Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections

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Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections *

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Abstract

Donald Trump's 2016 election and his nomination of climate skeptic Scott Pruitt to head the Environmental Protection Agency drastically downshifted expectations on U.S. policy toward climate change. Joseph Biden's 2020 election shifted them dramatically upward. We study firms' stock-price movements in reaction. As expected, the 2016 election boosted carbon-intensive firms. Surprisingly, firms with climate-responsible strategies also gained, especially those firms held by long-run investors. Such investors appear to have bet on a "boomerang" in climate policy. Harbingers of a boomerang already appeared during Trump's term. The 2020 election marked its arrival.

JEL Classification: G14, G38, G41

Keywords: Climate finance, climate policy, CSR, election surprise, ESG, event study, institutional investors, policy boomerang, stock returns

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1 Introduction

Survey evidence, complemented by anecdotal accounts, indicate that a growing number of investors are attending to environmental issues -- climate change in particular -- in their investment decisions (see, e.g., Krüger, Sautner, and Starks 2020). The widely cited 2021 letter to CEOs by Larry Fink, the chairman and CEO of Blackrock, the world's largest asset manager, also emphasizes this theme. If the marginal investor invests accordingly, the share price for less climate-conscious companies will suffer.[1] How strongly markets value firms' climate-related performance will reflect not merely investors' personal preferences, but also their assessments of how government regulations will change and how firms will adapt.

This paper provides clear evidence that firms' climate-related performance and perceived future performance affects their stock market valuations. It shows this by exploiting price reactions of US stocks to the shock to climate policy following the 2016 US election, and the opposite shock from the 2020 US election. These political events provide a rare opportunity to study the interconnections between climate regulation, firms' climate-related performance, and firm value. Four factors are important. First, although climate policy had arguably slowly been making progress up to the 2016 election, Donald Trump's victory sharply reversed that slow progress.[2] Second, the 2016 election outcome was largely unexpected.[3] Third, Trump followed through on his stated policy preferences when he appointed Scott Pruitt, a

[1]Moreover, it may nudge them toward more climate-sensitive business practices (Heinkel, Kraus, and Zechner, 2001).

[2]While Hillary Clinton had made fighting climate change a priority (see, e.g., Business Insider, ''Where Hillary Clinton and Donald Trump stand on climate change'', October 5, 2016), Trump vowed throughout the electoral campaign to dismantle a large part of the Obama-era environmental protection and climate policy, inter alia by scrapping the Clean Power Plan (CPP) and withdrawing the US from the 2016 United Nations Framework Convention on Climate Change (UNFCCC) Paris Agreement.

[3]On Election Day, Betfair gave Hillary Clinton a 83% probability of winning, and FiveThirtyEight gave her a 72% chance of victory.

climate change skeptic, to head the EPA. The withdrawal from the Paris Agreement and the replacement of the Clean Power Plan with the Affordable Power Plan in 2017 followed naturally from these events. Fourth, the outcome of the 2020 Presidential election strongly reversed expectations about US climate policy. During the campaign, Joe Biden vowed to re-enter the Paris Agreement on the first day of his administration, to commit the country to carbon-free electricity by 2035 and net-zero carbon emissions by 2050, and to rescind several of his predecessor's executive orders.

Discussions of firms' climate-related performance often neglect an important distinction. Firms differ with respect to both *current* environmental footprint (most saliently greenhouse gas emissions) and with respect to climate responsibility. That responsibility includes their *future*-oriented strategies and voluntary initiatives to prepare for the transition to a low-carbon economy, such as the adoption of ambitious emission reduction targets and green investment plans.

Our study treats these two dimensions separately. We measure current emissions using *Carbon intensity*, defined as the firm's annual greenhouse gases (GHG) emissions divided by its market value of equity. Management practices and efforts to curb future emissions, i.e., *Climate responsibility*, are proxied by climate-specific scores on ESG (Environmental, Social and Governance) measures. We obtain data on firms' climate-related performance from two leading providers of ESG data: MSCI KLD and Vigeo Eiris.

As expected given their conceptual differences, *Carbon intensity* and *Climate responsibility* are only weakly correlated. This confirms that they capture different dimensions of a firm's climate performance. Section 2 contains examples of firms that score well on one dimension but poorly on the other, thus indicating that they are separate indicators.

We begin by studying stock-price reactions to the 2016 shock. Two salient events comprised that shock: the election of Donald Trump on November 8, 2016 and the nomination of Scott Pruitt to head the Environmental Protection Agency (EPA) on December 7, 2016. The selection of Pruitt -- the candidate widely viewed as the most hostile to the environment -- reinforced beliefs about Trump's determination to dismantle environmental protection rules and plans in place at the time. The analysis controls for other characteristics of firms, such as taxes and trade exposure (Wagner, Zeckhauser, and Ziegler, 2018).

Our first result is that investors reacted to the election by rewarding carbon-intensive firms. This result accords with the common narrative reported in the media and with basic economic intuition. Large emitters are those most exposed to the costs of climate regulation. As such, they are penalized by financial markets when regulation is tightened or expected to be tightened, for instance through the adoption of a carbon tax. Conversely, they were rewarded when investor expectations shifted towards a loosening of climate policy.

Our second and main result regarding stock-price reactions is more surprising. After both the 2016 election and the Pruitt appointment, investors also rewarded companies demonstrating more responsible climate strategies. How should one interpret this finding?

The "boomerang hypothesis" offers a possible explanation. It holds that investors expected the roll-back in climate regulation over the Trump administration to be only transitory and to pave the way for a much more ambitious long-term climate policy than would have prevailed absent the Trump shock. Three pieces of evidence provide insight.

First, according to a long-standing tenet of asset pricing theory, a positive stock-price response can be due either to higher expected cash flows, lower uncertainty (discounting), or both. We investigate the cash-flow channel by considering analyst forecast changes around the election. Financial analysts indeed increased their expectations of earnings per share of carbon-intensive firms for the near term (for FY2017 and FY2018). However, analysts -- who only project for a few years forward -- did not change their forecasts for climate-responsible firms for the four years of the Trump presidency. Neither climate responsibility nor carbon intensity is related to changes in short-term measures of uncertainty. In sum, the evidence suggests that the observed climate responsibility premium likely reflects investors' considerations of a more distant future.

Second, prior research strongly suggests that different investors are likely to have been responsible for pricing assets over different horizons. Our focus is on institutional investors. These investors differ greatly in their temporal foci.[4] Therefore, we would expect them to have differing views on appropriate valuation of carbon intensity and climate responsibility. Short-term holders would tilt toward carbon-intensive firms, long-term holders toward climate-responsible ones. We find that investors do bifurcate that way. Specifically, in stocks heavily held by short-term investors, carbon intensity played a bigger role for stock-price reactions; in stocks heavily held by long-term investors, climate responsibility was a key driver.

Third, recent history has presented the unusual opportunity to actually witness a policy boomerang. The prospects for such a boomerang rose shortly after the mid-term elections of 2018, when a number of progressive Democrats upset incumbents, and put the Green New Deal on the party's agenda. During 2019, the Green New Deal, framed as a massive program for the environment, received support from several Democratic lawmakers, including serious candidates for the Presidency. The development of this support took place over too long a

[4]For example, Bushee (1998) shows that short-term oriented shareholders heavily discount the value of research and development, and Bushee (2001) finds that high levels of transient ownership are associated with an over- (under-) weighting of near-term (long-term) expected earnings. Cella et al. (2013) show that short-term investors responded most strongly to the financial crisis.

period to provide a clear event study testing ground.

Fortunately for event study research, the Presidential election of November 3, 2020, provided a crisp experiment. On November 3, 2020, Joe Biden defeated Donald Trump in a highly emotional election that pitched two very different visions for America and the world against each other, with particularly dramatic differences regarding climate and environmental policy. Interestingly, the election effectively provides two events for the price of one: First, just before the election, Biden was widely expected to win. However, Trump's showing in the election was stronger than expected. In the three days immediately following the election, no major news network called the election race for either of the two candidates. Consistent with this unexpected uncertainty, climate-responsible stocks actually fared poorly in these three days. Second, on the weekend of November 7 and 8, all major networks did call the election for Biden. Consequently, from Monday November 9 onwards, climate-responsible stocks enjoyed strong performance. They received a further boost when John Kerry was nominated for the newly created cabinet-level post as special envoy for climate, and then after the two Georgia Senate runoff races tilted Congress towards Democratic control.[5]

Overall, the expected environmental hostility of the Trump Administration appears to have led to increased demand for climate-responsible firms by long-term investors expecting such firms to do better in the long run due to a boomerang in climate regulation post-Trump.

Our analysis makes two central contributions. First, it provides evidence that corporate

[5]Besides the US election, the other major development of 2020 was of course the COVID-19 pandemic. In the COVID-19 crash, companies fared better if they had strong environmental and social (ES) performances (Albuquerque et al., 2020; Garel and Petit-Romec, 2020), though this result has been the subject of some debate (Demers et al., 2020; Mahmoud and Meyer, 2020). Albuquerque et al. (2020) suggest that this outperformance is due to greater trust that these firms command in crisis times. Another interpretation is that COVID-19 is a political event that dramatically boosted the election chances of the Democratic candidate, thus making a shift in environmental policy generally more likely.

environmental responsibility does affect firm values.[6] By contrast with regulatory changes considered in the existing literature, the 2016 policy shock is not the continuation of the prior trend towards tighter environmental regulation. Rather, it represented a largely unexpected reversal toward a *rollback* in regulation. This obviates a major concern of the existing literature on regulatory shocks and stock-price responses, namely that the observed effects are not causal but predominantly merely due to the continuation of pre-existing trends. A number of recent studies highlight the role of institutional investor horizon and tastes on ESG investing decisions (Dyck et al., 2019; Fernando et al., 2017; Gibson et al., 2020; Hwang et al., 2017; Ilhan et al., 2020; Krüger et al., 2020; and Starks et al., 2020). Our results indicate that long-term investors' preference for climate responsibility is likely to pay off in the long term, given climate-responsible firms' ability to better cope with future tightening in climate regulation.

Second, the analysis contributes to the burgeoning literature exploring the interconnections between climate change and financial markets. Recent studies include Addoum et al. (2020, 2019), Andersson et al. (2016), Baldauf et al. (2020), Bartram et al. (2019), Berkman et al. (2019), Bernstein et al. (2019), Bolton and Kacperczyk (2020a,b), Ceccarelli et al. (2021), Choi et al. (2020), Engle et al. (2020), Hong et al. (2019), Ilhan et al. (2021), and Pankratz and Schiller (2019).[7] Our paper complements this new strand of research by showing that

[6]Prior work has exploited firm-specific CSR events (Krüger, 2015b), narrow adoptions of shareholder resolutions (Flammer, 2015), and disclosure rules (Krüger, 2015a). See Gillan et al. (2021) for a survey of the literature on shareholder value effects of CSR/ESG.

[7]Berkman et al. (2019) investigate returns on portfolios formed using a measure of firm-specific climate risk based on a textual analysis of 10-Ks around the initial passage of the Paris agreement and the Trump election. That measure reflects a combination of a firm's risk exposure and risk management activities. Their analysis does not control for other expected policy changes following Trump's election, such as tax and trade policy. By controlling for these two policy dimensions and distinguishing current emissions and future-oriented strategies, our analysis provides a richer understanding of the valuation of firms' climate-related performance.

investor rewards to climate-responsible firms strongly depend on the regulatory environment on climate change expected in the long run. By rolling back climate regulation in the short run and fostering conditions for a boomerang in the long run, Trump's election increased the benefits for investors of holding climate-responsible firms.

2 Sample, empirical strategy, and data

2.1 Sample

Our sample includes all Russell 3000 firms on the day of the election for which the measures of climate-related performance and control variables described below are available. Together, the index constituents represent roughly 98% of the US equity market capitalization.

2.2 Empirical strategy

Because of the long-term trend towards sustainable investing, it is challenging to identify causal links between the sustainability performance of companies and firm values. Too many confounding and unobserved effects can drive either dimensions. Event studies exploiting share-price responses to specific events offer an attractive proposition in this respect (Schwert, 1981). It is particularly advantageous to be able to exploit the two opposite shocks, the first toward an expected rollback in climate regulation and the second that portends a more than complete reversal.

Our initial analysis focuses on the 2016 climate policy shock, following that year's Presidential election, namely the shock that led to the "puzzling" climate-responsibility result. Then, in Section 5.3, we turn to stock-price reactions to the 2020 Presidential election.

Throughout the 2016 electoral campaign, Donald Trump and Hillary Clinton expressed sharply divergent views on climate policy. Clinton's views were close to those of then-sitting President Obama. Accordingly, Clinton identified the fight against global warming as a policy priority.[8] By contrast, Trump vowed to undertake a radical U-turn on environmental regulation as a measure to promote economic well-being. Most notably, he expressed an intention to dismantle the Clean Power Plan and exit the Paris Agreement.

Trump's surprising victory was followed by a few weeks when the intentions of the President Elect to follow through on various of his promises, including those related to the environment, remained unclear. To illustrate, during an interview with *The New York Times* on November 23, 2016, asked the question "*Are you going to take America out of the world's lead of confronting climate change?*", Trump replied "*I'm looking at it very closely. I'll tell you what. I have an open mind to it.*" Asked whether he believed human activity causes climate change, he said "*I think right now...well, I think there is some connectivity. There is some, something.*"[9] A month later, following these equivocal statements, Trump appointed Scott Pruitt to head the EPA. That appointment clearly indicated that he was committed to a harsh scale back on environmental policies.[10] The nomination of a climate skeptic to lead the institution responsible for upholding and implementing federal environmental laws marked a real turning point in the US policy towards climate change (Glicksman, 2017).

[8]Clinton's proposals included the objective to "*reduce greenhouse gas emissions by up to 30 percent in 2025 relative to 2005 levels and put the country on a path to cut emissions more than 80 percent by 2050*" (from Clinton's 2016 electoral campaign site).

[9]The full transcript of the interview is available at `https://www.nytimes.com/2016/11/23/us/politics/trump-new-york-times-interview-transcript.html?_r=0`.

[10]The New York Times, "Trump Picks Scott Pruitt, Climate Change Denialist, to Lead E.P.A.", December 7, 2016.

The Trump election and Pruitt's nomination each has advantages and disadvantages for identifying the impact of a firm's climate-related performance on its value. The pluses and minuses of the two events as identifiers cut in opposite directions; therefore, they complement each other well for reaching conclusions. The Trump election offers the advantage of having a large surprise component. Its disadvantage is that it shifted expectations on an array of topics, many far removed from environmental policy. Pruitt's nomination has the advantage of being solely focused on environmental issues, shining particular intensity on policy toward climate change. Its main disadvantage is that although the date was not known in advance, it was a less surprising surprise. Though none of the five candidates the media rumored for the EPA appointment was strong on the environment, Pruitt was the candidate most hostile to climate regulation. Moreover, he was an announced skeptic on human activity being the cause of global warming.

The next sections describe the main climate-related variables of interest to our study and our data set.

2.3 Measures of climate-related performance

2.3.1 Climate responsibility

Our *Climate responsibility* measures capture whether a firm has undertaken investments that effectively improved its energy efficiency in recent years, has set targets to reduce its future emissions, has adopted frameworks to manage climate change, and/or has launched new products to directly address this class of problems. Such efforts would provide important forward-looking indicators of a company's climate performance and, hence, would represent plausible proxies for the perception of investors with respect to such actions.

Data on corporate climate-related strategies were taken from two different ESG providers, thereby strengthening the robustness of our results. First, following a large part of the finance literature on CSR, we use the MSCI KLD Research & Analytics (MSCI KLD) database (e.g., Hong and Kostovetsky, 2012, Krüger, 2015b, Lins et al., 2017, and Fernando et al., 2017). The MSCI KLD database provides a set of binary indicators specifying, for each company, the presence of either strengths or concerns on a series of environmental, social, and governance factors. We focus on the two MSCI KLD indicators that specifically address a firm's climate performance. The first, the strength indicator "Env-str-d", equals 1 for firms demonstrating best practices on the management of risks of increased costs linked to carbon pricing or regulatory caps, and 0 otherwise.[11] The second, the weakness indicator "Env-con-f", equals 1 for firms involved in serious controversies related to their climate change and energy-related policies and initiatives, and 0 otherwise.[12] For 2016, these two indicators as well as the accounting information required to compute our control variables are available for 2,102 Russell 3000 firms. (The required accounting information is described in detail in Section 2.4 below.) Accordingly, for each firm, we define the variable *Climate responsibility (kld)* to be the indicator "Env-str-d" minus the indicator "Env-con-f". Aggregating strengths and concerns to derive "net" CSR scores is a common practice in the finance literature using the KLD MSCI data (e.g., Fernando, Sharfman, and Uysal, 2017 and Lins et al., 2017).

