Financial Market Perception and Climate Political Leadership

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No adaptation if the risk is not perceived[1]
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1.0 Introduction

Climate change exposure constitutes a significant socioeconomic and political challenge to the financial markets and every facet of the global economy (Bartram et al., 2022; Battiston et al., 2021; Degryse et al., 2023; Sautner et al., 2023b). Recent evidence shows a close link between corporate activities and environmental pollution (Li et al., 2021), prompting ongoing discussions on the role of climate political leadership (CPL) in mitigating the long-term effects of the negative externalities of corporate polluting activities[2] through the implementation of stricter climate regulations (Bartram et al., 2022; Bose et al., 2021; Xu & Kim, 2022).

We broadly define CPL[3] as the conviction and disposition of the highest political leadership of a country/region to offer validation to the climate science consensus on anthropogenic causes of climate change. Furthermore, CPL also reflects the political leadership's approach to tackling climate change, including initiatives to establish the climate agenda and design regulatory frameworks to address climate-related challenges. Studies suggest that transitioning to a low-carbon economy requires CPL to play a vital role in fostering a climate-friendly regulatory environment (Karlsson & Symons, 2015; Martinsson et al., 2024; Wurzel et al., 2021a). Studies also claim that stringent climate-friendly regulatory policies promote the adoption of cleaner industrial technologies, effectively reducing the impact of climate change and other environmental risks without significantly impacting long-term economic growth (Acemoglu et al., 2012; Acemoglu et al., 2016). Such a climate regulatory environment should incentivize firms to pursue decarbonization policies or face punitive legal and

[1] https://euideas.eui.eu/2022/11/13/cop27-no-adaptation-if-the-risk-isnt-perceived/
[2] See Dolšak & Prakash, 2022; Degryse et al., 2023.
[3] The concept of climate political leadership as part of public climate governance has received attention in the literature. See; Gupta & Grubb, 2000; Wurzel et al., 2017; Wurzel et al., 2021).

financial consequences in addition to reputational damage (Brown et al., 2022; Eccles et al., 2012; Karpoff et al., 2005; Zou et al., 2015).

For our purpose, we define two contrary regimes of CPL: supportive climate political leadership (SCPL) and climate skeptic political leadership (CSPL). When CPL demonstrates a strong belief in climate science and a constructive willingness to address the climate change crisis, we refer to such leadership regimes as SCPL. Thus, SCPL exhibits a philosophy that believes in and accepts climate science consensus and design practices that support domestic and internationally coordinated climate mitigation and adaptation policies through regulatory and economic frameworks contributing to the transition to a low-carbon economy(Bai & Ru, 2024; Bartram et al., 2022; Dang et al., 2023; Ilhan, Sautner, & Vilkov, 2021; Martinsson et al., 2024). Contrary to the approach by SCPL, climate skeptic political leadership (CSPL) are climate-science denialists, reject consensus on climate change, promote deregulation, oppose stricter climate regulations, and institute frameworks to dismantle institutions that provide information on climate science or support globally coordinated climate actions (De Pryck & Gemenne, 2017).

In addition to the regulatory mechanisms of CPL, an effective market-based tool for managing corporate climate exposure is the instrumental role financial markets and investors play by allocating capital to sustainable firms through market-based pricing mechanisms (Bolton & Kacperczyk, 2023; Sautner et al., 2023b), and by employing various tools, such as engagement, monitoring, divestment, voting, etc., to initiate sustainable behavioral changes in their investee firms (Azar et al., 2021; Dyck et al., 2019; Gantchev et al., 2022) Additionally, the involvement of financial markets in supporting firms' efforts to manage climate change can create new investment opportunities, stimulate investment in climate-mitigating technologies, and enhance economic growth (Ceccarelli et al., 2024; De Angelis et al., 2023; Semieniuk et al., 2021).

However, theoretical arguments and empirical evidence also support the view that the ability of market participants[4] to anticipate the extent and impact of climate risk exposure is essential in asset pricing and capital allocation (Battiston et al., 2017; Schleussner et al., 2016). This implies that

[4] Market participants refer to investors, analysts, and other actors in financial markets present at the company's earnings conference calls.

investors may decarbonize their portfolio firms more effectively if CPL fosters a complementary regulatory environment, generating mandatory incentives for firms to embed sustainable business practices and invest in greener technologies. De Angelis et al. (2023) show that investors, particularly climate-sensitive ones, support companies' efforts to reduce exposure to climate change when they anticipate and perceive tighter climate regulations related to climate change. Further, Seltzer et al. (2022) suggest that corporate climate regulatory exposure intensifies with expectations of tightening climate regulation. Similarly, Bolton and Kacperczyk (2023) demonstrate that the carbon premium rises with anticipation of stringency in climate regulation. Thus, a stern regulatory regime should heighten firms' climate change exposure. Accordingly, this should attract greater attention and scrutiny from investors and analysts, further intensifying the firm-level market perception[5] of climate regulatory exposure (FL-MPCRE).

The heightened regulatory climate exposure that affects firms' long-term value should motivate investors to engage with their investee firms (Kim et al., 2019; Krueger et al., 2020). Thus, the more stringent the regulatory framework, the greater the climate regulatory exposure, and therefore, the more influential the financial markets' mechanisms should be in driving the firms' decarbonizing practices. Thus, appreciating the drivers of FL-MPCRE may significantly help manage climate change.

In this study, we ask: What happens to the intensity of FL-MPCRE when we observe unexpected regime changes in the belief and philosophy of CPL? In order words, how may CPL itself alter the degree and trend of FL-MPCRE? Our central economic hypothesis is that the emergence of CSPL attenuates FL-MPCRE more than SCPL. We refer to this as the *climate-skeptic leadership hypothesis* (CSLH)[6].

To appreciate the mechanisms through which CPL may influence FL-MPCRE, we draw on Pastor & Veronesi's (1912; 1913) equilibrium framework, highlighting how government actions and statements shape market participants' expectations through Bayesian updating. In the context of

[5] The authors note, "*Our measure captures market participants' perception of various upside or downside factors related to climate change, namely physical threats, regulatory interventions, and technological opportunities*" (Sautner et al., 2023, p.1450).
[6] See Section 3 for details on the logical formulation of the hypothesis.

climate change governance, economic agents revise their perceptions based on evolving political leadership policies, forming updated expectations about regulatory risks, costs, and opportunities.(Kräussl et al., 2024; Pastor & Veronesi, 2012; Pástor & Veronesi, 2013). Hence, the perception of climate change exposure incorporates attentional processes and inferences that reflect the real-time dynamic interpretation of evolving beliefs and market expectations, subsequently influencing market behavior[7] (Hahnel & Brosch, 2016; Kräussl et al., 2024; Smith, 2001; Smith, 2016; Zawadzki et al., 2020).

How are the perceptions of the market participants influenced by the ideological disposition of climate political leadership? Studies note that leadership is the asymmetric relationship of influence in which an individual directs the behavior of other agents toward achieving specific goals within a given timeframe(Skjærseth, 2017; Wurzel et al., 2017). The political leadership literature argues that the beliefs and expected actions of political leaders who hold authority and resources to implement regulations that create economic incentives (costs and benefits) can influence the perception and behavior of economic agents(Garland et al., 2018; Parker & Karlsson, 2010) .Specifically, in climate governance, a sizeable body of research documents that political leadership plays a crucial role as "agents of change" in effectively governing climate change mitigation and adaptation efforts, including the sustainable practices of firms (Edmans & Kacperczyk, 2022; Gulen & Ion, 2016; Pastor & Veronesi, 2012).

Studies document that a stringent climate regulatory environment increases attention to climate change exposure, which should incentivize firms to pursue decarbonization policies or face punitive legal consequences (See Bartram et al., 2022; Sautner et al., 2023; Semieniuk et al., 202.). Thus, a stringent climate regulatory environment initiated by SCPL should create and enhance the firm's regulatory climate risk exposure. Consequently, it should also attract greater attention and scrutiny from firms' stakeholders (investors, analysts, consumers, etc.) regarding the potential climate

[7] For example, Ceccarelli and Ramelli (2024) show that narratives and diverse subjective beliefs dynamically shape the perception of green investment opportunities. Seltzer et al. (2022) examine how credit ratings and yield spreads reflect the perceptions of analysts and investors regarding regulatory risk.

regulatory risk. Thus, SCPL, which introduces climate-friendly regulatory tools to tackle climate change, should be positively associated with FL-MPCRE.

However, following the above-noted theoretical argument on the role of climate governance, a more lax or less stringent climate regulatory environment of CSPL does not incentivize firms to pursue decarbonization policies since the firms face lesser or no punitive legal consequences for not adopting climate-friendly sustainable practices. Firms often view environmental pollution control as more costly than penalties for non-compliance (Bose et al., 2021; Shapira & Zingales, 2017). Thus, CSPL's less stringent climate regulatory environment should inhibit firms' regulatory climate risk exposure. Therefore, CSPL, which introduces more lax climate regulatory tools, should be negatively associated with the degree of FL-MPCRE.

We test our *climate-skeptic leadership* hypothes*is* by designing a quasi-natural experiment that exploits the 2016 United States (U.S.) presidential election as a source of exogenous shocks to CPL.[8] Recent empirical studies indicate that the CSPL era of 2017-2020 in the U.S. represents a period of climate regulatory decay accompanied by radical budgetary moves aimed at dismantling the apparatus of the pro-climate regulatory posture of the preceding period of 2013-2016 (Bomberg, 2021; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021; Wagner et al., 2018).We refer to the post-election period (2017-2020) as the era of CSPL and the pre-election period (2013-2016) as the era of SCPL.

During the CSPL period, while the U.S. experienced climate deregulatory changes, the European Union (E.U.) region witnessed the continuation of a pro-climate regulatory environment (Bomberg, 2021; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021; Wagner et al., 2018). Evidence suggests that the U.S. and the E.U. were partner political leaders in international climate governance efforts during the SCPL period of 2013-2016 (Gupta & Grubb, 2000; Wurzel et al., 2021b). However, their path diverged during the CSPL period of 2017-2020. While the E.U. continued its stringent

[8] Prior studies indicate that the election outcome was unexpected and constituted an exogenous shock that changed the course of the U.S. federal climate regulatory trajectory.(Child et al., 2021; Wagner et al., 2018).The event has been employed in empirical studies investigating stock price reaction(Wagner et al., 2018), value implications of political connection (Child et al., 2021), corporate climate responsibility(Ramelli, Wagner, Zeckhauser, & Ziegler, 2021), pollution premium(Hsu et al., 2023) the effect of regulation on firm value(Kundu, 2024) and tax policy expectations and investment(Gallemore et al., 2024).

climate-friendly regulatory approach to tackling climate change, the U.S. adopted a relatively more lenient regulatory attitude. [9]

Accordingly, to test our hypothesis, we assume all firms listed and headquartered in the U.S. during 2013-2020 are our treated group firms. We estimate our counterfactual (control group firms) using firms operating in the E.U. during 2013-2020. During the SCPL period of 2013-2016, treated and control group firms operated in similar climate-friendly regulatory environments. However, during the regime of CSPL, i.e., 2017-2020, the U.S. experienced climate deregulatory changes, while the E.U. witnessed the continuation of a pro-climate regulatory environment. This divergence in the regulatory climate instituted by CPL allows us to examine their impact on the treated group firms compared to the control group firms.

Prior literature suggests that it is challenging to estimate firm-level climate change risk exposure (Giglio et al., 2021). Sautner et al. (2023) addressed this challenge by exploiting information in the earnings conference calls to construct three market-based measures of climate change exposure: one related to physical threats, the other regulatory interventions, and finally, a measure capturing technological opportunities. Literature shows that earnings conference call (ECC) transcripts allow market participants to interact with management on material events related to the firm's future performance (Matsumoto et al., 2011; Mayew et al., 2013), which in our case is climate change exposure. Sautner et al. (2023) employ a computational linguistic algorithm that identifies unique combinations of words reflecting discussion related to climate regulatory exposures. They count the number of climate-change-related bigrams[10] and scale this number by the total bigrams used in the conference call transcripts. For example, if the number of climate-exposure-related bigrams is 300 out of 10,000 in a conference transcript, then the FL-MPCRE measure of the firm for the quarter is 300/10000, i.e., 0.03. Thus, the higher this proportionate figure, the higher the climate-change-related exposure of the firm perceived by the call participants. Examples of bigrams related to climate regulatory exposure include "carbon tax," "cap and trade market," and " environmental legislation."

[9] See Section 2 for a detailed discussion of our empirical setup.
[10] Bigrams refers to combination of two-words which in our case reflects climate regulatory exposure e,g "Cap and Trade", "climate regulation",.

For our investigation, we use the climate regulatory component of the measure as a proxy for FL-MPCRE as our outcome variable. It reflects how market participants in the conference calls evaluate firm-level climate regulatory exposure, indicating a forward-looking estimation.[11] Hence, the FL-MPCRE is not only a novel measure but an objective measure that provides valuable insights into how market participants perceive a firm's level of climate-change-related exposure based on the frequency of these bigrams in conference calls. Furthermore, Sautner et al. (2023a) show that this measure reflects investors' attention and demand for information relevant to climate regulatory exposure. As an empirical identification strategy, we design a quasi-natural experiment using propensity-scored matched difference-in-differences (PSM-DiD). Our empirical investigation and robust quasi-natural experiments reveal the following findings.

First, we examine the parallel trend for our outcome variable (FL-MPCRE scores) over the sample period of 2013-2020. In the SCPL period (i.e., the pre-CSPL period from 2013 to 2016), the average FL-MPCRE scores of the treated group (the U.S. firms) and the control group (the E.U. firms) in our sample exhibit similar trends and at almost similar levels. The average difference in the FL-MPCRE scores for the SCPL period is almost zero every year from 2013 to 2016. However, from 2018 onwards, i.e., two years post-CSPL period, we observed a significant divergence. In relative terms, from 2018, the yearly average FL-MPCRE scores of the treated firms (i.e., the U.S. firms) significantly lagged compared to the material growth observed for the control group firms (i.e., the E.U. firms), with the broadest divergence observed in 2020. The FL-MPCRE average for the treated group firms (i.e., the U.S. firms) is around 0.6 in 2020. However, this figure is approximately 1.4 for the control group firms (i.e., the E.U. firms), with a material difference of nearly 0.8[12]. Thus, in two years (from 2016 to 2018), the FL-MPCRE for U.S. firms significantly slowed compared to that of the E.U. firms, indicating that from 2018 onward, the regulatory incentives for firms to manage climate

[11] The literature suggests that financial markets can serve as valuable tools for uncovering true market perceptions by aggregating the beliefs of market participants who are actively invested and have "skin in the game"(Balvers et al., 2017). Hence, the conversations among market participants during earnings conference calls reflect the market participants' perceptions.(Atiase et al., 2005; Rennekamp et al., 2022).It captures both the demand-side perspective (from analysts) and the supply-side perspective (from management) in the information market, reflecting the collective forward-looking consensus of market participants on firm-level exposure to climate change (Sautner et al., 2023a).

[12] See Figure 2.

risk were much lower for U.S. firms than E.U firms. In conclusion, this suggests that while market participants perceived significant growth in climate regulatory risk for the E.U firms, the U.S. firms' exposure, in comparative terms, significantly lagged, particularly from 2018 onwards.

Next, the results of estimating PSM-DiD regression specifications indicate that the emergence of the CSPL regime significantly slowed the differential growth in FL-MPCRE scores for the U.S. firms compared to the E.U. firms during the CSPL regime (i.e., 2017-2020. In quantitative terms, compared to European firms, firms headquartered in the U.S. show a 0.308 unit (approximately 31%) decline in FL-MPCRE scores in the CSPL era. These findings suggest that when firms are exposed to a stringent climate regulatory environment (the E.U. from 2013 – 2020 and the U.S. from 2013-2016), analysts and investors express their concerns about climate regulatory exposure by enhancing the frequency of the climate bigrams used in the conference calls. However, under an exogenous shift to CSPL (the U.S. from 2013-2020), which significantly reduces the climate regulatory exposure of firms, the frequency at which market participants use climate-related bigrams during earnings conference calls materially declines relative to those firms under the CSPL regime, reflecting minimal concerns expressed by market participants on climate issues.

We also undertake several additional robustness checks to validate our core findings. First, we undertake a placebo test to rule out the existence of pre-existing trends driving our results. Second, we use a complementary matching approach within the framework of the DiD approach, known as the entropy-balanced technique. Third, we employ an alternative proxy of outcome variable by scaling individual FL-MPCRE scores for each year by the industry average of the FL-MPCRE scores for all the firms operating in the same industry classification following the Fama French- twelve industry classification code. Fourth, given our cross-country sample, we also rule out the possibility of alternative explanations driven by changes in politically induced firm-level tax and trade policy changes.

