Political Economy of Green Transition: Financial Markets and Corporate Green Revenue

PhD Thesis

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Declaration of Authenticity and Author's Rights

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination, leading to the award of a degree.

Signed:

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Dedicated to all seekers of Knowledge

Abstract

The lack of commitment by political leadership to a long-term policy pathway for green transition has been a long-standing problem in addressing climate change crises (Besley & Persson, 2023). One important but overlooked factor in the green transition is the influence of political leaders' climate science beliefs and ideological disposition and the consequent effect on the perception and behaviour of capital market participants. This thesis comprises three empirical essays that explore the political economy of the green transition through the lenses of climate political leadership beliefs, policy decisions, and their consequential impacts on financial markets and corporate green performance.

The first essay (Chapter Two) investigates the impact of Climate Political Leadership (Hereafter, CPL) on firm-level market perception of climate regulatory exposure (FL-MPCRE). Using the unexpected outcome of the 2016 U.S. Presidential election results in a quasi-natural experiment, I examine whether the surprising transition from supportive climate political leadership (SCPL) to climate sceptic political leadership (CSPL) creates exogenous variation in market participants' perceptions of firm-level climate regulatory exposure. Recent surveys of investors, firms, academics, and regulators indicate that regulatory risk is the most salient and immediate type of climate risk(Krueger, Sautner, & Starks, 2020; Stroebel & Wurgler, 2021a). Hence, I focus on the impact of climate political leadership on firm-level regulatory exposure. Leveraging the Bayesian investor belief updating model of Pastor & Veronesi (2012, 2013) and Social Identity Theory, I demonstrate that the emergence of CSPL significantly lowers FL-MPCRE, supporting the view that climate political

leadership is an upstream driver of cross-sectional and temporal variation in FL-MPCRE.

I identify the beliefs of political leaders through climate-deregulatory actions and public anti-climate rhetoric as the primary driver of market participants' perception of firm-level regulatory exposure, factoring in the associated perceived costs and benefits of the regulatory regime within a utility maximisation framework. The proposed mechanism updates market participants' prior beliefs, forming new expectations and forward-looking perceptions, which is the primary driver of investment behaviour.

Furthermore, institutional investor ownership concentration, financial constraints, and industry carbon intensity moderate this inverse relationship. Extending this analysis to capital market implications, I observe that institutional investors increased their holdings in firms operating under deregulatory regimes. These firms receive higher market valuations, highlighting the misallocation of capital and friction in the green transition process as consequential implications of an unexpected shock to supportive CPL.

The second essay (Chapter 3) builds on the findings of the first essay (Climate Political Leadership and Financial Market Perception) by exploring the relationship between climate-sceptic political leadership and corporate green innovation, using patent filings as a proxy for green innovation. Using the Race-to-the-bottom, Dynamic Complementarity, and signalling theories, I show that the emergence of climate sceptic political leadership dampens corporate green innovation. This adverse effect is more pronounced in financially constrained firms and firms in carbon-intensive industries.

The third essay (chapter four) examines the relationship between the European Union's green taxonomy policies under supportive CPL and corporate green revenue. I employ a novel global FTSE Green Revenue dataset and a difference-in-differences approach with entropy balance scores to adjust covariate weights. I demonstrate a positive causal relationship between Green Taxonomy policy and corporate green revenue. Further analysis reveals that environmental innovation is a key economic mechanism driving this relationship. Cross-sectional analysis strengthens these findings, showing that the effects are more pronounced in firms with higher stock liquidity, high analyst coverage, and those with lower financial constraints.

This thesis's findings collectively emphasise CPL's pivotal role in the political economy of the green transition. First, the finding suggests that climate-sceptic political leadership undermines the creation of sufficient climate risk signals necessary to drive corporate behavioural changes toward effective climate mitigation and adaptation strategies. Specifically, the beliefs and consequential regulatory actions of climate sceptic political leaders significantly sway the global decarbonisation effort.

Second, the results demonstrate the significant role of climate political leadership in fostering the regulatory environment necessary to catalyse necessary structural changes at production and consumption through the generation of appropriate incentives to stimulate corporate engagement in green innovation and the generation of green revenue through engagement in sustainable business practices. Such regulatory incentives modify market participants' behaviour and improve their climate-responsible activities. The results carry significant implications for green transition policies, highlighting the significance of political leaders' robust long-term climate regulatory commitment to incentivise corporate shifts towards sustainable business practices.