Our second source of data on firms' climate-related performance is Vigeo Eiris, now

[11]Factors affecting this assessment include efforts to reduce exposure through comprehensive carbon policies and implementation mechanisms, including carbon reduction targets, production process improvements, installation of emissions capture equipment, and/or switching to cleaner energy sources.

[12]Factors affecting this indicator include a history of involvement in GHG-related legal cases, widespread impacts due to corporate GHG emissions, resistance to improved practices, and criticism by NGOs.

the ESG affiliate of Moody's.[13] As a proxy for firms' climate responsibility, we use the Vigeo Eiris "Energy Transition" score, which we denote as *Climate responsibility (ve)*. The Energy Transition score assesses a firm's strategic approach to reduce carbon emissions and to adapt its business model to manage the risks and the opportunities presented by the regulatory and market environment in the transition to a low-carbon economy. The measure is a forward-looking assessment of firms' climate-related performance in terms of policies (e.g., adoption of ambitious emission reduction targets), measures implemented (e.g., investments in greener technologies), and evolution of key performance indicators (e.g., a recent-year reduction in its carbon footprint). The resulting scores range from 0 to 100. For 2016, this variable is available for 764 Russell 3000 firms. We also define a binary indicator *Climate responsibility leader*, which equals 1 for firms in the top quartile of the *Climate responsibility (ve)* scores, and 0 otherwise. This definition is intended to mirror the KLD "strength" measure.[14]

2.3.2 Carbon intensity

From Vigeo Eiris, we also obtain information on firms' total absolute yearly Scope 1 and Scope 2 greenhouse gases (GHG) emissions in kilotons of CO2 equivalents in 2015, the latest data available at the 2016 election.[15] These carbon emission data are based on information

[13]Vigeo Eiris evaluates firms in six ESG areas (environment, human rights, human resources, business behaviour, community involvement, and corporate governance). Vigeo Eiris scores have also been used in various academic contributions, e.g., Ferrell et al. (2016) and Liang and Renneboog (2017).

[14]Importantly, both MSCI KLD and Vigeo Eiris choose to cover firms based on index membership; coverage in no way reflects CSR performance. In particular, as of 2016, the MSCI KLD database covers the MSCI USA Investable Market Index (IMI), with indicatively 2,400 constituents. Vigeo Eiris uses different indexes, including primarily the Stoxx Global 1800 (hence, US firms part of the STOXX North America 600).

[15]The GHG Protocol identifies three emission categories: Scope 1 covers direct GHG emissions from sources that are owned or controlled by the firm. Scope 2 covers indirect GHG emissions caused by the organization's consumption of electricity, heat, cooling or steam purchased or brought into its reporting boundary. Scope 3 covers emissions that are a consequence of the operations of a company, but are not

filed through the "Carbon Disclosure Project" (CDP). When self-reported data are not available, Vigeo Eiris estimates the carbon emissions based on the size of the issuer, the nature of its activities, and the emissions of its peers. In total, carbon emissions are available for 764 companies.[16] We normalize the 2015 total emission data by the market value of equity in the same year and denote the resulting measure *Carbon intensity.* Normalizing GHG emissions by the market value of equity provides a simple indicator of a firm's reliance on GHG emissions in its business activities (Hoffmann and Busch, 2008; Ilhan et al., 2021). Similar results obtain when GHG emissions were scaled by total sales or total assets. We winsorize *Carbon intensity* at the 99th percentile to control for extreme values. *Carbon intensity* thus quantifies the firm's short-term exposure to the costs (or potential costs) of climate regulation, such as the cutback on permissible admissions, or a carbon tax.[17] However, it provides limited information on a firm's strategic positioning for a potential energy transition.

2.3.3 Descriptive statistics of *Climate responsibility* and *Carbon intensity*

Table 1 provides descriptive statistics of the climate-related variables our analyses employ. Table A1 in the Supplementary Appendix provides descriptive statistics by Fama-French 12

directly owned or controlled by the organization, including the supply chain and customers. Although Scope 3 emissions represent a major component of a firm's negative climate externalities, they are still rarely disclosed by firms due the lack of clear unified disclosure standards and the difficulty in their estimation. For instance, under the corporate standards of the GHG Corporate Protocol, companies are required to report all Scope 1 and 2 emissions, while reporting Scope 3 emissions is only optional (Greenhouse Gas Protocol, 2020).

[16] The carbon emission data are self-reported for 339 companies and estimated for 425 companies.

[17] Our samples include companies in the financial industry. Since these firms are exposed through their loan portfolios, their Scope 1 and Scope 2 GHG emissions provide an incomplete picture of their exposure to climate risks. However, the climate strategies of financial firms (e.g., limit the exposure to fossil fuel assets in loan portfolios, increase the financing of "green" projects, etc.) may be particularly relevant for climate-conscious investors. While we keep financial companies in our sample, analysis available on request shows that our results hold even when they are excluded.

industries.[18] The table reveals sizable variation across firms within industries on climate-related performance, and not merely across industries.

Table 1 here

Table A2 in the Supplementary Appendix reports correlations. Our two main variables of interest -- *Climate responsibility (kld)* and *Climate responsibility (ve)* -- are strongly positively correlated (0.55, $p < 0.001$). The fact that the correlation is not perfect reflects the difference in structure between the two indicators (one is binary, the other continuous), and the different methodological approaches of these two ESG data providers. The MSCI KLD measure to some extent captures firms' relative GHG emissions, while the Vigeo Eiris measure specifically focuses on a firm's managerial strategies to climate change. We consider these differences across indicators useful as they help us to cross-validate our findings.

Climate responsibility (kld) is modestly negatively correlated with *Carbon intensity* (-0.11, $p < 0.001$). The correlation between *Climate responsibility (ve)* and *Carbon intensity*, illustrated in Panel A of Figure 1, though still slightly negative, is insignificant (-0.02, $p > 0.1$). The same relation holds also when controlling for industry fixed effects and basic firm characteristics (see Panel B of the same figure). These low correlations highlight that these variables capture conceptually different dimensions of a firm's climate performance, one more static (carbon intensity) and one more forward-looking (climate responsibility).

Figure 1 here

Table 2 here

[18]To ensure that our analyses appropriately control for sector fixed effects, we analyzed all firms classified as "Other" in the Fama-French industry classifications. We reclassified two of these firms (AES Corporation and Calpine Corporation) to the utilities sector.

Table 2 reports the number of firms above and below the medians of *Climate responsibility (ve)* and *Carbon intensity* in the Vigeo Eiris sample. It may be interesting to consider a few concrete examples of firms falling into each of these four quadrants. The utility Xcel Energy is one of the top US emitters, responsible alone for more than 53,000 kilotons of CO2 emissions equivalent in 2015.[19] Despite its large carbon footprint, this company is considered climate-responsible (i.e., *Climate responsibility (kld)* and *Climate responsibility leader (ve)* equal to one). In 2016, Xcel had already committed to a carbon emission reduction target of 60% by 2030 from 2005 levels (increased to 80% in 2018, with the target of carbon neutrality in 2050), complemented by the progressive retiring of its coal-fired plants and large investments to increase its renewable capacity.[20] Conversely, an example of a high emitter not considered climate-responsible based on our measures is Valero Energy, a major US crude oil refiner also involved in the controversial Keystone XL Pipeline, recently terminated by the Biden Administration.

Firms involved in activities with relatively low Scopes 1 and 2 emissions can also be considered either climate-responsible or not. For instance, Intel and HP exhibit both relatively low carbon intensities and advanced climate strategies (*Climate responsibility (kld)* and *Climate responsibility leader (ve)* equal to one).[21] In addition to having clear emission

[19] This is equal to approximately 0.80% of the total 2015 US GHG emissions from all sources based on data from the US EPA's Greenhouse Gas Reporting Program database (GHGRP). Based on GHGRP data, Xcel Energy was ranked 12th in the 2016 Greenhouse 100 Polluters Index of the Political Economy Research Institute of the University of Massachusett Amherst (see `https://www.peri.umass.edu/greenhouse-100-polluters-index-2018-report-based-on-2015-data`).

[20] Another example of a large emitter with climate-responsibility features is Duke Energy (responsible for more than 100,000 ktCO2e in 2015). In 2016, this company was targeting a reduction of 40% in carbon emissions by 2030, increased to 50% in 2019.

[21] These companies are included, since 2016, in the Clean200 list listed by the NGO As You Sow and Corporate Knights, together with 37 other US companies, see `https://www.asyousow.org/clean200`. This list recognizes firms with a high share of "green" revenues, and it excludes all firms operating in fossil-fuel related activities and utilities that generate less than 50% of their power from renewable sources. Whether or not firms operating in high-emission sectors should be considered a priori "climate irresponsible" is up for

reduction targets for their operations, KLD and Vigeo Eiris assess these companies to be committed to improving the energy efficiency of their supply chain and final products, and accelerating the development of clean technologies that would support an energy transition. By contrast, the IT firm Citrix Systems, despite being a low emitter, at least as of 2016, was not considered climate-responsible.

2.4 Accounting information

We obtain standard accounting firm characteristics -- market value of equity, profitability (ROA), revenue growth, and market leverage -- from Compustat Capital IQ. For each company, we use the latest available accounting data before November 2016.[22]

Following the 2016 election, high-tax companies gained compared to low-tax firms, and domestically focused companies gained compared to internationally oriented ones (Wagner, Zeckhauser, and Ziegler, 2018). To control for these effects, we compute the cash effective tax rate (henceforth cash ETR, the ratio of total cash taxes paid to pretax income adjusted for special items during the previous 5 years) from Compustat data.[23] From Bloomberg (and Compustat geographical segments data), we collect the percentage of revenues from foreign sources.

Table 3 here

debate. For instance, Cohen et al. (2020) recently document that the energy sector has a large and growing percentage of patenting activity dedicated to green research, more than other less climate-sensitive sectors.

[22]For most companies, this means the December 31, 2015 data. However, several companies have fiscal years that end in other months. Thus, in the MSCI KLD and Vigeo Eiris samples we have, respectively, 26.7% and 32.4% of firms for which calendar year 2016 data are used.

[23]We use the 5-year cash ETR to ensure a larger sample than when using the prior-year cash ETR. The results with 1-year cash ETR are very similar, though slightly weaker because of the smaller number of observations. In line with the extant literature, we restrict the sample to those firms with positive tax rates below 100%.

Panel A in Table 3 provides descriptive statistics of accounting information. For space reasons, we show summary statistics only for the 2,102 firms included in the MSCI KLD sample. This sample represents around 88% of the total US market capitalization as of November 2016 (while the 764 firms in the Vigeo Eiris sample represents 78% of it).

Cash ETR and the share of foreign revenues are not always available for these companies. Given that previous research has already established the effect of these firm characteristics after the 2016 US election, to avoid reducing the sample sizes, we replace missing values of these variables with 0 and include a dummy variable equal to 1 (and 0 elsewhere) to absorb the effect of this adjustment in our empirical specifications. This treatment is employed for 274 firms with missing Cash ETR and for 637 firms with missing foreign revenues out of the 2,102 firms in the MSCI KLD sample.

2.5 Stock returns

We obtain daily stock-return data from October 1, 2015 through December 29, 2017 on all US common stocks (except closed-end funds) traded on NYSE, Amex and Nasdaq from CRSP. In our analysis, we consider returns on the Russell 3000 constituents as of November 8, 2016.

We consider three sets of returns: Raw returns, abnormal returns calculated with respect to the CAPM, and abnormal returns calculated with respect to the Fama-French three-factor model. To compute abnormal returns, we utilize daily data for the market excess return, the size and value factor returns (Fama and French 1993), and the return on the riskless asset from Ken French's website. Betas are estimated using one year of daily data, from October 1, 2015, through September 30, 2016.[24]

[24] For most firms, data are available for the entire estimation window. Where they are not, betas are

To obtain CAPM-adjusted returns, we first estimate each stock's market beta from an OLS regression of daily stock returns in excess of the riskless asset return on the market excess returns. We then compute abnormal returns for all days in the following quarter as the daily excess return on the stock minus beta times the market excess return. We compute Fama-French-adjusted returns in a similar fashion.

In what follows, CAPM-adjusted returns serve as our primary dependent variable. However, as we show in the robustness section, our main results are robust to using raw and Fama-French-adjusted returns. Section B.5 in the Supplementary Appendix discusses advantages and disadvantages of different adjustments to returns.

Throughout the paper, returns are reported in percentage points. Descriptive statistics of CAPM-adjusted returns for the MSCI KLD sample are reported in Panel B of Table 3.

3 Industry-level stock-price reactions

We first analyze stock-price reactions at the industry level. In 2016, 7,631 large facilities in nine industry sectors -- power plants, petroleum and natural gas systems, refineries, chemicals, waste, metals, minerals, pulp and paper, and others (including coal mines and electronics manufacturing) -- accounted for about half of US emissions.[25]

Figure 2 here

estimated using returns from the date the firm was first traded through the end of the estimation window, provided that the firm has at least 126 daily return observations available. If fewer than 126 observations are available, no abnormal returns are computed for that firm to avoid our results being affected by imprecise beta estimates.

[25] Data are from the EPA's Greenhouse Gas Reporting Program (GHGRP), which requires annual reporting of facility-level GHG data for the top emitting sectors of the US economy. Detailed information on the 2016 emissions of the top emitting industries is available at `https://www.epa.gov/ghgreporting/ghgrp-industrial-profiles`.

As Figure 2 shows, stock prices in these industries gained substantially following Trump's election victory, as one might expect. Specifically, this figure plots the industry coefficients when CAPM-adjusted returns on the first day after the election (light blue bars) and cumulative abnormal returns through year-end 2016 (red bars) are regressed on Fama-French 30-industry dummies and firm characteristics (log market cap, revenue growth, profitability, and market leverage) using all firms in the Russell 3000 sample for which all control variables are available (2,798 firms). The coefficients are reported in descending order by the abnormal returns achieved on the first post-election day.

Adjusting for the market's overall move, the stocks of "dirty" industries performed very well on the day after the election. In particular, investors immediately turned the coal, steel, metals, and petroleum and natural gas industries into notable relative winners. Shifts in investor expectations about other policy areas (such as Trump's pledge to revive American manufacturing and his tough announced stance on trade) undoubtedly account for some of these industry-level returns (see Wagner et al. (2018) for a discussion). Still, it is striking how great were the relative short-term gains that high-emission industries enjoyed.

Among the carbon-intensive industries, all but the utilities sector fared quite well after the election. Quite possibly, utilities suffered because investors pivoted from low-beta/low-risk industries (also including beer, tobacco, and food products) into high-beta industries in response to Trump's pledge to revive growth and the potential consequence of increased long-term interest rates.

Figure 2 also reveals that the cumulative abnormal returns through year-end 2016 differed substantially from the immediate market reaction. In particular, investors' optimism appears to have been excessive about the prospects for the coal[26] and metal industries in the new regime. On the other hand, petroleum and natural gas companies, as well as chemicals and steel works, enjoyed substantial increases in abnormal returns through year-end. Presumably, these adjustments reflected a normal digestive process of information conveyed by a shock.

Figure 2's simple descriptive results strongly suggest that the Trump's election, combined with Republican control of the House and the Senate, represented good news for high-emissions sectors. However, variability among firms within the same industry was typically as large as it was across industries, both in terms of abnormal returns and efforts to mitigate climate change. For instance, as Table A1 indicates, the energy sector included both firms trying to pro-actively manage climate-related issues and firms basically neglecting such concerns. (This is shown by the standard deviation of *Climate responsibility (ve)*, which actually exceeds the sector mean.) And while the average abnormal return on the day after the election of firms in that sector was 2.64 percentage points, the spread around that value was great. The 25th percentile was −0.06 percentage points and the 75th percentile was 3.33 percentage points.