Finally, we study cross-sectional differences based on the level of a firm's carbon intensity and financial constraints. In line with expectation, our analysis reveals that the observed relationship is stronger in firms that operate in carbon-intensive industries, consistent with the notion that such firms are perceived to have a higher regulatory burden under stricter climate regulation (Hsu et al., 2023;

Ramelli, Wagner, Zeckhauser, & Ziegler, 2021). Next, we consider the moderating role of financial constraint. Our analysis reveals a significantly greater effect on financially constrained firms, which we attribute to market expectation of lower future costs associated with CSPL deregulation policies (Bartram et al., 2022).

The outcomes of our baseline examination and all the subsequent robustness tests suggest that an unexpected shift in climate political leadership, i.e., from SCPL to CSPL, led to a significant differential reduction in the perception of climate regulatory exposure of the U.S.-headquartered firms relative to the European-headquartered firms in the CSPL regime compared to the SCPL regime. The implication of our study is stark but straightforward: the climate political leadership's belief and consequential regulatory regime significantly sway the global decarbonization effort.

Building on the core results mentioned above, we proceed to test the climate deregulatory mechanism. Aligned with existing literature, we use the country-level Climate Change Performance Index (CCPI) from Germanwatch as a proxy for climate regulatory stringency, as it autonomously evaluates and compares nations' efforts and progress in combating climate change to promote transparency in global climate politics (Bose et al., 2021; Kim et al., 2021). It is measured on a scale from 0 to 5, where 0 indicates the lowest level of climate regulatory stringency and 5 represents the highest. We find that compared to the E.U. countries in the post-SCPL era (2017-2020), the relatively lower level of CCPI for the U.S. negatively mediate the link between CPL and FL-MPCRE, supporting the claim that climate regulatory stringency is the mechanism that underpins the deregulatory channel as the mechanism through which CSPL institutes changes in FL-MPCRE.

Finally, we extend the analysis to firm-level financial implications of an adverse shock to CPL on FL-MPCRE. We investigate the effect of CPL and FL-MPCRE links on institutional investor ownership and capital market-based valuation. Studies argue that institutional investors care about the impact of climate risk on their portfolio firms by demanding higher expected carbon premiums (Bolton & Kacperczyk, 2021a, 2021b; Hsu et al., 2023; Krueger et al., 2020) and divesting from firms perceived to have high environmental footprints (Gantchev et al., 2022). This implies that when the market perceives lower climate regulatory exposure, institutional investors should increase their ownership. The capital market should reward firms operating in a relatively lower regulatory risk environment with comparatively higher market valuation. Consistent with this conjecture, our empirical analysis shows a significant differential increase in institutional investor ownership and firm market valuation for the U.S. firms (treated group) relative to the European firms (control group) in the post-shock period.

Our study makes the following important contributions to the literature. First, we add to a nascent body of research on the drivers of market participants' perceptions of climate risk during earnings conference calls (Borochin et al., 2018; Wali Ullah et al., 2023). Borochin et al. (2018) show that market participants' word tones affect market perception. Wali Ullah et al. (2023), using the transcript of an earnings conference call from Sautner et al. (2023a), document that firms with high managerial ability are associated with lower market perception of climate change exposure. Our study is the first to use a market-based measure[13] to identify the role of CPL in explaining cross-sectional and temporal variations in market participants' perceptions of a firm's exposure to climate regulatory risk. We show that CPL is a critical driver of cross-sectional and temporal variations in firm-level regulatory risk that alters the dynamics of FL-MPCRE through exogenous shifts in CPL (from SCPL to CSPL).

Second, we add to the body of studies investigating the role of politics and regulations, generally called climate governance, in driving climate change mitigating initiatives. For example, Dang et al. (2022) document that climate mitigation investment is higher under mandatory abatement regulations in financially unconstrained firms. Martinsson et al. (2024) show that the introduction of carbon tax regulation lowers firm-level carbon emissions. Similarly, Brown et al. (2022) document that firms increase their research and development expenditure in response to higher national toxic

[13] Literature suggests that it appears difficult to estimate the impacts of climate change exposure at the firm level (Giglio et al., 2021). A significant body of literature investigating climate change exposure focuses on carbon intensity or emission. Sakhel (2017) studies firm-level assessment of risk exposures among European firms using carbon emission data from the Carbon Disclosure Project (CDP) and documents greater risk exposure perception in sectors more subjected to climate regulation. However, Ramelli, Wagner, Zeckhauser, and Ziegler, 2021 argue that carbon emission as a proxy for climate risk exposure indicates a backward-looking assessment of a firm's climate change exposure measure. Furthermore, Sautner et al. (2023) argue that carbon estimate-based (e.g., carbon intensity) or rating-based proxies are flawed. Our study departs from these studies by employing a market-based forward-looking approach using a novel dataset by Sautner et al. (2023), which takes the perspective of market participants (analysts, investors, firms) present on earnings conferences to assess FL-MPCRE. However, our market-based measure of regulatory exposure does not suffer from estimation and rating biases.

emissions taxes. Exploiting a different theoretical approach and focusing on the firm-level perception of climate regulatory exposure, Lopez et al. (2017) investigate the role of government regulation and regulation-induced uncertainty in driving corporate decision-makers perceptions of climate mitigation strategies. However, to our knowledge, no studies offer a systematic scientific investigation on how climate political leadership's beliefs and ensuring regulatory frameworks shape financial market participants' perceptions of corporate climate regulatory exposure.

Third, we contribute by floating the policy debate on the role of an effective and complementary regulatory environment in which the capital market could be an important driver in managing the transition to a low-carbon economy. Given the emergence of climate regulatory risk, recent literature suggests that the capital market and institutional investors are crucial in shaping corporate behavior and influencing environmental policies (Azar et al., 2021; Benlemlih et al., 2023; Dyck et al., 2019). For example, Bolton and Kacperczyk (2021a) and Ilhan, Sautner, Vilkov, et al. (2021) show that investors demand carbon premiums. Institutional investors prefer better climate responsibility and divest from firms with perceived high carbon exposure or following environmental incidents (Cohen et al., 2023; Gantchev et al., 2022). Evidence also suggests that institutional investors drive firms to take action to curb greenhouse gas emissions (Azar et al., 2021; Benlemlih et al., 2023; Kim et al., 2019).Within our empirical framework, we show that when firms' climate regulatory risks are diminished, institutional investors increase their equity stakes, and the market responds by boosting the valuation of such firms.

Finally, our study is also related to the burgeoning literature on climate change beliefs and the pricing of climate change risk. Hong et al. (2020) suggest that climate belief is a critical driver of climate mitigation and adaptation strategies, which requires the characterization of the beliefs of investors and corporate insiders (such as CEOs). The associated studies characterize the beliefs of investors (retail and institutional) and corporate insiders. For example, Choi et al. (2020) characterize investors' climate change beliefs in response to warmer temperatures. The study uses international data to show that Google search volume increases carbon-intensive assets underperform in financial markets when the local temperature is abnormally higher than usual. Krueger et al. (2020) characterize the beliefs of institutional investors regarding climate risk and show that they believe in the saliency of climate change risk, in particular climate regulatory risk. More recently, using survey instruments, Ceccarelli and Ramelli (2024) show that climate belief is correlated with investors' expected risk and return, which drives green investment behavior. We contribute to this literature by empirically characterizing the climate beliefs of climate skeptic political leadership and the impact on market participants' perception of climate regulatory exposure.

The rest of the paper is organized as follows: Section Two deals with the empirical setup; Section Three deals with the relevant literature and hypothesis development; Section Four addresses the data and empirical strategy; Section Five presents the results and discussion; and Section Six presents the conclusion.

2.0 Empirical Setup: Adverse Shock to Supportive Climate Political Leadership

2.1 Climate Political Leadership: Background on 2016- U.S. Presidential Election

The election of President Donald Trump in 2016 was pivotal for the U.S. climate policy. It was a shock to climate political leadership (CPL), and the election's aftermath signals a change in the trajectory and dynamics of U.S. climate policy (Child et al., 2021; Ramelli, Wagner, Zeckhauser, Ziegler, et al., 2021; Wagner et al., 2018) and the emergence of climate-skeptic political leadership (Ilhan, Sautner, Vilkov, et al., 2021; Steg, 2023). Several factors make the regime change a unique laboratory for examining the impact of an exogenous shock to CPL on FL-MPCRE.

First, the election's outcome was largely unexpected and thus is a credible exogenous shock (Child et al., 2021; Gallemore et al., 2024; Hsu et al., 2023; Kundu, 2024; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021; Seltzer et al., 2022; Wagner et al., 2018). Even though the market knew the views of the Trump regime in advance, it never anticipated the election result with certainty, which, based on poll results, was anticipating Trump's loss.[14] As a result, there is no reason to believe the market adjusted Trump's policies in advance. For example, Ramelli et al. (2021) argue that the 2016

[14] Anthony J Gaughan (2016) notes: "*There really was a silent Trump vote that the polls failed to pick up on. The nationwide polling average gave Clinton about a 3-point lead overall, and the state-by-state polls indicated that she would win at least 300 electoral votes. But the polls were as wrong as the pundits.*" See https://www.scientificamerican.com/article/explaining-donald-trump-s-shock-election-win/ (Accessed: 27 June 2024). Also, see this link https://www.bbc.co.uk/news/world-37924701 (Accessed: 27 June 2024) on how the world media reacted to the shock.

U.S. presidential election outcome was unexpected by citing pre-election polling and betting market data, overwhelmingly favoring Hillary Clinton. They note that national polls consistently showed Clinton leading Trump in swing states and national averages, with many models giving her a probability of victory exceeding 70%. Betting markets like *PredictIt* similarly reflected low odds for a Trump win, typically below 30%. On election day, initial market reactions aligned with early voting projections favoring Clinton but reversed sharply as Trump gained in key swing states. This evidence further supports the assertion that Trump's victory represented a genuine exogenous shock to market expectations.

Second, compared to the period of 2013-2016, in which CPL supported climate science theories and predictions, the Trump administration was a climate science denialist.[15] For example, President Donald Trump noted in the New York Times article: "*This very expensive global warming bullshit has got to stop. Our planet is freezing, record low temps, and our G.W. scientists are stuck in ice"*.[16] This narrative denies the reality of global warming and the expertise of climate scientists.

Third, over 100 EPA environmental regulations were reversed during the Trump administration, including a lift on coal leases, withdrawal of federal guidance on greenhouse gas emissions standards, and cancellation of methane emission disclosure requirements.[17] Also, a halt to federal agencies computing the social cost of carbon using Obama-era criteria implies a weakened ability of the EPA to enforce, penalize, or sanction firms that violate the prior regulation. Other changes during Trump's presidency include approval to issue more drilling permits on previously protected federal lands and re-valuation of the Clean Power Plan Act[18], to mention a few.

Fourth, in 2017, the Trump administration announced the U.S. withdrawal from the Paris Climate Accord, effectively dismantling international collaboration in the fight against climate change (Lee Seltzer, 2021). Finally, the Trump administration appointed Scott Pruitt, a climate change

[15] See reference to several statements and decisions attributed to SCPL under President Trump: https://democrats.org/news/donald-the-denier-trump-thinks-climate-change-is-one-of-the-greatest-con-jobs-ever/ (Assessed: 23 May 2024).
[16] See https://twitter.com/realDonaldTrump/status/418542137899491328 (Assessed: 20 January 2024).
[17] Source: The New York Times: https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html. (Assessed: 2 November 2022).
[18]Source The New York Times: https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html (Assessed 2 November 2022).

denialist, as head of EPA, which demonstrated a U-turn in U.S. climate policy. As Attorney General of Oklahoma, Scot Pruitt instituted 14 legal actions to repeal Obama-Era environmental regulations (Ramelli, Wagner, Zeckhauser, Ziegler, et al., 2021). For example, the Obama Administration enacted the Clean Air Act through the EPA, which targeted emissions reduction from fossil fuel-fired plants (Fowlie, 2014; Glicksman, 2017).

However, the Trump administration dismantled the policy and accompanying rules[19]. Regarding carbon cost, writing on Yale Climate Connections, Nuccitelli (2020) notes, "*In 2010, a governmental interagency working group in the Obama administration established the first federal social cost of carbon estimate of $45 per ton of carbon dioxide pollution. In 2017, newly inaugurated President Donald Trump quickly disbanded the interagency group by executive order, and within months, his EPA slashed the metric to between $1 and $6. The latest research by an independent team of scientists concludes that the social cost of carbon should actually start at about $100 to $200 per ton of carbon dioxide pollution in 2020, increasing to nearly $600 by 2100*".[20] Furthermore, during the Trump administration(2017-2020), some government agencies obstruct climate change openness and disclosure and prevent investors from incorporating climate risks into their portfolio decisions(Condon, 2022).

One may argue that Republican presidents are usually associated with deregulation in the U.S. and may raise concerns about what makes the 2017-2020 period unique for our empirical set-up as an era of climate-skeptic political leadership. Belton and Graham (2019) review past republican presidents' regulatory (deregulatory) actions[21] and conclude that the Trump administration's deregulatory[22] actions were unique. They further argue that the Bush administration was relatively

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[19] See this link: https://www.energypolicy.columbia.edu/publications/trump-vs-obama-social-cost-carbon-and-why-it-matters/ (Assessed 31 January 2024).

[20]See this link: https://yaleclimateconnections.org/2020/07/trump-epa-vastly-underestimating-the-cost-of-carbon-dioxide-pollution-to-society-new-research-finds/#:~:text=Policy%20%26%20Politics-,The%20Trump%20EPA%20is%20vastly%20underestimating%20the%20cost%20of%20carbon,greater%20than%20the%20agency%27s%20estimate (Accessed on 22/02/2024).

[21] In its review, the study demonstrates that Bush 41 was deemed a “Regulatory President”. For example, Bush 41 improved urban air quality through a variety of new regulations and promoted global climate change by stimulating and signing the UN Framework Convention on Climate Change. Meanwhile, Bush 43 was a proponent of smarter regulation”.

[22] The study shows that just between 2017 and 2018, 514 deregulatory rulemaking has been implemented across various agencies.

more pro-regulation. Furthermore, the indirect deregulation tactic of the Trump administration during the 2017-2020 period through unfilled leadership positions at the various government agencies was unequal in American history (Heidari-Robinson, 2017). Kundu (2024) analyzes the regulations and rules passed from 1994 to 2019 and shows that those in 2017-2019 were the lowest in 25 years, irrespective of party affiliation. The study further documents 60% fewer rules passed during the 2017-2019 period than the 1981-2019 period. This further supports our empirical setup on why the era is the most climate-skeptic political leadership era in U.S. history.

Considering the above discussion and for our investigation purpose, we refer to 2013-2016 as a supportive climate political leadership (SCPL) regime. Similarly, we denote the period 2017-2020 as a regime of climate skeptic political leadership (CSPL). Thus, the 2016 U.S. election was a shock to CPL, triggering an unexpected transition from an SCPL to a CSPL.

3. Hypothesis Formulation: ***Climate Skeptic Political Leadership Hypothesis***

To appreciate how CPL influences FL-MPCRE, we borrow Pastor & Veronesi's (2012; 2013, referred to as PV hereafter) equilibrium framework's mechanism through which the government influences and re-evaluates investors' beliefs. PV's framework posits that investors adjust their beliefs about government policies over time using Bayesian learning based on observed economic outcomes. When policies change, prior learning about the old policy becomes less relevant, resetting belief systems and ultimately reshaping perceived risk. The spirit of the framework, when applied to the literature on climate change governance, suggests that changes in existing beliefs of economic agents (e.g., investors and analysts), based on signals from the government, generate new climate risk expectations, which should subsequently shape their perceptions of risk exposures (Ceccarelli & Ramelli, 2024; Dowell & Lyon, 2024; Ilhan et al., 2023; Kräussl et al., 2024; Schlenker & Taylor, 2021; Smith, 2001). These newly formed expectations influence forward-looking assumptions about policies, technologies, and economic impacts (risks and opportunities), ultimately reshaping beliefs through evolving perceptions (Gallemore et al., 2024; Kräussl et al., 2024; Schlenker & Taylor, 2021; Weber, 2010).