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List of Abbreviations

Abbreviations	Full Term
CDP	Carbon Disclosure Project
CGI	Corporate Green Innovation
CGR	Corporate Green Revenue
CPL	Climate Political Leadership
CSPL	Climate Sceptic Political Leadership
CSRI	Climate Regulatory Stringency Index
DiD	Difference-in-Differences
DiDiD	Tripple Difference-in-Differences
EU	European Union
EPS	Environmental Policy Stringency
EUC	European Union Commission
FL-MPCRE	Firm-Level Market Perception of Climate Regulatory Exposure
FTSE	Financial Times Stock Exchange
GIC	Global Industrial Classification
IPC	International Patent Classification
MB	Market to Book ratio
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
PATSAT	The World Patent Statistical Database
PSM	Propensity Score Matching
RND	Research and Development
RoA	Return on Asset
S&P	Standard and Paul
SCPL	Supportive Climate Political Leadership
SIC	Standard Industrial Classification of Economic Activities
TEG	Technical Expert Group
U.S	United States

Chapter 1 Introduction

" The scale and pace of structural, technological and social change must be large and rapid. That will require changes in behaviour, and institutions will require purposive and sustained political leadership and strong political pressure from society as a whole on decision-makers to deliver change[1] "

Sir Nicholas Sten

9th Nov. 2023

The essays in this thesis examine the political economy of the green transition through the lens of political leaders' beliefs in climate science, their political-ideological dispositions, and the resulting actions, including regulatory preferences and market incentives, which have a consequential impact on financial market perception, corporate green innovation, and corporate green revenue. I provide insight into the interaction between political leaders' ideological disposition, their climate beliefs, and financial market mechanisms in altering the behaviour of economic agents within a unique market setting. Given that the political processes and political actors' policy decisions influence green transition (Besley & Persson, 2023; Dolšak & Prakash, 2018; Hsu, 2013; Wurzel et al., 2021a), I delve into the long-standing yet unresolved economic problem of Political leadership's lack of long-term policy commitment to green transition which generates government failure (Besley & Persson, 2023) and the impact on economic agents perception and environmental behaviour. Specifically, I

[1] See:https://www.lse.ac.uk/granthaminstitute/publication/acceptance-speech-by-professor-lord-nicholas-stern-for-leadership-in-implementation-award-at-the-sustainability-awards/ . Assessed December 21 , 2024 11:50 am

provide novel insight into the influence of political leaders on financial market participants' behaviour.

The climate change problem is a long-term intergenerational, pan-sectoral and global problem(Goulder & Pizer, 2006; Maréchal, 2007; Stern, 2008; Stern, 2007), which demands long-term supportive policy commitment for complementary alignment of the financial market incentives and societal forces for the successful green transition (Besley & Persson, 2023; Ramiah et al., 2013). The absence of stable green policies undermines long-term incentives for corporate investment in climate responsibility, including green innovation (Besley & Persson, 2023; Brown et al., 2022; Jaffe & Stavins, 1995). As a result, it is difficult to maintain the dynamic complementarity required to address the climate crisis (Besley & Persson, 2023).

To study the political economy of the green transition in a financial market setting, I focus on the role of climate political leadership in driving the pace of the green transition through its influence on the perception of firm-level regulatory exposure among financial market participants and the modification of corporate green behaviour. I explore an empirical setting where an unexpected exogenous political event creates an adverse shock to supportive climate political leadership, allowing me to investigate a unique empirical setting in which political and market failures coexist. Specifically, I highlight how the lack of long-term policy commitment to a green transition influences economic agents' behaviour and subsequent implications for market efficiency and pricing of climate risk.

I draw insight from the social identity theory (Akerlof & Kranton, 2000; Tajfel et al., 1979) in distinguishing between supportive climate political leadership and climate sceptic political leadership. Specifically, using an exogenous shock to supportive climate political leadership, which leads to the emergence of a political leader that denies climate change science, I argue that the emergence of a climate sceptic political leader who engages in anti-climate science rhetoric and introduces lax climate regulation (evidence of political failure) influences market participants' evaluation of forward-looking firm level regulatory exposure. I demonstrate that when market participants perceive a lower future regulatory concern, they opportunistically increase their holdings in firms operating under lax climate regulatory regimes and reward them with higher market valuations. The observed market behaviour has implications for the pricing of climate risk, the social welfare cost of carbon, and the pace of the green transition.

Second, I investigate an important real economic outcome of the emergence of climate sceptic political leadership: corporate green innovation. Given that green innovation is crucial to addressing and mitigating the negative externalities of climate change (Kim et al., 2021a), I investigate whether exogenously induced adverse shocks to supportive climate political leadership impact corporate green innovation activities.

Third, I investigate the role of climate political leadership's regulatory framework in the European Union Green Taxonomy under the Sustainable Finance Action Plan in promoting corporate green revenue. I delve into the economic argument of dynamic complementarity theory (Besley & Persson, 2023), which posits that climate political leaders' regulatory actions affect the pace of the green transition through their catalytic function in inducing a structural shift in firms' production patterns and aligning with consumer shifting preferences, thereby accelerating a smoother green transition.