The next section capitalizes on this variability across firms to investigate how their climate responsibility affected their stock prices after the 2016 policy shock.

4 Within-industry stock-price reactions

Table 4 shows the results of regressions of individual stock CAPM-adjusted returns on firms' *Climate responsibility (kld)* following our two key events: the Trump election on November 8, 2016 and Pruitt's nomination on December 7, 2016. The results for raw and Fama-French-

[26]The relative decline of stock prices of the coal industry continued during the first year of the Trump Presidency. See Fisman and Zitzewitz (2017).

adjusted returns are very similar and are reported in Section B.5 in the Supplementary Appendix. Controls in the regression are the cash ETR, share of foreign revenues, market leverage, log market cap, revenue growth, profitability, and industry fixed effects.[27]

Table 4 here

Interestingly, firms displaying a high level of climate responsibility enjoyed a 44 basis points higher abnormal return on the first trading day after the election. Their cumulative abnormal returns grew strongly by the third day, reaching 139 basis points, and remain positive, although not quite statistically significant through the 10th trading day after the election. At that point firms with strong climate responsibility remained 72 basis points ahead of otherwise similar stocks. Companies at the forefront of climate responsibility benefited further following the nomination of Scott Pruitt, securing an additional 107 basis points higher abnormal return in the following 10 trading days.

Figure 3 here

To illustrate, Figure 3 shows the average residual cumulative abnormal returns of the top and bottom half of firms by *Climate responsibility (kld)* not explained by standard firm characteristics and the effect of other anticipated policy changes following the Trump election. By construction, the two lines move symmetrically, and the spread between them represents the return on an equally-weighted, long-short portfolio along climate responsibility, adjusting for other firm characteristics. Before the 2016 climate policy shock, the two lines are close

[27]The primary analysis includes industry fixed effects according to the Fama-French 12-industry classification in order to keep things comparable once we move to the smaller Vigeo Eiris sample. The robustness section in the Supplementary Appendix shows that the results continue to hold with Fama-French 30-industry fixed effects.

to zero, indicating common pre-trends of the two groups.[28] After each of the two events, climate-responsible firms significantly outperform otherwise similar companies.

The coefficients on the control variables in Table 4 accord with the results established in the prior literature. After the election, domestically focused firms and those with a higher cash ETR fared relatively better than did low-tax and internationally oriented companies, and market leverage had a negative and highly statistically significant effect. All these findings are consistent with those documented in Wagner, Zeckhauser, and Ziegler (2018), which had a larger sample available.

Overall similar results obtain when using the Vigeo Eiris sample, as Table 5 shows. The coefficients of the control variables, available on request, are in line with those discussed above but are omitted to conserve space.

Table 5 here

The point estimate on *Climate responsibility (ve)* on the first day is slightly negative, but becomes positive and economically important after three days, although not statistically significant. The directional effect becomes much clearer and more significant after Pruitt's nomination. The effect is economically important: A one standard deviation higher *Climate responsibility (ve)* secures a 49 basis point (16.32*0.030%) increase in three-day cumulative CAPM-adjusted returns after Pruitt's nomination, about a seventh of a standard deviation of those returns.[29]

[28]Indeed, when we run 253 cross-sectional regressions of daily abnormal returns from October 1, 2015 through September 30, 2016, using the same specification as in column (1) of Table 4, we obtain an average coefficient on *Climate responsibility (kld)* equal to -0.010 (with a standard deviation of 0.182). This check further confirms that the effect we identify is not a mere continuation of a pre-existing trend.

[29]Figure A5 illustrates these results in binned scatter plots.

When comparing the results in Table 4 with those in Panel A of Table 5, note that the two measures of firms' climate strategies are structurally different: The Vigeo Eiris measure is continuous, while the MSCI KLD measure is binary, merely separating out good performers (about 11% of firms). To facilitate comparisons, Panel B of Table 5 reports the regression results when using the binary variable *Climate responsibility leader (ve)*, equal to 1 for firms in the top quartile of *Climate responsibility (ve)* and 0 otherwise. (We use the top quartile rather than the top 11% given the smaller size of the Vigeo Eiris sample.)

As can be seen, a high level of *Climate responsibility (ve)* is associated with a 131 basis points higher cumulative abnormal return at the end of the third trading day after the election, similar to the level we observed in the MSCI KLD sample. This positive and significant effect persists through the 10th trading day after the election. Firms with high climate responsibility also outperform following Pruitt's nomination, securing an additional 68 basis points after 3 days.

Consider now the effects of *Carbon intensity*. The literature suggests that firms more exposed to the (actual or potential) compliance costs of climate regulation incur a firm-value penalty (e.g., Matsumura et al., 2014; Bolton and Kacperczyk, 2020a; Ilhan et al., 2021). Table 5 indicates that after the election, high carbon-intensity firms gained relative to those less carbon-intensive. This result reflects the common narrative, including anecdotal accounts in the press, that after the election investors reacted by boosting the prices of large GHG emitters. The coefficients on carbon intensity remain statistically significant and with a similar economic size through the end of day 10 post-election.

As columns (5) to (8) show, stock-price movements after Pruitt's nomination are unrelated to *Carbon intensity*. This suggests that this nomination did not affect investors' policy expectations on carbon pricing or regulatory caps on emissions. Results were similar when GHG emissions were scaled by total sales or total assets.

We conducted extensive robustness checks to ensure the reliability of our findings. First, because climate responsibility and carbon intensity are effectively uncorrelated, including them separately in a regression yields coefficients little different from those when both are included. Further results, reported in the Supplementary Appendix, show that our findings are robust to (i) using adjusted t-statistics based on the empirical distribution of coefficient estimates (ii) controlling for industry fixed effects at a finer level of granularity, (iii) controlling for other dimensions of corporate governance, (iv) using raw and Fama-French-adjusted returns, and (v) using the generic environmental score from Refinitiv's Asset4 database.

5 The boomerang hypothesis

Our results show that markets rewarded two distinct dimensions of firms' climate-related performance in response to policy shocks. Following the Trump election, both high carbon-intensive firms (and industries) got price boosts, as did climate-responsible firms.

The observed reward for carbon intensity is hardly surprising. Trump's ascension, with a Congress in Republican control, led investors to expect a substantial loosening of climate policy, particularly in controlling carbon emissions, that occurred.

Investor rewards to climate responsibility are of far greater interest, as they are contrary to conventional thinking. Why this reward? A potential explanation -- that we outlined in a 2018 version of this paper -- is that investors expected the reversal in climate policy during the Trump era to be transitory. The combination of a hostile regime, and deteriorated environmental conditions would heighten environmental concerns among both activist and middle of the spectrum voters. That concern in turn would pave the way for more aggressive regulatory action, enhancing the value of climate responsibility.

Two factors may have driven this expectation. First, investors may have expected that the regime's negative stance on environmental policy reinforced by a slide in environmental conditions would stimulate environmental concerns among both activist and moderate voters. That in turn would create a *boomerang effect* where direct government climate regulation post-Trump would end up being more stringent than it would have been had the election gone to Clinton. The Trump election shone a spotlight on global warming; his projected lax policies could be expected to spur a counter movement. Second, investors may have foreseen that pro-environmental consumers and investors, as part of the ESG movement more generally, would increase their demand for climate-responsible products and stocks, to the benefit of climate-responsible firms. Stronger climate preferences and stricter future policies are interconnected, as the former make a powerful comeback of climate regulation more likely.

In other words, the explanation we propose is that the 2016 climate policy shock had two contemporaneous effects: 1) Reduced costs to firms from climate regulation over the Trump presidency, favoring more carbon-intensive firms, and 2) an increase in the uncertainty and expected costs of climate policy in the longer run, with the possibility of a regulatory boomerang post-Trump (either after four or eight years). As a result, the competitive advantages of climate-responsible firms were boosted over what they were before the 2016 election. Together, we call this the *boomerang hypothesis*.

This section presents three analyses to test this hypothesis: First, it analyzes changes in analysts' earnings forecasts after the 2016 election. Second, it investigates the role of investor horizon for the pricing of the two climate-related dimensions. Finally, it documents stock-price effects after a swift and powerful boomerang came into view following the 2020 election.[30]

5.1 Changes in earnings expectations and short-term uncertainty

The classical decomposition (Campbell and Shiller, 1988) shows that stock returns are driven by changes in per-share earnings expectations and/or discount rates. A traditional approach to project the market's expectations about a firm's prospects is to use revisions in analysts' earnings forecasts as its proxy (Fried and Givoly, 1982; Brown and Rozeff, 1978).[31]

The IBES Detail History database (stock-split-adjusted) provided our financial analyst forecasts. For each analyst-firm combination, we employed the last forecast reported between June 30 and November 8, 2016, and the last forecast reported between November 9 and December 31, 2016. Four forecast horizons were analyzed, computed on the basis of the end date of the accounting period covered by the forecast (variable ‘‘Forecast period end date''): FY 2016 (fiscal year ending between December 30, 2016, and September 30, 2017), 2017 (between October 1, 2017, and September 30, 2018), FY 2018 (between October 1, 2018, and September 30, 2019), and FY 2019 (between October 1, 2019, and September 30, 2020).[32]

[30] In principle, an expected policy reversal in four years could affect carbon-intensive and climate-responsible firms differently if they had systematically different duration (for instance if a larger part of the value of climate-responsible firms came from the distant future). However, both our measures of climate performance are positively correlated with dividend yields, and negatively correlated with revenue growth.

[31] Recent applications of this method include, for instance, Liu et al. (2017), who use it to interpret stock-price effects of political uncertainty, and Landier and Thesmar (2020), who use it to better understand the drivers of stock prices in the early phase of COVID-19.

[32] Ideally, one would check whether longer-term forecasts correlated particularly positively with climate responsibility. However, for FY 2020, there are only 293 datapoints for our sample, too few for reliable inferences.

The EPS forecast at each horizon was normalized by the stock price at the end of the prior fiscal year.[33] For each firm, we compute the change in earnings forecasts as the difference before and after the election in the average forecast. We multiply this change by 100 to ease interpretation. To control for extreme values, we winsorize forecast revisions at the 1st and 99th percentiles for each horizon. As one would expect, there was a strong positive relation between forecast revisions from November 8 through December 31, 2016 and cumulative abnormal returns over the same period (see Figure A7 in the Supplementary Appendix).[34]

In Table 6, we test whether after the Trump election, financial analysts revised their expectations on future earnings to address firms' climate-related performance. Specifically, we regress forecast revisions on *Carbon intensity*, *Climate responsibility leader (ve)*, and control variables. As expected, we observe no significant relation between a firm's climate performance and the change in its average forecast for FY2016 (column (1)). Such short-term forecasts could not be influenced by Trump's policies and, thus, serve as a placebo test. However, as expected, we observe that financial analysts anticipated Trump's policies would bring a boost to carbon-intensive firms' earnings in FY2017 and FY2018 (columns (2) and (3)). Climate responsibility is not associated with any statistically significant revisions over these time horizons.[35]

[33] Our definition of forecast revisions follows the approach used, e.g., in Liu et al. (2017). We obtain similar results when measuring forecast revisions as the percentage change in EPS forecasts, excluding observations with negative baseline forecasts (as done, e.g., in Landier and Thesmar, 2020) or using their absolute value at the denominator (as in, e.g., Ivković and Jegadeesh, 2004). We also obtain similar results when looking at the change in the median EPS forecast, instead of the average forecast.

[34] The positive relation between stock returns and analyst's forecast revisions is a well-established finding. Investors and analysts react to new information and also influence each other. See Kothari et al. (2016) for a review of the literature on analysts' forecasts and asset pricing.

[35] The same finding holds when adopting the climate responsibility measure from MSCI KLD. In results available on request, we find that there is no clear relation between the change in dispersion and either carbon intensity or climate responsibility. This result suggests that the observed stock-price effect of the two climate-related dimensions were not significantly driven by a further polarization of investors' green preferences.

Table 6 here

Table 7 analyzes other possible determinants of the stock-price effects of firm's climate performance following the 2016 climate policy shock. The regression results in column (1) indicate that between January and December 2017, carbon-intensive firms experienced a decrease in the Amihud (2002)'s measure of stock illiquidity compared to what happened between October 2015 and September 2016 (the equivalent length pre-event period). The decrease in illiquidity further strengthens when comparing 2019 with the pre-event period. We interpret this result as a further signal of the short-term benefits of the rolling-back of climate regulation for investors holding stocks of carbon-intensive firms.[36]

Table 7 here

Columns (3) to (6), show the percentage changes between 2016 and 2017 and between 2016 and 2019 in market beta (columns (3) and (4)) and return volatility (columns (5) and (6)) for individual stocks. No relation is observed between these proxies of realized short-term risk with our measures of corporate climate performance.

Overall, these results indicate that following the 2016 election, a) the stock-price effect of carbon intensity was driven by an increase in cash flow expectations for carbon-intensive firms, but not necessarily by a decrease in their short-run uncertainty, and that b) the observed climate-responsibility premium was likely driven by a change in earnings expectations and/or uncertainty over a far longer run. For the climate responsibility finding, the above analyses

[36]An interpretation for this result is that the Trump election caused a release in the average selling pressure on carbon-intensive stocks. Selling pressure is a significant driver of stock illiquidity and its effect on stock prices (Brennan et al., 2013). As investors demand a premium to hold illiquid stocks (Amihud, 2002; Acharya and Pedersen, 2005), the stock-price effect of carbon intensity after the 2016 election may also be partially motivated by an expected reduction in the associated stock illiquidity.

have the limitation that the analyst forecasts only extend for a few years. Therefore, they cannot capture (in the manner that stock prices do as a distillation) market participant's projections about longer run developments. These limitations prompted the next section's analysis of stock-price reactions as a function of the institutional shareholder structure of companies.

5.2 The role of investor horizon

The investment horizon of institutional investors is a major determinant of various corporate actions, and how those actions are priced in financial markets.[37] The horizons of institutional investors are particularly important with respect to pricing corporate and environmental responsibility, which is likely to pay off only in the long run.[38] Posit that markets anticipated the roll-back of climate policy to be temporary, with probable intensification to follow -- as the boomerang hypothesis suggests. The Trump era would still be a boon to carbon-intensive firms, despite their required change in ways later. Investors with a myopic view of firm value would happily pursue and thereby boost the price of carbon-intensive firms.

Conversely, we expect the climate responsibility premium to be amplified by the presence of more far-sighted and longer-term investors. An analogy is helpful here. Cella et al. (2013) show that long-term investors helped mitigate the impact of the financial crisis on stocks.

[37]For instance, Derrien et al. (2013) find that a longer-horizon shareholder base attenuates the effect of stock mispricing on corporate policies. Cella et al. (2013) show that stocks held by more long-term investors are more resilient to market downturns. Gaspar et al. (2013) find that shareholder investment horizons influence payout policy choices. Cremers et al. (2020) find that an increase in short-horizon investors is associated with cuts to long-term investment and increased short-term earnings.

[38]Starks et al. (2020) provide evidence of a segmentation of institutional investors based on their investment horizon. Long-term investors have higher stakes in high-ESG firms and behave more patiently towards them. Chen et al. (2020) find that institutions with longer investment horizons are more likely to positively influence portfolio firms' CSR policies. Similarly, Glossner (2019) finds that long-term investors lead to more CSR activities. See Matos (2020) for a review of the literature on institutional investors and ESG.

The Trump election is effectively a crisis for climate-responsible stocks. In the presence of a large fraction of long-term investors for these stocks, the stocks will incur less selling pressure; hence, they will outperform. Moreover, firms whose institutional owners have longer horizons can more easily keep their focus and policies oriented towards long-term value.

To test for these conjectures, we follow the existing literature and posit that a high (low) portfolio turnover by an investor indicates a short (long) investment horizon (Froot et al., 1992). We compute investors' portfolio turnover based on Thomson Reuters 13-F data following the definition of Carhart (1997), i.e., the minimum between total buys and total sells divided by average assets during the quarter. We then classify as short- and long-horizon institutional investors the 13-F institutions in the bottom and top quartiles of portfolio turnover in Q3-2016.[39] We then define the variables *Short-horizon IO* and *Long-horizon IO* as the percentage of the total 13-F institutional ownership held by short-horizon and long-horizon investors as of September 30, 2016.

