 2021)

The aforementioned suggests that companies face an increasing exposure to *transition risk*, highlighting the importance of adapting their business activities in line with regulators and investors' requirements to remain competitive in the future. Transition risk is used as a term by the IPCC to describe risks associated with the transition to a low carbon economy. This might entail any extensive policy, legal, technology and market changes to address mitigation and adaptation requirements related to climate change (IPCC, 2020). An essential component of the transition risk that companies face are the risks associated with future climate policies and regulations, often referred to as *climate regulatory risk.* In a recent survey, professionals in finance, public sector regulators and policy economists has, in fact, identified this climate regulatory risk as the most essential climate risk in the coming years to investors and corporations, (Stroebel & Wurgler, 2021)

With the increasing amount of climate regulations being implemented worldwide, companies' different exposure to climate regulatory risk becomes valuable and timely to investigate. By studying an event that shifted expectations on climate policies, one can measure how stocks of firms with different exposure to this risk reacts to shifts in climate policies, providing insight into how investors will act on climate policies in the future.

Previous financial literature concludes that investors already price in the risk associated with carbon emissions, meaning investors demand a premium for holding stocks with higher carbon emissions through a return premium (Bolton & Kacperczyk, 2021). Other studies have evolved around the uncertainty associated with changes to climate policies and conclude that reduced uncertainty regarding climate policies is in fact reflected in the market (Ilhan, Sautner & Vilkov, 2021).

Since this climate regulatory risk has been shown to be more likely to affect firms that emit higher levels of carbon emissions, higher levels of carbon emissions should be associated with an increased exposure to climate regulatory risk. (Ilhan et al., 2021) Building on the aforementioned studies and this global market concern, we want to specifically investigate how investors price in the regulatory risk associated with carbon emissions of firms.

1.2. Research question and hypothesis

The research question we hence aim to answer is how a shift in climate policy expectations affect returns depending on the firm's level of carbon emissions.

We hypothesize that investors perceived the election outcome to reduce the climate regulatory risk for firms. Firms emitting higher levels of carbon emissions, being the most exposed to the climate regulatory risk, are expected to experience a relatively greater regulatory relief as Trump was elected president compared to firms emitting lower levels of carbon emissions. Therefore, we expect stocks of higher emitting firms to earn higher abnormal returns on average following the election, becoming the relative winners.

The shift in climate policy expectations is measured through the U.S. presidential election shock, held on November 8, 2016, when Donald J. Trump, rather surprisingly, was elected president. This election is especially interesting to investigate as it is the only time, to this day, in U.S. modern history to see a radically climate skeptic president come to power in an era in which climate change and sustainability has become increasingly important.

By using the event study methodology of Wagner, Zeckhauser and Ziegler (2018), studying how expectations on corporate taxes affected stock prices following the election, we study the impact of climate policy expectations on U.S. stock returns by adapting their methodology to a measure of carbon emissions. Our findings suggest that, for some time periods measured, firms emitting higher levels of carbon emissions earn higher abnormal returns following the 2016 U.S. presidential election.

2. Previous financial literature on carbon emissions and climate regulatory risk

2.1. Asset prices and environmental performance metrics

Due to the increased awareness of climate change in the international community, the financial literature on sustainability, ESG, and the effect of climate change on asset prices has increased during recent years. However, the phenomenon studied and the findings differ, which is why it is a relevant area of research to contribute to.

Some scholars focus on showing the broader relationship between investor preferences and ESG scores (Pedersen, Fitzgibbons & Pomorski, 2021) while others study how asset prices are affected by uncertainty regarding a firm's ESG profile (Avramov, Cheng, Lioui and Tarelli, 2021). Pedersen et al. (2021) use carbon emissions as a proxy for E in constructing their "ESG efficient frontier", finding that some ESG-motivated investors seek portfolios with less carbon emissions. With the measure of carbon emissions being a part of the E in many ESG metrics (Refinitiv, 2022), these studies highlight the increasing importance of researching the relationship between publicly available ESG data and firm performance. We contribute to this literature through a deep dive in the measure of carbon emissions specifically.

Studies have found that in equilibrium, agents prefer green assets. Hence, the study suggests that firms generating positive externalities for society, have low expected returns because investors enjoy holding them as they hedge climate risk (Pastor, Stambaugh and Taylor, 2021).

For the more specific relationship of carbon emissions and financial performance, Azar, Duro, Kadach and Ormazabal (2021) find a strong negative association between large private equity firms' holdings and carbon emissions, especially during the past years. Another study, which we build much of our work upon, is the study on how carbon emissions affect the cross-section of U.S. stock returns. Bolton & Kacperczyk identify a positive relationship between the cross section of U.S. firms' carbon emissions and its stock returns over time, concluding that investors demand a "carbon risk premium". (Bolton & Kacperczyk 2021) Contrasting Bolton & Kacperczyk findings, Garvey, Iyer and Nash (2018) and In, Park and Monk (2019) find that portfolios that are long stocks of companies with low carbon emissions and short stocks of companies with high emissions generate positive abnormal returns. This is referred to as the "carbon alpha hypothesis".

2.2. Climate policy uncertainty

Other financial literature on climate risks includes the study by Engle, Giglio, Kelly, Lee and Stroebel (2020), exploring the subject of hedging climate change risk, including the associated regulatory risk. Barnett, Brock and Hansen (2020) examine the pricing uncertainty induced by climate change and provide a framework for this in the context of social decision-making.

The topic covered in the study by Ilhan et. al (2021) is most closely related to ours, measuring how climate policy uncertainty is priced in the option market. They research how the cost of option protection against downside tail risk is larger for firms with more carbon-intensive business models. In their study, they refer to the framework provided by Kelly, Pastor and Veronesi (2015), suggesting that while investors can only learn how policies will impact asset prices when a new policy is actually adopted, *political signals* allow them to learn about political costs before the implementation of a new policy. We use this theoretical framework of political signals in our study to analyze how political signals affected investor expectations as Trump became elected president. By measuring stock returns, a more short-term and frequently traded security compared to options, we differ from Ilhan et. Al in this sense.

Furthermore, Ramelli, Wagner, Zeckhauser and Ziegler (2021) study climate policy uncertainty and stock returns. This study is similar to ours in many aspects, although we differ by studying a different measure of carbon emissions. While we use the total level of carbon emissions, they study carbon intensity (total emissions divided by market value of equity). Furthermore, we aim to measure the more long-term effects of Trump being elected, whereas they focus on short term effects. The recent publication of Ramelli et al. (2021) highlights the relevance of our study and the importance of research on climate policy uncertainty.

3. Event study methodology

The U.S. presidential election in 2016, being one of the most recent events that amplified climate policy uncertainty through its surprising outcome, is a suitable event for studying whether investors price climate regulatory risk.

3.1. Market efficiency hypothesis

According to the market efficiency hypothesis, market-based asset prices should reflect all information available (Fama, 1970). The assumption of efficient markets is therefore essential for event studies, requiring the market to respond immediately to the event for it to be possible to study the associated price change of assets. Investigating daily stock returns as part of our study amplifies the importance of this assumption since an immediate price reaction is expected.

3.2. Event study on the Trump election

Using the event study methodology, as provided by Wagner et al. (2018), a specific event's impact on investor behavior can be analyzed by observing the associated impact on company stock prices. To be able to investigate the impact of an event on company stock prices, the information that the event reveals should optimally be considered new to the market. In the context of the 2016 U.S. presidential election, there were two important aspects indicating the event was a shock to investors.

Firstly, the likelihood of Trump winning was considered significantly low and secondly, his climate political agenda differed significantly from the alternative candidate, Hillary Clinton. The assumed chances of Trump winning were low even on the morning of the election day (17% on Betfair), indicating that the election outcome came as a surprise to many observers. In an alternative scenario, where the outcome of the election had been certain prior to the election, no reaction to stock prices would be observed following the election. Furthermore, Clinton’s and Trump’s different approaches to climate change and climate policies had become clear to voters already prior to the election (Trump, 2016). Neither would the stock prices react following the election if the climate political agenda of the two candidates were alike or similar, since the climate politics to be pursued would be certain regardless of who was elected president.

In accordance with the market efficiency theory, in their tax study, Wagner et al. (2018) expected the change in asset prices to reflect the difference in expected discounted payoff between the two election outcomes, as well as the probability of the outcome prior to the election. This holds for our study as well and is illustrated in the following formulas.

$$E(P_i) = \pi_C P_{i,C} + \pi_T P_{i,T} \qquad \text{Equation 1.}$$

$E(P_i)$ is the expected price of asset i prior to the election. π_C is the ex-ante probability that Clinton wins the election. $P_{i,C}$ is the expected price of asset i given that Clinton wins, π_T is the ex-ante probability that Trump wins and $P_{i,T}$ is the expected price given that Trump wins the election. The above equation shows that given that the probability of Trump winning is low, the expected price of an asset mainly reflects a world where Clinton wins.

This following equation (Equation 2) then shows that the price change after the election is the difference between the expected prices for the two election outcomes multiplied with the ex-ante probability that Trump would not win, representing the election surprise.

$$\Delta P_i = P_{i,T} - E(P_i) = (P_{i,T} - P_{i,C})(1 - \pi_T) \qquad \text{Equation 2.}$$

Where ΔP_i is the difference between the actual price of asset i after the election outcome became known and the expected price of asset i prior to the election. $P_{i,T}$ is the price of asset i given that Trump wins, $E(P_i)$ is the expected price of asset i prior to the election, $P_{i,C}$ is the price of asset i given that Clinton wins the election and π_T is the ex-ante probability that Trump wins the election.