Section 1.1 outlines the motivation, research questions and thesis contribution for each of the three essays in this thesis: "*Climate Political Leadership and Financial Market Perception*", "*Race-to-the Bottom: ffect of Climate Political Leadership on Corporate Green Innovation*", *and "Green Taxonomy and Corporate Green Revenue "*.

Section 1.5 provides the outlines of this thesis.

1.1 Motivation and Research Questions

1.1.1 Climate Political Leadership and Financial Market Perception

First, I draw motivation for this essay from the literature investigating the role of Politics in the financial market, the Pastor and Veronesi market belief updating framework (Pastor & Veronesi, 2012; Pástor & Veronesi, 2013) and Socio-Psychology literature on political leadership beliefs(Swinkels, 2020; Zawadzki et al., 2020). These theoretical views drawn from rational expectation and behavioural views allow me to investigate the political economy of green transition through the lens of climate sceptic political leadership's regime influence on the financial market participants' behaviour.

Existing research in Finance, Accounting and Management has focused on the effect of CEO, individual investors, and institutional Investors' ideology on corporate outcomes and investment decisions(Bayat & Goergen, 2025; Bolton et al., 2020; Busenbark et al., 2023; Chen et al., 2023; Elnahas et al., 2024; Elnahas & Kim, 2017; Esplin et al., 2024; Gupta et al., 2019; Kiss et al., 2024). However, the impact of Political leaders' ideology on economic agents' behaviour is yet to be empirically analysed. Furthermore, political science literature emphasises the symbolic role of political leadership ideology in shaping the beliefs and behaviours of individuals (Zawadzki et al., 2020; Parker & Karlsson, 2014). Concerning climate science, political leaders' ideological disposition can shape market perceptions of future regulatory stringency, enforcement credibility, and long-term transition risk.

Political Leadership involves the strategic use of power and resources to design and implement policies that alter the incentive structures, costs, and benefits influencing firm behaviour (Parker & Karlsson, 2014; Parker et al., 2017). Political leadership remains a driving force influencing public opinion and, most importantly, firms' business environment (Liefferink & Wurzel, 2017; Zawadzki et al., 2020). Given that Political leaders possess the authority to shape climate regulation, influence institutional priorities, and allocate resources that directly affect the incentives and constraints facing firms (Gulen & Ion, 2016; Pastor & Veronesi, 2012; Pástor & Veronesi, 2013), their actions(inactions) may have far-reaching consequences on corporate outcomes, especially on the corporate transition to a net-zero economy.

Lord Nicholas Stern, whose influential report on climate change created awareness about the exigency of climate change, noted in his acceptance speech for the Leadership in Implementation award at The Sustainability Awards in 2023 the critical importance of political leadership in driving sustainable, carbon-free economy: "*Good politics and sound practice rest on a clear strategy, effective delivery mechanisms, and an understanding of the economics of fundamental change. Powerful communication and inspirational leadership will be critical.*"

The beliefs and expected actions of political leaders who hold the authority and resources to implement regulations that create economic incentives (costs and benefits) can influence the perception and behaviour of economic agents (Garland et al., 2018; Parker & Karlsson, 2010). Zawadzki et al. (2020) argue that, despite growing interest in the actions of political leaders, the literature has yet to demonstrate how changes in the political landscape shape climate beliefs and the psychological pathways through which these beliefs drive pro-environmental attitudes and behaviours.

Political leaders play a central role in shaping the institutional and policy environment within which economic agents operate(Gulen & Ion, 2016). Among the critical challenges confronting political leaders globally is climate change, with significant socioeconomic and geopolitical implications (Dolšak & Prakash, 2018; Stern, 2007). Effectively addressing climate change requires resolving complex collective action problems, making political leadership essential for meaningful progress (Wurzel et al., 2017; Young, 1991).

The literature on leadership and regulation emphasises that the policy orientations of political leaders directly shape corporate responses to regulatory environments (Ahlquist & Levi, 2011; Harrison & Sundstrom, 2010; Wurzel & Connelly, 2011). While the role of climate political leadership (CPL) in global and transnational dimensions has received attention, growing evidence underscores the importance of domestic leadership in influencing national climate policy formulation and enforcement (Christmann, 2004; Wurzel et al., 2021a). Since national climate regulation often targets corporate environmental behaviour (Henriques & Sadorsky, 1996), the strength and credibility of a country's CPL serve as a critical determinant of firms' incentives to invest in climate-related governance and innovation (CGI).