Consistent with the spirit of PV's framework, several studies show that economic agents gain insights into the costs and benefits of government regulations by observing signals from political leadership (Bartram et al., 2022; Ilhan, Sautner, & Vilkov, 2021; Pastor & Veronesi, 2012). Theory suggests that leadership, defined as the asymmetric relationship where individuals direct the actions of others toward specific objectives, is pivotal in shaping economic incentives through regulation (Parker & Karlsson, 2014; Parker et al., 2017). In climate governance, political leaders act as "agents of change," driving climate mitigation and adaptation efforts and influencing sustainable corporate practices[23]. Research highlights the critical role of political leadership in creating and implementing policies that affect the expectations and behaviors of economic agents (Edmans & Kacperczyk, 2022; Gulen & Ion, 2016; Grubb & Gupta, 2000; Jordan et al., 2012; Oberthür & Roche Kelly, 2008; Parker & Karlsson, 2010; Wurzel et al., 2017; Wurzel et al., 2019; Pastor & Veronesi, 2012). Empirical evidence supports such conjecture whereby governments shape firms' operating environments and corporate outcomes by imposing taxes, offering subsidies, enforcing laws, regulating competition, and establishing environmental policies (Aldy, 2017; Pastor & Veronesi, 2012; Selby, 2019).

In our case, as we argue in the following paragraphs, investors' perception of firm-level climate change regulatory exposure reflects a dynamic, real-time process of attentional focus and inference driven by evolving beliefs and expectations in light of signals from climate political leadership (Hahnel & Brosch, 2016; Kräussl et al., 2024; Smith, 2001; Smith, 2016; Zawadzki et al., 2020).Thus, we expect CPL's climate change beliefs, statements, actions, and decisions to influence economic agents' (institutional investors, rating agencies, financial analysts, etc.) beliefs and perceptions.[24]

[23] efforts (see Grubb and Gupta, 2000; Oberthür & Roche Kelly, 2008; Wurzel et al., 2019).

[24] The literature on political leadership suggests that the beliefs and anticipated actions of leaders, who possess the authority and resources to enforce regulations and create economic incentives (both costs and benefits), significantly influence the perceptions and behaviors of economic agents (Parker & Karlsson, 2014; Parker et al., 2017). In the context of climate governance, extensive research highlights the pivotal role of political leadership as "agents of change" in driving efforts to mitigate and adapt to climate change, including influencing firms' environmentally sustainable practices (Edmans & Kacperczyk, 2022; Gulen & Ion, 2016; Pastor & Veronesi, 2012). In particular, U.S. presidents hold significant authority, which enables them to implement substantial policies without the oversight of Congress or the judiciary

Given the above discussions, we examine how the regime of SCPL and CSPL shape the insights of financial markets' beliefs following PV's framework. SCPL's climate-friendly signals and actions may include stringent and punitive regulatory provisions for managing greenhouse gas (GHG) emissions, toxic waste release, and other corporate polluting activities. Such a regulatory environment should create deadweight costs for firms by enforcing higher abatement costs and encouraging high costs of investments in green technologies (Becker & Henderson, 2000; Brown et al., 2022; Greenstone et al., 2012; Xu & Kim, 2022)

Moreover, enforcement and compliance costs can adversely affect a company's production, profitability, corporate investment decisions, and cost of capital.[25] Matsumura et al. (2014) note that strict climate regulation may also increase the costs of lawsuits filed by the public or organizations, further motivating other public interest groups to push for more regulation under an SCPL. Studies also document higher bank lending costs for polluting firms subjected to stricter environmental regulations and enforcement (Fard et al., 2020; Javadi & Masum, 2021; Wu et al., 2023). Evidently, with potential high abatement regulatory costs, possible costs of investments in green technologies, and other indirect costs, it is logical to argue that under SCPL, investors perceive the climate regulatory exposure to be high.

However, under an exogenous shift in CPL from SCPL to CSPL, investors should substitute their prior beliefs as CSPL introduces deregulatory policies. Economic agents expect the climate deregulatory framework to lower firms' direct and indirect climate regulatory costs under CSPL. Investors substitute these new beliefs of lower regulatory costs under CSPL with the prior beliefs of perceived high climate mitigation costs under SCPL. With the new beliefs formed by investors, perceived risks associated with climate change exposure should decrease as investors may focus more on the positive impact of reduced operational constraints and the expected positive effect on shareholder wealth.

[25] An extensive body of literature documents the negative impact of stringent environmental regulations on productivity, financial performance, financial constraints, and investment. For example, Gray(1987) shows the adverse effect of environmental regulation enforcement by the EPA on the growth of the U.S. manufacturing industry. Similarly, Greenstone et al. (2012) document the negative impact of environmental regulation on firm productivity.

Literature notes that the deregulatory signals of CSPL include dismantling climate regulations, scrapping government incentives for low carbon investments, licensing and permitting carbon-intensive activities like coal and oil production, and rollback of motor vehicle emission standards. (Bomberg, 2017, 2021; De Pryck & Gemenne, 2017; Glicksman, 2017; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021). This reduces firms' compliance and abatement costs diminishing incentives for low-carbon investments (Berardo & Holm, 2018). Evidence also corroborates that climate deregulatory policies reduce the potential costs of stringent regulations, whereby firms focus more of their investments on growth opportunities at the cost of imposing severe climate externalities (Aldy, 2017; Glicksman, 2017; Selby, 2019; Wagner et al., 2018). With potential lower abatement regulatory costs, it is reasonable to argue that under CSPL, investors perceive the climate regulatory exposure to be low.

Thus, the exogenous shift in CPL from SCPL to CSPL may yield the following implications for the firms and investor perception. First, we should expect the exogenous shift to induce sustainability-related changes in firms' policies and strategies. Second, the expected corporate behavioral changes should influence financial markets' perception of climate regulatory exposure.

We explain the consequences by employing a simple example of two hypothetical firms, A (U.S. firm) and B (E.U. firm), to provide further insight into the dynamic relationship between exogenous shifts in CPL and FL-MPCRE. Under an equilibrium assumption of stringent climate regulatory policy in period 1 (2013-2016), suppose firms A and B operate in the same industry, enjoy similar economic environments, and are competitors in the global market. This implies that both firms have more or less identical high environmental abatement costs during period 1. Following an exogenous shift in CPL (from SCPL to CSPL), firm A in period 2 (2017-2020) operates in a climate-deregulatory environment, whereby the perceived regulatory compliance costs are expected to reduce significantly. Thus, firm A's climate regulatory equilibrium should shift from a high regulatory abatement cost state, as observed in period 1, to a lower regulatory abatement cost state going forward under the CSPL regime in period 2. However, firm B continues to operate under a stringent climate regulatory environment in period 2 as in period 1 and, hence, continues to incur high climate regulatory costs.

The exogenous shifts in CPL should also influence how market participants (e.g., investors) perceive the risk of climate regulations, which is reflected in the frequency of climate-related bigrams used during ECC. When investors update their beliefs under an exogenous shift from SCPL to CSPL, we expect a reduced use of climate-related bigrams for Firm A in period 2 during the ECC, relative to period 1, in line with the new market beliefs of lower regulatory costs. This reinforces the new narrative of lower climate change exposure, which may reflect the level of concern market participants express regarding the future impact of climate risk exposure. However, for firm B, which continues the stringent regulatory trajectory in period 2 relative to period 1, market participants may continue to express similar-level concerns for climate risk exposure and the economic cost of the associated regulatory burden, such as compliance costs, resulting in sustained use of climate-related bigrams or increased frequency of usage. This narrative aligns with the notion of unchanged or sustained regulatory pressures.

Within our empirical setup of an exogenous shift from SCPL to CSPL, the afore-stated argument suggests that the sudden emergence of CSPL and the associated anti-climate rhetoric may undermine efforts to address the climate crisis in the CSPL era because market participants' beliefs and perceptions of firm-level climate change exposure, particularly regulatory exposure, may significantly alter (Smith & Mayer, 2018).

Based on the arguments above, we contend that CSPL's deregulatory policies will modify financial markets' perceptions of the future impact of climate deregulatory policies, which will lower regulatory burdens, climate compliance, and abatement costs. As a result, CSPL would attenuate FL-MPCRE. Accordingly, we formulate and test the following CSPL hypothesis.

H_1: Ceteris paribus, climate-skeptic political leadership attenuates market participants' perception of firm-level climate regulatory exposure.

4.0 Data, Summary Statistics, and Empirical Strategy

4.1 Data and Sample

Our beginning sample comprises all firms covered by firm-level climate change regulatory exposure data obtained from Sautner et al. (2023a). The financial and accounting data come from Compustat Global and North America databases. Following extant literature, we exclude financial firms (SIC 6000-6999) and utility firms (SIC4900-4999) due to distinct regulatory standards for these industries. We further restrict firms in our sample to those without missing asset value and firms with more than $10m in asset value. We exclude firms with a negative book value of equity and those with leverage greater than 100% of asset value to avoid distress risk biasing our findings. The initial samples consist of a dataset including 22,803 firm-year observations derived from 3,324 unique U.S. firms and 1,298 European-headquartered firms between 2013 and 2020. Our treatment group consists of firms headquartered and listed in the United States and their counterparts in developed European markets, including the United Kingdom. Wurzel et al. (2021b) note that during the SCPL period (2013-2016), the United States and the European Union were considered climate political leaders, and both had similar climate regulatory trajectories, hence the choice of the treatment and control groups.

We obtain the country-level climate regulatory stringent index (CRSI) from Germanwatch.[26] We obtain the real gross domestic product growth rate and the governance index variables from the World Bank Group. In the following section, we describe the variables used in the study, which are also briefly defined in Appendix A1.

4.2 Variables

4.2.1 Outcome Variable: FL-MPCRE

To capture the firm-level market perception of climate regulatory exposure (FL-MPCRE), we employ the novel dataset of Sautner et al. (2023a) constructed using textual information from participants' quarterly earnings conference calls (ECC) discussions. Prior literature suggests that ECC is an essential source of soft information disclosure by firms in the market (Blau et al., 2015; Borochin et

[26] See https://www.germanwatch.org/en/CCPI

al., 2018; Sautner et al., 2023a). The conversations in such ECCs involve information exchanges between analysts, investors, and top executives, generating insights into how market participants perceive the issues related to firms' past performance, including prospects and potential risks (Bushee et al., 2003; Hassan et al., 2019).

Studies underscore the importance of utilizing conference call scripts as a source of information on corporate disclosure and enumerate numerous advantages to firms and market participants (Hollander et al., 2010). Brown et al. (2004) show that ECC lowers investor information asymmetry. It provides market participants (investors, analysts, rating agencies, etc) a unique opportunity to voice their concerns and listen to other participants' discussions, thus giving access to up-to-date information, generating insights into a company's potential risk and opportunities (Botosan, 1997; Bushee et al., 2003; Hollander et al., 2010). Furthermore, studies suggest that ECC offers significant information on discussing events and policies necessary for optimal investment and financial decision-making. (Frankel et al., 1999; Kimbrough, 2005)

Using textual information from participants' discussions on climate-risk-related bigrams in the ECC, Sautner et al. (2023a) developed four quantitative measures of climate change exposure (CC_EXP_{iq}) for firm i at quarter q. The first one is a broad measure of overall climate change exposure, and the other three reflect exposure related to physical threat, regulatory intervention, and technological opportunity. As a proxy for FL-MPCRE, we adopt the regulatory component of the measure, which measures how market participants in conference calls perceive the degree of firm-level climate regulatory exposure, indicating a forward-looking estimate. Here, we briefly define the measure using the model below[27].

$$CC\_EXP_{iq} = \frac{1}{B_{it}} \sum_{b_{iq}}^{m} D(b) \times 1000$$

where CC_EXP_{iq} represents individual components of climate change exposure measures (regulatory, physical, and technology). In our setup, it is the FL-MPCRE. $B_{i,q}$ are all bigrams of firm i that appear

[27] For a detailed methodology based on the Equation below, see Saunter et al. (2023a).

in the earnings conference call transcript in quarter q. b_{iq} relates to the number of bigrams associated with FL-MPCRE of firm i in quarter q. D(b) is a binary variable that takes a value of one if the bigram b is associated with FL-MPCRE and zero otherwise. The overall measure is multiplied by 1000 to ensure it is a quantitatively tractable measure. For example, suppose there are 800 firm-level climate regulatory exposure-related bigrams out of 10,000 bigrams in a conference call's transcript of a particular firm for a specific quarter; the FL-MPCRE score for the quarter is 800/10000, or 0.08. Consequently, the higher this proportionate figure, the greater the firm's perceived climate change exposure. Examples of bigrams related to climate regulatory exposure include "carbon tax," "cap and trade market," "environmental legislation," and others.

Sautner et al. (2023) validate the climate regulatory exposure measures following a rigorous methodology to ensure their accuracy and relevance. First, face validity is tested by examining the bigrams related to regulatory interventions, such as "carbon tax," "air pollution," and "environmental legislation," to ensure they align with the expected vocabulary of climate-related regulatory discussions. This step ensures that the selected bigrams are meaningful and relevant. Second, the keyword discovery algorithm expands the initial bigrams, capturing additional context-specific language indicative of regulatory exposure. This adaptive approach identifies relevant terms not initially included, providing more comprehensive coverage of regulatory discussions. Third, the robustness of the measure is tested by iteratively excluding individual bigrams from the initial set and recalculating the regulatory exposure scores, known as the perturbation test. The resulting high correlations (above 85%) with the original measures indicate that the measure is not overly dependent on specific keywords, ensuring its stability and reliability.

Fourth, the measures generated using the keyword discovery approach are compared to those developed from pre-defined keyword lists sourced from authoritative texts. The comparison demonstrates that the discovery-based method is superior in capturing the evolving and specialized regulatory language used in corporate earnings calls. Fifth, the exposure measures are aggregated at the industry level to assess logical patterns. Sectors like utilities and transportation exhibit higher regulatory exposure, reflecting their susceptibility to policies such as carbon taxes and emissions regulations. These patterns validate the economic plausibility of the measures. Sixth, statistical tests reveal that climate change exposure scores correlate with observable measures of real outcomes, such as green innovation and differentiated financial risk profiles.

Estimation reveals that firms with higher climate change exposure scores engage more in green innovation and green hiring (Sautner et al., 2023a; von Schickfus, 2021), validating the practical relevance of the measures. Seventh, a snippet-based audit by trained coders evaluates the algorithm's accuracy in identifying regulatory discussions. Coders analyze text fragments around the identified bigrams, confirming that the algorithm reliably captures regulatory climate discussions. Finally, the performance of the entire keyword discovery approach is compared to using only the initial bigrams. The discovery-based approach identifies significantly more regulatory discussions, especially for firms with lower exposure levels, demonstrating its added value.

Since our sample is at a yearly level, we average the quarterly transcript to obtain annual measures of FL-MPCRE for our analysis. Sautner's climate change exposure dataset is a market-based objective measure, thus widely used in academic studies (Agoraki et al., 2024; Feng et al., 2024; Ginglinger & Moreau, 2023; Hossain et al., 2023; Nguyen & Huynh, 2023; Sautner et al., 2023b).

4.2.2 Key Independent Variable: CPL Shock

For our purpose, we define CPL as the highest political leadership's belief in the scientific consensus on anthropogenic causes of climate change and their response to address climate change, including actions for establishing the climate agenda and coordinating/designing climate-related regulatory frameworks. We classify CPL into two categories. The first is called supportive climate political leadership (SCPL), which demonstrates a strong belief in the anthropogenic cause of climate change and is willing to take positive action to address climate change. The second is climate skeptic political leadership (CSPL), which rejects the scientific consensus on climate change science. CSPL, thus, engages in deregulatory activities or opposes stricter regulations and seeks to dismantle supporting institutions that provide climate science information or support climate change mitigation and adaptation solutions.

As noted earlier, we test our hypothesis in a quasi-natural experiment that exploits the 2016 United States (U.S.) presidential election as a source of exogenous shocks to CPL. We refer to the post-election period (2017-2020) as the era of CSPL and the pre-election period (2013-2016) as the period of the SCPL. We measure the firms affected by the exogenous shift from SCPL to CSPL using a dummy variable named $Treat_{i,}$ which takes the value of one if the firm is in the treatment group, i.e., firms headquartered and listed in the U.S. and zero if in the control group, i.e., firms headquartered and listed in the European Union. $Post_{t,}$ takes the value of one for the CSPL regime period of 2017-2020 and zero for the SCPL regime period of 2013-2016. The interaction of $Post_t$ and $Treat_i$ variables is our key independent variable of interest ($Post_t * Treat_i$). Since our dependent variable is FL-MPCRE, the regression coefficient of $Post_t * Treat_i$ indicates to what extent, compared to the control firms, the FL-MPCRE is different for the treated group firms in the CSPL period relative to that of the SCPL period.

4.2.3 Covariates for PSM

Since we employ the PSM technique to ensure the credibility of our counterfactual, we obtain several covariates to generate, statistically, on average, identical treated and control group firms at the baseline period, i.e., before the shock of 2016. Following climate finance literature (Azar et al., 2021; Balachandran & Nguyen, 2018), we incorporate a vector of the following firm-level covariates. The first represents firm size (*Size*), defined as the natural logarithm of total assets, which controls for the scale of a firm's operations and public attention, which elicits significant environmental pressure (Azar et al., 2021).