The shock of the election outcome is the same across assets. However, given the different probabilities, different assets will respond differently depending on which of the election outcomes (Trump or Clinton) the asset was expected to benefit from and to what extent. Hence, these theoretical implications of the election makes it possible to study the reaction of asset prices given a specific firm characteristic that would respond differently depending on who won. This can be measured through abnormal returns, as suggested by Equation 2, being the difference in the realized and expected return after the election. Hence, using abnormal returns as our variable of interest allows U.S. the study effect of this certain event across assets. (Wagner et al., 2018)

3.2.1. Disadvantages of the Trump election

Noteworthy is that there are a few disadvantages of using the 2016 U.S. presidential election as an event to study. Firstly, except for the candidates' differing views on climate issues, the two candidates also differed in many other aspects of their politics. Consequently, the election outcome of Trump changed expectations about many things, besides those on climate regulations.

Trump had stated that he aimed to withdraw from the Paris Agreement (The New York Times, 2016) as well as end the Clean Power Plan (Donald J. Trump for President Inc, 2016). Despite this, the climate policies that Trump was to ultimately implement, or roll back, were highly uncertain which makes it complex to know for certain what people actually expected from him. Hence, this becomes a second disadvantage of using this event.

Another disadvantage to the event, which is more specific to our purpose of study, is that the Paris Agreement came into force a few days before the election on November 4, 2016 (UNFCCC, 2022). The Paris Agreement, being one of the first international treaties on climate change, could thus also have affected the stock prices in the U.S. at the time. If that is the case, one would expect investors to believe future policies to affect higher-emitting firms negatively following this agreement. Hence, this event might have reduced or even canceled out the impact of the U.S. election outcome.

However, it could be argued that the implementation of the Paris Agreement was not new information to the market since it became known that the agreement would come into force already when it was signed in December 2015. It is therefore reasonable to assume that the

Paris Agreement should have been priced into the market already before the election and therefore not have any major impact on our study, although we can't eliminate the potential effect entirely.

4. Data and empirical strategy

4.1. Data and sample

The sample of U.S. companies used in this study is a result of having matched three datasets necessary to perform our regressions of interest. Primarily, the set of companies in our sample cover stocks traded in the U.S. (with the U.S. as "Country of Exchange") that has carbon emissions data available for the financial year of 2016 retreived from the Thomson Reuters Refinitiv ESG database (hereinafter, referred to as Refinitiv). After having obtained the necessary yearly accounting data as well as daily returns data from the database Wharton Research Data Services (WRDS), we matched all these three datasets together, ending up with a final sample of 1,495 firms.

The data of carbon emissions obtained from Refinitiv is the measure of "Estimated CO2 Emissions Equivalent Total", which provides either reported or estimated carbon emissions depending on the availability of companies' carbon emissions data. When reported carbon emissions data is not available, Refinitiv follows a certain methodology to calculate an estimated value. Refinitiv's methodology of calculating the CO2 emissions of a company is conducted in four steps. Firstly, if there is available carbon emissions data reported by the company, Refinitiv provides the reported data. Secondly, if a company has not yet reported its total CO2 emissions for the current year, then the latest reported CO2 emissions data is used, scaled by the number of employees and sales for the year of interest through a comprehensive model. Thirdly, if none of the aforementioned is possible to compute, the latest total energy consumed by the company is used to calculate the emissions. Lastly, if none of the above can be provided, a "median model" is triggered using an industry benchmark. A more thorough explanation of how these models work in detail can be found on Refinitiv's webpage, with a link provided in the References. (Refinitiv, 2022)

Using the ticker symbol of the companies in our sample, "TIC", as the company identifier, daily returns data (the holding period return variable "RET" from CRSP's database 'Daily Stock File') was collected through WRDS. This was downloaded for the full period of interest, of 30 September 2015 - 28 April 2017.

The list of companies with available emissions data, obtained from Refinitiv, was used to retrieve the accounting data used for the computation of control variables. These were downloaded from Compustat's database 'Fundamentals Annually' through WRDS for the fiscal year of 2015. With regard to the event in our study taking place at the end of 2016, accounting data reported for the fiscal year of 2015 makes sense to use since it should have been disclosed to investors. For the companies with financial years deviating from the average fiscal year (Jan-Dec), we make sure no accounting data is reported after November 2016, so that all accounting data used in our regressions has been available to investors before the election in November 2016.

From Compustat, we retrieved the following variables: market capitalization (MKTVT), Net Income (NI), Total Long-Term Debt (DLTT), Debt in Current Liabilities (DLC), Total Assets (TA), Sales Net (SALE), Earnings per share including extraordinary items (EPSPI), Capital

Expenditures - Total (CAPEX), Stockholder's Equity (SEQ), Balance Sheet Deferred Taxes and Investment Tax Credit (TXDITC), Preferred stock (PSTK) Total Property Plant and Equipment (PPENT), GIC Industry Sector (GSECTOR) and Gic Industry (GIND).

When there were several metrics to choose from representing the same desired variable, the logic followed was to extract the metric available to investors *as reported* in the books. For example, Compustat suggests that the EPSPI variable is as reported to investors (Compustat, 2022).

Based on the data sources that were available to us, we believe that the final sample retrieved of 1,495 companies covers all companies with the U.S. as their country of exchange with all available data to perform our regressions for the specific period of interest.

4.2. Regression over various time periods

Following the methodology of Wagner et al. (2018), abnormal returns are regressed on firm characteristics. In contrast to Wagner et al. (2018), we replaced their tax metrics, as they intended to measure the impact of tax metrics on stock returns following the election, with our variable of carbon emissions. Finally, the control variables were added in the final regression, displayed in Equation 3 below.

The following regression is run across different time periods.

$$RET_{i,t} = a_0 + a_1 LN\ (TOT\ Emissions)_{i,t} + a_2 Controls_{i,t-1} + \varepsilon_{i,t} \qquad \text{Equation 3.}$$

In the above formula, $RET_{i,t}$ is either the abnormal or cumulative abnormal return (AR or CAR) or the raw or cumulative raw return (R or CR) of firm *i* of day *t* or until day *t*. $Controls_{i,t-1}$ includes firm-specific variables further explained in section 4.3.2.The regressions are conducted both with and without controls for industry-fixed effects. The coefficient of interest is a_1.

4.2.1. Time periods chosen to study

The time periods we run our regressions on are based on the reasoning of Wagner et al. (2018) once again.

The time periods we run our regressions on are then as follows.

$t_1 = 9\ November\ 2016\ (1\ day\ after\ the\ election)$
$t_2 = 10\ November\ 2016\ (2\ days\ after\ the\ election)$
$t_3 = 18\ November\ 2016\ (10\ days\ after\ the\ election)$
$t_4 = 9\ November\ 2016 - 30\ December\ 2016$
$t_5 = 9\ November\ 2016 - 28\ Febuary\ 2017$
$t_6 = 9\ November\ 2016 - 28\ April\ 2017$

The regressions were run across these several different time periods for a number of reasons. Firstly, the market may need time to digest new information as it becomes available to investors. For a large and impactful event such as the election, this becomes even more relevant, indicating when investors actually reacted to a shift in policy expectations specifically for climate policies. It seems as if expectations about what policies the Trump administration would in fact implement became clearer during the time following the election, looking at the news media of this time, why it is interesting to look at both shorter and longer horizons.

Following the reasoning outlined above, the variable of interest is obtained across six different time periods. For the periods t1-t3, the regressions are run using daily abnormal returns, respectively raw returns. For the time periods of t4-t6, the regressions are run using cumulative and cumulative abnormal returns.

In order to measure the short-term reaction, the regressions were run on one day, two days and respectively ten days following the election. The long-term effects were measured through regressing the cumulative returns through the year-end, the two-month period after year-end until February 28 2017 as well as the four-month period after year-end until April 28 2017. The day of April 28 2017 also marks Trump's hundredth day in office. As suggested by Wagner et al. (2018), this is an appropriate ending point of the studied time horizon, since this is an often cited day in newspapers across the U.S., well known to investors. At this point, the media can often provide analysis on how the newly president-elect has performed. In the study of Wagner et al. (2018), little actually happened in terms of tax policies before this date. However, in the case of Trump and climate policies, some things did actually happen until April 28 2017 that might have impacted stock returns with respect to carbon emissions. In fact, even as early as December 7 2016, expectations might have shifted even further as Trump assigned the climate denialist Chris Pruitt as head of the U.S. Environment Protection Agency (The New York Times, 2016), which makes the measuring of the year-end reaction specifically motivated for our study.

4.3. Variables

4.3.1. Dependent variables

Following the methodology of Wagner et al. (2018), the variable of interest is abnormal returns and cumulative abnormal returns. The abnormal returns are computed using the Fama-French three-factor model to calculate expected returns, which is then subtracted from realized returns to obtain abnormal returns, as shown in Equation 4. For the sake of comparison, and in order to see if the findings from the regressions using abnormal returns also hold for raw returns, we additionally run the regressions with unadjusted raw or cumulative raw returns as the variable of interest.

$$AR_{i,t} = R_{i,t} - E(R)_{i,t} \qquad \text{Equation 4.}$$

Where $AR_{i,t}$ is the abnormal return for firm i at day t, $R_{i,t}$ is the realized return for firm i at day t and $E(R)_{i,t}$ is the expected return for firm i at day t.