Empirical studies further support the notion that the ideological orientation of political leadership materially influences regulatory priorities and implementation (Blyth et al., 2007; Pastor & Veronesi, 2012). Fowlie (2014) highlights the role of executive leadership in steering U.S. climate policy. Political shifts that reduce support for environmental regulation, like abrupt leadership changes, can weaken enforcement mechanisms and delay or dilute key environmental policies. For instance, Bomberg (2021) documents how the deregulatory agenda pursued by the 45th U.S. administration undermined the goals of federal environmental agencies, thereby weakening corporate incentives to undertake CGI initiatives.

To motivate how climate political leadership influences firm-level perceptions of climate regulatory exposure, I draw on two complementary theoretical frameworks: the investor belief-updating model proposed by Pástor and Veronesi (2012, 2013) and Social Identity Theory (Tajfel & Turner, 1979).

First, Pástor and Veronesi's (2012, 2013) investor belief-updating model presents a rational expectation framework based on Bayesian updating of prior belief through the incorporation of new information. The framework captures how investors revise expectations and update beliefs in response to new information that contradicts their previously held beliefs. For climate change, the exogenous shift in political leadership signals the arrival of new information that may affect climate policies and market incentives(disincentive) for green transition. It involves investors updating their prior beliefs with signals from new information (Pastor & Veronesi, 2012; Pástor & Veronesi, 2013). It also suggests that market participants objectively form new expectations and update their prior beliefs conditioned on their probabilistic inference about the future impact of future climate policy outcomes, which could negatively impact firms' fundamentals through associated costs, which alters the prior expected payoff structure.

While the rational expectations framework typically emphasises the role of new information processing, interpretation and creation of incentive structures as drivers of market participants' expectation formation and belief update, the behavioural political economic perspective drawn from the Social identity theoretical view highlights the role of ideology and identity in shaping belief formation (Akerlof & Kranton, 2000; Barrios & Hochberg, 2021). The theory posits that individuals categorise others into social groups and update their beliefs and behaviours based on perceived group affiliation and group norms. It underscores the role of identity-based cues and group affiliations in shaping the perception and behaviour of economic agents.

According to Social Identity Theory, political leaders represent more than policy actors; they are identity symbols for broader ideological and policy coalitions(Huddy, 2001; Swinkels, 2020; Zawadzki et al., 2020). A new administration's climate stance could be viewed not only in terms of its immediate policy implications but also as a social identity cue signalling alignment with a broader belief system(Huddy, 2001). When a leader with climate-sceptic views assumes power, market participants may re-categorise the policy environment into a lower regulatory threat group, leading to adjusted perceptions of climate risk and expected regulatory stringency. This identity-based signal may influence not only investors' expectations but also corporate strategic behaviour. Firms may anticipate relaxed enforcement and diminished climate-related compliance costs, affecting their incentives to invest in green transition.

Consequently, exogenous change in Political leadership may serve as a signal to market participants about future policy direction and enforcement credibility. In sum, political leadership is a critical upstream determinant of market participants and corporate behaviour. The strength, direction, and credibility of CPL directly shape the regulatory environment, thereby influencing the strategic calculus of firms considering investment in climate governance and innovation.

Importantly, I focus on how political leaders' climate science beliefs impact the firm-level perception of climate regulatory exposure, thus gaining insight into the psychological pathways by which political leaders' ideology influences economic agents' beliefs, perceptions, and pro-environmental behaviour in a financial market setting.

I extend the debate on the role of political leaders in climate change mitigation, introducing the concept of "*Climate political leadership*" to the finance literature. I ask the following empirical questions: 1. What happens to the dynamics of Financial Market perception of Climate Regulatory Exposure when we witness an unexpected transition from a supportive climate political leadership to a climate sceptic Political Leadership? 2. How are the perceptions of the market participants influenced by the climate beliefs and ideological disposition of climate political leaders? 3. What are the financial market implications for firms' institutional investor ownership and market valuation?

1.1.1.1 Findings and Discussion

In the first essay (Chapter 2), I examine whether the emergence of climate-sceptic political leaders influences market perceptions of firm-level climate regulatory exposure. I develop and test the *climate-sceptic leadership hypothesis* within the PV Theoretical framework(Pastor & Veronesi, 2012; Pástor & Veronesi, 2013) by designing a quasi-natural experiment that exploits the 2016 United States (U.S.) presidential election as a source of exogenous shocks to CPL. I employ a time-varying measure that reflects firm-level climate regulatory exposure from Sautner et al. (2023a) over a period spanning 2013-2020, covering the supportive climate political leadership era (2013-2016) and the climate sceptic political leadership era (2017-2020).

The evidence suggests that climate political leadership is an important upstream driver of firm-level climate regulatory exposure. Specifically, these results indicate that climate sceptic political leadership's climate alters the perception of market participants, lowering the perception of future regulatory exposure of firms, leading to misallocation of capital, evidenced by capital market rewarding firms subject to lax climate regulation with higher market valuation relative to their contemporaries under stricter climate regulatory regime. I argue that the emergence of a climate sceptic leader generates significant friction in the green transition process.