The second is the book value of the firm's leverage (*Lev*), which is the ratio of the total debt to the book value of total assets. Firms with higher leverage may have more interest payment obligations, crowding out climate mitigation investments(Azar et al., 2021). The covariate vector also consists of asset tangibility (*Tang*), measured as the value of the net property plant and equipment scaled by the book value of assets. It represents a firm's stock of physical capital and is positively associated with the level of carbon risk. Firms with higher tangible assets are more exposed to climate risk exposure due to regulatory changes or physical destruction through natural disasters (Brown et al., 2022; Wang, 2023). Finally, we include the return on assets (*RoA*), capturing firm profitability, computed as the ratio of earnings before interest and tax to the book value of assets. The effect of firm profitability on climate exposure is related to the ability to invest in climate mitigation strategies(Atif et al., 2021).Hence, more profitable firms can invest more in climate mitigation strategies. All covariates were winorized at one and ninety-ninth percentiles in both tails to exclude the influence of obvious outliers.

4.2.4 Time-varying Country-Level Controls

Although the firm-level covariates may near-randomize the treated and control groups, there still could be country-level factors that may drive our results. As such, we also include time-varying country-level variables reflecting differences in macroeconomic and institutional quality. First, we use each country's real gross domestic product growth rate (*GdpGrt*) to capture its macroeconomic performance(Kim et al., 2021). As a result, we anticipate a favorable link between a country's *GdpGrt* and *FL-MPCRE*. Following Kim et al. (2021), we control institutional quality by utilizing the country's rule of law *(RuleLaw)* indicator from the World Bank Governance Indicator. The *RuleLaw* indicator measures a country's quality of state governance and institutions with a standardized scale of -2.5 to 2.5 (Kim et al., 2021). A higher score indicates a higher level of institutional quality, which underscores economic agents' confidence in the effectiveness of property rights, contract enforcement, the legal system, and the likelihood of crimes and violent acts (Mundial et al., 2010).

4.3 Summary Statistics

Table 1 presents the summary statistics of the total sample from 2013 through 2020, which we employ to analyze the impact of CSPL. The average of the main dependent variable in our sample is approximately 0.41, with a standard deviation of 2.08. Regarding firm-level variables, a typical firm in the sample has an average book value of assets of $7.3bn with a standard deviation of $2.36bn. Regarding borrowing behavior, an average firm in our sample borrows a proportion of 0.25 of its total assets, exhibiting a standard deviation of 0.19. The average firm exhibits 0.06 profitability as a proportion of total assets. The proportion of tangible assets to total assets is 0.24, with a standard deviation of 0.23.

[Table 1 about here]

The country-level time-varying *GdpGrt* shows an average annual growth rate of 1.41% and a standard deviation of 2.27%, reflecting the variations in economic growth rates across different countries in our sample. Finally, the average score of 1.55 for the *RuleLaw* variable for a typical country in our sample and a significantly smaller standard deviation of approximately 0.17 indicates a relatively stable rule of law across our sample countries.

4.4 Empirical Identification Strategy

Following the literature on climate finance (Bartram et al., 2022; Bose et al., 2021; Kim et al., 2021; Roy et al., 2022) and as noted earlier, we design a difference-in-differences (*DiD*) technique by exploiting the U.S. 2016 election as a source of an exogenous shock to CPL to establish a credible causal relationship between *CPL* and FL-MPCRE. Since the shock to CPL affects all firms headquartered and listed in the U.S. (treated group), we need to estimate a control set of firms unaffected by the shock. We employ European companies as our control group (estimate of the counterfactual. Further, post-2016, European firms have not been exposed to CSPL climate-policy shocks compared to those headquartered in the U.S. However, we need to ensure that before the shock of 2016, both groups are, on average, statistically similar. Panel A of Table 2 reports the mean differences between the treated and control groups for 2013-2016 against the four sets of covariates, i.e., *Size, Lev, RoA,* and *Tang.*

[Table 2 about here]

As seen in Panel A of Table 2, except for the *Tang* firm-level characteristic, the treated and control group firms significantly differ in *Size*, *Lev,* and *RoA.* The statistically different characteristics before the shock of 2016 could drive our empirical estimation. As discussed below, we thus employ the propensity score matched balancing technique to simulate a near-randomization empirical setup before the 2016 shock.

4.4.1 Propensity Scored Matched (PSM) Randomization

As noted above, we employ PSM to sharpen our identification strategy to address the potential endogeneity concerns. Literature suggests that causal inferences must generate randomized treated and control (estimate of counterfactual) group firms, which should be highly comparable against average statistical measures based on key differentiating characteristics (Rosenbaum & Rubin, 1983). Accordingly, we use the propensity score matching (PSM) technique to match treated (U.S. firms) and control groups (European firms) based on observed covariates before the shock (Austin, 2011). We discussed these covariates in sub-section 4.2.3.

Before matching, we run a probit model, as stated in Equation (1) below, on the sample period 2013 -2016 to evaluate the PSM technique's validity.

$$Treat_{it} = \alpha_i + \beta.\, \boldsymbol{X}_{it} + \delta_i + \varepsilon_{it} \tag{1}$$

$Treat_{it}$ is the dependent variable in the probit model. It is a dummy indicator variable, with a value of one if the firm is in the treated group or zero otherwise. $\boldsymbol{X}_{it}$ is a vector of covariates consisting of *Size, Lev, RoA,* and *Tang,* discussed in sub-section 4.2.3 and defined in Table A1 of the appendix. δ_i represents firm-fixed effects, and ε_{it} indicates the error term. We winsorize all covariates at the 1% and 99% levels. Following the standard procedure outlined in the literature and using data from 2013 to 2016 (pre-shock), we report the outcomes of estimating Equation 1 in Panel B, Column 2 (Pre-PSM, Model 1). We observe that all the covariates differentially explain the probability of differentiating the treated and control group firms before the shock of 2016. Thus, in statistical terms, the application of PSM is justified.

We then run the PSM, generate the propensity scores, and identify comparable treated and control group firms using the nearest neighbor approach and 0.04 caliper distance with replacement. Next, we employ several diagnostic tests to validate our matching. First, we re-estimate Equation (1) probit regression using the PSM-matched treated and control group firms for 2013-2016. We present the results in Panel B. Compared to the results of Panel B (i.e., Column 2, Pre-PSM Model), the outcomes in Column 3 (Post-PSM, Model 2) imply that none of the covariates can statistically predict the treatment.

Second, we generate standardized percentage bias (SPB) reduction measures between unmatched (pre-PSM) and matched (post-matched) covariates, as described by Rosenbaum and Rubin (1985). SPB is a commonly used metric for evaluating the differences between the treatment and control groups, which quantifies the extent of variance reduction in the distribution of covariates between the unmatched and matched samples. Regarding interpretation, we should expect higher variance in the covariates for the unmatched sample relative to the matched firms' sample. If the matching is effective, we should observe a significant reduction in the SPB for the covariates for the matched firms, i.e., the variance should be close to zero for the matched firms and further away from zero for the unmatched firms. For our sample, the standardized percentage bias variance measures for the covariates in the matched and unmatched samples are reported in Figure 1.

[Insert Figure 1 here]

As expected, Figure 1 illustrates that the SBS for the covariates of the matched sample, relative to the unmatched sample, are all close to zero. This ensures, to a considerable extent, that any pre-existing disparities do not influence the observed effects during the post-shock periods in covariates. Given the results of both diagnostic tests, we can be confident that the PSM addresses the methodological prerequisite of ensuring statistical similarity (on average) between the treatment and control groups before the shock.

5. Empirical Results and Discussions

5.1 Parallel Trend Analysis

Before estimating the PSM-DiD regression, we conduct a parallel trend test over the sample period of 2013-2020 to establish the credibility of our research design as consistent with the difference in the research design. We report the yearly visual trend inspection in Figure 2 and the statistical test for parallel trend yearly in Table 3.

[Figure 2 about here]

As seen in Figure 2, the treatment and control groups' yearly averages of FL-MPCRE were almost identical until 2017. After 2017, the annual average FL-MPCRE figures began diverging, with the broadest divergence observed in 2020. Similarly, the parallel trend indicates that the coefficient of the parallel trend is not statistically significant until 2018 through 2020. The observed trend demonstrates that the treated and control units, from 2013 onwards, show a very close alignment concerning the generation of regulatory risk sources for the firms but unexpectedly diverge from 2017 onwards

[Table 3 about here]

The result indicates that in the pre-treatment period, the yearly average difference is not discernible from zero, indicating no significant difference between the treatment and the control firms FL-MPCRE in 2013-2016. However, from 2017 onwards, we begin to observe material differences. To further authenticate the graphical observations, we report the yearly difference in coefficients of the parallel trend test in Table 3. The result indicates that you confirm a parallel trend between 2013 and 2016, a material divergence with a change in the coefficient from 2017 to 2020, and a significant divergence starting from 2018.

5.2 CPL and FL-MPCRE: PSM-DiD

Following the PSM matching and the parallel trend tests, we run difference-in-differences employing the PSM-matched sample, i.e. (PSM-DiD). Evidence suggests that the PSM-DiD framework ensures that any shock-based quasi-experiment employing comparable treated and control groups should effectively establish causal links (Atanasov & Black, 2021). Thus, the estimation of PSM-DiD assures us that any observed difference in outcomes between treatment and control firms' FL-MPCRE following the 2016 shock could be attributed to the 2016 U.S. election shock, which unexpectedly altered the *CPL* regime from *SCPL* to *CSPL.*

Finally, although in the post-2016 shock period (i.e., in the CSPL era), the PSM-DiD design ensures that time-varying firm-specific characteristics affect treatment and control groups identically, our estimate could still be prone to time-varying country-level factors, time-invariant firm-fixed and year-fixed effects. Thus, we adjust for time-varying country-level factors in our regression approach by including the *GdpGrt* and *RuleLaw* variables and include the firm- and time-fixed effects to achieve a near-perfect randomized empirical setup (Rubin & Waterman, 2006).

We quantify the average treatment effect of CPL on FL-MPCRE by estimating a PSM-DiD regression specification using a PSM-matched firm for eight years between 2013 and 2020 using the specification below.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i *Post_t] + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \qquad (2)$$

where *i* and *t* represent the firm and time (years). $FL\text{-}MPCRE_{it}$ is the dependent variable, which, for ease of interpretation, is scaled by 10^4. $Treat_i$ is an indicator variable that takes the value of one for the firms (*i*) in the treated group (U.S. headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes the value for the post-shock period (2017-2020) and zero for the pre-shock period (2013-2016). Thus, our central coefficient of interest is the DiD factor ($Treat_i$* $Post_t$), which captures the differential average treatment effect of the CSPL on FL-MPCRE. .$\boldsymbol{X}_{it}$ is a vector of firm-level covariates *Size, Lev, RoA,* and *Tang.* Furthermore, $\boldsymbol{X}_{it}$ includes time-varying country-level control variables *GdpGrt* and *Rule Law.* We define all the variables in Table A1 of the Appendix. δ_j *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The outcomes are reported in Table 4. Standard errors are corrected for clustering at the firm level and are presented in parentheses.

[Table 4 about here]

Column (1) shows the univariate DiD regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and Column (3) includes the country-level controls. As evident from the results in columns (1) to (3), the coefficients of DiD estimates carry negative signs and are statistically significant. In quantitative terms, Column (3) results indicate that firms in the treated group experienced a differentially lower value of FL-MPCRE score, i.e., by 0.31, approximately than those in the control group. These -0.31 figures suggest that the shock to CPL led to a 0.31-unit differential decrease in the FL-MPCRE scores for the treated firms in the post-treatment period, compared to the control group and the pre-treatment period.

The above results imply that compared to the European firms, market participants perceive a lower degree of climate regulatory exposure for the U.S. firms during the Trump regime (i.e., the CSPL era covering the period of 2017-2020) relative to that of SCPL era covering the period of 2013-2016. Thus, the lower differential effect on FL-MPCRE in the post-shock period (era of CSPL) in our treated group compared to the control group indicates that market participants paid less attention to the negative impact of near-term climate regulatory exposure in the U.S. than their European counterparts in the control group. Such lower attention denotes that CSPL significantly lowered the source of regulatory risk exposure for investors and other financial market participants through deregulatory actions (or future expectations of deregulatory actions).

5.3 Robustness Checks

In this section, we undertake robustness checks to validate our baseline results reported in Table 4. First, we administer a placebo test, then a complementary matching technique, and finally, we employ an altered measure of FL-MPCRE.

5.3.1 Robustness Check: Placebo Test

Although our main findings indicate that the exogenous shock to SCPL in 2016 directly caused variations in FL-MPCRE, it is plausible that these findings are due to pre-existing trends or cyclical variations. To rule out this alternative explanation, we conduct a placebo test using 2015 as the shock year. We re-estimate the model specification by using 2015 as the shock year, followed by the pre-shock period (2013-2015) and the post-shock period (2016-2017). We present the results of the regressions in columns [1]to [3] of Table 5.

[Table 5 about here]

The results of our analysis show that the DiD coefficients are not statistically significant. The results further support the main findings shown in Table 4, which are unaffected by any other events and alleviate concerns about any pre-existing patterns in FL-MPCRE.

5.3.2 Robustness Check: Entropy Balancing Approach

Following existing literature (Cook et al., 2021; Hasan et al., 2021; Hossain et al., 2023; Çolak & Öztekin, 2021), we use the entropy balancing technique developed by Hainmueller (2012) to generate a balanced sample of treated and control firms. The entropy balancing technique adjusts the weights of observations within the control sample, resulting in distributions of matched covariates showing no discernible differences between the treatment and the re-weighted control groups (Hainmueller, 2012). The purpose is to balance the predetermined distribution moments of the covariates (mean, variance, and skewness) between the treatment and re-weighted control groups.

The entropy balancing technique is a quasi-matching approach that ensures balance across all covariates by constructing a set of matching weights that meet the specified balancing constraints for each observation in the sample. This method addresses disparities in covariate representation in the treatment and control firms, reducing reliance on specific modeling assumptions and ensuring balance improvements across all included covariates such that re-weighted observations have identical post-weighting distributional characteristics for the treatment and control units. Simultaneously, entropy balancing calculates precise weights for the control observations, ensuring sample integrity and covariate balance (Chapman et al., 2019). The reweighing procedure eliminates endogeneity bias caused by a latent variable that distorts the covariate distribution. For more technical distribution, see Hainmueller, 2012 and Chapman et al., 2019.

The incremental advantage of entropy balance is that we significantly enhance the efficiency of our regression estimations by exploiting information in a much greater number of observations than

PSM matching. Also, unlike PSM matching, which relies solely on using the mean, it could balance covariates across variance and skewness in addition to the mean. We re-estimate DiD specification 2 using the entropy-balanced sample using mean, variance, and skewness moments. We report the results in Table 6, columns (1) to (9).

[Table 6 about here]

We use the three moments (mean, variance, and skewness) to estimate the entropy balance technique. First, we estimate the matching using the mean in the entropy balance matching. Consistent with our main PSM-DiD estimation results, the results in columns 1-3 remain statistically significant at a 1 % significance level. The coefficient of the DiD estimated, as reported in Column (3), is approximately -0.19. Second, we re-estimate the entropy balance matching using the first and second moments and present the results in Table 6 columns (4-6). After adjusting for covariates, firm and year fixed effects, the results remain significant at a 1 % level but indicate a smaller effect size relative to the PSM-DiD regression results.

Lastly, we employ all three moments (mean skewness and kurtosis) in the entropy balance matching and present the results in Table 6 columns (7-8). Again, after considering all covariate, firm, and year-fixed effects, the results remain statistically significant at a 1 % significance level but indicate a smaller effect size relative to the result using PSM-DiD and the first and second-moment entropy balance estimation. Although the effect size reduces when other moments are included, the results remain consistent. Such non-trivial reduction in the size effect is expected due to the more conservative matching mechanism imposed by the entropy balance technique when additional moments are used in the estimation. In summary, these outputs of the entropy balancing technique align with our main findings reported in Table 3 and thus further validate the baseline results, supporting the CSPL hypothesis.

5.3.3 Robustness Check: Altered Measure of FL-MPCRE

Next, we estimate the PSM-DID regression using an altered measure of the outcome variable. As shown below, we amend equation 2 by replacing FL-MPCRE with an industry-adjusted FL-MPCRE.

$$Adj\_FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i * Post_t] + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \quad (3)$$

where $Adj\_FL\text{-}MPCRE_{it}$ indicates industry-adjusted FL-MPCRE for firm i in year t. We present the result in Table 7, columns (1) to (3). Consistent with our baseline results and further supporting our CSPL hypothesis, the effect of CSPL on Adj_FL-MPCRE is still negative and statistically and economically significant. As shown in Column (3), on average, CSPL lowers the Adj_FL-MPCRE by a differential of 0.61 units for the treated relative to the control group of firms in the post-shock period. This further validates our hypothesis that the emergence of CSPL is associated with a negative and statistically significant negative annual growth in FL-MPCRE.