For the cumulative abnormal return, the CAR is measured through the equation below.

$$CAR_{i,t_1;t_k} = \sum_{t=t_1}^{t_k} AR_{i,t} \qquad \text{Equation 5.}$$

Where $CAR_{i,t_1;t_k}$ is the cumulative abnormal return for firm i for the period from day t_1 to day t_k. $AR_{i,t}$ is the abnormal return for firm i at day t which is any day during the period from day t_1 to day t_k. The cumulative raw return is calculated as shown in Formula 1 in Appendix.

To highlight the value of the Fama-French model, compared to the Capital Asset Pricing Model (CAPM) as an asset pricing model, Fama-French also controls for the "size" (Small-Minus-Big (SMB)) and "value" (High-Minus-Low (HML)) risk factors in addition to the traditional market factor as in CAPM. In essence, since Fama and French has historically found that small cap stocks generally outperform big cap stocks and stocks with a high book-to-market (B/M) outperform those with a low one, including these factors of SMB and HML further controls for this historical tendency. Consequently, the Fama-French three-factor model is able to provide additional explanatory value and has empirically shown to be superior at predicting stock returns. (Fama, 1970)

During the sample period, value stocks, i.e. those with a high B/M, outperform growth stocks and small-cap stocks do outperform large-cap stocks. Hence, it must be noted that there is a risk that this outperformance may be driven by expectations on climate policies. In such a case, one should expect to find a positive correlation between the individual firms' loadings on each of the Fama-French factors and carbon emissions. As Wagner et al. (2018) points out, in the case of correlation, the impact of the coefficient of interest on returns would be underestimated. Following Wagner et al. (2018), we therefore investigate whether firms' level of carbon emissions (natural log of) correlate with their respective loadings on the size-, value- and market- factors. The results of these correlations are displayed in Figure A1 to A3 in the Appendix. Although loadings on stock's individual value factors seem to correlate somewhat with their carbon emissions levels, carbon emissions are seemingly not the sole driver of the performance on the size-, value- and market factors. Additionally, Bolton and Kacperczyk (2021) find that firm-level emissions are related to firms' size and growth opportunities, highlighting the value of including SMB and HML factors in regressions along with carbon emissions. To conclude, we can expect controlling for size- and value risk in accordance with the Fama-French model to provide explanatory value to our regressions.

In order to obtain abnormal returns, the expected returns in accordance with the Fama-French model were calculated. As a first step, this implies calculating each individual stock's loadings (or betas) on the Fama-French factors. (Fama, 1970). An individual stock's betas correspond to the correlation between a stock's daily excess returns and the value, (HML_t) , size (SMB_t) and market $\left(r_{m,t} - r_{f,t}\right)$ factors over an *estimation window*. Following the methodology in the study by Wagner et al. (2018), the estimation window used is the period from September 30 2015 - October 1 2016.

The individual factor betas were computed using the following equation, running an OLS regression across the estimation window, regressing each firm's excess returns on the daily Fama-French factor returns.

$$E(r_{i,t}) - r_{f,t} = \beta_1^i(r_{m,t} - r_{f,t}) + \beta_2^i(SMB_t) + \beta_3^i(HML_t) + \varepsilon_{i,t} \quad \text{Equation 6.}$$

Where $E(r_{i,t}) - r_{f,t}$ is the daily excess return for firm i at day t, $(r_{m,t} - r_{f,t})$ is the market factor returns of day t, SMB_t is the size factor returns of day t and HML_t is the value factor return of day t. $\beta_{1,2,3}^i$ are the factor loadings for each firm i which are ultimately obtained.

The Fama-French daily factor returns and the daily risk-free rate ($r_{f,t}$) are obtained from Ken French's website for the given estimation window. Following Equation 6, the individual firm betas are then used to compute the expected returns for each firm where $E(r_{i,t})$ is the expected return. The expected returns are then the result of taking the betas extracted from the previous regression for each firm, multiplied with the actual daily factor returns. The daily factor betas and $r_{f,t}$ is retrieved from Kenneth French's website, across the total period of t_1-t_6.

$$E(r_{i,t}) = \beta_1^i(r_{m,t} - r_{f,t}) + \beta_2^i(SMB_t) + \beta_3^i(HML_t) + \varepsilon_{i,t} \quad \text{Equation 7.}$$

Where $E(r_{i,t})$ is the expected return of firm i at day t, $r_{f,t}$ is the risk-free rate at day t, $(r_{m,t} - r_{f,t})$ is the market risk premium at day t, SMB_t is the size premium at day t and HML_t is the value premium at day t. $\beta_{1,2,3}^i$ are the factor loadings for firm i.

As a final step, we compute the daily abnormal returns or cumulative returns across the time periods we are interested in observing, covering the time period from 9 Nov 2016 - 28 April 2017. The abnormal returns are calculated as in Equation 4 and the cumulative abnormal returns as in Equation 5.

All the above computations are done in R.

4.3.2. Independent variables

The carbon emissions variable we use is the level of a firm's carbon emissions in tons of CO2. We retrieved this data for the fiscal year of 2015. However, the sample becomes very limited in size using this data. Building upon the reasoning of previous literature, suggesting that carbon emissions are highly persistent over time across larger samples, suggest that it is reasonable to use the more extensive carbon emissions data for 2016 instead, since it should yield similar results (Bolton & Kacperczyk, 2021). When having run the regression with 2015 data, we can see that we retrieve similar to when using 2016 but insignificant results across all variables, possibly because of the small sample size. Hence, the data used in the regressions is from 2016. The descriptive statistics of our sample is shown in Table 1.

Table 1. Descriptive Statistics

Variable	Obs	Min	P25	Median	Mean	P75	Max	Std. Dev.
Panel A. Returns								
Raw return on Nov 9	1,495	-0.373	-0.024	-0.005	-0.003	0.016	0.423	0.045
Raw return on Nov 10	1,495	-0.313	-0.008	0.014	0.014	0.035	0.346	0.036
Raw return on Nov 18	1,495	0,000	-0.006	0.002	0.002	0.01	0.121	0.018
CR from Nov 9 to Dec 30	1,495	-0.746	-0.043	0.012	0.019	0.07	1.074	0.120
CR from Nov 9 to Feb 28	1,495	0.138	0.043	0.038	0.018	0.157	0.131	0.157
CR from Nov 9 to Apr 28	1,495	-1,000	-0.043	0.012	0.019	0.07	1.074	0.138
AR (Fama-French adjusted) on Nov 9	1,495	-0.373	-0.024	-0.005	-0.003	0.016	0.423	0.043
AR (Fama-French adjusted) on Nov 10	1,495	-0.266	-0.020	0.001	-0.001	0.020	0.306	0.038
AR (Fama-French adjusted) on Nov 18	1,495	-0.170	-0.008	-0.001	-0.001	0.008	0.106	0.018
CAR (Fama-French adjusted) from Nov 9 to Dec 30	1,495	-1.194	-0.081	0.000	-0.011	0.076	0.926	0.157
CAR (Fama-French adjusted) from Nov 9 to Feb 28	1,495	-0.839	-0.062	-0.003	0.006	0.062	1.168	0.131
CAR (Fama-French adjusted) from Nov 9 to Apr 28	1,495	-0.887	-0.056	-0.001	-0.002	0.049	0.965	0.118
Panel B. Firm loadings on Fama-French factors								
Loading on market excess returns (market beta)	1,495	-0.748	0.793	1.006	1.042	1.238	2.73	0.387
Loading on size factor returns (size beta)	1,495	-0.858	0.149	0.575	0.669	1.047	8.652	0.778
Loading on value factor returns (value beta)	1,495	-3.128	-0.249	0.135	0.175	0.542	4.643	0.848
Panel C. Emission variables								
LN (Carbon Emissions (tons CO2e))	1,495	5.107	8.893	10.551	10.775	12.377	18.620	2.56
Carbon emissions (tons CO2)	1,495	0	7 162	38 182	1 421 908	236 189	122 000 000	7 261 172
Panel D: Firm-independent variables								
LNSIZE	1,495	3.346	6.672	7.673	7.829	8.813	13.33	1.585
B/M (winsorized at 2.5%)	1,495	-2.979	0.253	0.442	0.557	0.748	7.261	0.491
LEVERAGE (winsorized at 2.5%)	1,495	0,000	0.067	0.225	0.247	0.384	0.991	0.204
INVEST/A (winsorized at 2.5%)	1,495	0,000	0.005	0.022	0.038	0.051	0.556	0.052
ROE (winsorized at 2.5%)	1,495	-32.063	0.037	0.102	0.101	0.18	22.214	1.132
LNPPE	1,495	-3.058	4.055	5.54	5.565	7.102	12.436	2.374
SALESGR (winsorized at 0.5%)	1,495	-1,000	-0.034	0.042	0.106	0.137	20.934	0.668
EPSGR (winsorized at 0.5%)	1,495	-85.609	-0.392	0.022	0.092	0.282	162,000	7.910

This table reports on the descriptive statistics of our sample of U.S. firms. Panel A: In the paper, all returns are denominated in nominal values and not percentage points. AR indicates abnormal return.

Panel B: The market, size and value betas are calculated as mentioned in section 2.2. Panel C: The data on firm carbon emissions from Thomson Reuters Refinitiv, taken the natural log of them as explained in section 4.2.2 and here further displayed as the total level in tons of carbon emissions for comprehension.

Panel D: The following metrics are used as control variables and are directly downloaded or computed from data from Compustat ad mentioned in section 4.2.2.: LNSIZE, B/M, LEVERAGE, INVEST/A, ROE, LNPEE, SALESGR, EPSGR.