These results hold, even after accounting for several firm-level and time-varying country-level factors that are known to influence climate regulatory exposure, including confounding factors from other regulatory decisions of climate political leadership, including Tax, Trade, and economic policies. In addition, the results are robust to several robustness checks, including altered measures of firm-level market perception of regulatory exposure, parallel trend tests, placebo tests, and the use of entropy balance scores at the three distributional moments (mean, variance, and skewness). The results further indicate that the negative association between climate-sceptic political leadership and firm-level market perception of climate regulatory exposure becomes stronger when firms are financially constrained, operate in high-carbon-intensive industries, and have fewer institutional investors holding their equities.

1.1.1.2 Contribution

This essay contributes to several areas of the literature. First, I contribute to the 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). My thesis is the first to use a market-based measure to identify the role of climate political leaders in explaining cross-sectional and temporal variations in market participants' perceptions of a firm's exposure to climate regulatory risk.

Second, this essay contributes to the burgeoning literature on the political economy of green transition by documenting the role of climate political leadership incentives, or the lack thereof, in shaping market participants' perceptions of firm-level regulatory exposure and the subsequent implications for capital market resource allocation. This thesis demonstrates that a climate sceptic political leadership regime leads to a lower perception of climate regulatory risk among economic agents, resulting in the misallocation of capital to firms operating in a lax regulatory environment and weakening the incentive for firms to pursue climate mitigation activities.

Third, this essay contributes to the literature on the evolution of climate change beliefs and the formation of market participants' expectations, which influence 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 characterisation of the beliefs of investors and corporate insiders(e.g. CEOs).

Ceccarelli and Ramelli (2024) demonstrate that investors' expected risk and return, which is a product of their belief, influence green investment behaviour. Building on the need to understand the psychological pathway through which political leaders influence economic agents' perception and subsequent pro-environmental behaviour(Zawadzki et al., 2020), I explore a financial market information exchange setting involving the firm and financial market participants to empirically characterise climate sceptic political leadership's climate beliefs, its impact on market participants' perception of climate regulatory exposure, and the capital market implications for sustainable finance.

Finally, this essay contributes to the debate on the role of supportive climate political leaders in creating effective complementary regulatory environments for green transition. Evidence suggests that institutional investors drive firms to act to curb greenhouse gas emissions (Azar et al., 2021; Benlemlih et al., 2023; Kim et al., 2019). However, within the empirical framework of this study, I demonstrate that when market participants' firm-level perceived climate regulatory risks diminish due to the actions of a climate-sceptic political leadership, institutional investors increase their equity stakes, and the market responds by boosting the valuation of such firms. Hence, I float the debate on whether market mechanisms alone can sustain the pace of green transition without effective and complementary supportive climate political leadership. The study offers a distinct perspective on examining the role of politics in finance within a unique setting where market and government failures coexist.

1.1.2 Race-to-the Bottom: Effect of Climate Political Leadership on Corporate Green Innovation

1.1.2.1 Motivation and research questions

In the second essay (chapter three), I build on my first essay's empirical setting and findings (Climate Political Leadership and Financial Market Perception) to examine the real effects of an adverse shock to climate political leadership on Green Innovation.

Political science literature suggests that Political leadership involves leveraging power and resources to implement policies that shape the incentives, costs, and benefits influencing the behaviour of economic agents (Parker & Karlsson, 2014; Parker et al., 2017). Studies note that climate change, with its socioeconomic and geopolitical consequences, represents one of the most pressing global policy challenges for political leaders (Dolšak & Prakash, 2018; Stern, 2007). Therefore, Political Leadership is critical in addressing complex collective action problems like climate change (Thapa & Hillier, 2022; Wurzel et al., 2017; Young, 1991).

Given that Political leaders have the power to create incentives(disincentives) that influence the trajectory of climate regulation(Garland et al., 2018; Parker & Karlsson, 2010). I argue that climate regulation does not occur in a vacuum but is one of the tools to shape policy preferences consistent with their ideological disposition on climate change science. The leadership literature indicates that the policy preferences of political leaders directly impact corporate behaviour (Ahlquist & Levi, 2011; Harrison & Sundstrom, 2010; Wurzel & Connelly, 2011). Therefore, political leadership may be the primary driver behind the presence, design, and stringency of climate-related regulations.

Economic theory suggests that climate deregulation can affect the dynamics of technology transitions by disincentivising investment in green innovation and altering the profitability and attractiveness of green technologies (Besley & Persson, 2023; Popp, 2010). Without supportive climate political leadership through pro-climate policies, which generate optimal market incentives for firms to invest in green innovative activities, they may find it less economically viable to invest in green technologies, which can slow down the transition process and hinder innovation.(Acemoglu et al., 2016; Jaffe et al., 2002; Popp et al., 2009).