As one would expect, we observe that *Short-horizon IO* correlates positively with *Carbon intensity* (0.08, p <.05) and negatively with *Climate responsibility (ve)* (-0.14, p <.001). By contrast, *Long-horizon IO* correlates negatively with *Carbon intensity* (-0.08, p <.05), and positively with *Climate responsibility (ve)* (0.29, p <.001). In short, long-term holders both shun carbon-intensive firms and embrace firms that are climate-responsible.

Table 8 regresses (cumulative) abnormal returns after the Trump election on the interactions of *Carbon intensity* and *Climate responsibility leader (ve)* with *Short-horizon IO* and *Long-horizon IO* as the independent variables. The regressions control for firm

[39]Specifically, we identify as long-term investors those with portfolio turnover below 0.023 and as short-term investors those with turnover above 0.137 (the median turnover is 0.058). We compute the turnover through the algorithm used in Ben-David et al. (2012). We thank the authors for making their SAS code available on WRDS.

characteristics and industry. We observe that a higher short-horizon institutional investor base is associated with an amplified price effect of carbon intensity.[40] Conversely, a higher long-horizon institutional investor base is associated with an amplified price effect of climate responsibility.

Table 8 here

Overall, these results suggest that the time horizon of institutional investors plays a significant role for the pricing of climate performance. Corporate climate responsibility appears to appeal to long-term investors, but to repel short-term investors.

5.3 The boomerang shows on the horizon

Survey evidence suggests that already shortly after the Trump election it was possible to identify early indicators of a possible boomerang to stricter policy than expected before the election.[41] At the corporate level, Sautner et al. (2020) find increased coverage of climate-related topics during firms' earnings calls after the Trump election, even with specific reference to regulation. In 2019, harbingers of a strongly intensified future climate policy began to be seen. For instance, in February 2019, several prominent Democratic candidates for the 2020 Presidential nomination supported a resolution in Congress to develop a "Green New Deal". Their resolution set for a policy plan aspiring, among other things, to power the U.S. economy with 100% renewable energy within ten years.[42] Events like the "climate strike"

[40] Table A10 in the Supplementary Appendix shows that the same result holds when we define short-horizon IO as the percentage of Q3-2016 institutional ownership held by "transient" investors according to the Bushee (1998, 2001) classification.

[41] In a March 2017 poll, 45% of Americans declared to worry "a great deal" about global warming, up from 37% in March 2016 (Gallup, 2017). A December 2018 survey found that 29% of Americans are now "alarmed" about climate change (up 8 percentage points since March 2018), and another 47% are "concerned" or "cautious" (Gustafson et al., 2019).

[42] See Financial Times, "The week in energy: A Green New Deal", January 12, 2019.

in September 2019 revealed growing political support for bolder climate actions, actions that would represent a direct backlash to Trump lax and loosened policies.

Drastically tightened policies later became a cornerstone of Joe Biden's announced policies on the environment, and a major element in his electoral campaign. Specifically, and basically immediately, Biden promised to rejoin the Paris Agreement on the first day of his administration. However, he promised to "go much further" (from Biden's 2020 electoral campaign site). For example, he announced his intention to decarbonize the entire US power sector by 2035 and to "ensure the U.S. achieves a 100% clean energy economy and reaches net-zero emissions no later than 2050". Importantly, Biden's stated intentions imply a much more ambitious climate regulation than under the Obama Administration, and what would have likely ensued under a Clinton Administration. Biden's big picture climate goals were supplemented by concrete intended actions in related areas, such as the rescinding the contentious Department of Labor's "Financial factors in selecting plan investments" rule, which was issued on October 30, 2020. That rule explicitly limited the ability of pension funds to consider non-pecuniary factors in their investment strategies.[43]

Just before the 2020 election, a boomerang was clearly expected to arrive should Biden triumph and should Democrats control Congress. Given such an outcome, climate-responsible stocks would thrive. The step-by-step support for the Green New Deal makes it difficult to identify a clean event window during the Trump presidency. The 2020 Presidential election, by contrast, provided sharp and swift shifts in probabilities of vastly disparate climate policies.

[43]See, e.g., The National Law Review, "Trump Era DOL Rules - Will They Remain Under a Biden Administration?", January 4, 2021.

For an event study, the 2020 election offers intriguing features. The final outcome was mostly anticipated by market participants. On the 2020 Election Day, Betfair gave Joe Biden a 78% probability of winning and FiveThirtyEight gave him 89%. In principle, the outcome of a high-probability event is not well suited for an event study. If the favored event comes in, there is little update of expectations. However the event turned out to experience short-term shocks in both directions. On the day after the election, no winner had emerged, an implicit uptick for Trump. For three days, from Wednesday November 4 to Friday November 6, the major news networks refrained from calling the election. They finally did so on the weekend of November 7 and 8. Given the surprisingly close result and the realistic possibility of a second Trump term, we expect investors to have reconsidered what they had presumably already priced-in before the election. Conversely, we expect markets to have (re-)priced the expected effects of tighter climate regulation when outcome uncertainty was progressively resolved and Biden emerged as the final winner.[44] Despite these advantages for testing, one should keep in mind that in the days after the election also brought a mini-torrent of news on COVID-19 vaccines and related topics. That news too, no doubt affected relative stock-price moves.

For all firms included in our baseline dataset, we retrieve stock prices for the most recent period from Compustat Security daily and compute CAPM-adjusted returns as the daily excess return on the stock minus the stock's beta in 2019 times the market excess return.[45]

[44]Prediction markets, such as PredictIt, and gambling houses, such as Ladbrokes, did tip odds towards a Biden win late on November 4 and in advance of the market open on November 5. On the other hand, even after most political commentators called the race for Biden, Trump refused to concede and made several attempts to hold up the final ratification by the Electoral College, so some residual uncertainty about the change in Administration remained for some time.

[45]The 2019 market beta is estimated by regressing daily excess returns from January 2, 2019 through December 31, 2019, on a constant and the daily market factor. The market excess return and the return on the riskless asset (the daily one-month U.S. Treasury-bill rate) are from Kenneth French's website. As the Fama-French market factors from French's website, at the time we are writing, are available only up to

From Compustat, we also retrieve standard 2019 accounting information: revenue growth, profitability, market leverage, and market cap (as of November 3, 2020). The percent of foreign revenues is drawn from Compustat segment data and refers to 2018. For cash ETR, we use the ratio of total cash taxes paid to pretax income adjusted for special items during the five years before the Trump election. That treatment provides a relatively clean proxy for the potential winners and losers from a rollback of the corporate tax cut that was implemented by the 2017 Tax Cuts and Jobs Act. For *Climate responsibility (kld)* and *Climate responsibility (ve)* we use the 2018 scores obtained from MSCI KLD and Vigeo Eiris. For *Carbon intensity*, we use the 2017 Scope 1 and Scope 2 GHG emissions, divided by the market value of equity before the election. Appendix Table A11 shows descriptive statistics.

We analyze two sets of abnormal returns. The first starts from the day after the election (Wednesday, November 4, 2020) and the second starts on the first trading day after Biden was declared a winner by the major media networks (Monday, November 9, 2020).

Table 9 Panel A shows the results for *Climate responsibility (kld)*. On the days immediately following the election, climate responsibility is associated with *lower* abnormal returns, net of the effect of other firm characteristics. Following the surprisingly close result, markets appear to have enhanced the chances of a Trump second term relative to pre-election expectations. Thus, the observed negative coefficient on climate responsibility represented a diminution of the effects of the expected climate policy change that markets had priced in the run up to the election.[46]

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the end of November 2020, we compute the market factor from November onward as the value-weighted portfolio return of all firms listed on NYSE, NYSE Arca, AMEX, or NASDAQ for which data is available on Compustat. Our computed market factor and the Fama and French's market factor in November 2020 have a correlation of 99.9%.

[46]This reversal is also interesting because it suggests that the correlation of stock returns and climate responsibility really can be attributed to changes in the political balance of power, and not merely to an

In columns (3) to (6), we investigate what happened after Biden was announced as the winner. *Climate responsibility (kld)* is associated with an out-performance of almost 2.2% on November 9, which increases to 3.1% after 10 trading days. This effect is highly statistically significant and economically important. It represents more than one-fifth of the standard deviation of cumulative returns over the same period (14.65%).

A similar pattern emerges in Panel B for *Climate responsibility leader (ve)* (and similar findings are also obtained with the continuous variable *Climate responsibility (ve)*). Interestingly, the coefficients on *Carbon intensity* are not statistically significant. We interpret this finding to indicate that investors, even under the concrete possibility of a slender victory by Trump, had no hope for another consequential boost for high carbon-intensive firms.

Table 9 here

The results for the control variables are also informative. First, they too reflect the shift in signs between the first three days after the election and thereafter. Second, for the tax status and foreign revenues, in the days after Biden's win became clear, we observe effectively the opposite effect of what the Trump election had produced (Wagner et al., 2018). Thus, these results reconfirm the relevance of corporate taxes and international orientation for firm value.

Finally, Figure 4 shows how climate-responsible firms generally outperformed beyond the ten-day window after Biden was declared the winner. They received additional boosts when John Kerry was nominated Presidential Envoy for Climate with a seat on the National Security Council (a sign that climate change would be a priority for the incoming Administration

increase in attention on the topic of climate change.

in its foreign policy) and Cabinet status. After a brief pause, climate-responsible firms gained again after the two runoff elections for Senate seats (both in Georgia) where both Democrats triumphed. These two outcomes meant that (with Vice President Harris casting the deciding vote in the Senate), Congress had flipped to Democratic control, albeit razor thin in the Senate. Arguably, this situation would allow Biden to achieve sweeping pro-climate legislation, i.e., beyond Executive Orders, at least through the 2022 midterm elections.

Figure 4 here

6 Conclusion

With Donald Trump's 2016 surprise election, expectations about US climate policy took a punch on the chin. Stock prices responded to the anticipation of laxer regulation during the Trump administration and carbon-intensive firms enjoyed a short-run bump in price, as conventional theory would predict.

What about climate-responsible firms, those displaying ESG-like forward-looking strategies to deal with the energy transition? If investors expected the timeline of climate regulation and control to be bumped down during the Trump presidency, but then return to the same slope, with no other expected consequences, climate responsibility would have been penalized in stock prices. In fact, however, climate responsibility was rewarded.

The "boomerang hypothesis" offers a possible explanation. It holds that investors anticipated the down draft for climate regulation over the Trump administration to be transitory, but more important to be impactful for the future. It would pave the way for climate regulation post-Trump that was significantly more stringent than it would have been otherwise.

Three analyses support this explanation. First, analysts' short-term earnings forecast revisions following the 2016 election are positively related to carbon intensity, but not to climate responsibility. This indicates that the climate responsibility premium we observed depended on investors' considerations regarding a more distant future.

Second, we show that the stock-price effect of climate responsibility following the 2016 election was amplified by a firm's long-term institutional ownership base. By contrast, the boost associated with carbon intensity was amplified by the presence of short-term institutional investors.

Finally, after the 2020 US election, the value of climate-responsible firms soared in anticipation of the costs and opportunities for firms from Biden's ambitious climate agenda.

While some observers assert that financial markets put a premium on short-termist thinking, our analysis identifies a significant group of investors who take a long-term perspective when assessing a firm's value. In this instance, they value a firm's climate-responsible strategies as preparation for a more climate-conscious economy.

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Figures and Tables

Figure 1. Relation between *Carbon intensity* and *Climate responsibility (ve)*
Binned scatter plots of firm's *Carbon intensity* against *Climate responsibility (ve)*. Panel A shows the plain relation between the two variables. Panel B controls for Fama-French 12-industry indicators and basic firm characteristics (market cap, leverage, profitability, and revenue growth).

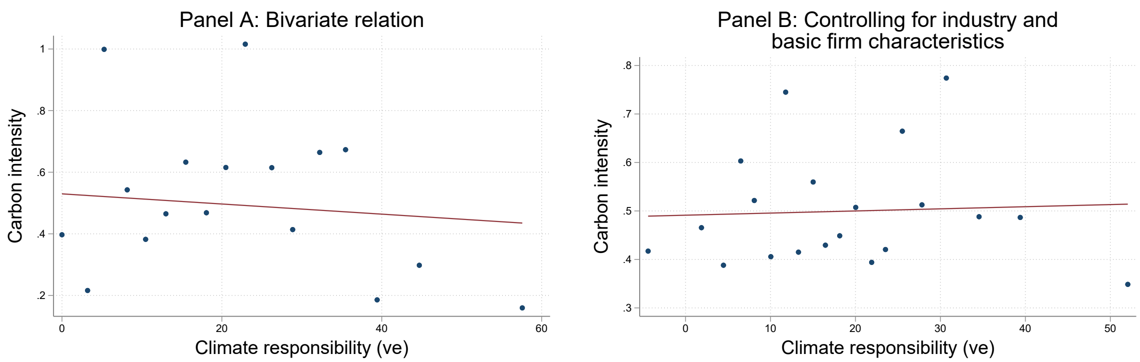


Figure 2. Abnormal returns after the 2016 election by industry
This figure plots the industry coefficients when regressing CAPM-adjusted returns on the day after the election (light blue bars) and through year-end 2016 (red bars) on Fama-French 30-industry dummies and firm characteristics (log market cap, revenue growth, profitability, and market leverage). The sample includes the 2,798 Russell 3000 index constituents as of November 8, 2016 for which controls are available. The ‘‘Everything else’’ industry is used as the base level.

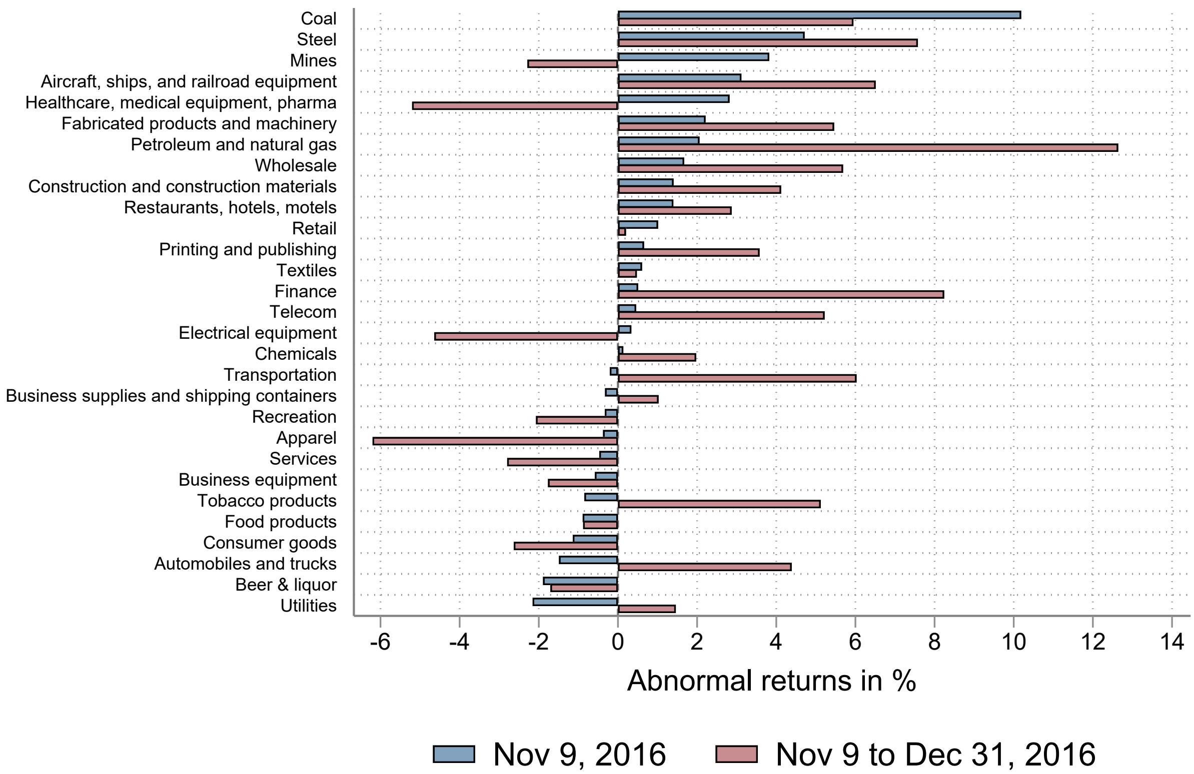


Figure 3. Rewards to climate responsibility after the 2016 climate policy shock This figure shows cumulative CAPM-adjusted returns for high and low climate-responsibility firms net of the combined impacts on returns of standard firm characteristics (log market cap, revenue growth, profitability, market leverage, and Fama-French 12-industry fixed effects) and other anticipated policy changes following the Trump election (cash ETR, foreign revenues). The cumulation of returns starts 20 trading days before the 2016 Presidential election. The high (low) climate responsibility category includes firms with a 2016 climate responsibility score by MSCI KLD above (below) the sample median after orthogonalizing by standard firm characteristics. The vertical lines indicate Election Day (Nov 8, 2016) and the day after the Pruitt nomination (Dec 7, 2016). The sample includes 2,102 Russell 3000 constituent firms as of November 8, 2016.