The firm-independent variables, used as controls, are the following: market capitalization (logarithmized using the natural logarithm, referred to as LNSIZE), return on equity (ROE), leverage (LEVERAGE), book-to-market ratio (B/M), sales growth (SALESGR), EPS growth (EPSGR), capital expenditures in percentage of assets (INVEST/A) and total property, plant and equipment (logarithmized using the natural logarithm, referred to as LNPPE).

ROE is calculated as Net Income(t)/Book Value of Equity(t-1)), Leverage is calculated by adding Total Long-Term Debt (DLTT) and Debt in Current Liabilities (DLC) together, then divided by Total Assets (AT), as done in Wagner et al. (2018). Sales growth (SALESGR) is calculated as the yearly dollar change in firm revenue divided by last year's revenue ((Sales Net(t)-Sales Net(t-1))/Sales Net(t-1)). EPSGR is calculated by dividing the yearly dollar change in EPS by the previous year's EPS ((EPS(t)-EPS(t-1))/EPS(t-1)). INVEST/A is calculated as Capital Expenditures - Total (CAPEX) divided by total assets (AT). B/M is the book-to-market ratio, calculated as the book value of equity (BVE) at the end of year t divided by market value of equity at the end of year t (MKTVT as from Compustat). The book value of equity (BVE), used for the calculation of ROE and B/M calculation, is calculated using the methodology of Fama and French (French, 2022). Following this definition, the book value of equity is calculated as the value of stockholder's equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock.

Since the explanatory variable we were interested in investigating differs from the Wagner et al. (2018) study, we decided to base the selection of control variables on the study by Bolton & Kacperczyk (2021), also having analyzed carbon emissions effect on stock returns. In that way, we were able to control that the relationship between the carbon emission variable and returns were not due to other factors highly related to carbon emissions. For example, it is reasonable to believe that size, or market capitalization, is predicted to be highly related to the level of carbon emissions, why it became reasonable to use this as a control. Furthermore, B/M, Leverage, INVEST/A are also evidently highly correlated with the measure of carbon emissions, which Bolton & Kacperczyk (2021) find by regressing their carbon emission variable of interest on these various firm characteristics. To make sure our usage of these control variables coincides with theirs, we also run such a regression, with the results shown in table A1in the Appendix, yielding a high R-squared (0.99) similar to theirs, confirming our choice.

Finally, in order to avoid outliers, B/M, LEVERAGE, INVEST/A and ROE were winzorized at 2.5 %. SALESGR and EPSGR were winsorized at 0.5 % before having used these as final controls in our regressions.

Using the Global Industry Classification Standard (GICS) sector classification, we were able to divide the firms into several industries, and control for industry-fixed effects. Controlling for industry-fixed effects is reasonable since one might hypothesize there to be a difference across investor preferences across industries with regard to carbon emissions. As Bolton & Kacperczyk (2021) points out, one must make a reasonable division of industries in order for the industry-fixed effects to have meaning. That is, controlling for industry-fixed effects would be meaningless if the classification in theory would be so coarse so that it would include all firms in one industry or so fine that it only includes one firm per each industry.

Regarding the small sample size, when dividing it per GICS industry (which are 69 in total), the division becomes too fine, where some industries simply include only 0, 1 or 2 firms.

Hence, after running this check, we finally run the industry-fixed effects using the GICS sector classification instead. That results in the following 11 sectors as factors in our regressions: Utilities, Energy, Materials, Industrials, Consumer Staples, Communication Services, Consumer Discretionary, Information Technology, Real Estate, Health Care and Financials.

The division of firms into sectors can be found in Table 2 below. In Table A2 in the Appendix we report the division per GICS industry to display the division that is too fine.

Table 2. Sample divided by GICS sector

GIC Sector Name	GIC Sector Code	# of firms
Materials	15	267
Financials	40	236
Information Technology	45	216
Consumer Discretionary	25	214
Health Care	35	195
Industrials	20	88
Energy	10	75
Consumer Staples	30	75
Utilities	55	57
Communication Services	50	49
Real Estate	60	23
Total		**1,495**

This table represents our sample as divided by industry sector according to the GICS Industry Classification Standard.

5. Results

5.1. Regressions controlling for industry and firm-independent variables

The results from the regressions, displayed in Table 3 below, suggest that carbon emissions had a positive impact on the cross section of U.S. stock returns both measuring the daily impact after the election, and across a longer time period through the year-end. All regression results are displayed after having run t-tests of the estimated coefficients. The regressions outputted 1,477 observations after having omitted the remaining non-available (NA) data in R.

On November 9, on the first day after the election, one can see that the market responded negatively to differences in carbon emissions across U.S. stocks. The coefficient on the carbon emission variable on November 9 is -0.002. Considering the standard deviation of carbon emissions of 2.56 in our sample, this coefficient implies that a one standard deviation increase in carbon emissions lead to a 0.512 % (-0.002*2.56) decrease in daily abnormal returns on this day. The results are not statistically significant, although indicative of such an effect.

However, on Nov 9, similar to the negative coefficient displayed for abnormal returns on this day, the coefficient obtained using raw returns instead implies a 0.768 % (2.56*-0.003) decrease in raw returns for a one standard deviation increase in carbon emissions, significant at the 1 % level. Looking at the mean raw return on this date after the election also suggests that for the firms in our sample, the average firm reacted negatively on the day following the election.

Table 3. OLS regression results

	(1) Nov 9	(2) Nov 10	(3) Nov 18	(4) Nov 9 - Dec 30	(5) Nov 9 - Feb 28	(6) Nov 9 - April 28
Panel A: Abnormal returns		AR			CAR	
Ln(CO2)	-0.002	0.002*	0.0002	0.008**	0.006	0.006
	(0.001)	(0.001)	(0.0004)	(0.004)	(0.004)	(0.006)
Observations	1,477	1,477	1,477	1,477	1,477	1,477
R-squared	0.130	0.225	0.038	0.147	0.089	0.046
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Raw returns		R			CR	
Ln(CO2)	-0.003***	0.001	-0.0001	0.004	0.004	0.004
	(0.001)	(0.001)	(0.0004)	(0.003)	(0.004)	(0.005)
Observations	1,477	1,477	1,477	1,477	1,477	1,477
R-squared	0.130	0.225	0.038	0.147	0.089	0.046
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the OLS regression results of individual stock returns on the logarithmized (ln) total volume of corporate carbon emissions (Ln(CO2)), controlling firm characteristics and industry-fixed effects. Panel A reports the regression results for abnormal returns with AR representing abnormal returns and CAR representing cumulative abnormal returns. Panel B reports the results of the regressions of raw returns as the dependent variable where R represents raw returns and CR represents cumulative returns. All regressions are controlled for industry fixed effects in accordance with the Global Industry Classification Standard across 11 sectors. The regression results cover the time periods of Nov 9 2016 (Column 1), Nov 10 2016 (Column 2), Nov 18 2016 (Column 3) for R and AR and Nov 9 2016 - Dec 30 2016 (Column 4), Nov 9 2016 - Feb 28 2016 (Column 5) and Nov 9 2016 - April 28 2016 (Column 6) for cumulative returns (CR and CAR).The sample includes 1,496 firms with the U.S. as the country of exchange. In the parentheses T-statistics are presented based on robust standard errors. The reported Rsquared is the Adjusted R-squared.
*** p<0.01, ** p<0.05, *p<0.1.

When comparing these effects from the regressions run on raw returns, as displayed in Panel B of Table 3, the coefficient is similar in directional effect on November 10, although not significant.

Looking at Table 3 at Panel A, focusing on the variable of interest of abnormal returns, the results imply that carbon emissions are first positively correlated with abnormal returns on November 10, two days after the election day of November 8. Carbon emissions now seem to significantly, explain some of the variation in the abnormal returns on this day, at the 10 % level. The coefficient for abnormal returns on this date was 0.002 according to our findings. Once again, considering the standard deviation of 2.56 of carbon emissions in our sample, a one standard deviation increase in a firm's carbon emissions then corresponds to a 0.512 % increase in abnormal returns. The effect is similar for raw returns, although somewhat less positive and not significant, yielding a coefficient of 0.001. The R-squared is also the highest on this date, at a level of 22.54 % for abnormal returns meaning that carbon emissions along with controls are somewhat better at explaining the variation in abnormal returns on this date than on other dates.

On Nov 18, ten days after the election, the coefficient for both abnormal returns and raw returns seem to have declined. For abnormal returns, the coefficient has now decreased to a coefficient of 0.0002 and is not statistically significant. However, observing the coefficient obtained from the regression using raw returns suggests a negative market reaction to carbon emissions on this day. This might indicate that the shock had subsided somewhat until this day.

Looking across the longer time periods, all coefficients on the carbon emission variable are positive. Measuring the aggregated effect over time, looking at the cumulative abnormal returns over the three longer time periods, the relation between corporate carbon emissions and cumulative abnormal returns remains positive. The magnitude of the coefficients for the three longer time periods were greater than those for the first days following the election.

The cumulative effect as of December 30, looking at the CAR in Panel A, measuring the through year-end effect of carbon emissions on stock returns, is economically sizable and statistically significant at the 5 % level, at a value of 0.008. The effect of carbon emissions on abnormal returns during this period implies that one standard deviation increase in carbon emissions leads to a 2.088% (2.61*0.008) increase in abnormal returns. Although not generating significant results, a similar pattern emerges when comparing this to the relationship with raw returns with the effect being at its highest point on this date. However, while the coefficient on abnormal returns decrease towards the end of April, with no change between February and April, when looking at the raw returns the effect seems to stay constant over time at a level of 0.004. No significant results are obtained for the two later time periods of February 28 and April 28.