Beyond political leadership’s regulatory initiatives, the literature argues that leaders' climate beliefs influence public perception and pro-environmental behaviour(Acuto, 2013; Hahnel & Brosch, 2016; Zawadzki et al., 2020). Hence, climate political leadership beliefs and actions may have downstream consequences for corporate environmental behaviour.

While CPL’s global and transnational aspects are well-documented, the research underscores its significance at the national level in shaping climate policies and enforcement.(Christmann, 2004; Wurzel et al., 2021b). Political leadership’s climate regulatory policies aim to influence corporate environmental behaviour (Christmann, 2004; Henriques & Sadorsky, 1996). Therefore, the intensity of the CPL's climate regulatory push may significantly impact corporate incentives to address climate change through CGI investments. Therefore, climate regulation is an incentive mechanism created by climate political leaders to effect changes in the behaviour of economic agents.

Empirical studies demonstrate the effects of political leadership ideology on national policy preferences (Blyth et al., 2007; Pastor & Veronesi, 2012). Gulen and Ion (2016) document the impact of political leadership decisions on the firm's operating environment, while Fowlie (2014) notes that the executive branch of the

U.S. government has a substantial impact on U.S. climate policy. Unexpected shocks to supportive CPL often translate into weakened climate-related policies, including emission curbs or regulations governing toxic waste disposal, disposal permits, and drilling and mining permits[2]. Bomberg (2021) suggests that the Trump(45) administration's deregulatory approach significantly undermined the objectives of federal environmental agencies, thereby altering corporate incentives for CGI.

The literature further suggests that market forces, including consumer and investor demand, pressure firms to act responsibly regarding climate issues (Dimson et al., 2015; Dyck et al., 2019; Ramelli, Wagner, Zeckhauser, Ziegler, et al., 2021). Nevertheless, stringent regulatory pressure is required to substantially influence CGI magnitude and direction (Popp, 2010; Rugman & Verbeke, 1998). Amber and Ehlers (2016) and Besley and Persson (2023) argue that a sufficiently high carbon tax (or stringent regulation that raises the cost for polluting firms) on environmentally harmful activities (a "brown tax") can drive a green transition, even if there are few or no environmentally conscious consumers. Without such a carbon tax, a successful transition requires a critical mass of green consumers, implying that effective climate policy reduces reliance on consumer preferences for a sustainable transition (Besley & Persson, 2023). Owing to market failures, the literature argues that such regulatory

[2] For example, according to Bomberg (2021), the Trump administration initiated the process of revoking or climate deregulatory policies aimed at reducing emissions, safeguarding wildlife, prohibiting hazardous pesticides, and mitigating the pollution of water, land, and air. In contravention of the prevailing scientific consensus regarding the factors contributing to climate change, the Trump Administration authorised the exploration of previously untapped territories for the extraction of oil and gas resources while also granting permissions for the construction of contentious oil pipelines coupled. Additionally, with a commitment to terminate the perceived antagonism towards coal, the Trump Administration endeavoured to dismantle the Clean Power Plan implemented by the Obama administration which was specifically formulated to establish regulations for controlling carbon emissions from power plants. (Bomberg, 2021)

intervention is necessary to generate sufficient incentives to encourage CGI (Johnstone et al., 2010; Popp, 2006, 2010; Popp et al., 2009).

When a climate political leader creates a deregulatory environment, firms are more likely to engage in environmentally degrading activities due to the absence of constraining climate policies. For example, Xu et al. (2022) document an increase in toxic waste emissions by publicly listed US firms under climate deregulation and weaker enforcement. The Trump(45) Administration's aggressive deregulatory policies exemplify the role of political leaders in climate mitigation (Aldy, 2017; Bomberg, 2021).

One of the channels through which climate political leaders influence corporate environmental behaviour is altering the stringency of climate regulation. Climate regulation can induce environmental innovation, which can be costly and lead to higher production costs for both ends of pipes and cleaner production technologies (Acemoglu et al., 2016; Frondel et al., 2008; Popp et al., 2009; Rennings & Rammer, 2011).

Despite CGI's high cost, it contributes significantly to overall firm performance and enhances knowledge spillovers and clean technology adoption(Bennedsen, 2015). For example, it contributes significantly to overall innovation (Aghion et al., 2013), pollution abatement (Carrión-Flores & Innes, 2010), higher efficiency (Abdullah et al., 2015), core competencies (Albort-Morant et al., 2016), and superior financial performance (Hao et al., 2022; Xie et al., 2019). Furthermore, it facilitates firms to meet the increasing demand for their products without endangering the environment(Albort-Morant et al., 2016; Takalo & Tooranloo, 2021). Albort-Morant et al. (2016) further argue that investment in green innovation provides economic incentives for generating environmentally sustainable products and boosts competitiveness.