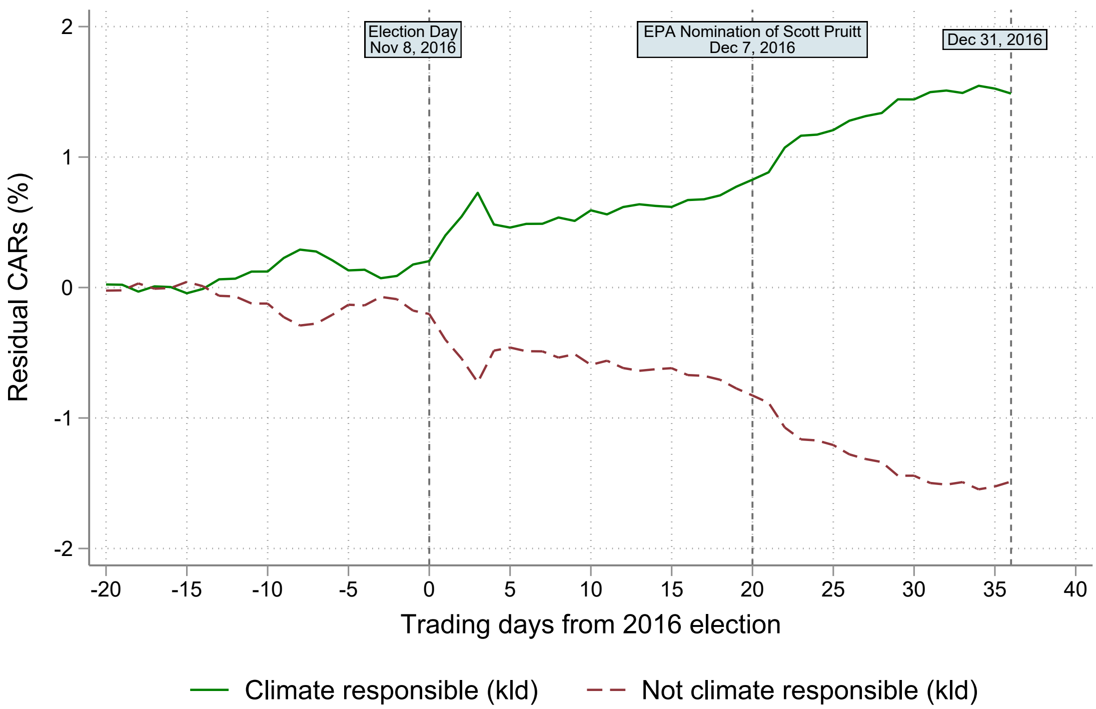


Figure 4. Rewards to climate responsibility after the 2020 election
This figure shows cumulative CAPM-adjusted returns for high and low climate-responsibility firms net of the combined impacts on returns of standard firm characteristics (log market cap, revenue growth, profitability, market leverage, and Fama-French 12-industry fixed effects), the cash ETR, and foreign revenues. The cumulation of returns starts 20 trading days before the 2020 Presidential election. The high (low) climate responsibility category includes firms with a 2018 climate responsibility score by MSCI KLD above (below) the sample median after orthogonalizing by standard firm characteristics. The vertical lines indicate events of interest for the final electoral outcome and climate policy. As of November 3, 2020, the sample includes 1,643 Russell 3000 constituent firms also included in the main (2016) sample.

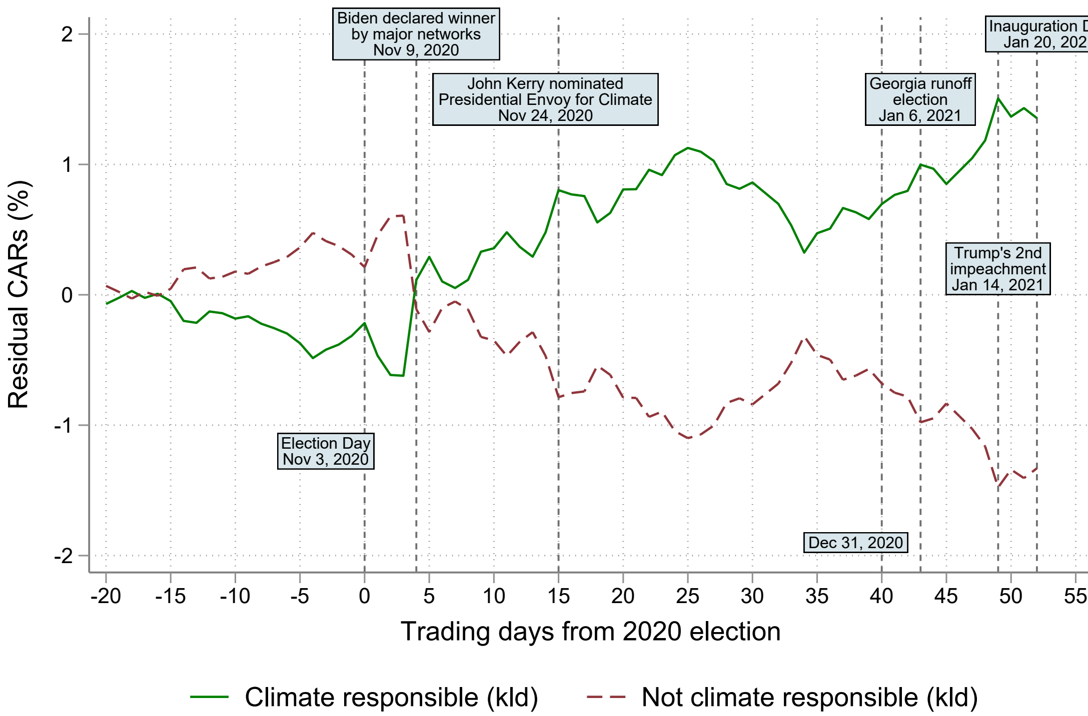


Table 1: Descriptive statistics of climate-related variables

This table shows descriptive statistics of climate-related variables for the Russell 3000 constituents for which standard controls (log market cap, revenue growth, profitability, and market leverage) are available. *Climate responsibility (kld)* is computed as the climate strength indicator (Env-str-d, 0 or 1) minus the climate weakness indicator (Env-con-f, 0 or 1) from MSCI KLD. *Climate responsibility (ve)* is an absolute score from 0 to 100 from Vigeo Eiris assessing firms' strategic approach to climate change risks and opportunities. *Climate responsibility leader (ve)* is a dummy variable equal to 1 for firms in the top quartile of *Climate responsibility (ve)*. *Carbon intensity* is computed as the 2015 Scope 1 and Scope 2 GHG emissions in kt of CO2 equivalents (ktCO2eq) provided by Vigeo Eiris, divided by the market value of equity in million USD, winsorized at the 99th percentile.

	N	min	p25	mean	p50	p75	max	sd
Climate responsibility (kld)	2,102	0.00	0.00	0.11	0.00	0.00	1.00	0.31
Climate responsibility (ve)	764	0.00	4.00	18.81	16.50	30.50	78.00	16.32
Climate responsibility leader (ve)	764	0.00	0.00	0.26	0.00	1.00	1.00	0.44
Carbon intensity	764	0.00	0.01	0.50	0.04	0.21	10.13	1.44

Table 2: Sample composition by firm characteristics, Vigeo Eiris

This 2-by-2 matrix shows the number of firms with *Climate responsibility (ve)* and *Carbon intensity* below or equal to the median and above the median.

	Carbon intensity		
Climate responsibility (ve)	Below or equal median	Above median	Total
Below or equal median	181	201	382
Above median	201	181	382
Total	382	382	764

Table 3: Descriptive statistics of firm accounting characteristics and abnormal stock returns

This table shows descriptive statistics of firm accounting information (Panel A) and stock returns (Panel B) for Russell 3000 constituent firms for which the MSCI KLD climate-related indicators and standard controls (log market cap, revenue growth, profitability, and market leverage) are all available. Accounting data refer to fiscal year 2015 for 1,541 companies and to fiscal year 2016 for 561 companies. Revenue growth, profitability, market leverage, and the cash ETR are obtained from Compustat or computed based on Compustat data. The market value of equity (market cap) is obtained from Bloomberg. Percent foreign revenue is from Bloomberg, supplemented by Compustat segment data. Individual stocks' abnormal returns are calculated with respect to the CAPM, and are expressed in percentage points. (We also consider raw returns and abnormal returns relative to the the Fama-French three-factor model, whose descriptive statistics are reported in Appendix Table A3.) To obtain CAPM-adjusted returns, we first estimate each stock's market beta from an OLS regression of daily excess returns from October 1, 2015, through September 30, 2016, on the market excess returns, when at least 126 daily return observations are available. We then compute abnormal returns for all days in the following quarter as the daily excess return on the stock minus beta times the market excess return.

Panel A: Accounting information

	N	min	p25	mean	p50	p75	max	sd
Log market cap	2,102	4.99	6.76	7.89	7.69	8.72	13.31	1.45
Revenue growth	2,102	-100.00	-3.66	15.54	4.13	13.76	3,380.13	139.06
Profitability	2,102	-291.46	0.71	2.73	4.13	9.68	133.64	18.58
Market leverage	2,102	0.00	0.08	0.27	0.24	0.41	3.02	0.25
Cash ETR	1,828	0.00	9.44	20.87	21.19	29.69	99.54	14.82
Percent foreign revenues	1,465	0.00	0.00	25.25	18.53	44.62	100.00	26.54

Panel B: Abnormal stock returns

	N	min	p25	mean	p50	p75	max	sd
Election (Nov 9, 2016)	2,102	-33.99	-1.21	1.20	0.87	3.22	42.01	4.58
Cumulative 3-Day	2,102	-34.92	-1.25	3.94	3.58	8.77	106.47	8.25
Cumulative 5-Day	2,102	-56.12	-1.33	4.32	4.06	9.32	114.96	8.96
Cumulative 10-Day	2,102	-52.78	-1.28	4.75	4.18	10.44	101.68	9.53
Pruitt Nomination (Dec 7, 2016)	2,102	-17.91	-1.41	-0.53	-0.22	0.80	17.30	2.49
Cumulative 3-Day	2,102	-25.53	-1.61	0.04	0.27	1.93	44.70	3.99
Cumulative 5-Day	2,102	-86.18	-3.26	-1.15	-0.76	1.23	45.11	5.08
Cumulative 10-Day	2,102	-86.85	-3.60	-0.82	-0.56	2.25	83.74	6.85

Table 4: Climate responsibility, stock returns and the 2016 climate policy shock (MSCI KLD sample)

This table shows results of OLS regressions of CAPM-adjusted returns on *Climate responsibility (kld)*, cash ETR, share of foreign revenues, and other control variables (market leverage, log market cap, revenue growth, and profitability). For firms with missing cash ETR and/or foreign revenues data we apply a dummy variable adjustment to preserve the sample size. All models also include Fama-French 12-industry fixed effects. Columns (1) through (4) refer to the Trump election and cover the following periods: November 9, 2016 (column (1)); November 9 through 11, 2016 (column (2)); November 9 through 15, 2016 (column 3); and November 9 through 22, 2016 (column (4)). Columns (5) through (8) refer to Pruitt's nomination and cover the following periods: December 7, 2016 (column (5)); December 7 through 11, 2016 (column (6)); December 7 through 14, 2016 (column (7)); and December 7 through 20, 2016 (column (8)). The sample includes all Russell 3000 firms covered by MSCI KLD in 2016 for which the climate-specific indicators and the control variables are available. t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Trump's election				Pruitt's nomination			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CAPM-adjusted returns							
		Cumulative				Cumulative		
Days:	Nov 9	3 days	5 days	10 days	Dec 7	3 days	5 days	10 days
Climate responsibility (kld)	0.438*	1.394***	0.847*	0.723	0.274**	0.571***	0.788***	1.072***
	(1.68)	(3.19)	(1.85)	(1.40)	(2.00)	(2.64)	(2.97)	(2.60)
Cash ETR	0.006	0.041***	0.046***	0.059***	0.003	0.009	0.019**	0.040**
	(0.72)	(3.04)	(3.06)	(3.72)	(0.93)	(1.28)	(2.25)	(2.30)
Cash ETR missing	-0.378	-0.972	-1.128	-0.947	0.021	-0.391	-0.590	-0.122
	(-0.97)	(-1.39)	(-1.43)	(-1.16)	(0.11)	(-1.20)	(-1.24)	(-0.18)
Foreign revenues	-0.016***	-0.035***	-0.036***	-0.029***	0.003	0.015***	0.024***	0.018**
	(-3.79)	(-4.58)	(-4.46)	(-3.07)	(1.05)	(3.06)	(4.65)	(2.27)
Foreign revenues missing	-0.442	-0.364	-0.044	0.136	-0.091	-0.117	-0.634**	-0.632
	(-1.56)	(-0.75)	(-0.08)	(0.24)	(-0.70)	(-0.53)	(-2.00)	(-1.41)
Leverage	-1.723***	-3.915***	-3.584***	-2.891***	0.495*	0.200	0.261	0.314
	(-3.60)	(-4.75)	(-4.16)	(-2.95)	(1.93)	(0.50)	(0.49)	(0.44)
Profitability	-0.019***	-0.058***	-0.065***	-0.028	0.024***	0.032***	0.038***	0.023
	(-2.66)	(-3.13)	(-3.91)	(-1.60)	(5.79)	(3.71)	(3.79)	(1.25)
Percent revenue growth	0.000	0.001	0.002	-0.002	-0.001**	-0.002***	-0.002**	-0.001
	(0.59)	(0.53)	(0.80)	(-0.92)	(-2.28)	(-4.00)	(-2.41)	(-1.51)
Log market cap	-0.584***	-1.872***	-1.645***	-2.211***	0.085**	-0.472***	-0.212**	-0.564***
	(-8.20)	(-15.53)	(-12.64)	(-15.50)	(2.11)	(-6.58)	(-2.53)	(-4.98)
Observations	2,102	2,102	2,102	2,102	2,102	2,102	2,102	2,102
R-squared	0.145	0.265	0.218	0.215	0.280	0.147	0.129	0.100

Table 5: Climate responsibility, stock returns and the 2016 climate policy shock (Vigeo Eiris sample)

Panel A reports the results of OLS regressions of CAPM-adjusted returns on *Climate responsibility (ve)*, *Carbon intensity*, control variables (cash ETR, share of foreign revenues, market leverage, log market cap, revenue growth, and profitability), and Fama-French 12-industry fixed effects. For firms with missing cash ETR and/or foreign revenue data we apply a dummy variable adjustment to preserve the sample size. Regressions in Panel B replace *Climate responsibility (ve)* with a dummy variable equal to 1 for firms in the top quartile of *Climate responsibility (ve)* and zero otherwise. Table 4 describes the columns. t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p< 0.05, * p<0.1.