Even though the R-squared is at its highest for abnormal returns on November 10, one can see that, when comparing the results to raw returns, the R-squared is comparatively higher on December 30 compared to other dates for both variables of interest. This implies that on this date, the variables in our regressions explain more of the variance in returns than other dates.

The results above indicate that, overall, the market's reaction seems to be in line with the hypothesis of carbon emissions having a positive impact across U.S. stocks following the election. The regression using raw returns, controlling for industry-fixed effects, also shows a positive relationship between stock returns and carbon emissions, supporting the findings from the regressions using abnormal returns. However, as the coefficients obtained using raw returns are insignificant, data does not support this finding. The only significant coefficient for raw returns is on Nov 9, when the coefficient is negative.

Noteworthy are the similar coefficients on the carbon emission variable obtained using abnormal returns and raw returns, both with regard to magnitude and direction. This is in line with our findings from the regression of carbon emissions on the loadings on the Fama French factors, showing no significant correlation between the carbon emission variable and loadings on market, size and value factors.

The R-squared values obtained from the regression are rather low, both when using abnormal returns and when using raw returns. For abnormal returns the R-squared value ranges from 0.046 (Apr 28) to 0.225 (Nov 10). For raw returns, the R-squared ranges from 0.112 (Nov 18) to 0.542 (Nov 9 - Dec 30). The low R-squared values from the Fama-French returns implies that the independent variables' explanatory values are limited, only being able to explain parts of the movements in abnormal returns.

5.2. Regressions without industry-fixed effects

Only results controlled for industry-fixed effects have been included in the above section. The results from the regressions without industry-fixed effects are displayed in Table 4 below for abnormal returns and raw returns.

Table 4. OLS regression results for abnormal and raw returns without industry F.E.

	(1)	(2)	(3)	(4)	(5)	(6)
	Nov 9	**Nov 10**	**Nov 18**	**Nov 9 - Dec 30**	**Nov 9 - Feb 28**	**Nov 9 - April 28**
Panel A: Abnormal returns		AR			CAR	
Ln(CO2)	-0.002**	-0.001**	-0.001	-0.008***	-0.011***	-0.010***
	(0.001)	(0.001)	(0.0003)	(0.003)	(0.004)	(0.003)
Observations	1,477	1,477	1,477	1,477	1,477	1,477
R-squared	0.130	0.225	0.038	0.147	0.089	0.046
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Raw returns		R			CR	
Ln(CO2)	-0.003**	-0.002***	0.0002	-0.010***	-0.008**	-0.003
	(0.001)	(0.001)	(0.0005)	(0.003)	(0.004)	(0.005)
Observations	1,477	1,477	1,477	1,477	1,477	1,477
R-squared	0.130	0.225	0.038	0.147	0.089	0.046
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No

This table presents the OLS regression results of individual stock returns on the logarithmized (ln) total volume of corporate carbon emissions (Ln(CO2)), controlling for firm characteristics. Panel A reports the regression results for abnormal returns with AR representing abnormal returns and CAR representing cumulative abnormal returns. Panel B reports the results of the regressions of raw returns as the dependent variable where R represents raw returns and CR represents cumulative returns. The regression results cover the time periods of Nov 9 2016 (Column 1), Nov 10 2016 (Column 2), Nov 18 2016 (Column 3) for R and AR and Nov 9 2016 - Dec 30 2016 (Column 4), Nov 9 2016 - Feb 28 2016 (Column 5) and Nov 9 2016 - April 28 2016 (Column 6) for cumulative returns (CR and CAR).The sample includes 1,496 firms with the U.S. as the country of exchange. In the parentheses T-statistics are presented based on robust standard errors. The reported Rsquared is the Adjusted R-squared. *** p<0.01, ** p<0.05, *p<0.1.

When we control for industry-fixed effects, we can see that the R-squared becomes higher, indicating that industry-fixed effects omit some of the noise that the regression model yields when not testing for industry-fixed effects. As a result, the model explains more when controlling for industry-fixed effects.

The different results obtained differ both in terms of direction and magnitude of coefficients, when including controls for industry-fixed effects compared to when excluded. When excluding industry-fixed effects, the relationship between abnormal returns and carbon emissions were negative across all observed time periods while they became positive when industry-fixed effects are included except from the day after the election, on November 9. The decrease in significance observed when testing for industry-fixed effects is not surprising since much of the effect of carbon emissions on abnormal returns is explained by the fact that carbon emissions differs across industries. Since we hypothesize there to be a difference across industries, this is an important bias that is omitted when controlling for industry, proven in our findings.

5.3. Control variables

Lastly, looking at the control variables as part of our regressions, as they were not displayed in the tables above for simplicity, one can see that the significance varies across different time periods. Turning to Table 5, the varying significance across different time periods indicates that the control variables do not always add explanatory value to movements in abnormal returns. No coefficient on any control variable is significant across all regressions. While the coefficient computed on SALESGR is never significant for the regressions using abnormal returns. The control variable EPSGR also adds different explanatory value depending on the time period measured. Noteworthy is that the coefficient on ROE is never significant for the regressions of abnormal returns, indicating that it does not really provide explanatory value in any regression for abnormal returns. When comparing this to the set of raw returns, shown in Table A3 in Appendix, these findings suggest that the explanatory value of control variables differ across the different sets of returns.

Table 5. OLS regression results for abnormal returns (displayed with controls)

	AR			CAR		
	(1)	(2)	(3)	(4)	(5)	(6)
	Nov 9	Nov 10	Nov 18	Nov 9 - Dec 30	Nov 9 - Feb 28	Nov 9 - April 28
Ln(CO2)	-0.002	0.002*	0.0002	0.008**	0.006	0.006
	(0.001)	(0.001)	(0.0004)	(0.004)	(0.004)	(0.006)
LEVERAGE	-0.027***	-0.015***	0.001	-0.051**	0.018	0.016
	(0.007)	(0.005)	(0.003)	(0.024)	(0.029)	(0.038)
INVEST_A	-0.009	-0.013	0.018	-0.174*	-0.039	0.043
	(0.026)	(0.021)	(0.011)	(0.095)	(0.117)	(0.151)
LNPPE	-0.001	-0.002**	-0.001**	-0.005	-0.004	-0.006
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.007)
LNSIZE	0.004***	0.002*	0.001*	-0.007	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.007)
EPSGR	-0.00002	0.0002**	0.00002	0.001*	0.001	0.001
	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.001)	(0.001)
SALESGR	-0.003	0.002	0.0001	-0.007	0.005	0.006
	(0.002)	(0.001)	(0.001)	(0.006)	(0.008)	(0.010)
BM	-0.010***	-0.005**	0.003***	-0.045***	-0.011	-0.003
	(0.003)	(0.002)	(0.001)	(0.010)	(0.013)	(0.016)
ROE	-0.001	-0.0002	0.0004	0.004	0.0001	-0.0005
	(0.001)	(0.001)	(0.0004)	(0.003)	(0.004)	(0.005)
Observations	1,477	1,477	1,477	1,477	1,477	1,477
R-squared	0.130	0.225	0.038	0.147	0.089	0.046
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the OLS regression results of individual stock abnormal returns (Fama-French adjsuted) on the logarithmized (ln) total volume of corporate carbon emissions, along with displaying the coefficients on the control variables. All regressions are controlled for industry fixed effects in accordance with the Global Industry Classification Standard across 11 sectors. The regression results cover the time periods of Nov 9 2016 (Column 1), Nov 10 2016 (Column 2), Nov 18 2016 (Column 3) for abnormal returns and Nov 9 2016 - Dec 30 2016 (Column 4), Nov 9 2016 - Feb 28 2016 (Column 5) and Nov 9 2016 - April 28 2016 (Column 6) for cumulative abnormal returns. The sample includes 1,496 firms with the U.S. as the country of exchange. In the parentheses T-statistics are presented based on robust standard errors. The reported R-squared is the Adjusted R-squared. *** p<0.01, ** p<0.05, *p<0.1.

5.4. Robustness

As mentioned in section 4 regarding our variables and data, we use the control variables as from Bolton & Kacperczyk (2021). Since we use a different sample, as a robustness check, we also investigate whether our explanatory variables are normally distributed. If they are not, we take the natural logarithm of them, which we later finally use as our control variables. It turns out, the variables Bolton & Kacperczyk (2021) logarithmized go in line with our findings as well. Through a test that we run, it is proven that when we don’t logarithmize the emissions variable, results are not significant.

To see if heteroskedasticity is present for our explanatory variables, we run Breusch-Pagan tests to test this. At most dates, except for November 9 without industry-fixed effects, we find that we are not able to reject the null hypothesis of homoscedasticity. On all other dates, the p-value is less than 5 % and we can assume heteroskedasticity is present. Since heteroskedasticity is present in our model, we conduct t-tests f type HC1 across all variables each time to obtain robust standard errors. We do this in R along with all other regressions we run and hence re-calculate the coefficient table of the regressions run using a different variance-covariance matrix. For some coefficients on our explanatory variables, this results in their significance decreasing or disappearing, which shows the effect that the t-test has.

To be sure that our results are not driven by multicollinearity, we check for correlation between variables. We report the cross correlation in the Table A4 in the Appendix. As can be observed, there is generally little correlation between the independent variables. Not surprisingly, total volume of carbon emissions is strongly positively correlated with firm size. This is expected since larger firms generally tend to emit larger volumes of carbon emission.