CGI also significantly alleviates environmental burdens (e.g., greenhouse gas emissions) through pollution abatement and modernisation of the economy. Furthermore, CGI can alleviate the associated costs of environmental regulation and enhance corporate brand equity and consumer perceptions of greenness(Chen, 2010; Rennings,2011). It can enhance financial performance through increased sales and margins from new green product development, especially among environmentally conscious clients and new market entries (Cheng et al., 2014; Hao et al., 2022; Xie et al., 2019). The existing research indicates that green patenting enhances a firm's value and competitive position(Chen, 2008; Kim et al., 2021a; Porter & Van der Linde, 1995).In addition, CGI enhances green reputation, which benefits numerous firm stakeholders (Chen, 2007; Hart, 1995; Sharma & Vredenburg, 1998)

Henriques and Sadorsky (1996), Ilhan, Sautner, Vilkov, et al. (2021), and Brown et al. (2022) argue that regulatory actions are required to combat climate change and address its existential threat. Bennedsen (2015) examines US firms using the enactment of anti-takeover laws and shows that firms with poor corporate governance generate lower green patents. Kim et al. (2021b) document lower CGI activities among firms with high foreign sales in countries with weaker climate regulations by CPL.

Motivated by the urgent need for companies to transition to a sustainable economy and the role of climate-sceptic political leaders in the green transition process, I ask: Does the unexpected emergence of climate-sceptic political leadership, through its deregulatory stance and belief-driven signalling, lead to a measurable decline in CGI (as proxied by patent filings)?

I develop the climate irresponsibility hypothesis mainly based on the Race to the Bottom theory, Dynamic Complementarity theory (Besley & Persson, 2023), and relevant empirical literature. Wilson (1996) suggests that suboptimal regulatory standards waste resources and distort the economy's prudent and efficient allocation of resources. Therefore, I characterise climate sceptic political leadership beliefs through its deregulatory actions, resulting in a suboptimal approach and political and institutional failure to address climate change risks.

1.1.2.2 Findings and Discussion

My analysis shows that the emergence of climate sceptic political leaders negatively impacts green patenting. I provide an economic interpretation for this empirical evidence based on the theoretical view of dynamic complementarity, which argues that a market incentive mechanism by the social planner is necessary to stimulate risky investment in green innovation(Besley & Persson, 2023). The emergence of climate sceptic political leadership disincentivises firms through its deregulatory actions and open expression of climate sceptic ideological disposition, which lower environmental abatement costs, leading to lower utility from green innovative investment relative to brown investment.

The effect of climate sceptic political leaders on green innovation is stronger in financially constrained firms. The literature documents the role of financial constraints in corporate investment and environmental policies(Dang et al., 2022; Xu

& Kim, 2022; Xu et al., 2022). My analysis reveals that financially constrained firms underinvest more under a climate-sceptic regime. This result is consistent with the notion that binding financial constraints lead to underinvestment in environmental abatement projects. My analysis further reveals that firms in the energy-intensive industry under-invest more in green innovation under a climate-deregulatory regime.

1.1.2.3 Contribution

This essay makes several contributions to the literature. It delves into the literature investigating the factors influencing the direction and magnitude of CGI(Amore & Bennedsen, 2016; Bennedsen, 2015; Chen, 2007; Kim et al., 2021b; Ley et al., 2016; Lin et al., 2024). For example, several studies document the effect of drivers of green innovation, like corporate governance structure (Aggarwal & Dow, 2012; Kock et al., 2012; O'Connor & Rafferty, 2012), Analyst coverage(Fiorillo et al., 2022; Guo et al., 2019), and energy prices (Ley et al., 2016) The essay contributes to this strand of literature by documenting the impact of the emergence of climate sceptic political leadership that introduces climate deregulatory policies on the magnitude and direction of corporate green innovation.

The second contribution of the essay is related to the literature on the effect of climate policies on firms (Johnstone et al., 2010; Nguyen et al., 2022; Ramadorai & Zeni, 2021; Seltzer et al., 2022). I contribute to this strand of the literature by documenting the effect of climate sceptic leadership as the key driver of CGI through climate deregulatory channels, which substantially affect financially constrained firms and firms in energy-intensive industries.

Third, the essay expands the literature on modelling macroeconomic consequences of the direction of climate political leadership's climate policies on the economy. Given that, in the absence of regulation, firms are unwilling to internalise the cost of pollution (Acemoglu et al., 2016; Ambec et al., 2013; Brown et al., 2018, 2022; Calel & Dechezleprêtre, 2016). This essay contributes to the debate on how political failure exacerbates corporate failure to internalise the cost of their pollution externalities, which society bears.