	Trump's election				Pruitt's nomination			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CAPM-adjusted returns							
		Cumulative				Cumulative		
Days:	Nov 9	3 days	5 days	10 days	Dec 7	3 days	5 days	10 days
Panel A: *Climate responsibility (ve)* and *Carbon intensity*								
Climate responsibility (ve)	-0.009	0.020	0.025	0.023	0.020***	0.030***	0.024***	0.016
	(-0.82)	(1.24)	(1.38)	(1.12)	(4.15)	(4.15)	(2.86)	(1.44)
Carbon intensity	0.548***	0.419**	0.495**	0.654**	-0.014	0.079	-0.059	0.060
	(3.64)	(2.21)	(2.46)	(2.08)	(-0.27)	(0.60)	(-0.36)	(0.38)
Observations	764	764	763	763	761	761	761	761
R-squared	0.159	0.231	0.260	0.244	0.324	0.168	0.203	0.160
Panel B: *Climate responsibility leader (ve)* and *Carbon intensity*								
Climate responsibility leader (ve)	0.165	1.312**	1.260**	1.275*	0.382***	0.676**	0.720**	0.683*
	(0.52)	(2.57)	(2.35)	(1.95)	(2.59)	(2.55)	(2.42)	(1.75)
Carbon intensity	0.548***	0.421**	0.496**	0.656**	-0.013	0.081	-0.057	0.062
	(3.67)	(2.20)	(2.45)	(2.08)	(-0.24)	(0.62)	(-0.35)	(0.39)
Observations	764	764	763	763	761	761	761	761
R-squared	0.158	0.235	0.262	0.246	0.312	0.157	0.201	0.161
Constant and controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Changes in analysts' earnings forecasts after the 2016 election
This table shows the results of OLS regressions of average earnings forecast revisions from November 9 through December 31, 2016, on firms' climate-related performance and control variables (cash ETR, foreign revenues, log market cap, revenue growth, market leverage, profitability, and industry). t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p< 0.05, * p<0.1.

	(1)	(2)	(3)	(4)
Dependent variable:	Δ EPS forecasts			
Horizon:	FY2016	FY2017	FY2018	FY2019
Carbon intensity	-0.025	0.125*	0.132**	-0.046
	(-0.62)	(1.76)	(2.30)	(-1.33)
Climate responsibility leader (ve)	-0.027	0.041	0.023	0.054
	(-0.72)	(0.49)	(0.50)	(1.14)
Observations	719	729	684	396
R-squared	0.045	0.075	0.102	0.035
Controls	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes

Table 7: Changes in stock illiquidity, market beta, and volatility after the 2016 election

This table shows regression results of percentage changes in stock illiquidity (columns (1) and (2)), market beta (columns (3) and (4)), and return volatility (columns (5) and (6)) on *Climate responsibility leader (ve)*, *Carbon intensity*, and controls variables (cash ETR, foreign revenues, size, leverage, revenue growth, profitability, and industry). *Stock illiquidity* is the Amihud (2002) illiquidity measure computed as the average daily ratio of the absolute value of daily return to the dollar volume. *Volatility* is the standard deviation of daily returns. *Market beta* is the estimated coefficient of the CAPM model. The three measures are computed based on daily returns over the pre-event (from October 2015 through September 2016), 2017 (from January 2017 through December 2017), and 2019 (from January 2019 through December 2019), when at least 126 daily returns are available. The percentage changes are trimmed at 1st and 99th percentiles to control for extreme values. t-statistics based on robust standard errors are reported in parentheses. *** $p<0.01$, ** $p< 0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Δ Illiquidity (%)		Δ Market beta		Δ Volatility (%)	
	2016-2017	2016-2019	2016-2017	2016-2019	2016-2017	2016-2019
Carbon intensity	-0.020**	-0.046*	-0.004	-0.015	0.020	-0.005
	(-2.30)	(-1.85)	(-0.69)	(-1.47)	(1.43)	(-0.32)
Climate responsibility leader (ve)	0.019	0.055	0.010	0.010	0.005	-0.003
	(0.82)	(0.39)	(0.56)	(0.40)	(0.20)	(-0.11)
Observations	748	695	748	695	748	695
R-squared	0.067	0.056	0.175	0.132	0.280	0.218
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: The role of investor horizons for the climate responsibility premium after the 2016 election

This table shows the results of OLS regressions of CAPM-adjusted returns after Trump's election on the interactions of *Climate responsibility leader (ve)* and *Carbon intensity* with *Short-horizon IO* (Panel A) and *Long-horizon IO* (Panel B), controlling for firm characteristics (cash ETR, foreign revenues, market leverage, log market cap, revenue growth, and profitability) and Fama-French 12-industry fixed effects. *Short-horizon IO* and *Long-horizon IO* are the percentage of total institutional ownership as of Q3-2016 held by investors in the top and bottom quartiles of portfolio turnover, respectively. Conventional t-statistics based on robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)
Dependent variable:	CAPM-adjusted returns			
		Cumulative		
Days:	Nov 9, 2016	3 days	5 days	10 days
Panel A: Effects of Short-horizon IO				
Climate responsibility leader (ve) ×	-0.077	-0.164	-0.018	0.116
Short-horizon IO	(-0.88)	(-1.30)	(-0.11)	(0.56)
Carbon intensity ×	0.051***	0.064***	0.077***	0.105***
Short-horizon IO	(3.03)	(2.78)	(3.12)	(2.74)
Climate responsibility leader (ve)	0.385	1.778**	1.033	0.258
	(0.85)	(2.57)	(1.31)	(0.29)
Carbon intensity	0.122	-0.076	-0.161	-0.235
	(0.70)	(-0.39)	(-0.77)	(-0.85)
Short-horizon IO	-0.005	0.019	0.001	0.027
	(-0.27)	(0.55)	(0.01)	(0.60)
Observations	694	694	693	693
R-squared	0.193	0.265	0.284	0.287
Panel B: Effects of Long-horizon IO				
Climate responsibility leader (ve) ×	0.074**	0.099**	0.091*	0.052
Long-horizon IO	(2.45)	(2.16)	(1.83)	(0.87)
Carbon intensity ×	-0.015*	-0.024**	-0.022**	-0.032**
Long-horizon IO	(-1.87)	(-2.55)	(-2.09)	(-2.05)
Climate responsibility leader (ve)	-4.214**	-4.658*	-4.255	-2.118
	(-2.29)	(-1.68)	(-1.41)	(-0.57)
Carbon intensity	1.235***	1.586***	1.519***	2.197**
	(2.92)	(3.14)	(2.59)	(2.46)
Long-horizon IO	0.017	0.023	0.020	0.016
	(1.17)	(0.96)	(0.79)	(0.60)
Observations	694	694	693	693
R-squared	0.198	0.270	0.285	0.279
Firm controls	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes

Table 9: Climate performance, stock returns, and the 2020 election

This table shows results of OLS regressions of CAPM-adjusted returns on firms' climate-related variables, cash ETR, share of foreign revenues, and other control variables (market leverage, log market cap, revenue growth, and profitability). Regressions in Panel A investigate the effect of *Climate responsibility (kld)*, while those in Panel B the effects of *Climate responsibility leader (ve)* and *Carbon intensity*. Columns (1) and (2) refer to the one and three days following the 2020 Presidential election (November 4 through 6, 2020). Columns (3) to (6) cover the periods from the first trading day after Biden was announced as a winner (November 9, 2020) through after 10 trading days (November 10, 2020). t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	CAPM-adjusted returns					
		Cumulative		Cumulative		
Days:	Nov 4	3 days	Nov 9	3 days	5 days	10 days
Panel A: Regressions with MSCI KLD sample						
Climate responsibility (kld)	-0.969***	-1.614***	2.180***	1.067**	2.111***	3.123***
	(-3.29)	(-4.52)	(3.81)	(2.43)	(3.39)	(3.43)
Cash ETR	-0.008	-0.006	-0.046***	-0.048***	-0.065***	-0.073***
	(-1.04)	(-0.53)	(-2.75)	(-3.39)	(-3.35)	(-2.86)
Cash ETR missing	0.564*	0.407	-2.371***	-0.985	-2.160**	-0.298
	(1.79)	(0.75)	(-2.98)	(-1.47)	(-2.40)	(-0.23)
Foreign revenues	-0.021***	0.011	0.031***	0.032***	0.044***	0.054***
	(-5.31)	(1.62)	(3.30)	(3.85)	(3.87)	(3.54)
Foreign revenues missing	-2.013***	-0.748*	2.019***	1.534***	1.782**	1.429
	(-7.07)	(-1.90)	(3.08)	(3.08)	(2.50)	(1.51)
Log market cap	0.830***	1.028***	-1.760***	-0.904***	-1.798***	-2.875***
	(13.10)	(10.92)	(-12.22)	(-7.97)	(-11.06)	(-11.05)
Market leverage	-0.020***	0.001	0.036**	0.010	0.050***	0.160***
	(-2.86)	(0.14)	(2.10)	(0.64)	(2.61)	(5.58)
Profitability	0.015	0.035**	0.028	-0.009	0.031	0.018
	(1.34)	(2.42)	(1.39)	(-0.48)	(1.45)	(0.63)
Percent revenue growth	0.005*	0.005	-0.008**	-0.005	-0.011**	-0.011*
	(1.82)	(1.14)	(-1.97)	(-1.10)	(-2.38)	(-1.69)
Observations	1,643	1,642	1,643	1,643	1,642	1,641
R-squared	0.294	0.200	0.264	0.176	0.269	0.310
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Regressions with Vigeo Eiris sample						
Climate responsibility leader (ve)	-0.609	-0.594	2.670***	1.558**	2.346***	3.200***
	(-1.62)	(-1.33)	(3.14)	(2.38)	(2.62)	(2.74)
Carbon intensity	-0.060	-0.073	0.233	0.135	0.098	0.305
	(-0.54)	(-0.63)	(0.66)	(0.56)	(0.28)	(0.83)
Observations	501	500	501	501	501	501
R-squared	0.287	0.272	0.271	0.216	0.277	0.401
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Supplementary Appendix

A Additional Descriptive Statistics

Table A1: Descriptive statistics of climate-related firm characteristics

This table shows the descriptive statistics of climate-related variables provided by MSCI KLD (Panel A) and Vigeo Eiris (Panel B), by Fama-French 12-industry classification. The samples consist of Russell 3000 constituents as of November 8, 2016 for which information on standard control variables (log market cap, revenue growth, profitability, and market leverage) is available. *Climate responsibility (kld)* is a three-valued measure computed as firms' MSCI KLD climate strength (env-str-d, 0 or 1) minus climate concern (env-con-f, 0 or 1) indicators for 2016. *Climate responsibility (ve)* denotes the Vigeo Eiris Energy Transition score (from 0 to 100) for 2016. It measures a firm's strategic approach to climate change. *Carbon intensity* is defined as the firm's kilotons of CO2 emission equivalents (total Scopes 1 and 2) in 2015 normalized by the market value of equity (in million USD).

Panel A: MSCI KLD sample

	Climate responsibility (kld)	
	N	mean
Consumer non-durable	96	0.30
Consumer durable	45	0.09
Manufacturing	207	0.13
Energy	72	0.07
Chemicals	59	0.22
Business equipment	338	0.11
Telecom	56	0.09
Utilities	73	0.23
Wholesale	224	0.10
Healthcare	229	0.07
Finance	467	0.06
Other	236	0.08
Total	2,102	0.11

Panel B: Vigeo Eiris sample

		Climate responsibility (ve)					*Carbon intensity*				
	N	p25	mean	p50	p75	sd	p25	mean	p50	p75	sd
Consumer non-durable	43	11.00	24.84	26.00	33.00	15.84	0.01	0.08	0.02	0.06	0.15
Consumer durable	14	14.00	18.86	21.00	27.00	11.27	0.06	0.22	0.10	0.19	0.29
Manufacturing	61	9.00	22.20	24.00	33.00	14.86	0.02	0.73	0.11	0.37	1.77
Energy	42	5.00	14.90	14.00	20.00	11.83	0.27	1.27	0.59	1.34	1.73
Chemicals	28	17.50	30.57	32.00	43.00	18.13	0.02	0.83	0.13	0.89	1.91
Business equipment	127	0.00	15.97	12.00	27.00	16.09	0.01	0.10	0.02	0.05	0.36
Telecom	22	0.00	19.45	0.00	42.00	25.34	0.01	0.11	0.03	0.06	0.32
Utilities	52	21.00	27.19	27.50	35.50	12.57	0.37	2.69	2.02	3.48	2.86
Wholesale	66	2.00	17.00	17.00	28.00	13.55	0.02	0.27	0.06	0.11	1.25
Healthcare	63	0.00	14.65	4.00	28.00	19.84	0.00	0.09	0.01	0.06	0.24
Finance	162	4.00	16.65	11.50	26.00	14.98	0.00	0.03	0.01	0.03	0.04
Other	84	2.50	18.94	17.00	27.00	16.62	0.02	0.85	0.24	0.81	1.76
Total	764	4.00	18.81	16.50	30.50	16.32	0.01	0.50	0.04	0.21	1.44

Table A2: Correlations between variables

This table reports correlations between variables included in the MSCI KLD and Vigeo Eiris samples. Number of observations in parentheses. *** p<0.01, ** p< 0.05, * p<0.1.

Variables	1	2	3	4	5	6	7	8
1 Climate responsibility (kld)								
2 Climate responsibility (ve)	0.55***							
	(718)							
3 Carbon intensity	-0.11***	-0.02						
	(718)	(764)						
4 Log market cap	0.48***	0.49***	-0.22***					
	(2,102)	(764)	(764)					
5 Profitability	0.10***	0.14***	-0.12**	0.19***				
	(2,102)	(764)	(764)	(2,148)				
6 Revenue growth	-0.04	-0.14***	-0.11***	-0.05**	-0.7***			
	(2,102)	(764)	(764)	(2,148)	(2,148)			
7 Market leverage	0.06***	-0.06	0.13***	0.12***	-0.05*	-0.01		
	(2,102)	(764)	(764)	(2,148)	(2,148)	(2,148)		
8 Cash ETR	-0.02	-0.03	-0.07*	0.03	0.23***	-0.10***	-0.11***	
	(1,828)	(671)	(671)	(1,871)	(1,871)	(1,871)	(1,871)	
9 Foreign revenues	0.14***	0.20***	-0.07	0.16***	0.06*	-0.05*	-0.06*	0.12***
	(1,665)	(643)	(643)	(1,705)	(1,705)	(1,705)	(1,705)	(1,502)

Table A3: Descriptive statistics of alternative sets of stock returns

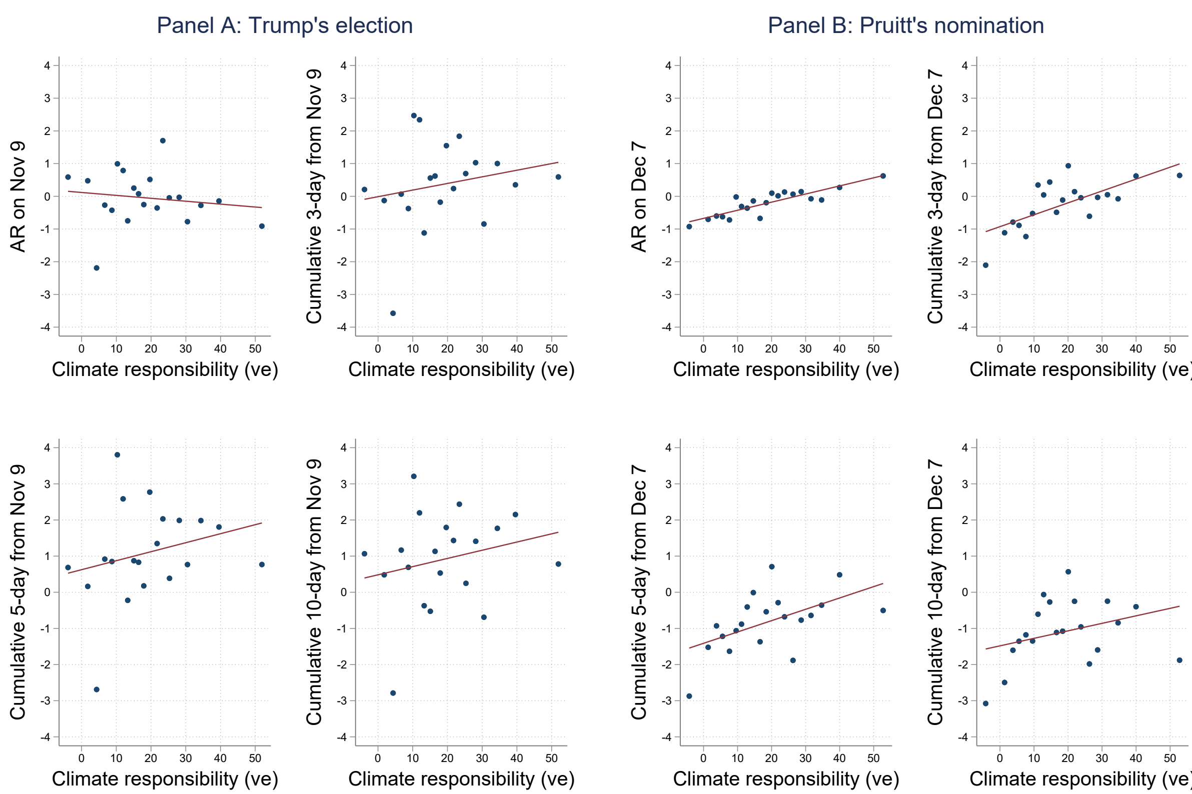
This table reports descriptive statistics of individual raw returns and abnormal returns calculated with respect to the Fama-French three-factor model. To obtain Fama-French-adjusted returns, we first estimate each stock's factor loadings from an OLS regression of daily stock returns in excess of the riskless asset return on the market excess returns, size, and value factor returns using one year of daily data.