As can be observed in column 5, the correlation coefficient between LNCO2 and LNSIZE is 0.603. The most notable correlation is between total volume of carbon emissions (LNCO2) and property plant and equipment (LNPPE). As can be seen in column 4, LNCO2 and LNPPE are strongly positively correlated with a correlation coefficient of 0.839. Due to the coefficient having reached the correlation coefficient threshold of 0.8 from a Pearson correlation test one might consider excluding LNPPE from the control variables. However, when running the regressions without LNPPE as a control variable and obtaining similar results as when included, we have chosen to keep LNPPE as our control variable.

Furthermore, our results also show that controlling for industry significantly matters when looking at the relationship between carbon emissions and stock returns. Obtaining negative coefficients when not controlling for industry while becoming positive across all dates except for November 9 when including industry effects, suggest that investor preference differs across industries. This is not unexpected since investors would require different compensation in returns for increases in carbon emissions depending on whether the stock is of a firm in a high or low emitting industry.

6. Discussion

6.1. Comparison to previous literature

Our results can be explained in the light of the carbon risk premium found by Bolton & Kacperczyk (2021), which suggests that investors of carbon-intense firms require higher returns for holding those assets. Following a decrease in climate regulatory risk, the carbon risk premium should be reduced as firms emitting higher levels of carbon emissions are the most exposed to that certain risk. Consequently, firms emitting higher levels of carbon emissions should gain higher abnormal returns following the election which is what the results suggest. Our findings, proposing that higher emitting firms earn higher abnormal returns following the election, goes in line also with what Ilhan et al. find in their study on the downside tail risk, suggesting that the risk for firms with higher levels of carbon emissions decreased following the election due to a reduction in climate policy uncertainty.

It is also worthwhile to analyze the results in the light of changes to investor preferences for green assets. Our results suggest that the market's overall preference for green assets, which Pastor et al. (2015) has found in their study, does not hold for the observed period following the election. Additionally, while Pedersen et al.'s (2021) study suggests that investors seek portfolios with less carbon emissions over time, our study suggests they do not short term.

Furthermore, our study contradicts the carbon alpha hypothesis observed over time by Garvey et al. (2018) and In et al. (2019). While they find that portfolios that are short stocks of companies with higher carbon emissions generate positive abnormal returns over time, our results suggest that the opposite holds over a short time period. Referring back to the survey conducted by Stroebel & Wargler (2020), it seems as if the climate policy risk, which they identified as one of the greatest risks for companies going forward, in fact is partially priced in by the market already as carbon emissions have been found to have a significant impact on stock prices following the U.S. presidential election in 2016.

Ramelli et al. (2021), also studying the impact of a shift in climate policy expectations following the election, have found that the election rewarded carbon-intense firms, in line with our results. As they also regress abnormal returns on a carbon emissions measure, it becomes interesting to compare our results to theirs. In their study they find the relationship between carbon intensity and abnormal returns to be positive already one day after the election, on November 9. This opposes our results, why it is worth reflecting upon what these differences might depend on. A possible explanation for this might be that they measure the coefficient of carbon intensity (carbon emissions scaled by total equity), while we measure the total volume of carbon emissions.

Since we are only able to compare the date which we have in common of November 9, we can not say much more about this difference across time. However, when looking at the longer time-horizons that we study, the difference in results vanishes. Comparing the carbon emissions coefficient for November 18 (the cumulative effect for their study, daily effect for our study), it is significantly positive in both of our studies. The similar results supports that the effect of carbon emissions on returns turned positive as the general market shock of the election had subsided and investors had time to think about the real implications of the eventual policy shift. Since Ramelli et al. (2021) measured the cumulative effect from the election to November 18, while we only measured the daily coefficient, we can't for certain say that our cumulative effect would be the same on this date. However, the results at least indicate that this could be the case.

Since our findings show that the aggregate effect over time of carbon emissions on abnormal returns is significantly positive through the year-end of December 30, our study suggests that the effect remains after some time similar to Ramelli et al. (2021). Investors seem to have adjusted their expectations over time with regard to Trump's relaxed climate politics, even through year-end.

Furthermore, as a last explanation for our somewhat differing results from Ramelli et al. (2021), we identified our control variables to be rather different. They control for another measure of profitability (return on assets instead of return on equity) and additionally control for the cash ETR and share of foreign revenues. The tax variable is controlled for, building upon the research of Wagner et al. (2018), finding that the cash ETR affect abnormal returns significantly following the election due to a shift in tax policy expectations. Due to the scope of this study, we did not include cash ETR. However, one might find it to have been reasonable for U.S. to control for this due to this tax effect previously having been studied and proved. We therefore attribute this as a flaw in our study. To be noted is that we use an greater amount of control variables compared to Ramelli et al. (2021) such as EPSGR, B/M, INVEST/A, LNPPE and ROE as done in the Bolton & Kacperczyk study (2021).

The drift in reaction, or the continuous reaction over time, due to a shift in policy expectations that we find opposes what Wagner et al. (2018) finds in their study. Wagner et al. (2018) finds that, when looking at the effect of a firm's cash ETR on abnormal returns, there was a strong effect already the day after the election. We can't compare the effect of our different measures of policy exposure directly, but it is interesting to reflect upon which policies investors might have reacted more directly to. Since Wagner et. al (2018) finds their tax coefficient to be significant both on the first day, through year-end and even until April 28, this sheds a light on what policies people priced in and prioritized when adjusting their portfolios post the election. Trump's tax policies were not either certain nor particularly pronounced but might have been of a higher importance to investors at the time than climate policies. With ambiguity remaining for carbon emissions as a measure to investors, not even directly disclosed for some of the firms in our sample, it is not unexpected that people seem to have reacted more to tax policy expectations than to climate policy expectations, with the latter being very unclear in terms of scope and implications (Ilhan et al. 2021).

Comparing our coefficients for the control variables to Wagner et al. (2018), controlled for industry, we can see that our results go in line for the coefficient on sales growth. Both our regressions show that firms with higher sales growth and that firms with higher leverage reacted negatively to the election. The direction of our variable of market capitalization (LNSIZE) opposes the direction of their market value of equity variable as we find that larger firms performed better on the day after the election, whereas they find the opposite. However, when observing the coefficient for raw returns the picture changes, showing that larger firms do perform worse following the election, statistically significant on November 10.

6.2. Political signaling and market expectations

6.2.1. In the light of the event study methodology

As have been previously outlined in section 2.2, covering the theory behind this event study, the expected return before the election was based on the probability of Trump and Clinton respectively winning along with the expected prices depending on the two different outcomes. With regards to the probability of Trump winning being much lower than the probability of Clinton winning, the expected price prior to the election mainly reflected the price expected in the case Clinton was elected president. As Trump was surprisingly elected, the realized returns became drastically different from the prices expected prior to the election, supporting the market efficiency hypothesis.

According to our findings, firms emitting higher levels of carbon emissions actually benefited from Trump winning as their exposure to climate policy risk decrease with his more relaxed approach to climate regulations. This is implied by the magnitude and the direction of the coefficient on the carbon emission variable for the two days following the election and for the aggregate effect over time. However, the negative coefficient on the first day following the election suggested the opposite reaction. Hence, that the realized returns were in line with those expected if Clinton would have won that would have penalized, or not had any impact at all on firms emitting higher levels of carbon emissions. This leads U.S. into the discussion of how the expectations changed over the observed time period following the election.

Although the results are not significant on the first day following the election, the negative market response is rather surprising with regard to the positive market reaction observed for the following time periods. With regard to Trump's unreliable rhetoric in combination with him not having made many clear statements about the exact measures he would take regarding climate regulations, investors might have expected a more uncertain future for higher emitting, and hence more climate regulatory risk exposed, firms. Consequently, investors might have become reluctant to hold such firms' stocks, explaining the negative coefficient on the carbon emission variable on the first day.

However, the rather drastic directional development of the coefficient on the carbon emission variable from the first day to the second following the election, suggesting that the market reaction to carbon emissions across U.S. stocks changed in the opposite direction over one night, is rather unreasonable. It is therefore important to highlight, once again, that one of the disadvantages of using the 2016 U.S. election as the event to study is that Trump may in fact have affected the expectations of investors in other areas apart from those on climate regulations. For instance, as evident in the tax study by Wagner et al. (2018), tax policies affected investors' expectations significantly across U.S. stocks. The shift in expectations in many other political areas, such as for taxes, may have been negatively correlated with corporate carbon emissions, which might be why a negative market reaction to carbon emissions is observed on the first day. We have not controlled for this and thus can't say for certain that this is the case. However, if a more thorough analysis had been conducted on what news reached investors following the election, one would have been able to say more about what the policy expectations were on the day after the election and why it changed drastically for the day that followed.

Along with Trump affecting other expectations, the Paris Agreement, signed just a few days before the election on November 4, might have added to the skeptic view of investors in what climate policies were actually going to be implemented or rolled back. Once again, the "political noise" around the election might have offset the potential positive market reaction to carbon emissions on the first day following the election along with other factors prioritized by investors which have been highlighted above.

6.2.2. The long-term effect

Once again, we have to comment on the significance of the through year-end reaction to carbon emissions with respect to political signals. Since the coefficient was positive already on Nov 10, and yet so on December 30 cumulatively, this suggests that investors continued to adjust with regards to the new policies even until the year-end. During that period, Trump was not the official president yet and had hence not been able to roll back or implement any new climate policies. The market reaction observed to carbon emissions can then be assumed to only reflect the change in expectations of investors. If we build this reasoning upon the analysis of political uncertainty by Kelly et al. (2016), the results become more explainable. As Kelly et al. suggest, using their framework on stock prices, even though investors can not know what climate regulations Trump were to implement and exactly how it would affect asset prices, through political signals they are able to learn about the political costs even before any regulation has been adopted.