[Table 7 about here]

5.3.4 Robustness Check: Politically- induced Firm-level Tax, Trade and Policy

In this section, we conduct additional tests to rule out further alternative explanations that may potentially capture politically induced firm-level policy changes. For example, many U.S. firms may have international trade links with the E.U., so they must comply with E.U. regulations. Such firm-level cross-atlantic political influence may confound our results (Child et al., 2021). Similarly, in the post-2016 elections, both the regimes (the U.S. and the E.U.) may have had different broader regulatory regimes, not just climate regulation, which may correlate with FL-MPCRE and the CPL measure in our empirical set-up. This is particularly relevant to the lower-tax regime of the U.S. administration post-2016 election.

While our identification strategy accounts for firm-level characteristics (using PSM and entropy balance techniques), firm and year-fixed effects, and a set of country-level control variables to mitigate these concerns, we address the possibility of the firm-level effect of politically induced tax, trade, and economic policies driving our results. We employ the firm-level political risk (*P_Risk*) index from Hassan et al. (2019), capturing the effect of those policies at the firm level. Hassan et al. (2019) construct the *P_Risk* index using earnings conference call transcripts, which often detail firms' risks and uncertainties. Political risk is identified through textual analysis, focusing on keywords such as "regulation," "legislation," "tariffs," and "policy," analyzed using machine learning and natural language processing (NLP). The index measures the proportion of politically related terms in each transcript, quantifying a firm's exposure to political risk and its efforts to mitigate it.[28]

The index facilitates comparisons across firms, industries, and periods, capturing systematic exposure to political risk (e.g., in finance or healthcare) and fluctuations due to external events like elections or geopolitical crises. A higher index value indicates greater concern or exposure. The authors link higher political risk to reduced investment, lower hiring, and increased precautionary cash holdings while examining mitigation strategies, such as lobbying or geographic shifts. This approach offers a granular, firm-level, real-time measure of political risk, surpassing traditional reliance on macroeconomic or survey-based indicators.

Further, Hassan et al. (2019) construct separate sub-indices within their *P_Risk* index framework to analyze specific dimensions of political risk. Among them, separate tax, trade, and economics indices are included, each focusing on aspects of political uncertainty. The tax index (*P_Risk_Tax*) focuses on political risks related to taxation policies and reforms. The keywords include "tax reform," "taxation," "corporate tax," and "tax policy." The *P_Risk_Tax* index captures how discussions about politically induced tax-related risks affect firm decision-making. Similarly, the trade index (*P_Risk_Trade*) measures the political risk associated with trade policies, tariffs, and international trade relations. The keywords include "trade policy," "tariffs," "trade agreements," and "import/export barriers”. This *P_Risk_Trade* index highlights firms' exposure to geopolitical shifts in trade dynamics. Finally, the economics index (*P_Risk_Economics*) captures broader macroeconomic

[28] For instance, if 5% of the words in a transcript pertain to political risk, the firm has a political risk index of 0.05.

risks tied to political uncertainty, such as economic policy, monetary policy, or fiscal policy discussions. The keywords include "economic policy," "inflation," "recession," and "monetary policy." The *P_Risk_Economics* index reflects concerns about overarching economic conditions shaped by political factors.

By disaggregating the overall *P_Risk* index into these sub-indices, the authors provide a more granular understanding of how specific political risks affect firms across different industries and periods. These sub-indices allow for a nuanced analysis of how distinct risks—such as tax reforms or trade wars—impact corporate decision-making and performance. For our purpose, employing these sub-indices allows us to capture firm-level time and cross-sectional tax and trade-related variation in our empirical setting.

We rerun our main regression specification (2), controlling for firm-level politically induced risk related to tax (*P_Risk_Tax*), trade (*P_Risk_Trade*), and (*P_Risk_Economic*) in our regression specifications. We report the results in Table 8, columns 1-4.

[Table 8 about here]

In column 1, we first control for firm-level trade risk (*P_Risk_Tax*); in column 2, we control for tax risk (*P_Risk_Tax*); in column 3 we control for economic risk (*P_Risk_Economic*); and in column 4, we control for the three indices (*P_Risk_Tax, P_Risk_Tax* and *P_Risk_Tax*) in the full specification model. After controlling for the politically associated tax and trade-related indices, our key coefficients of interest are statistically significant, carry expected signs, and are also economically (quantitatively) similar to the baseline regression results, implying that these factors do not play a significant role in the market assessment of future climate regulatory exposure.

5.3.5 *Robustness Checks: Firm Heterogeneity*

In this section, we further offer several other robustness checks in the form of cross-sectional heterogeneity tests. We exploit the firm-level cross-sectional heterogeneity and test two different predictions drawn from the arguments of the climate-finance literature on firm-level characteristics that could moderate the link between CPL and FL-MPCRE. Specifically, we take advantage of characteristics related to a firm's carbon intensity, i.e., whether the firm is in a high or low-carbon-intensive industry and the extent of financial constraint.

5.3.5.1 Robustness Check: High vs. Low Carbon Intensive Firms

Firms in carbon-intensive industries are most vulnerable to the stringency of carbon regulation owing to higher costs of non-compliance and pollution abatement (Bose et al., 2021; Nguyen & Phan, 2020). Further, studies also show that relative to their less carbon-intensive counterparts, high carbon-intensive firms face higher costs of equity and debt and the prospect of higher carbon prices in the emission trading market(Balachandran & Nguyen, 2018; Bolton & Kacperczyk, 2023; Bose et al., 2021). Moreso, carbon-intensive firms may be compelled to increase investment in efficient and greener technologies, which promotes a switch to cleaner production, thus leading to substantial costs (Brown et al., 2022; Dang et al., 2022; Sautner et al., 2023a).

Hsu et al. (2023) study the determinants of environmental pollution premium using a general equilibrium framework. They empirically document that constructing a portfolio short on high carbon-intensive firms and long on low carbon-intensive firms (high-minus-low) results in statistically significant positive returns. The result relation to our study implies that firms' future profitability may depend on environmental regime changes since the political leadership creates climate regulatory risks through their climate policy preferences. Their model predicts that in the event of a stricter environmental policy regime, the operating performance of high carbon-intensive firms may be adversely affected. They conclude that risks related to environmental regulations and changes in policy regimes may explain the cross-section of environmental pollution premiums.

Given the above discussion on high and low-carbon-intensive firms' potential risks and costs, what changes should we expect in their FL-MPCRE in our experimental setup when the CPL regime unexpectedly changes from SCPL to CSPL? As noted earlier, the emergence of climate-skeptic political leadership, which institutes deregulatory policies characterized by loosening strict emission standards, lower compliant costs, and lower environmental mitigation costs, may lead to cost savings for firms. For example, by allowing higher emission levels without penalties, firms can avoid the costs of implementing expensive emission reduction technologies. Additionally, lower compliance costs mean that firms do not have to allocate as many financial resources toward meeting environmental regulations, resulting in potential savings. Therefore, ex-ante, it is safe to conjecture that carbon-intensive firms are more likely to benefit from CSPL climate-deregulatory policies.

In the context of our argument, U.S. firms under climate-skeptic political leadership are likely to face lower regulatory exposure compared to their European Union counterparts. This is because, post-2017, the trajectory of stricter climate regulations in the European Union continued (see Figures 2 and 3). Simultaneously, deregulatory policies characterize the CSPL era in the U.S. This difference in regulatory approach implies that U.S. firms may face less stringent requirements and associated climate mitigation and abatement costs than their E.U. counterparts. This argument suggests that market participants will perceive a significantly lower level of climate regulatory risk for U.S. firms than their European counterparts.

Ramelli et al. (2021) show that high carbon-intensive firms were rewarded more with higher market valuations than non-carbon-intensive firms after the U.S. 2016 Presidential elections. This suggests that investors may perceive the impact of deregulation positively on carbon-intensive firms, leading to higher market valuations for these companies. This evidence further supports the argument that climate-skeptic political leadership may favor carbon-intensive firms regarding market performance. Therefore, to the extent that CSPL deregulatory policies lower the regulatory burden, we argue that carbon-intensive firms under the influence of the CSPL deregulatory regime may be perceived to exhibit lower climate regulatory exposure than their non-carbon-intensive counterpart. We follow Matsumura et al. (2014) and Balachandran and Nguyen (2018) in classifying a firm as carbon-intensive if it operates in a carbon-intensive industry. For the list, see Table A2 in the appendix. The Carbon Disclosure Project (CDP2012) designates these firms as a significant source of highly toxic emissions intensity. (Balachandran & Nguyen, 2018; Choi et al., 2020).

Studies show that carbon-intensive firms are particularly vulnerable to stricter climate regulations as compliance could make technologies that rely on fossil fuels (thus, the risk of assets being stranded[29]), leading to disruption in the production process and an increase in the unit cost of output[30]. Therefore, as the level and stringency of climate regulations grow, firms in carbon-intensive industries are more likely to incur higher environmental liabilities and competitive costs (Balachandran & Nguyen, 2018; Burby & Paterson, 1993; Grewal et al., 2019; Wu et al., 2023; Xu & Kim, 2022).

To empirically test this conjecture, we construct a carbon dummy variable (*CarbonDummy*) that equals one if the firms have been classified as high carbon-intensive and zero otherwise following prior literature (Balachandran & Nguyen, 2018; Choi et al., 2020).We estimate model specification (4) by interacting the DiD variable($Treat_i$ $*Post_t$) with the *CarbonDummy* to form a triple interaction term and present the regression results in Table 9, Columns (1) to (3).

[Table 9 about here]

As seen in columns 1 to 3 of Table 9, the DiD coefficients carry negative signs and are statistically significant at the 1% level. The coefficients of the regressions are negative and economically significant, indicating the moderating effect of high carbon intensive. We interpret this finding to indicate that the average negative differential relationship between treated and control units is more pronounced among carbon-intensive firms. This is consistent with our argument and supports the conjecture that the effect of CSPL on FL-MPCRE is more substantial for high-energy-intensive firms.

5.3.4.2 Robustness Check: Role of Financial Constraints

We finally examine the relationship between CSPL and FL-MPCRE conditioned on a firm's level of financial constraint. One of the unintended consequences of the stringency of climate policy is that it may exacerbate the financial constraint for the firms given the high regulatory compliance costs and

[29] Welsby et al. (2021) predict that approximately 60% of oil and 90% of coal may need to remain buried and thus unexploited if the world limits global warming to 1.5ºC by 2050.
[30] See :Balachandran & Nguyen, 2018; Bartram et al., 2022; Bolton & Kacperczyk, 2021a; Bose et al., 2021; Hoffmann & Busch, 2008; Ilhan et al., 2021; Nguyen & Phan, 2020; Kim et al., 2021

double-binding capital constraints in the debt and equity markets (Bartram et al., 2022; Hoberg & Maksimovic, 2015). Prior studies show that stricter regulatory regimes increase pollution abatement costs, and carbon tax crowds out firm-level investments and negatively lowers the ability of firms to compete in the product market (Brown et al., 2022; Jaffe et al., 1995; Nguyen & Phan, 2020). However, such costs have been documented to modify corporate behavior to increase investment in the marginal value of research and development expenditure focused on pollution reduction, especially among high-polluting firms (Brown et al., 2022).

Brown et al. (2022) further argues that environmental costs, specifically emissions taxes, increase the operational costs for firms with high pollution levels, making it financially burdensome for them to continue utilizing their existing, less environmentally friendly production technologies. Consequently, these taxes serve as a catalyst, prompting polluting firms to invest in and transition towards cleaner, more sustainable production processes. Firms can draw from the internal capital market or seek external capital to fund pollution control costs, which may divert resources that could be used for capital and R&D(Dang et al., 2022).

Therefore, under strict and costly climate regulatory regimes, we expect market participants to perceive higher climate regulatory exposure for high-financially constrained firms than those with low-financially constrained firms. Prior literature documents the high cost of capital for firms with high carbon exposure (Chava, 2014; Sharfman & Fernando, 2008). This is consistent with the notion that financially constrained firms under strict climate regulation would have to either borrow at huge costs or sacrifice investment in growth opportunities to meet environmental abatement expenditure or pay associated fines (Fard et al., 2020; Javadi & Masum, 2021; Wu et al., 2023). Conversely, when the cost of regulatory burden is drastically reduced under the SCPL, which creates a lax and less costly climate regulatory regime policy for financially constrained firms, it implies that relative to less financially constrained firms, the observed effect of SCPL on FL-MPCRE should be stronger in high-financially constrained firms.

Translating the implications in our empirical setup, we expect financially constrained firms to experience reduced compliance and pollution abatement costs[31] in the CSPL regime relative to that of the SCPL era. We argue that the market may view the corporate cost savings from deregulation as positive because it implies that financially constrained firms can allocate their limited resources more efficiently towards other productive activities, such as expansion or improving their market competitiveness. The perceived improvement in financial flexibility and the potential for lower compliance costs should translate into a lower perception of climate regulatory exposure.

Intuitively, in a high-cost climate regulatory regime (SCPL), financially constrained firms may experience the cost of strict regulation more intensely. Hence, when CSPL's climate deregulations alleviate the high climate-regulatory costs, the expected impact on financially constrained firms may be more pronounced than on non-financially constrained firms owing to perceived cost reduction by market participants. Therefore, we expect the differential negative effect size to be more pronounced in the CSPL era for financially constrained firms.[32]

To empirically study the relationship between CSPL and FL-MPCRE conditioned on a firm's financial constraints, we proxy for financial constraints using the Kaplan-Zingales Index (*KZ_Index*). We follow prior literature in constructing the *KZ_Index*[33] that reflects the firm-level degree of financial constraint (Bartram, Kaplan, and Zingales, 1997; Lamont et al., 2001; Xu & Kim, 2022). Higher scores on the *KZ_Index* indicate a higher degree of financial constraints the firms face. The index is computed as a linear combination of several metrics, such as the ratio of cash flow to one-period lagged net property plants and equipment ($cash\_flow/ppe_{t-1}$), cash balances to one-period lagged property plants and equipment ($cash\_bal/ppe_{t-1}$), cash dividends to one-period lagged book value of assets ($div/asset_{t-1}$), total debt to book value of assets (*Lev*), and Tobin's Q (*T.Q.*), which is measured as the sum of the

[31]As noted in section 2, the federal social cost of carbon estimate under the Obama administration was $45 per ton of carbon dioxide pollution. However, the same cost was revised to between $1 and $7 under the Trump regime (see this **link**, accessed on 22/02/2024).

[32] A plausible counterargument could be that financially constrained firms may still face significant climate risk exposure even after the relaxation of regulations. Other transition climate-risk factors, such as reputational risks, technological change risks, and changing customer preferences for environmentally supportive firms, may worsen the financial constraints. While deregulation may provide significant relief from compliance and pollution abatement costs, it does not eliminate the underlying climate risks these firms face in absolute terms. However, in this study, we only focus on the perception of markets on regulatory exposure.

[33] KZ Index = $[-1.002*(cashfloww/ppe_{t-1})] + [-1.315*(cash / ppe_{t-1})] + [-39.368*(div/ ppe_{t-1})] + [3.139 *Lev] + [(0.285*TQ)]$

book value of total assets and market value of equity less common equity divided by the total book value of assets. To mitigate the impact of extreme values, we winsorize the index at the 1st and 99th percentiles to exclude the effect of outliers.

We then construct a financial constraint dummy to analyze the effect of CSPL on FLMPCRE on two subsamples of firms. The binary indicator for financial constraints (*FinCon*) takes a value of one if the firm-year observation is above the median of the *KZ_Index* and zero otherwise. To estimate the CSPL-FL-MPCRE nexus conditioned on a firm's level of financial constraints, we run a triple interaction term ($Treat_i*Post_t*FinCon_{it}$) following the specification (4) and report the findings in Table 10. The coefficients of both triple interactions capture the differential impact of CSPL on FL-MPCRE, conditioned on their level of financial constraints.

[Table 10 about here]

The results are in columns (1) to (3); the coefficients are statistically significant at the 1% significance level (β = -0.332, -0.333, -0.316), respectively, in columns (1) to (3). This implies that financially constrained firms' FL-MPCRE is significantly lower in CSPL than in the SCPL regime in the CSPL era.