	N	min	p25	mean	p50	p75	max	sd
Raw returns								
Election (Nov 9, 2016)	2,102	-31.26	0.39	2.97	2.61	5.07	43.13	4.79
Cumulative 3-Day	2,102	-31.59	1.14	6.40	6.01	11.36	116.06	8.67
Cumulative 5-Day	2,102	-54.33	1.98	8.12	7.63	13.39	130.78	9.75
Cumulative 10-Day	2,102	-50.00	3.58	10.38	9.76	16.58	124.28	10.60
Pruitt Nomination (Dec 7, 2016)	2,102	-15.33	0.09	1.00	1.18	2.07	18.75	2.33
Cumulative 3-Day	2,102	-22.05	0.89	2.58	2.53	4.22	49.43	3.90
Cumulative 5-Day	2,102	-86.02	-0.02	1.73	1.90	3.91	50.58	4.95
Cumulative 10-Day	2,102	-86.68	-0.56	2.16	2.28	4.95	89.40	6.86
Fama-French-adjusted returns								
Election (Nov 9, 2016)	2,102	-37.17	-2.31	-0.20	-0.38	1.63	42.07	4.53
Cumulative 3-Day	2,102	-42.69	-4.32	-0.54	-0.25	4.02	93.41	8.20
Cumulative 5-Day	2,102	-54.28	-4.66	-0.34	-0.10	4.39	107.78	9.08
Cumulative 10-Day	2,102	-51.47	-5.29	-0.78	-0.39	4.59	90.08	9.64
Pruitt Nomination (Dec 7, 2016)	2,102	-15.88	-0.90	0.01	0.14	1.14	18.15	2.30
Cumulative 3-Day	2,102	-28.06	-1.71	-0.12	0.12	1.87	44.75	4.03
Cumulative 5-Day	2,102	-84.73	-2.16	-0.10	0.04	2.11	48.00	4.92
Cumulative 10-Day	2,102	-85.50	-3.29	-0.43	-0.20	2.65	85.98	6.87
Average factor loadings								
Market	2,102	0.12	0.82	1.06	1.01	1.25	4.21	0.38
Size	2,102	-0.85	0.25	0.79	0.68	1.21	4.53	0.79
Value	2,102	-3.12	-0.24	0.20	0.15	0.58	6.83	0.89

B Additional Findings and Robustness Checks

B.1 Graphical depiction of results on climate responsibility and carbon intensity

Figure A5. Scatter plots of CAPM-adjusted returns against *Climate responsibility (ve)*
Binned scatter plots of CAPM-adjusted abnormal returns against *Climate responsibility (ve)* following the Trump election (Panel A) and Pruitt's nomination (Panel B). All graphs control for Fama-French 12-industry fixed effects, *Carbon intensity* and control variables (cash ETR, foreign revenues, log market cap, revenue growth, profitability, and market leverage).



B.2 Empirical standard errors

Given the potential cross-sectional correlation of stock returns, conventional t-statistics, which posit independently distributed errors, could be biased upwards (Fama and French, 2000). To control for the effect of this potential problem, in this robustness check we test the statistical significance of coefficients in our main cross-sectional regressions using adjusted t-statistics based on the empirical distribution of coefficient estimates, following the approach of Cohn, Gillan, and Hartzell (2016). Specifically, we compute the adjusted t-statistics as follows. First, we run the cross-sectional regression using daily (abnormal) returns over a non-event period ranging from October 1, 2015 through September 30, 2016. Market betas over this non-event period are estimated using one year of daily stock-return data going back up to October 1, 2014, and are then used to compute the abnormal returns for the following quarter. Then we run the same cross-sectional regression using event-period returns. The adjusted t-statistic is computed by subtracting the mean time-series coefficients over the non-event period (the adjusted "null" hypothesis) from the estimated event coefficients, and then dividing this difference by the standard deviation of the time-series coefficients over the non-event period. When using cumulative (abnormal) returns, we combine returns in the pre-event period as done post-event to estimate coefficients over comparable non-overlapping periods. (For instance, the adjusted t-statistics for the 5-day CAR regressions are based on the mean and standard deviation of 50 pre-event coefficient estimates.)

Note that this method can yield adjusted t-statistics that are higher or lower than the ones based on robust standard errors, because the mean time-series coefficients over the non-event period can be either positive or negative. In addition, the standard deviations of the estimated coefficients over the pre-event period are likely to be particularly high in 5-day and 10-day CAR regressions, because they are based on only 50 and 25 pre-event coefficient estimates.

Results in Table A4 show that our main results (both in the MSCI KLD and Vigeo Eiris samples) remain statistically significant even when considering the empirical distribution of coefficients. Differences in statistical significance are minor. The average one-day coefficient on *Climate responsibility (kld)* over the pre-event period is equal to -0.010 (with a standard deviation of 0.182), while the average coefficient on *Climate responsibility leader (ve)* is -0.028 (with a standard deviation of 0.33).

Table A4: Climate responsibility, stock returns and the 2016 climate policy shock (Adjusted t-statistics)

This table shows results of OLS regressions of CAPM-adjusted returns on firms' climate-related variables (*Climate responsibility (kld)* in Panel A, and *Climate responsibility (ve)* and *Carbon intensity* in Panel B), cash ETR, share of foreign revenues, and other control variables (market leverage, log market cap, revenue growth, and profitability). The regressions are the same as in Tables 4 and 5, but statistical significance is assessed based on adjusted t-statistics (reported in brackets) calculated from the empirical time-series distribution of returns on trading days between October 1, 2015 and September 30, 2016, following Cohn et al. (2016). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	Trump's election				Pruitt's nomination			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CAPM-adjusted returns							
		Cumulative				Cumulative		
Days:	Nov 9	3 days	5 days	10 days	Dec 7	3 days	5 days	10 days
Panel A: Regressions with MSCI KLD sample								
Climate responsibility (kld)	0.438**	1.394***	0.847**	0.723	0.274	0.571*	0.788**	1.072*
	[2.46]	[4.32]	[2.22]	[1.32]	[1.56]	[1.83]	[2.07]	[1.85]
Observations	2,102	2,102	2,102	2,102	2,102	2,102	2,102	2,102
R-squared	0.145	0.265	0.218	0.215	0.280	0.147	0.129	0.100
Panel B: Regressions with Vigeo Eiris sample								
Climate responsibility leader (ve)	0.165	1.312***	1.260***	1.275	0.382**	0.676**	0.720*	0.683
	[0.96]	[4.01]	[3.17]	[1.55]	[2.15]	[2.10]	[1.86]	[0.85]
Carbon intensity	0.548***	0.421	0.496	0.656	-0.013	0.081	-0.057	0.062
	[3.88]	[1.48]	[1.37]	[0.80]	[-0.14]	[0.21]	[-0.28]	[-0.07]
Observations	764	764	763	763	761	761	761	761
R-squared	0.158	0.235	0.262	0.246	0.312	0.157	0.201	0.161
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF30 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

B.3 Controlling for a finer industry classification

Our regressions in Section 4 controlled for industry-level return differentials using the Fama-French 12-industry classification. This classification appropriately preserves the variability of climate-related measures when using the relatively small Vigeo Eiris sample.

For consistency, we adopted the same methodological approach for the larger MSCI KLD sample. That larger sample permits a finer industry classification, as a robustness check. Table A5 presents the results for the MSCI KLD sample controlling for Fama-French 30-industry fixed effects. We observe minor differences compared to our baseline results in Table 4. Specifically, the coefficients on *Climate responsibility (kld)* are now more strongly significant in the immediate post-election period and slightly reduced in magnitude following Pruitt's nomination.

Table A5: Stock returns and *Climate responsibility (kld)*, controlling for Fama-French 30 industries

This table reports the results of OLS regressions of CAPM-adjusted returns on *Climate responsibility (kld)* and control variables (cash ETR, foreign revenues, log market cap, revenue growth, profitability, and market leverage). All models include Fama-French 30-industry fixed effects. Table 4 describes the columns. t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p< 0.05, * p<0.1.

	Trump's election				Pruitt's nomination			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CAPM-adjusted returns							
		Cumulative				Cumulative		
Days:	Nov 9	3 days	5 days	10 days	Dec 7	3 days	5 days	10 days
Climate responsibility (kld)	0.544**	1.572***	0.983**	0.873*	0.251*	0.551***	0.692***	0.900**
	(2.10)	(3.72)	(2.20)	(1.70)	(1.85)	(2.63)	(2.64)	(2.22)
Observations	2,102	2,102	2,102	2,102	2,102	2,102	2,102	2,102
R-squared	0.166	0.278	0.235	0.229	0.295	0.161	0.145	0.120
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF30 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

B.4 Controlling for corporate governance

One concern with our findings could be that the out-performance of climate-responsible firms could be driven by their higher score on corporate governance more generally. For example, it is conceivable that investors believe that environmental deregulation would go hand-in-hand with deregulation in the financial realm as well. Positing that such regulation, on net, benefits investors, better-governed firms would get a relative benefit from the broad theme of the Trump election and Pruitt's nomination. We re-run the analysis controlling for corporate governance.

We conduct this analysis using two alternative measures of governance. First, we compute a measure of governance based on the MSCI KLD database, as follows: For each firm, we divide the number of governance strengths by its possible maximum value, and we then subtract the number of governance concerns divided by its possible maximum value. The resulting measure, Corporate governance (kld), ranges from -1 to +1. We use information on governance as of year-end 2013, the latest available data on the MSCI KLD database. Second, we use firms' institutional ownership, a corporate governance proxy extensively used in the literature (e.g., Chung and Zhang, 2011). We compute this measure as the percentage of firms' common stocks held by 13-F institutional investors at the end of Q3-2016. The results in Table A6 reveal that our main results hold after controlling for each of these two measures of firms' corporate governance.

Table A6: Climate responsibility and corporate governance
This table shows results of OLS regressions of our main models when controlling for firms' corporate governance performance. Panel A shows the results when using the corporate governance score from the MSCI KLD database. (We use information on governance as of year-end 2013, the latest available data on the MSCI KLD database.) Panel B shows the results when including the share of firms' institutional ownership as of Q3-2016. All models include control variables (cash ETR, foreign revenues, market leverage, log market cap, revenue growth, and profitability) and Fama-French 12-industry fixed effects. Table 4 describes the columns. t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Corporate Governance score, MSCI KLD

	Trump's election				Pruitt's nomination			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CAPM-adjusted returns							
		Cumulative				Cumulative		
Days:	Nov 9	3 days	5 days	10 days	Dec 7	3 days	5 days	10 days
Climate responsibility (kld)	0.295	1.364***	0.781*	0.684	0.389***	0.738***	0.895***	1.113***
	(1.15)	(3.10)	(1.70)	(1.29)	(2.86)	(3.35)	(3.32)	(2.78)
Corporate governance (kld)	0.817	0.299	0.491	-0.037	-0.424	0.320	0.420	0.419
	(1.05)	(0.25)	(0.38)	(-0.03)	(-1.36)	(0.50)	(0.59)	(0.44)
Observations	1,693	1,693	1,693	1,693	1,693	1,693	1,693	1,693
R-squared	0.159	0.298	0.245	0.249	0.262	0.137	0.124	0.086

Panel B: Share of institutional ownership

Climate responsibility (kld)	0.321	1.395***	0.901*	0.704	0.285**	0.667***	0.853***	1.118***
	(1.19)	(3.10)	(1.88)	(1.30)	(1.96)	(2.93)	(3.04)	(2.58)
Institutional ownership	-0.016**	-0.013	0.002	-0.014	-0.004	0.002	-0.004	-0.004
	(-2.40)	(-1.28)	(0.19)	(-1.13)	(-1.19)	(0.35)	(-0.53)	(-0.35)
Observations	1,877	1,877	1,877	1,877	1,877	1,877	1,877	1,877
R-squared	0.152	0.264	0.211	0.210	0.289	0.158	0.136	0.110
Constant and controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

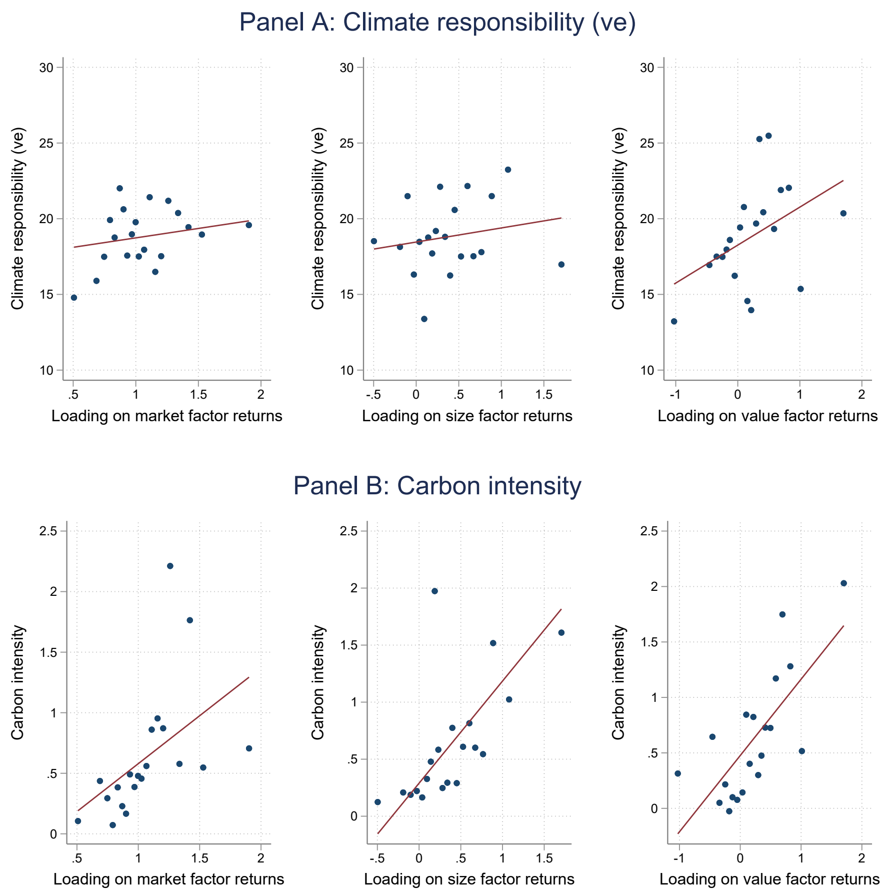
B.5 Alternative sets of returns

It is useful to reflect on the relative advantages in our setting of using raw returns, CAPM-adjusted returns, or Fama-French-adjusted returns. Conceptually, the purpose of using adjusted returns is to eliminate the impact of factors that are unrelated to the effects being investigated.