Trump's social media presence, both before and following the election can in fact be viewed as political signals that affected investor expectations. Having called climate change a "hoax" and promising to dismantle the Environment Protection Agency in "almost every form" (The

New York Times, 2016), he signaled that he aimed to drastically change and relax the climate regulation landscape. Many news articles in fact reported on what changes could come as an effect. For example, on November 11, 2016, the Financial Times published an opinion article stating that Trump was "likely to slash and burn" Obama climate policy (Financial Times, 2016). National Geographic reported on Nov 9 about "The Global Dangers of Trump Climate Denial", the New York Times reported on Nov 10 about how "Donald Trump could put Climate Change on course for 'Danger Zone'" (The New York Times, 2016) and then, on Nov 18, The Guardian published an article with the title "Trump seeking quickest way to quit Paris climate agreement, says report" (The Guardian, 2016).

Investors seem to have anticipated a decrease in climate regulatory risk, with expectations continuing to affect asset prices through year-end. Trump's continuing presence on social media and him eventually also taking action on his suggested climate regulatory agenda during the spring of 2017 could explain why the coefficient on the carbon emission variable remained positive for the two longer time periods, although not significant.

In fact, even though many small changes were made after his inauguration, investors' expectations seem to have been confirmed on March 29. On this date, Trump did in fact sign an order dismantling Obama-era climate policies, keeping a campaign promise to support the coal industry (Reuters, 2017). On June 1, Trump officially announced that the U.S. would withdraw from the Paris Agreement deal. To summarize, although the coefficients indicate a positive market reaction to carbon emissions across U.S. stocks, after year-end it seems as if carbon emissions do not have any significant impact on stock returns anymore. When Trump nominated his candidate for the Environment Protection Agency, no surprise with significant impact was found according to Ramelli et al. (2021).

Without controlling for industry-fixed effects, we are not able to draw the conclusion that investors expected Trump to relax the climate regulatory environment. The differing results obtained when including, respectively excluding industry-fixed effects means that it is carbon emissions that drives the preference for carbon intense stocks, rather than a specific industry. Although, it shall be noted that when looking at longer time periods, it becomes difficult to assess the impact of a certain factor on returns. This is because changes in company and industry factors, and many other aspects also influencing returns, are difficult to control for when looking over such a long period of time.

6.3. Limitations

The literature on carbon emissions and stock returns is generally lacking and there is not enough literature on what actually impacts stock returns with regard to carbon emissions. One might hypothesize that other factors that are not controlled for could have affected the market sentiment during the investigated period which in turn could have affected the observed stock returns across our sample. This might include other ESG measures or the general reputation of the firm. For example, a firm that has a high ESG score is not directly assumed to have low carbon emissions or vice versa. These effects could potentially offset each other.

This is also highlighted in the study by Bolton & Kacperczyk (2021), stating that firms are more likely to disclose their emissions if they perform better on that dimension. Also, firms choosing to report their carbon emissions tend to have taken steps to reduce their emissions, showcasing them for commercial reasons. The reasoning should hold also for our sample even though it also includes firms with estimated carbon emissions, as the estimations are based on previously reported data. This issue should be particularly relevant for our sample with regard to the observed time period, covering 2016 and 2017, when climate reporting requirements were still very limited.

Regarding the measure of carbon emissions, one could have been more thorough in the choice of variable to be measured. Dividing the CO2 emissions into the scopes (1-3) that are often referred to in accounting of carbon emissions, one would avoid double-counting and more fine results could be obtained. However, we have not been able to do this in our study.

Furthermore, there are issues with looking at the election as an event, which we have already mentioned. For instance, there is much "political noise" around the studied event which indeed becomes difficult to control for and that might affect the results we get. Additionally, looking at the effect of the election shock over such a long period of time can become biased and, naturally, not include all things relevant to control for over time. The betas used to compute expected returns according to Fama-French are for instance not adjusted for over time. We have hence not controlled for changes to those over time, which is a limitation of our study.

We find that there is heteroskedasticity across our regressions, which is a clear flaw in our study but not unusual for cross-sectional studies. There is a low R-squared across our regressions which implies the explanatory value of our models overall is rather low.

6.4. Further research

Regarding further research, one could have also observed the timeline of events regarding climate policies in the U.S. even more closely. Some studies in the financial literature focus on this very specific factor such as the study of Engle et. al (2020) which one could combine with our study to conduct a more fine analysis of the election and the political signals around it.

Furthermore, the relationship between institutional investors' holdings and carbon emissions following the election would be an interesting area to further research on. This has been studied by Azar et al. (2021) but only over a longer time horizon. This could provide insight into how institutional investors attitudes looked like following the election, and whether they actually expected the decreased climate regulatory risk to stay or not. Building upon the research of Barnett et al. (2020), it would have been further interesting to see how one could explain the phenomena in this study with the help of social decision-making.

However, worth noting, while still comparing our results to Ramelli et al.'s (2021), is that Bolton & Kacperczyk (2021) find that carbon intensity as a measure has no significant impact on stock returns over time. This once again shows the opposing results that the financial literature within this area has put forward, highlighting the importance of further research using different measures of carbon emissions to investigate what matters for investor expectations the most.

It would further also be interesting to test our study for other time periods, such as through another event closer in time, for instance when Biden was elected instead. In such case, we could compare our results to the results of this study, providing insight into whether investors act differently then and now.

Furthermore, the study of asset prices and environmental metrics has much more to explore. It will be interesting for further research to investigate how investors balance the internal initiatives of companies, their promises and their actual performance of important environmental metrics such as carbon emissions. Additionally, further studies are needed on how informed investors are around these subjects and what actually affects their preferences.

7. Conclusion

The previous literature in the chosen area to study shows that investors price in the risk associated with holding stocks of higher emitting firms. Our findings show that when such a risk decreases, in the form of reduced climate regulatory risk, investors respond by rewarding the stocks most exposed to this risk.

In a world where investors seem keen to invest more responsibly, it becomes interesting to hypothesize what would happen in an opposite scenario to what we have measured. That is, how investors would react, and already are reacting, when climate regulations are being implemented - instead generating an *increased* climate regulatory risk. Due to the nature of legislative processes, implementations of policies do not usually create appropriate shocks to conduct event studies on. Hence, studying a scenario when climate regulatory risk unexpectedly decreases and with that investors' attitudes, we believe our study to have valuable implications for understanding how investors react to and, consequently, how companies will be affected by a stricter climate regulatory environment in the future.

With uncertainty remaining regarding future policies, it is interesting to see how investors' shifted their expectations even before the implementations of such policies. Although often cited as a populist, overly-promising and turning to the "mass", we find that investors saw it as likely that Trump would actually carry out his proposed climate policies, indicating that expectations matter, even when the rhetoric of policy-makers seem ambiguous.

Analyzing our findings through the perspective of companies, they suggest that, in a world where transition risk becomes less present, such as when climate-skeptic Trump was elected president, businesses emitting higher levels of carbon emissions will continue to be rewarded. However, with regard to the increasing climate change awareness we currently see, investors' response to climate regulation shifts, or even just indications of such a shift, should incentivize companies to actively work with aligning their businesses with climate regulations in order to reduce their exposure to transition risk and be able to compete in a greener future.

Overall, connecting the micro, meso and macro perspectives we find that all these interact with each other in the mitigation of climate change. Governments play a role, and the possible regulations they implement impact the behavior of investors and how they reward companies. This becomes clear in our study. When a politician, being skeptic of the climate, comes to power, even in an era of increased climate change awareness, investors seem to seek profit and firms, despite their business activities, are rewarded. One might find this rational, only supporting what the efficient market hypothesis suggests, that a sudden decrease in firm risk would lead to an increase in firm value. However, one might also find this irresponsible of investors. Whatever the case, governments clearly play a role in the expectations they create in people's minds. Even before Trump had been inaugurated into his new position as president, investors had reacted, supporting this view and the role that political signals can have. This highlights the fact that governments can do more, as suggested by the IPCC, once again.

The relevance of studying the U.S. 2016 election in the year of 2022 may not seem prominent. However, we argue that it is of utmost relevance even today. The era of protectionism, populism and climate-skepticism is not over yet, and probably, so is not the one of Trump. We cannot take governments being pro-climate mitigation for granted. Neither can we take the responsibility of investors for granted. Investors sought profit in 2016, and further studies might tell U.S. what their attitudes are today. What is truly needed of investors, governments and corporations to shift their actions and create real change?

The Principles of Responsible Investment, the Paris Agreement and government policies all have one thing in common. They are initiatives to make people act. It is clear that they have the power to do so. With this study, we hope to highlight the importance of the interplay between governments and the financial market in mitigating probably the world's greatest challenge, climate change. Further, we believe it contributes to the overall financial literature of carbon emissions and stock returns, something that will become increasingly important going forward as companies become more pressured to report their environmental metrics.