5.4 Mechanism Test: Climate Deregulatory Channel

In Section 3, we argued and extensively discussed that changes or anticipated changes in the national regulatory tools and degree of information asymmetry are the fundamental mechanisms through which CPL could influence FL-MPCRE. In line with existing literature, we use the country-level climate change performance index (CCPI) from Germanwatch[34] as a proxy of climate regulatory stringency measure (Bose et al., 2021; Kim et al., 2021). It is an autonomous country-level measure designed to promote transparency in global climate politics and facilitate evaluating individual countries' efforts and advancements in combatting climate change (Bose et al., 2021). The index is constructed by

[34] See https://www.germanwatch.org/en/CCPI

monitoring and assessing the activities undertaken by individual nations to combat climate change, thus enabling comparisons of their efforts towards climate protection.

For our purpose, we obtained the specific index reflecting the assessment of a country's climate policy, which is a unique section of the CCPI that evaluates countries' progress in implementing policies that contribute to the achievement of the goals of the Paris Agreement[35] . In our empirical setting, we refer to it as the climate regulatory stringency index (CRSI). It is scaled from zero (0) to five (5). Zero (0) represents the lowest level of climate regulatory stringency, and five (5) represents the highest. We first examine whether there is any difference in the yearly trend of the *CRSI* index between the treated and control group countries over the sample period. We plot the average trend of the yearly CRSI figure of the treated group firms' countries (i.e., for the U.S.) and that of the control group firms' countries (all the E.U. countries). We present the graph in Figure 4.

[Figure 4 about here]

As seen and expected, we observe that after 2017, there was a drastic drop in the CRSI score for the U.S. In contrast, the CSRI scores for the E.U. countries' scores increased after 2017. This suggests dramatic changes in the climate regulatory environment in the U.S. after 2017, relative to the E.U. countries. While the E.U. countries continued their stringent regulatory regime to mitigate climate change, the CSPL in the U.S. embarked on a deregulatory path, leading to lower stringency of climate change policies after 2017.

To examine the deregulatory channel empirically, we construct a dummy variable that takes a value of one if the CSRI score is below the median and zero otherwise. We interact the DiD variable (*Treat*Post*) with the *deregulatory dummy (CRSI_Dummy) variable*, creating a triple interaction ($Treat_i$*$Post_t$* *CRSI_Dummy*), and run the following specification (4).

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i * Post_t * CRSI\_Dummy_{ct}] + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \quad (4)$$

[35] CCPI evaluates 63 countries and the European Union, which produce approximately 90% of the global greenhouse gas emissions. For more details on the methodology, see: https://ccpi.org/

We estimate specification (3) and report our findings in Table 11, columns [1] to [3]. Column (1) shows the regression of the triple difference in differences (DiDiD) regression, including the firm and year fixed effects. Column (2) reports the outputs, including firm-level covariables, while Column (3) includes country-level controls. All regressions are clustered at the firm level to account for errors due to autocorrelation.

[Table 11 about here]

As reported, all the coefficients (0.5051, 0.497, and 0.408, respectively) of the triple interaction ($Treat_i*Post_t*CRSI\_Dummy_{ct}$) estimates are negative and statistically significant at the conventional 1% significance level. The results suggest that the climate deregulatory channel is the mechanism through which CSPL influences FLMPCRE.

5.5 Implication Tests

So far, our empirical analysis and subsequent tests support the negative differential effect of adverse shock to CPL on FLMPCRE. Prior studies indicate that perception translates into changes in beliefs and expectations, such as pricing of assets, allocating capital, or corporate behavioral changes (Atiase et al., 2005). The following sub-sections examine the financial implications of the link between FLMPCRE and CPL, particularly on firms' institutional investors' ownership and capital-market-based market valuation.

5.5.1 Market Implication Test: Institutional Investor's Ownership

Institutional investors are crucial in shaping corporate behavior and corporate environmental policies(Dyck et al., 2019). Evidence suggests that institutional investors are paying increasing attention to climate change exposure (Krueger et al., 2020; Stroebel & Wurgler, 2021). For example, Bolton and Kacperczyk (2021a) and Ilhan, Sautner, Vilkov, et al. (2021) note that the risk of corporate climate exposure is a consistent risk factor in the equity market, documenting investors' demand for carbon premiums. Theory and empirical evidence also imply that institutional investors' stakes in companies accord them the clout to advocate for better climate performance and encourage/compel firms to curb greenhouse gas emissions (Azar et al., 2021; Kim et al., 2019). This implies that, *ceteris paribus*, the higher the level of ownership, the higher the pressure and engagement of firms to decarbonize (Azar et al., 2021; Gantchev et al., 2022).

However, such climate-friendly pressure and risk assessment of institutional investors may only yield positive outcomes if they perceive higher climate regulatory risk for their portfolio firms. For example, prior literature suggests that investors' climate beliefs and perceptions are critical to climate mitigation strategies such as green investments (Ceccarelli & Ramelli, 2024; Ilhan et al., 2023). Similarly, Huber et al. (2019) and Ma et al. (2019) document evidence indicating that the market perception of risk factors impacts equity market asset pricing and stock liquidity (Huber et al., 2019). In terms of conference calls, Borochin et al. (2018) show that the tones of the calls influence equity market valuation.

What happens to the climate regulatory perception of the same institutional investor when it attends the earnings conference calls of two very identical firms, except that one operates in the stricter climate regulatory environment of SCPL and the other in the regulatory regime of CSPL? As discussed earlier, compared to the SCPL era, firms operating in the regime of CSPL, which creates a deregulatory environment and reduces the cost of environmental abatement, should pose much lower climate regulatory exposure.

Comparatively, the reduced regulatory climate risk for the treated group firms should translate into a lower perception of near-term regulatory climate-policy exposure among institutional investors. Consistent with the fact that investors' perceptions influence asset prices and investment decisions (Krueger et al., 2020; Pflueger et al., 2020) and *ceteris paribus*, we expect institutional investors to increase their differential ownership in the U.S. firms compared to their European counterparts following an exogenous shift in CPL from SCPL to CSPL that lowers the FLMPCRE. Consistent with deregulation lowering perceived climate regulatory and abatement costs, we conjecture that firms with lower perceived regulatory risks will attract more institutional investor ownership. Empirical evidence shows that institutional investors who participate in the earnings conference calls engage and discuss environmental and sustainable practices and that the tones of the calls influence equity market valuation(Blau et al., 2015; Borochin et al., 2018; Rennekamp et al., 2022)

To test our conjecture, we measure the percentage (%) of total annual institutional ownership (*OWN_{it}*) as the number of shares held by all types of institutional owners in a firm (*i*) at the end of the year (*t*), which is the total number of shares outstanding for institutional ownership. We obtain data on institutional ownership from the Capital I.Q. Institutional Ownership Database. .Following the extant literature on institutional ownership, we set the value of institutional ownership to zero if data is missing(Bena et al., 2017; Ferreira & Matos, 2008). To test the implication conjecture, we estimate different specifications of the following equation (5)

$$OWN_{it} = \alpha_i + \beta.\ [Treat_i*Post_t] + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \qquad (5)$$

$\boldsymbol{X}_{it}$ includes the covariates (*Lev, Size, RoA,* and *Tang*) employed in PSM balancing. We argue that the PSM balancing takes care of the observed firm-varying characteristics reported in the literature (Bena et al., 2017; Ferreira & Matos, 2008; Gelos & Wei, 2005), such as benchmark allocation, corporate governance, liquidity, internationalization, etc, which could be simultaneously associated with OWN_{it} and [$Treat_i*Post_t$] factors. Moreover, following Gelos and Wei (2005), we also include time-varying politically induced tax, trade, and economics factors (*P_Risk_Tax*, *P_Risk_Trade,* and *P_Risk_Economic*) at the firm level (data source: Hassan et al. (2019) along with time-varying country-level variables (*GdpGrt* and *RuleLaw*). We report our results in Table 12, columns 1- 4.

[Table 12 about here]

As seen across all four specifications, the estimates of [$Treat_i*Post_t$] are statistically significant and carry expected positive signs. The minimum value of 1.2 % indicates a differential increase in institutional investor ownership in the treated group in the post-shock period relative to the control group. Thus, compared to the control group of firms, U.S. firms enjoy higher institutional ownership in the CSPL regime, potentially driven by significantly lower perceived climate regulatory exposure. This result supports the conjecture that the market perceives the CSPL regime as favorable to firms concerning climate regulatory exposure.

55.2 Market Implication Test: Capital Market-based Valuation

Within the investor belief framework of Pastor & Veronesi (2012), when governments announce policies, the uncertainty is partially resolved, and investors adjust their valuations accordingly. If the announcement aligns with positive expectations, stock prices rise; if it contradicts them, prices fall. The magnitude of the adjustment depends on how surprising the announcement is relative to prior beliefs. In our empirical set-up, the unexpected results of the 2016 Election revised the perceptions of the market participants, whereby the expected higher carbon risk premium of the climate-supportive regime should be revised down in the climate skeptic regime. The argument is that if higher climate risk exposure entails a higher risk premium (Bolton & Kacperczyk, 2021a, 2023; Hsu et al., 2023), any perceived lowering of such risk should translate into a lower risk premium and, thus, higher valuations.

Prior studies show that firms operating in a regime of climate deregulatory policies, especially in the aftermath of the 2016 U.S. presidential elections and those in carbon-intensive industries, enjoy higher market valuation (Kundu, 2024; Ramelli, Wagner, Zeckhauser, Ziegler, et al., 2021). This implies that if investors and the market view those firms favorably due to the impact of the new lower-cost climate regulatory regime, then in our empirical set-up, we expect that the U.S. firms should experience differentially higher market valuation relative to their European counterparts. Accordingly, we test whether U.S. firms' lower market perception of climate regulatory exposure relative to their European counterparts translates into higher capital-market-based valuations employing the following general regression framework (6).

$$VALUE_{it} = \alpha_i + \beta.\ [Treat_i{*}Post_t] + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \tag{6}$$

As a proxy of market-based value, we employ the Tobins Q(*TQ*) following prior literature (Bardos et al., 2020; Berkman et al., 2024). $\boldsymbol{X}_{it}$ features the covariates (*Lev, Size, RoA,* and *Tang)* employed in PSM balancing. Moreover, given the cross-country sample, we also include time-varying politically induced tax, trade, and economics factors (*P_Risk_Tax*, *P_Risk_Trade,* and *P_Risk_Economic*) at the firm level (data source: Hassan et al. (2019) along with time-varying country-level variables (*GdpGrt* and *RuleLaw*). We report our results in Table 13, columns 1 - 3.

[Table 13 about here]

As documented across all three specifications (Columns 1-3), estimates of $[Treat_i*Post_t]$ are statistically significant at the 1% level and exhibit the anticipated positive signs. In an economic sense, the figures indicate a minimum differential increase of 0.23% in market valuation for U.S. firms (column 4), relative to their European firms, attributable to reward for the lower perception of future climate regulatory exposure. This indicates that reduced perceived regulatory exposure following the exogenous CPL shock and the emergence of CSPL results in higher market valuations for U.S. firms compared to European counterparts. The result is consistent with prior studies on the market valuation implications of the regulatory shock of 2016 U.S. presidential elections (Kundu, 2024; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021)

Our findings indicate that investors factor in the reduced climate abatement costs under the CSPL regime, as evidenced by the association between lower perceived climate regulatory exposure and higher institutional ownership and market valuation. Our result is consistent with the idea that investors favor deregulatory policies consistent with similar findings by Kundu (2024). This suggests that investors prioritize firm-level climate risk exposure only when it is imposed by the CPL. Thus, the findings on the market effects of the adverse shock to CPL on FL-MPCRE carry significant implications for climate risk pricing and decarbonization efforts. Given that the perception of climate regulatory exposure is critical to fostering pro-environmental behavior (Ceccarelli & Ramelli, 2024;

Kräussl et al., 2024), an exogenous shock that diminishes this perception may hinder the transition process or contribute to the mispricing of climate regulatory risk.

6. Conclusion

A wealth of academic and anecdotal evidence corroborates a significant positive nexus between corporate activities and higher carbon footprints. Devising and enforcing strict climate regulatory mechanisms is an effective means to decarbonize economies. Thus, science suggests that fostering a climate-friendly regulatory environment should expedite the transition to a low-carbon economy. Climate political leadership (CPL) is the conviction and disposition of the highest political leadership that reflects the approach to tackling climate change by establishing the climate agenda, designing regulatory frameworks, and fostering global coordination to address climate-related challenges. A supportive climate political leadership (SCPL) believes in climate science consensus, thus designing practices that support domestic and internationally coordinated climate mitigation and adaptation policies through climate-friendly regulatory and economic frameworks. However, a climate skeptic political leadership (CSPL) exhibits climate-science denialism, thus promoting a climate-unfriendly regulatory environment and dismantling institutions that provide information on climate science or support climate actions.

Further, studies also note that financial market participants (e.g., analysts and institutional investors) can play a crucial role in engaging with their portfolio firms to decarbonize if they perceive significant climate regulatory risk. However, market participants' ability to contribute to decarbonizing their portfolio depends on their perception of the extent to which CPL fosters a climate-friendly regulatory environment, generating mandatory incentives to embed sustainable business practices and invest in greener technologies. The ensuing climate-friendly strict regulatory regime should generate the firm-level market perception of climate regulatory exposure (FL-MPCRE), incentivizing investors to engage with their investee firms to manage regulatory exposure. Thus, appreciating the drivers of firm-level regulatory exposure may significantly help address climate change at the micro-business level. This study provides comprehensive and systematic evidence that an unexpected CPL shift significantly generates firms' climate regulatory exposure.

Using a recently constructed market-based objective dataset that reflects FL-MPCRE, our study shows that an adverse shock to CPL, i.e., unexpected regime changes from SCPL, which exhibits a strong belief in climate science and the associated stringent regulatory regime, to CSPL, that denies climate science and demotes a climate-friendly regulatory environment, attenuates FL-MPCRE. Thus, the lower degree of FL-MPCRE does not incentivize businesses and their investors to promote greener business practices. However, we also demonstrate that investors seem to price in such deregulatory lower climate abatement cost as our study shows that a lower perception of climate regulatory exposure under the CSPL regime is associated with higher institutional investor ownership and market valuation. This implies that investors seem to care less about the carbon footprint of their portfolio firms unless CPL complements by generating firm-level climate risk exposure.

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Appendix

Table A1: Variable Definitions

Variable name	Description
CPL	Climate political leadership (*CPL*) is a dummy variable that takes the value of zero for the four years before the result of the 2016 U.S. presidential elections, i.e., 2013–2016 and one for 2017-2020. It represents the perception/belief of political leadership related to climate change science and the regulatory initiatives adopted by the regime. We term 2013-2016 as an era of supportive climate political leadership (*SCPL*) (i.e., *CPL* = 0) and 2017-2020 as climate skeptic political leadership (*CSPL*) (i.e., *CPL* = 1)
FL-MPCRE	For firm *i* at the end of year *t, FL-MPCRE* is the firm-level market perception of climate regulatory exposure. It captures market participants' (analysts, institutional investors, firms) perceptions of various upside or downside factors related to climate regulatory exposure. It is computed based on the number of climate regulatory exposure bigrams (e.g., "carbon tax," "air quality," "environmental legislation," etc.) featured in the transcripts of earnings conference calls. For each firm and each quarter of the year, the total occurrence of climate regulatory bigrams is divided by the total number of bigrams in the transcripts. To illustrate, if 300 out of 10,000 bigrams for the entire year are associated with climate regulatory exposure, the corresponding value is 300/10,000, or 0.03. As this proportionate value increases, so does the firm's perception of its exposure to climate-related risks. Source: Sautner et al. (2023)
Adj_FL-MPCRE	Industry-adjusted firm-level climate regulatory exposure using a two-digit SIC code.
Size	For firm *i* at the end of year *t, Size* is the natural logarithmic of the total assets measured in US$ millions. Source: Compustat
Lev	For firm *i* at the end of year *t,* leverage (*Lev*) is the ratio of the total book value of debt over the total book value of the asset. Source: Compustat
RoA	For firm *i* at the end of year *t*, *RoA* is the return on assets computed as the ratio of pre-tax earnings over total assets. Source: Compustat
Tang	For firm *i* at the end of year *t*, *Tang* represents the tangibility of the assets. It is the net property and plant value scaled by the firm's book value of assets. Source: Compustat
Own	For firm *i* at the end of year *t*, *Own* is the percentage of equity (of the total share outstanding) held by institutional investors. Source: S&P Capital IQ
KZ_Index	The proxy for financial constraint. It reflects the degree to which a firm is financially constrained. Kaplan and Zingales (1997).
TQ	For firm *i,* at the end of the year *t,* TQ is the Market value of equity plus total asset net of book value of equity scaled by total book value of asset at the end of the year *I* Compustat
P_Risk_Tax	It is a firm-level politically induced tax risk measure for firm *i* in year *t. Source: (Hassan et al., 2019) (https://policyuncertainty.com/firm_pr.html).*
P_Risk_Trade	It is a firm-level politically induced trade risk *measure* for firm *i* in year *t. Source: (Hassan et al., 2019) (https://policyuncertainty.com/firm_pr.html).*

P_Risk_Economics	It is a firm-level politically induced economic risk *measure* for firm *i* in year *t*. *Source: (Hassan et al., 2019) (https://policyuncertainty.com/firm_pr.html).*
Treat	*Treat* is a dummy variable that takes the value of one if the firm is headquartered and listed in the U.S. and zero if headquartered and listed in the developed European country. Source: Author constructed
Post	*Post* is a dummy variable that takes the value of one if the year is post-2016 election and zero otherwise. Source: Author constructed
GdpGrt	For country j at the end of year t, the real Gross Domestic Product growth rate (*GdpGrt*), which measures the percentage annual growth rate of each country's Gross Domestic Product represented in the sample—source: The WBG: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG
RuleLaw	For country *j* at the end of year *t*, the Rule of Law indicator (*RuleLaw*) reflects a country's institutional quality and ranges between zero and five. This indicator captures the extent to which economic agents have trust in and adhere to the norms and regulations of the society with a specific focus on the effectiveness of contract enforcement, protection of property rights, law enforcement agencies, judicial systems, and the probability of criminal activities and violence. It is ranked from -2.5 to 2.5. A higher value indicates better institutional quality, while a lower value indicates otherwise—source: World Bank Governance Indicator. https://www.worldbank.org/en/publication/worldwide-governance-indicators
CRSI	For country *c* at the end of year *t*, the Climate Regulatory Stringency Index (CRSI) is the time-varying country-level climate policy stringency score. It evaluates a country's climate policy performance and indicates country-level climate mitigation regulatory stringency and efforts. It is scaled from zero (0) to five (5). Zero (0) represents the lowest level of climate regulatory stringency, and five (5) represents the highest. Source:GermanWatch: https://www.germanwatch.org/en
CarbonDummy	Carbon Intensive dummy (*CarbonDummy*) is an indicator variable that takes a value of one if the firm *i* is in the high energy-intensive sector as classified by Carbon disclosure project (CDP) or zero otherwise. Source: CDP
FinCon	The financial constraint dummy variable (*FinCon*) has a value of one if the firm-year observation is above the median of the sample K.Z. Index and zero otherwise.Author

Table A2: List carbon-intensive industries based on the Carbon Disclosure Project (CDP) GIC industry classification.