To illustrate, small stocks outperformed large stocks and value stocks outperformed growth stocks after the 2016 election. However, this out-performance could itself be driven by the new administration's expected policies. Indeed, in their analysis of the effect of expected changes in tax policy after the election, Wagner et al. (2018) find that firms with high loadings on the size and value factors have higher ETRs on average. They then note that to the extent that the size and value returns are themselves driven by expected changes in tax policy, regressions using Fama-French-adjusted returns will tend to understate the impact of taxes on stock returns. Similar effects could obviously arise if the climate-related variables correlate significantly with some of the Fama-French factor loadings.

Figure A6 indicates that firms graded higher on *Climate responsibility (ve)* on average load more highly on the value factor, controlling for other firm characteristics. This relation is statistically significant ($p < 0.001$). However, *Climate responsibility (ve)* appears to be uncorrelated with either the market or the size factor loadings. Similar results hold with *Climate responsibility (kld)* ($p < 0.05$). Figure A6 also reveals that in the Vigeo Eiris sample, firms with higher *Carbon intensity* have, on average, higher loading on the market, value and size factors (controlling for sector and firm characteristics). Each of these three relations is statistically significant ($p < 0.01$).

Figure A6. Climate-related variables against Fama-French factor loadings
Binned scatter plots of loadings on (from left to right) Fama-French market, size, and value factor returns against firm *Climate responsibility (ve)* (Panel A) and *Carbon intensity* (Panel B) for the firms in the Vigeo Eiris sample. The plots control for Fama-French 12-industry fixed effects and firm characteristics (log market cap, percentage revenue growth, profitability, and market leverage). The factor loadings are computed by regressing firms' daily excess returns on the daily market excess returns, size, and value factor returns (from Ken French's website) from October 1, 2015 through September 30, 2016.



Due to these differences in factor exposures, differences in the magnitude of the effects that we document across alternative sets of returns are to be expected. We therefore replicate our analysis using two alternative sets of returns: Raw returns and Fama-French-adjusted returns. Table A7 shows the results of this robustness check.

The effects of the factor loadings are intuitive. Recall from Figure A6 that in the Vigeo

Eiris sample, firms with higher *Climate responsibility (ve)* have, on average, higher loadings on the value factor (after controlling for sector and firm characteristics). The results in Table A7 reflect this correlation: Although the coefficients on *Climate responsibility leader (ve)* when using raw returns (Panel B.1) are close to those obtained with CAPM-adjusted returns, they are reduced when using Fama-French-adjusted returns (Panel B.2).

Similar effects arise in the case of *Carbon intensity*. When using Fama-French-adjusted returns, the coefficient on *Carbon intensity* is smaller than with CAPM-adjusted returns, especially after the first day. This result again emerges because *Carbon intensity* is highly positively correlated with the value and size loadings. This implies that, if we utilize returns net of their size and value factor components, the coefficients on *Carbon intensity* capture the general out-performance of value (versus growth) stocks after the election. Conversely, when using raw returns, the coefficients on *Carbon intensity* are slightly larger in magnitude than those obtained with CAPM-adjusted returns, reflecting the positive correlation of this variable with the market beta.

Overall, our main inferences are robust to the use of returns in any of the three traditional forms.

B.6 Using the more generic E(SG) score from Asset4

We here provide a further robustness check by replicating our results using another proxy of a firm's strategic positioning on climate change, the 2016 Environmental score from the Thomson Reuters Refinitiv Asset4 database (used, e.g., in Dyck et al., 2019 and Albuquerque et al., 2020). Since this score reflects policies and actions on several environmental fronts other

Table A7: Results with alternative sets of returns

This table shows results of OLS regressions of our main models when using raw and Fama-French-adjusted returns as dependent variables. Panel A shows the results for the MSCI KLD sample. Panel B shows those for the Vigeo Eiris sample. Panels A.1 and B.1 report results for raw returns, while Panels A.2 and B.2 present them for Fama-French-adjusted returns. In addition to the climate-related variables, all models include firm characteristics (cash ETR, foreign revenues, log market cap, revenue growth, profitability, and market leverage), and Fama-French 12-industry fixed-effects. Table 4 describes the columns. t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: MSCI KLD sample

	Trump's election				Pruitt's nomination			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Cumulative				Cumulative		
Days:	Nov 9	3 days	5 days	10 days	Dec 7	3 days	5 days	10 days
Panel A.1								
Dependent variable:	Raw returns							
Climate responsibility (kld)	0.402	1.372***	0.803	0.671	0.243*	0.533**	0.752***	1.039**
	(1.48)	(3.02)	(1.62)	(1.18)	(1.82)	(2.49)	(2.95)	(2.53)
R-squared	0.171	0.276	0.235	0.234	0.232	0.110	0.092	0.076
Panel A.2								
Dependent variable:	Fama-French-adjusted returns							
Climate responsibility (kld)	0.368	1.176**	0.532	0.376	0.229*	0.469**	0.720***	0.972**
	(1.45)	(2.51)	(1.07)	(0.66)	(1.70)	(2.08)	(2.77)	(2.36)
R-squared	0.107	0.206	0.201	0.165	0.186	0.132	0.084	0.093
Observations	2,102	2,102	2,102	2,102	2,102	2,102	2,102	2,102
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Vigeo Eiris sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B.1								
Dependent variable:	Raw returns							
Climate responsibility leader (ve)	0.186	1.369**	1.365**	1.437*	0.404***	0.722***	0.776***	0.738*
	(0.55)	(2.54)	(2.30)	(1.93)	(2.78)	(2.82)	(2.78)	(1.93)
Carbon intensity	0.629***	0.534***	0.685***	0.959***	0.057	0.199	0.070	0.196
	(4.08)	(2.64)	(2.99)	(2.64)	(1.12)	(1.56)	(0.45)	(1.24)
R-squared	0.194	0.252	0.295	0.291	0.249	0.111	0.135	0.097
Panel B.2								
Dependent variable:	Fama-French-adjusted returns							
Climate responsibility leader (ve)	0.010	0.816*	0.632	0.547	0.382***	0.578**	0.734**	0.622
	(0.03)	(1.72)	(1.27)	(0.90)	(2.60)	(2.12)	(2.53)	(1.57)
Carbon intensity	0.330**	-0.241	-0.303	-0.281	0.011	-0.024	-0.001	0.019
	(2.44)	(-1.30)	(-1.55)	(-1.05)	(0.22)	(-0.18)	(-0.01)	(0.12)
R-squared	0.142	0.333	0.323	0.325	0.221	0.217	0.129	0.179
Observations	764	764	763	763	761	761	761	761
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

than climate change (such as biodiversity and waste management), it is a more imperfect proxy of climate responsibility than the measures used in our primary analyses.

Despite the differences in scope with our main climate-specific proxies, the environmental score from Asset4 (*ENV score (a4)*) correlates strongly positively with both *Climate responsibility (ve)* (0.73, p <0.001) and *Climate responsibility (kld)* (0.60, p <0.001). By contrast, *ENV score (a4)* correlates mildly and not statistically significantly with *Carbon intensity* (-0.03, p >0.1), confirming once again the difference between ESG-like environmental processes indicators and current carbon emissions.

Table A8 shows the stock-price effect of a firm's generic environmental score after Trump's election and Pruitt's nomination. Regressions in Panel A include the continuous environmental score from 0 to 100 while those in Panel B include an indicator equal to 1 for firms in the top quartile of the environmental score (to allow a comparison with *Climate responsibility (kld)* and *Climate responsibility leader (ve)*). We observe a positive effect of the environmental score both after Trump's election and Pruitt's nomination, providing further reassurance on the reliability of our main findings.

Table A8: Environmental responsibility, stock returns and the 2016 climate policy shock (Asset4 sample)

This table reports the results of OLS regressions of CAPM-adjusted returns on the firm's 2016 environmental pillar score from Asset4 and control variables (cash ETR, foreign revenues, log market cap, revenue growth, profitability, and market leverage). Regressions in Panel A use the continuous score from 0 to 100 (*Env score (a4)*), and those in Panel B an indicator equal to 1 for firms in the top quartile of the environmental score (*Env score (a4) leader*). The sample includes all Russell 3000 firms covered by Asset4 in 2016 for which control variables are available. t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Trump's election				Pruitt's nomination			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CAPM-adjusted returns							
		Cumulative				Cumulative		
Days:	Nov 9	3 days	5 days	10 days	Dec 7	3 days	5 days	10 days
Panel A: Env score from Asset4								
ENV score (a4)	0.001	0.010	0.014	0.024***	0.007***	0.009***	0.013***	0.017***
	(0.28)	(1.29)	(1.64)	(2.65)	(3.16)	(2.63)	(3.00)	(2.77)
Observations	2,101	2,101	2,101	2,101	2,101	2,101	2,101	2,101
R-squared	0.161	0.276	0.226	0.241	0.288	0.176	0.129	0.095
Panel B: Env score from Asset4 (top quartile)								
ENV score (a4) leader	0.088	0.456	0.847*	1.252***	0.271**	0.370*	0.596**	0.714**
	(0.32)	(1.12)	(1.94)	(2.67)	(2.24)	(1.93)	(2.58)	(2.25)
Observations	2,101	2,101	2,101	2,101	2,101	2,101	2,101	2,101
R-squared	0.161	0.276	0.227	0.241	0.287	0.175	0.128	0.094
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

B.7 Descriptive statistics and additional results for the boomerang hypothesis

Figure A7. Correlation between returns and analysts' forecast revisions
This figure compares cumulative CAPM-adjusted returns from November 8, 2016, through year-end 2016 with the change in mean earnings forecasts over the same period. The sample includes 6,762 average forecast revisions (at FY 2016, FY 2017, FY 2018, or FY 2019 horizons) for 2,346 individual Russell 3000 constituents.

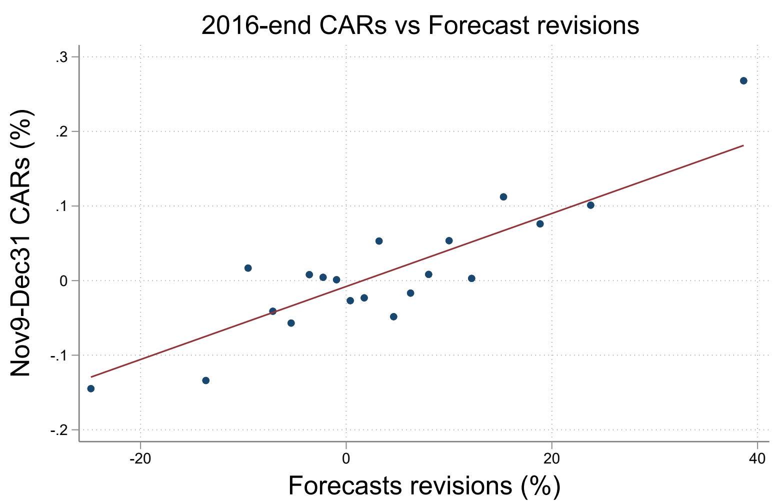


Table A9: Summary statistics of changes in analysts' earnings forecasts
This table shows descriptive statistics of changes in analysts' average earnings forecasts between November 9 and December 31, 2016, for Russell 3000 firms with available earnings forecast information and climate-related data from Vigeo Eiris. Changes in earnings forecasts are defined as the difference between the mean EPS forecast as of December 31, 2016, and the mean EPS forecast as of November 7, 2016, normalized by the share price at the end of the last fiscal year and multiplied by 100. All changes are winsorized at the 1th and 99th percentiles.

				Δ EPS forecasts				
	N	min	p25	mean	p50	p75	max	sd
FY2016	720	-4.39	-0.02	-0.04	0.00	0.01	6.11	0.65
FY2017	730	-5.20	-0.04	0.03	0.00	0.04	8.85	0.93
FY2018	685	-2.87	-0.06	0.05	0.00	0.07	7.21	0.72
FY2019	396	-1.89	-0.02	0.01	0.00	0.01	8.59	0.61

Table A10: The role of transient investors

This table shows the results of OLS regressions of CAPM-adjusted returns after Trump's election on the interactions of *Climate responsibility leader (ve)* and *Carbon intensity* with *Transient IO*, firm controls (cash ETR, foreign revenues, market leverage, log market cap, revenue growth, and profitability), and Fama-French 12-industry fixed effects. *Transient IO* is the percentage of total institutional ownership as of Q3-2016 held by transient (short-term) investors according to the Bushee (1998) classification. t-statistics based on robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
Dependent variable:	CAPM-adjusted returns			
		Cumulative		
Days:	Nov 9, 2016	3 days	5 days	10 days
Climate responsibility leader (ve) × Transient IO	-0.041	-0.047	-0.012	0.071
	(-0.91)	(-0.66)	(-0.15)	(0.76)
Carbon intensity × Transient IO	0.043***	0.059***	0.069***	0.110***
	(3.50)	(4.03)	(4.52)	(5.45)
Climate responsibility leader (ve)	0.991	2.129	1.258	-0.747
	(0.98)	(1.31)	(0.70)	(-0.38)
Transient IO	-0.020	-0.030	-0.041	-0.029
	(-0.94)	(-0.94)	(-1.12)	(-0.76)
Carbon intensity	-0.640*	-1.182***	-1.409***	-2.371***
	(-1.80)	(-2.83)	(-3.13)	(-3.91)
Observations	694	694	693	693
R-squared	0.199	0.269	0.290	0.304
Firm controls	Yes	Yes	Yes	Yes
FF12 industry FE	Yes	Yes	Yes	Yes

Table A11: Descriptive statistics of 2020 sample

This table shows descriptive statistics of variables used in Section 5.3 (''The boomerang arrives''). The sample includes Russell 3000 constituents in 2020 that are also included in the 2016 sample used in Section 4 (''Within-industry stock-price reactions''). Returns (adjusted for stock splits and dividends) are computed based on stock prices retrieved from Compustat. To compute CAPM-adjusted returns, we first estimate each stock's market beta by regressing its daily excess returns from January 2, 2019, through December 31, 2019, on a constant and the daily value-weighted market return (in excess of the daily one-month U.S. Treasury-bill rate). CAPM-adjusted returns are the daily excess returns on the stock minus beta times the market excess return. *Climate responsibility (kld)*, *Climate responsibility (ve)*, and *Climate responsibility leader (ve)* are the updated 2018 values of the variables used in the rest of the paper. *Carbon intensity* is computed as the Scope 1 and Scope 2 GHG emissions in kt of CO2 equivalents (ktCO2eq) in 2017 divided by the market value of equity in million USD, winsorized at the 99th percentile. Revenue growth, profitability, market leverage, and the cash ETR are obtained from Compustat and refer to 2019. Market cap (as of Nov 3, 2020) is also computed based on Compustat data.

	N	min	p25	mean	p50	p75	max	sd
Climate-related variables								
Climate responsibility (kld)	1,643	-1.00	0.00	0.17	0.00	0.00	1.00	0.38
Climate responsibility (ve)	501	0.00	7.00	21.52	20.00	33.00	72.00	16.75
Climate responsibility leader (ve)	501	0.00	0.00	0.23	0.00	0.00	1.00	0.42
Carbon intensity	501	0.00	0.01	0.61	0.04	0.24	16.78	2.01
Accounting information								
Log market cap	1,643	17.31	20.73	21.92	21.73	22.97	28.26	1.64
Revenue growth	1,643	-100.00	-1.12	9.41	4.88	12.44	682.90	39.80
Profitability	1,643	-107.96	0.97	2.46	3.32	6.93	33.86	11.78
Market leverage	1,643	0.00	6.53	19.48	15.60	28.02	95.43	16.70
Cash ETR	1,564	0.00	9.65	20.71	21.48	29.46	99.54	14.23
Percent foreign revenues	1,340	0.00	0.00	26.03	20.20	45.44	100.00	26.14
CAPM-adjusted stock returns								
Election (Nov 4, 2020)	1,643	-19.59	-5.60	-2.92	-2.69	-0.31	42.49	4.30
Cumulative 3-Day	1,642	-28.11	-7.38	-3.90	-3.88	-0.70	43.04	5.86
Election result announced (Nov 9, 2020)	1,643	-30.31	-1.67	3.73	2.34	8.28	50.45	9.34
Cumulative 3-Day	1,643	-27.59	-2.82	1.28	0.38	4.60	42.97	7.20
Cumulative 5-Day	1,642	-35.10	-2.88	3.64	2.01	8.79	50.67	10.51
Cumulative 10-Day	1,641	-40.18	-3.15	5.49	2.55	10.69	116.50	14.70