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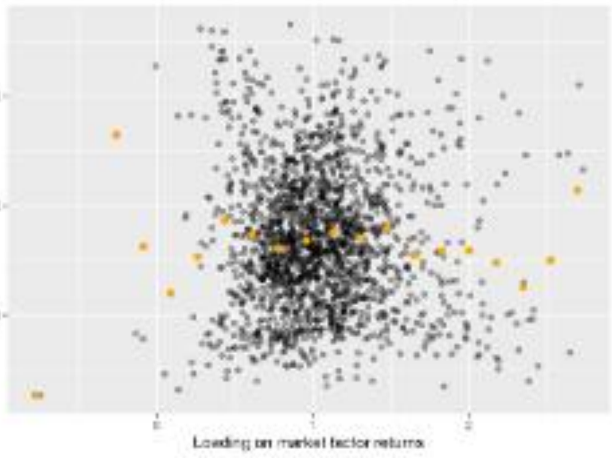
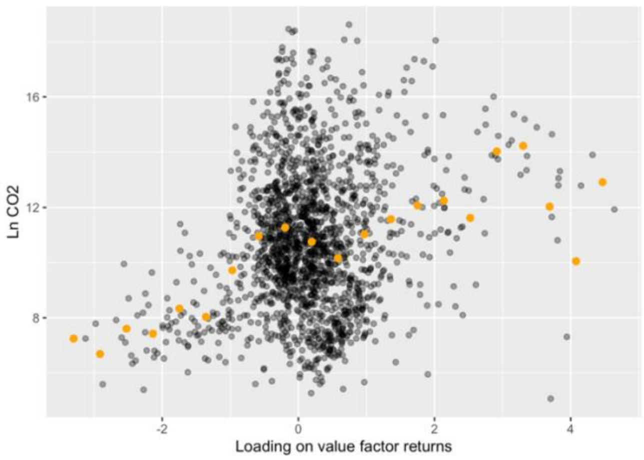
Appendix

Figure A1.



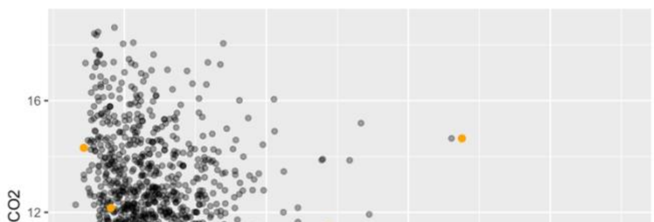
This figure presents a binned scatter plot of the correlation between the independent ln(CO2) variable and loading on market factor returns for firms across our sample.

Figure A2.



This figure presents a binned scatter plot of the correlation between the independent ln(CO2) variable and loading on the value factor returns for firms across our sample.

Figure A3.



This figure presents a binned scatter plot of the correlation between the independent ln(CO2) variable and loading on the size factor returns for firms across our sample.

$$CR_{i,t_1;t_k} = \left(\left(1 + r_{i,t_1}\right) * \left(1 + r_{i,t_2}\right) * \ldots * \left(1 + r_{i,t_K}\right)\right) - 1 \qquad \text{Formula 1.}$$

Table A1. Determinants of carbon emissions

Variable	LNCO2
LEVERAGE	0.721***
	(0.174)
INVEST_A	-1.082
	(0.698)
LNPPE	0.586***
	(0.028)
LNSIZE	0.314***
	(0.034)
EPSGR	-0.010***
	(0.003)
SALESGR	-0.010
	(0.045)
BM	0.168**
	(0.075)
ROE	0.040
	(0.024)
Observations	1,495
R-squared	0.990

This table represents the results from an OLS regression run with ln(CO2) as the dependent variable and the control variables as the independent variables. *** $p<0.01$, ** $p<0.05$, *$p<0.1$.

Table A2. Firms divided per GICS Industry

GIC 6	Industry Name	# of Firms
1	Energy Equipment & Services	18
2	Oil, Gas & Consumable Fuels	57
3	Chemicals	40
4	Construction Materials	5
5	Containers & Packaging	15
6	Metals & Mining	23
7	Paper & Forest Products	5
8	Aerospace & defense	22
9	Building Products	23
10	Construction & Engineering	15
11	Electrical Equipment	16
12	Industrial Conglomerates	4
13	Machinery	64
14	Trading Companies & Distributors	21
15	Commercial Services & Supplies	35
16	Professional Services	28
17	Air Freight & Logistics	8
18	Airlines	11
19	Marine	3
20	Road & Rail	17
21	Transportation Infrastructure	0
22	Auto Components	19
23	Automobiles	6
24	Household Durables	34
25	Leisure Products	10
26	Textiles, Apparel & Luxury Goods	20
27	Hotels, Restaurants & Leisure	41
28	Diversified Consumer Services	12
29	Distributors	3
30	Internet & Direct Marketing Retail	11
31	Multiline Retail	9
32	Specialty Retail	49
33	Food & Staples Retailing	18
34	Beverages	9
35	Food Products	33
36	Tobacco	2
37	Household Products	6
38	Personal Products	7
39	Health Care Equipment & Supplies	52
40	Health Care Providers & Services	35
41	Health Care Technology	8
42	Biotechnology	57
43	Pharmaceuticals	26
44	Life Sciences Tools & Services	17
45	Banks	141
46	Thrifts & Mortgage Finance	20
47	Diversified Financial Services	2
48	Consumer Finance	12
49	Capital Markets	34
50	Mortgage Real Estate Investment Trusts (REI	2
51	Insurance	25
52	IT Services	33
53	Software	63
54	Communications Equipment	21
55	Technology Hardware, Storage & Peripherals	12
56	Electronic Equipment, Instruments & Compon	41
57	Semiconductors & Semiconductor Equipment	46
58	Diversified Telecommunication Services	8
59	Wireless Telecommunication Services	5
60	Media	16
61	Entertainment	13
62	Interactive Media & Services	7
63	Electric Utilities	24
64	Gas Utilities	10
65	Multi-Utilities	14
66	Water Utilities	7
67	Independent Power and Renewable Electricity	2
68	Equity Real Estate Investment Trusts (REITs)	17
69	Real Estate Management & Development	6
Total		**1495**

This table presents our sample as divided by GICS Industry (69 industries) as classified by the GICS Industry Classification Standard.

Table A3. OLS regression results for raw returns (displayed with controls)

	AR			CAR		
	(1)	(2)	(3)	(4)	(5)	(6)
	Nov 9	**Nov 10**	**Nov 18**	**Nov 9 - Dec 30**	**Nov 9 - Feb 28**	**Nov 9 - April 28**
Ln(CO2)	-0.003***	0.001	-0.0001	0.004	0.004	0.004
	(0.001)	(0.001)	(0.0004)	(0.003)	(0.004)	(0.005)
LEVERAGI	-0.012*	-0.005	0.003	0.002	0.058**	0.031
	(0.007)	(0.005)	(0.003)	(0.022)	(0.028)	(0.035)
INVEST_A	0.010	-0.007	0.018*	-0.244***	-0.169	-0.132
	(0.026)	(0.019)	(0.011)	(0.086)	(0.113)	(0.140)
LNPPE	-0.0001	0.0004	-0.001	0.010**	0.004	-0.006
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.006)
LNSIZE	-0.001	-0.003***	-0.001*	-0.041***	-0.021***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.006)	(0.007)
EPSGR	-0.0001	0.0002	0.00000	0.0004	0.0004	0.001
	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.001)	(0.001)
SALESGR	-0.003	-0.00002	-0.0002	-0.015***	0.003	0.019**
	(0.002)	(0.001)	(0.001)	(0.006)	(0.007)	(0.009)
BM	0.004	0.008***	0.007***	0.027***	0.017	-0.002
	(0.003)	(0.002)	(0.001)	(0.009)	(0.012)	(0.015)
ROE	-0.002*	-0.0003	0.0004	0.003	-0.002	-0.003
	(0.001)	(0.001)	(0.0004)	(0.003)	(0.004)	(0.005)
Observations	1,477	1,477	1,477	1,477	1,477	1,477
R-squared	0.4079	0.3584	0.1124	0.5417	0.4765	0.4371
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the OLS regression results of individual stock raw returns on the logarithmized (ln) total volume of corporate carbon emissions, along with displaying the coefficients on the control variables. All regressions are controlled for industry fixed effects in accordance with the Global Industry Classification Standard across 11 sectors. The regression results cover the time periods of Nov 9 2016 (Column 1), Nov 10 2016 (Column 2), Nov 18 2016 (Column 3) for raw returns and Nov 9 2016 - Dec 30 2016 (Column 4), Nov 9 2016 - Feb 28 2016 (Column 5) and Nov 9 2016 - April 28 2016 (Column 6) for cumulative raw returns. The sample includes 1,496 firms with the U.S. as the country of exchange. In the parentheses T-statistics are presented based on robust standard errors. The reported R-squared is the Adjusted R-squared. *** p<0.01, ** p<0.05, *p<0.1.

Table A4. Correlation Matrix of Control Variables

	ROE	LEVERAGE	INVEST_A	LNPPE	LNSIZE	EPSGR	SALESGR	BM	LNCO2
ROE	1.000	0.015	-0.016	0.041	0.065	0.009	-0.018	-0.031	0.050
LEVERAGE	0.015	1.000	0.146	0.397	0.217	-0.021	-0.062	0.024	0.414
INVEST_A	-0.016	0.146	1,0000	0.380	0.034	-0.026	-0.047	0.046	0.343
LNPPE	0.0410	0.397	0.380	1,00	0.698	-0.029	-0.145	0.159	0.839
LNSIZE	0.065	0.217	0.034	0.698	1,0000	0.002	-0.067	-0.209	0.602
EPSGR	0.009	-0.021	-0.026	-0.029	0.002	1,0000	0.004	-0.065	-0.057
SALESGR	-0.018	-0.062	-0.047	-0.145	-0.067	0.004	1,0000	-0.072	-0.141
BM	-0.031	0.024	0.046	0.159	-0.209	-0.065	-0.072	1.000	0.097
LNCO2	0.050	0.414	0.343	0.839	0.602	-0.057	-0.141	0.097	1.000

This table presents the correlation matrix of our independent variables, following a Pearson correlation test conducted in R.