S/N	GIC Industries	Industries name
1	101020	Oil, Gas & Consumable Fuels
2	551010	Electric Utilities
3	551020	Gas Utilities
4	551050	Independent Power producers
5	551030	Multi-Utilities
6	151010	Chemicals
7	151020:	Construction Materials
8	151040	Metals & Mining
9	151050:	Paper and Forest Products

Table A3: Lists the distribution of countries in the sample, consisting of 16 European countries as the control group and the U.S. as our treated group from 2013 to 2020 in our sample

	Country		Obs	Freq
1	Austria		104	0.46
2	Belgium		131	0.57
3	Switzerland		448	1.96
4	Germany		688	3.02
5	Denmark		245	1.07
6	Spain		212	0.93
7	Finland		220	0.96
8	France		617	2.71
9	United Kingdom		1600	7.02
10	Ireland		282	1.24
11	Italy		228	1.00
12	Luxembourg		153	0.67
13	Netherland		329	1.44
14	Norway		271	1.19
15	Portugal		41	0.18
16	Sweden		562	2.46
17	United States		16672	73.11
		Total	22,803	100.00

Table A4. Distribution of sample based on Fama French 12 Industry classification

1	Consumer non-durables	1,356	5.95
2	Consumer durables	721	3.16
3	Manufacturing	3,039	13.33
4	Energy	1,338	5.87
5	Chemicals	869	3.81
6	Business Equipment	4,646	20.38
7	Telecommunications	802	3.52
9	Shops	2,680	11.76
10	Healthcare	3,550	15.57
12	Others	3,802	16.65
	Total	22,804	100.00

Table 1: Descriptive Statistics.

This table shows the descriptive statistics of our sample dataset. We report the corresponding number of observations (*Obs*) and the *Mean*, the Standard Deviation (*S.D.*), the Minimum (*Min*), and the Maximum value (*Max*) values. The sample period is from fiscal years 2013 to 2020. We define all these variables in the Table A1 of the Appendix. The variable *FL-MPCRE* is scaled to 10^4 for ease of interpretation. All the firm- and country-level continuous variables are winsorized at the 1st and 99th percentiles.

Variables	Obs	Mean	SD	Min	Max
Dependent					
FL-MPCRE	22,803	0.401	2.084	0.000	91.292
AdjFL-MPCRE	22,803	0.975	5.260	0.000	178.992
Covariates					
Size	22,803	7.312	1.941	2.360	11.81
Lev	22,803	0.251	0.190	0.000	0.937
RoA	22,803	0.060	0.192	-1.106	0.385
Tang	22,803	0.238	0.230	0.002	0.905
Other Variables					
KZ Index	20,961	-6.695	23.052	-173.43	3.196
MB	22,734	4.998	8.052	0.189	57.983
OWN	22,803	0.646	0.298	0.037	1.000
TQ	22,734	2.329	1.994	0.604	12.500
P_Risk_Trade (10^4)	22,779	0.261	0.398	0.000	2.600
P_Risk_Tax (10^4)	22,779	0.293	0.349	0.000	2.088
P_Risk_Economic (10^4)	22,779	0.307	0.343	0.000	2.035
Country-level					
GdpGrt	22,803	1.414	2.274	-10.36	4.978
RuleLaw	22,803	1.547	0.171	0.862	2.008
CSRI	22,803	2.385	1.049	1.000	4.250

Table 2: Propensity Score Matching [PSM]
Panel A reports the t-test of mean differences in covariates between treated and control firms over the SCPL period (i.e., from 2013-2016), and Panel B shows the result of the probit regression model for propensity score-matched treated and control firms of the following specification:

$$Treat_{it} = \alpha_i + \beta.\, \boldsymbol{X}_{it} + \delta_j + \varepsilon_{it}$$

i and *t* are indexed as firm and time (years). $Treat_{it}$ is a dummy variable that takes a value of one if the firm is in the treatment group or 0 otherwise. X_{it} is a vector of control variables consisting of *Size, Lev, RoA,* and *Tang,* as defined in Table A1 of the Appendix. δ_j is industry fixed-effects, and ε_{it} represents the error term. All covariates are winsorized at 1% and 99%, respectively. The symbols *, **, and *** indicate significance levels at 10%, 5%, and 1 %, respectively. In Panel B, the model predicting the likelihood of being a treated firm for the entire (unmatched) sample of firms over the pre-shock period (2013-2016) is presented in Model 1. In contrast, Model 2 presents the results of the PSM-matched sample.

Panel A: Mean Differences in covariates between treated and control groups (2013-2016)

Variables	Total	Treated	Control	Diff (T-C)	t-test	p-value
Size	7.294	6.938	8.631	1.693***	39.156	0.000
Lev	0.233	0.231	0.238	0.007	1.610	0.107
RoA	0.073	0.062	0.116	0.054***	12.743	0.000
Tang	0.239	0.239	0.240	0.000	0.039	0.969
Obs.	10,557	8,335	2,222			

Panel B: Pre and Post Propensity score diagnostic regression

The dependent variable is *Dummy* = one for the treated and zero for the control group.

	Pre-PSM	Post-PSM
	Model 1	**Model 2**
Size	-0.3361***	-0.0055
	(-34.90)	(-0.26)
Lev	0.9158***	-0.2508
	(10.00)	(-1.21)
RoA	-0.2361	0.1035
	(-1.78)	(0.45)
Tang	0.2951***	0.217
	(4.35)	(-0.14)
Constant	3.1388***	0.0969
	(45.32)	(0.62)
Pseudo R^2	0.1498	0.0014
Obs.	10,557	9,918

Table 3: Parallel Trend Test

The table shows the yearly difference in the mean of the *FL-MPCRE* variable between the treated and the control, including 95% confidence firms between 2013 and 2020 for the parallel trend test shown in Figure 3.

Year	Coefficient	t-stat	P value
$Treat^{*}post_{2013}$	0.054	0.90	0.37
$Treat^{*}post_{2014}$	0.010	0.16	0.88
$Treat^{*}post_{-2015}$	0.048	0.89	0.37
$Treat^{*}post_{2017}$	-0.010	-0.17	0.863
$Treat^{*}post_{2018}$	-0.173***	-2.67	0.008
$Treat^{*}post_{2019}$	-0.393***	-4.82	0.000
$Treat^{*}post_{2020}$	-0.704 ***	-6.57	0.000

Table 4: CPL and FL-MPCRE: Propensity Scored-Matched DiD
This table presents the results of the PSM-DiD regressions following the general specification below.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i{*}Post_t] + \Upsilon.\ \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i and *t* are indexed as firm and time (years). The dependent variable is $FL\text{-}MPCRE_{it}$, scaled to 10^4 for ease of interpretation. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one for the post-shock (2017-2020) period and zero for the pre-shock period (2013-2016). $\boldsymbol{X}_{it}$ is a vector of firm-level covariates *Size, Lev, RoA,* and *Tang*$\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang)* along with time-varying country-level control variables *GdpGrt* and *RuleLaw*. All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate DiD regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	**Col. 1**	**Col. 2**	**Col. 3**
Treat$_i$ *Post$_t$	**-0.3458*** **	**-0.3387*** **	**-0.3084*** **
	(0.0482)	**(0.0481)**	**(0.0479)**
Size		-0.1835**	-0.1969**
		(0.0906)	(0.0906)
Lev		-0.0321	-0.0303
		(0.0263)	(0.0263)
RoA		-0.0917	-0.0906
		(0.1234)	(0.1236)
Tang		0.1075	0.1058
		(0.1912)	(0.1913)
GdpGrt			-0.0487***
			(0.0175)
RuleLaw			1.0996***
			(0.2692)
Obs.	19,436	19,436	19,436
Adj. R^2	0.3839	0.3842	0. 3869
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 5: Robustness Check: Placebo Test

This table reports the results of falsification tests using the PSM- DiD of the following general specification.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i{*}Post_t] + \Upsilon.\ \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i and *t* are indexed as firm and time (years). The dependent variable, FL-MPCRE$_{it}$, which is the regulatory exposure of firm *i* in year *t* is scaled by 10^4 for ease of interpretation. All the other variables reported in this table are defined in Table A1 of the Appendix. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one for the post-shock (2016-2017) period and zero for the pre-shock period (2013-2015). $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang)* along with time-varying country-level control variables *GdpGrt* and *RuleLaw*. All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate DiD regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	**Col. 1**	**Col. 2**	**Col. 3**
Treat$_i$ *Post$_t$	**-0.0579**	**-0.0631**	**-0.0497**
	(0.0423)	**(0.0422)**	**(0.0604)**
Size		-0.0679	-0.0624
		(0.1074)	(0.1073)
Lev		0.0673**	0.0686**
		(0.0323)	(0.0323)
RoA		0.1273	0.1250
		(0.1098)	(0.1098)
Tang		0.3046	0.3040
		(0.2397)	(0.2398)
GdpGrt			0.0351*
			(0.0205)
RuleLaw			0.1392
			(0.3176)
Obs.	12,730	12,730	12,730
Adj. R^2	0.4394	0.4398	0.4399
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 6: Robustness Check: Entropy-Balanced DiD

This table reports the results of the multivariate entropy-balanced DiD regressions examining the effect of CSPL on *FL-MPCRE* following the specifications below.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta. [Treati*Post_t] + \Upsilon. \mathbf{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i and *t* are indexed as firm and time (years). The dependent variable, $FL\text{-}MPCRE_{it,}$ which is the regulatory exposure of firm *i* in year *t* is scaled by 10^4 for ease of interpretation. All the other variables reported in this table are defined in Table A1 of the Appendix. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one for the post-shock (2017-2020) period and zero for the pre-shock period (2013-2016). $\mathbf{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang)* along with time-varying country-level control variables *GdpGrt* and *RuleLaw*. All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1-3) shows the mean-based entropy-balanced DiD regression. Columns (4-6) report mean and variance-based entropy-balanced DiD regression. Columns (7-9) report mean, variance, and skewness-based entropy-balanced DiD regression.

Moments		**Mean**			**Mean and variance**			**Mean, variance, and skewness**	
Variables	**Col. 1**	**Col. 2**	**Col. 3**	**Col.4**	**Col.5**	**Col.6**	**Col.7**	**Col.8**	**Col.9**
$Treat_i$ *$Post_t$	**-0.2032*** **	**-0.1993*** **	**-0.1921*** **	**-0.1651** **	**-0.1683** **	**-0.1345** **	**-0.1629** **	**-0.1668** **	**-0.1325** **
	(0.0440)	**(0.0438)**	**(0.0441)**	**(0.0689)**	**(0.0691)**	**(0.0630)**	**(0.0696)**	**(0.0699)**	**(0.0632)**
Firm-Level Covariates	NO	YES	YES	NO	YES	YES	NO	YES	YES
Country-level Controls	NO	NO	YES	NO	NO	YES	NO	NO	YES
Obs.	22,233	22,233	22,233	22,233	22,233	22,233	22,233	22,233	22,233
Adj. R^2	0.3863	0.3868	0.3876	0.4428	0.4441	0.4449	0.4574	0.4586	0.4593
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: Robustness Check: Altered Measure of FL-MPCRE

This table presents the results of the PSM-DiD regressions following the general specification below.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i{*}Post_t] + \Upsilon.\ \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

where *i* and *t* are indexed as firm and time (years), the dependent variable is the industry-adjusted $FL\text{-}MPCRE_{it,}$ which is the regulatory exposure of firm i in year *t* is $FL\text{-}MPCRE_{it}$ scaled by 10^4 for ease of interpretation and thereafter adjusted by the average of all the $FL\text{-}MPCRE_{it}$ of all firms in the same two-digit SIC industry classification. All the other variables reported in this table are defined in Table A1 of the Appendix. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one for the post-shock (2017-2020) period and zero for the pre-shock period (2013-2016). $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang)* along with time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are defined in Table A1 of the Appendix. δi and λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate DiD regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	**Col. 1**	**Col. 2**	**Col. 3**
$Treat_i$ *$Post_t$	**-0.6406*****	**-0.6614*****	**-0.6114*****
	(0.1581)	**(0.1590)**	**(0.1599)**
Size		-0.0659	-0.0856
		(0.4310)	(0.4315)
Lev		0.1852	0.1874
		(0.1174)	(0.1174)
RoA		0.3620	0.3662
		(0.3214)	(0.3213)
Tang		0.6026	0.6038
		(0.6649)	(0.6654)
GdpGrt			-0.0791**
			(0.0315)
RuleLaw			1.2313
			(0.8078)
Obs.	19,436	19,436	19,436
Adj. R^2	0.4087	0.4088	0.4090
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 8: Robustness Check: Tax Trade and Economic-related Political Risks
This table reports the regression results using the PSM- DiD of the following general specification.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta. [Treat_i{*}Post_t] + \Upsilon. \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i and *t* are indexed as firm and time (years). The dependent variable, $FL\text{-}MPCRE_{it}$, the regulatory exposure of firm *i* in year *t,* is scaled by 10^4 for ease of interpretation. All the other variables reported in this table are defined in Table A1 of the Appendix. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one for the post-shock (2016-2020) period and zero for the pre-shock period (2013-2016). $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang).* $\boldsymbol{X}_{it}$ also includes *P_Risk_Tax, P_Risk_Trade,* and *P_Risk_Economic* along with time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate DiD regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	**Col.1**	**Col.2**	**Col.3**	**Col.4**
Treat$_i$ *Post$_t$	**-0.3083*** **	**-0.3087*** **	**-0.3087*** **	**-0.3081*** **
	(0.0480)	**(0.0480)**	**(0.0480)**	**(0.0480)**
Size	-0.1978**	-0.1972**	-0.1975**	-0.1993**
	(0.0907)	(0.0907)	(0.0907)	(0.0907)
Lev	-0.0306	-0.0305	-0.0305	-0.0304
	(0.0263)	(0.0263)	(0.0263)	(0.0263)
RoA	-0.0882	-0.0914	-0.0885	-0.0894
	(0.1237)	(0.1236)	(0.1235)	(0.1235)
Tang	0.0993	0.1043	0.1023	0.0995
	(0.1917)	(0.1915)	(0.1915)	(0.1919)
GdpGrt	-0.0488***	-0.0489***	-0.0490***	-0.0489***
	(0.0175)	(0.0175)	(0.0175)	(0.0175)
RuleLaw	1.0984***	1.0937***	1.0986***	1.0969***
	(0.2694)	(0.2695)	(0.2695)	(0.2695)
P_Risk_Tax	0.0430			0.0538
	(0.0265)			(0.0392)
P_Risk_Trade		-0.0051		-0.0321
		(0.0238)		(0.0322)
P_Risk_Economic			0.0297	0.0096
			(0.0294)	(0.0494)
Obs.	19,424	19,424	19,424	19,424
Adj. R^2	0.3869	0.3869	0.3867	0.3868
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 9: Robustness Check- Energy Intensity
This table reports the regression results using PSM-DiD for the following general specifications.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i\ {*}Post_t\ {*}\ CarbonDum_{it}] + \Upsilon.\ \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i, t, and *c* are indexed as a firm, time (years), and country. The dependent variable is $FL\text{-}MPCRE_{it}$, which, for ease of interpretation, is scaled by 10^4. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one in the post-shock period (2017-2020) and zero for the pre-shock period (2013-2016). $CarbonDum_{it}$ *is* a proxy for a firm's energy intensity level. $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang)* along with time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate triple interaction regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	Col. 1	Col. 2	Col. 3
$\boldsymbol{Treat_i\ {*}Post_t\ {*}CarbonDum_{it}}$	**-0.3977****	**-0.4032****	**-0.3994****
	(0.1810)	**(0.1807)**	**(0.1803)**
Size		-0.1479*	-0.1619*
		(0.0895)	(0.0895)
Lev		-0.0099	-0.0080
		(0.0256)	(0.0256)
RoA		-0.1489	-0.1475
		(0.1222)	(0.1225)
Tang		0.1198	0.1199
		(0.1853)	(0.1853)
GdpGrt			-0.0495***
			(0.0172)
RuleLaw			1.0517***
			(0.2636)
Obs.	19,436	19,436	19,436
Adj. R^2	0.3904	0.3905	0.3931
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 10: Robustness Check- Role of Financial Constraints
This table reports the regression results using PSM-DiD for the following general specifications.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i * Post_t * FinCon_{it,}\ ] + \Upsilon.\ \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i, t, and *c* are indexed as a firm, time (years), and country. The dependent variable is $FL\text{-}MPCRE_{it}$, which, for ease of interpretation, is scaled by 10^4. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one in the post-shock period (2017-2020) and zero for the pre-shock period (2013-2016). $FinCon_{it}$ *is a* proxy for the firm's financial constraint level. $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang)* along with time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate triple interaction regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	**Col.1**	**Col. 2**	**Col. 3**
Treat$_i$ *Post$_t$ *FinCon	**-0.3321*** **	**-0.3332*** **	**-0.3162*** **
	(0.0914)	**(0.0913)**	**(0.0916)**
Size		-0.1834**	-0.1960**
		(0.0907)	(0.0908)
Lev		-0.0198	-0.0176
		(0.0260)	(0.0260)
RoA		-0.1015	-0.0995
		(0.1240)	(0.1244)
Tang		0.1092	0.1099
		(0.1904)	(0.1907)
GdpGrt			-0.0452***
			(0.0173)
RuleLaw			1.1121***
			(0.2722)
Obs.	19,436	19,436	19,436
Adj. R^2	0.3862	0.3864	0.3889
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 11: Mechanism Tests: Climate Deregulatory Channel

This table reports the results of the deregulatory and analyst coverage channel using PSM-DiD for the following general specifications.

$$FL\text{-}MPCRE_{it} = \alpha_i + \beta.\ [Treat_i * Post_t * CCPI\_dummy_{ct}] + \Upsilon.\ \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i, t, and *c* are indexed as a firm, time (years), and country. The dependent variable is $FL\text{-}MPCRE_{it}$, which, for ease of interpretation, is scaled by 10^4. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one in the post-shock period (2017-2020) and zero for the pre-shock period (2013-2016). $CCPI\_dummy_{ct}$. takes a value of 1 if the country's level of climate regulatory stringency is below the median (capturing deregulation) and zero otherwise. The CCPI index is the yearly proxy of the country-level(c) climate regulatory stringency index, or with variable $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang)* along with time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate triple interaction regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	Col. 1	Col. 2	Col. 3
$Treat_i$ *$Post_t$ *CCPI_dummy	**-0.5056*** **	**-0.4970*** **	**-0.4077*** **
	(0.1205)	**(0.1208)**	**(0.1284)**
Size		-0.1858**	-0.1921**
		(0.0904)	(0.0905)
Lev		-0.0243	-0.0243
		(0.0264)	(0.0264)
RoA		-0.0961	-0.0960
		(0.1234)	(0.1237)
Tang		0.1165	0.1164
		(0.1906)	(0.1911)
GdpGrt			-0.0398**
			(0.0181)
RuleLaw			0.7115**
			(0.3325)
Obs.	19,436	19,436	19,436
Adj. R^2	0.3863	0.3865	0.3874
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 12: Implication Test: Institutional Ownership

This table reports the regression results using the PSM- DiD of the following general specification.

$$OWN_{it} = \alpha_i + \beta. [Treat_i{*}Post_t] + \Upsilon. \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i and *t* are indexed as firm and time (years). The dependent variable OWN_{it} is the proportion of institutional investors holding firm I in year *t*. All the other variables reported in this table are defined in Table A1 of the Appendix. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one for the post-shock (2016-2020) period and zero for the pre-shock period (2013-2016). $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang).* $\boldsymbol{X}_{it}$ also includes *P_Risk_Tax, P_Risk_Trade,* and *P_Risk_Economic* along with time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are defined in Table A1 of the Appendix. δi *and* λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate DiD regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	**Col.1**	**Col.2**	**Col.3**	**Col.4**
$Treat_i$ *$Post_t$	**0.0248*** **	**0.0180*** **	**0.0176*** **	**0.0171*** **
	(0.0052)	**(0.0052)**	**(0.0052)**	**(0.0051)**
Size		-0.0491***	-0.0479***	-0.0479***
		(0.0164)	(0.0164)	(0.0164)
Lev		0.0781***	0.0789***	0.0790***
		(0.0058)	(0.0057)	(0.0057)
RoA		0.0696***	0.0671***	0.0668***
		(0.0156)	(0.0154)	(0.0154)
Tang		0.0442	0.0451*	0.0447
		(0.0272)	(0.0273)	(0.0273)
P_Risk_Tax			0.0033	0.0033
			(0.0035)	(0.0035)
P_Risk_Trade			-0.0019	-0.0019
			(0.0025)	(0.0025)
P_Risk_Economic			-0.0040	-0.0040
			(0.0044)	(0.0044)
GdpGrt				0.0007
				(0.0010)
RuleLaw				0.0375*
				(0.0215)
Obs.	19,436	19,436	19,436	19436
Adj. R^2	0.8749	0.8832	0.8838	0.8838
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 13: Implication Test: Market Valuation
This table reports the regression results using the PSM- DiD of the following specification.

$$VALUE_{it} = \alpha_i + \beta.\ [Treat_i{*}Post_t] + \Upsilon.\ \mathbf{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i and *t* are indexed as firm and time (years). The dependent variable $VALUE_{it}$ is the firm market valuation of firm *i* in year *t* proxied by *TobinsQ*. All the other variables reported in this table are defined in Table A1 of the Appendix. $Treat_i$ is equal to one if the firm is headquartered and listed in the United States and zero if headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value one for the post-shock (2017-2020) period and zero for the pre-shock period (2013-2016). $\mathbf{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, RoA,* and *Tang).* $\mathbf{X}_{it}$ also includes *P_Risk_Tax, P_Risk_Trade,* and *P_Risk_Economic* along with time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are defined in Table A1 of the Appendix. δi and λ_t represent the firm and year-fixed effects, respectively, and ε_i represents the error term. We winsorize all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) shows the univariate DiD regression, including the firm and year-fixed effects. Column (2) reports the outputs with further inclusion of firm-level covariates, and column (3) includes the country-level controls.

Variables	**Col.1**	**Col.2**	**Col.3**	**Col.4**
Treat_i *Post_t	**0.1927*** **	**0.2534*** **	**0.2556*** **	**0.2324*** **
	(0.0480)	**(0.0472)**	**(0.0472)**	**(0.0454)**
Size		-0.5967***	-0.5982***	-0.5944***
		(0.1581)	(0.1583)	(0.1579)
Lev		-0.3827***	-0.3845***	-0.3839***
		(0.0491)	(0.0492)	(0.0490)
RoA		1.4636***	1.4625***	1.4554***
		(0.1975)	(0.1977)	(0.1975)
Tang		-0.4571**	-0.4504**	-0.4586**
		(0.2028)	(0.2029)	(0.2026)
P_Risk_Tax			-0.0010	0.0008
			(0.0345)	(0.0345)
P_Risk_Trade			0.0444**	0.0455**
			(0.0222)	(0.0222)
P_Risk_Economic			-0.0955**	-0.0972**
			(0.0390)	(0.0392)
GdpGrt				0.0339***
				(0.0090)
RuleLaw				0.6617***
				(0.2139)
Obs.	19,385	19,385	19,374	19,374
Adj. R^2	0.7479	0.7583	0.7584	0.7583
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

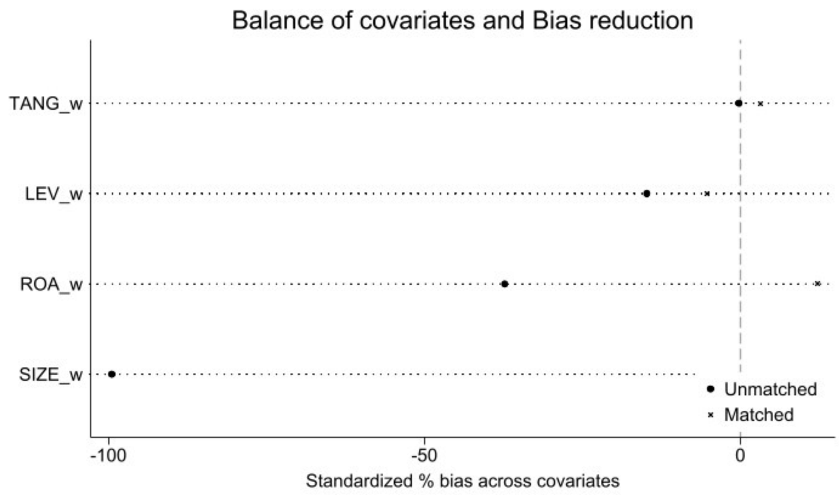

Figure 1: Bias Reduction

The figure shows the standardized percentage bias (SPB) measures of the variables *Size*, *Lev*, *RoA*, and *Tang* used in propensity score matching (PSM). We define all these covariates in Table A1 of the appendix. The small bold circles and the crossed figures reflect the SPB measures of the covariates before and after PSM.

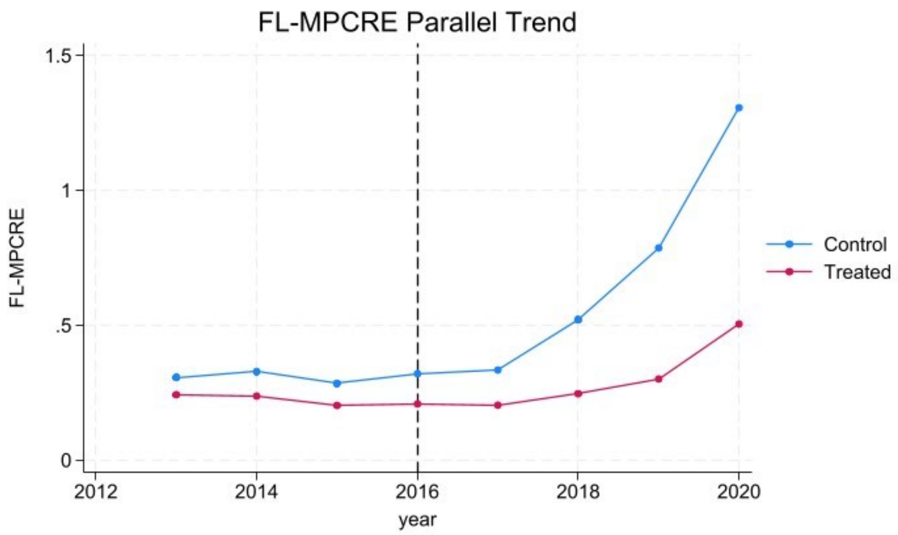

Figure 2: Parallel Trend of Yearly Average FL-MPCRE

This figure shows a time-series plot of treated and control firms' yearly mean (average) statistics of *FL-MPCRE*. For the definition of the variable *FL-MPCRE*, please see Table A1 of the appendix. Our sample's treated group (*Treated*) is headquartered in the United States, and the control group (Control) is headquartered in 16 European countries, as listed in Table A3 of the Appendix.

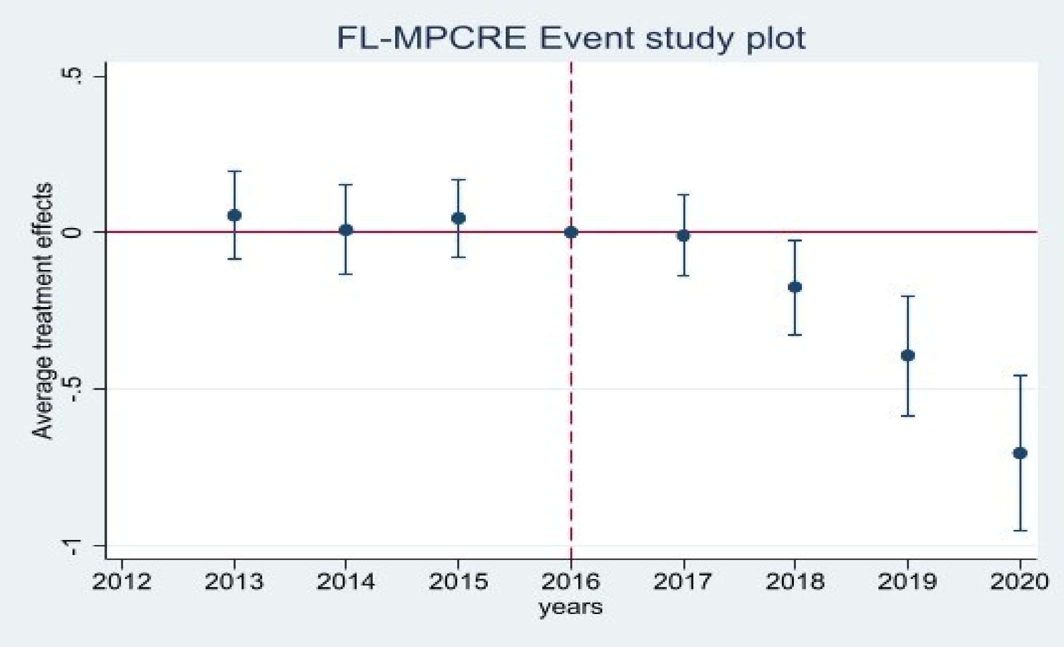

Figure 3: Parallel Trend Test

This figure shows the trend in the yearly difference between the treated and control groups' average FL-MPCRE.

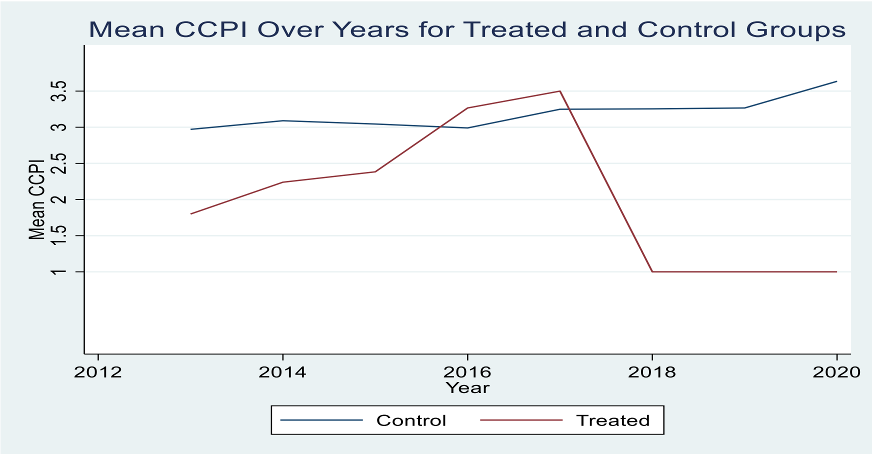

Figure 4:Country-level CRSI Plots

This figure shows a graph of the yearly mean value of the country-level Climate Regulatory Stringency Index (CRSI) score over the sample period for the treated (the United States) and control groups (16 European Countries). The control group of 16 European countries is listed in Table A3 of the Appendix.