1.1.3 Green Taxonomy and Corporate Green Revenue Behaviour

1.1.3.1 Motivation and research questions

In the third essay (chapter four), I examine whether and to what extent supportive climate political leadership's green taxonomy initiative influences corporate green revenue. Amid growing concerns over climate change, the extent to which firms adapt their behaviour, and the magnitude of these changes motivates the investigation of the impact of the Green Taxonomy Policy on corporate green revenue performance.

Furthermore, I draw motivation from a long-standing economic view that the green transition demands a structural shift in corporate production processes and consumer preferences(Besley & Persson, 2023). I ask whether firms shift their products and services in alignment with the European Commission's adoption of a set of policy initiatives under the Sustainable Finance Action Plan, specifically the Green Taxonomy Action Plan. I argue that understanding how firms' green revenue practices respond to the Green Taxonomy Action Plan is essential for advancing the debate on the pace and effectiveness of the green transition.

1.1.3.2 Findings and Discussion

In the third essay (Chapter Four), I delve into the role of the Green Taxonomy Action Plan in corporate green revenue performance. My analysis reveals a positive relationship between the Green Taxonomy Policy and corporate green revenue. I further document environmental innovation as the economic mechanism for the effects. My cross-sectional test indicates that financially less constrained firms and firms with higher stock market liquidity and analyst coverage generate more green revenue after introducing the green Taxonomy policies.

1.1.3.3 Contribution

This essay contributes to the literature in several ways. First, it is a part of the growing literature studying corporate green revenue (Bassen et al., 2025; Bassen et al., 2023; Guo & Zhong, 2023; Klausmann et al., 2024; Kruse et al., 2020; Lel, 2024; Quaye et al., 2024; Yan & Yin, 2023). This essay contributes to this burgeoning literature by documenting the role of the Green Taxonomy as a critical driver of firms' green revenue behaviour.

Second, this essay contributes to the literature on the intersection between climate regulation and corporate environmental performance. Previous studies have focused on the impact of climate regulation on the operational dimensions of climate responsibility, like carbon emissions, toxic waste release, air pollution, and biodiversity destruction(Bartram et al., 2022; Ivanov et al., 2024; Martinsson et al., 2024b; Tomar, 2023). This essay empirically examines the impact of political leadership's green initiatives on corporate green revenue performance, utilising global green revenue data. It addresses the corporate structural shift toward greener production and the negative externalities associated with production output at the consumption level.

1.2 The Structure of the Thesis

The rest of this thesis proceeds as follows: Chapter 2 presents the first essay (Climate Political Leadership and Financial Market Perception); Chapter 3 presents the second essay (Race-to-the-bottom: The Effect of Climate Political Leadership on Corporate Green Innovation); Chapter 4 presents the third essay(Green Taxonomy Policy and Corporate Green Revenue), and Chapter 5 presents the concluding remarks.

Chapter 2 Climate Political Leadership and Financial Market Perception

Abstract: Exploiting a quasi-natural experimental setup of the 2016 United States presidential election results, which unexpectedly shifted the government's position from being supportive of climate science to being openly sceptical, we show that political leadership's climate science belief significantly influences financial markets' perception of firm-level climate regulatory exposure. Further investigation reveals that the climate regulatory channel is the mechanism through which political leaders sway markets' perception of firm-level climate regulatory exposure. The effect is stronger in carbon-intensive and financially constrained firms. Regarding the implications of the link, the capital market rewards the weakened climate regulatory exposure through higher institutional ownership and market valuations.

GEL Classifications: *034, G38, Q55*

Keywords*:* *Financial Market Perception, Climate Political Leadership, Climate Deregulation, Climate Regulatory Exposure,*

2.1 Introduction

Climate risks constitute a significant threat to corporate operations, performance, and the overall stability of the global economy (Bartram et al., 2022; Battiston et al., 2017; Degryse et al., 2023). Firms' exposure to climate risks stems from Physical, Technological and Regulatory changes and changing consumer preferences (Bolton

& Kacperczyk, 2021a, 2021b, 2023, 2024; Stroebel & Wurgler, 2021a). Among these sources of climate risk, investors and market participants consider regulatory exposure as salient and have become increasingly central to their investment decisions(Dang et al., 2024; Krueger, Sautner, & Starks, 2020; Seltzer et al., 2022). Moreover, financial markets are increasingly pricing climate regulatory exposure in asset prices (Agliardi & Agliardi, 2021; Nguyen et al., 2022; Sautner et al., 2023b; Seltzer et al., 2022).

However, a critical upstream driver of how market participants perceive firm-level regulatory exposure remains underexplored: the role of political leadership. Political leaders, through their beliefs, signals, and institutional authority, play a central role in shaping the climate policy and economic environments of firms and investors (Gulen & Ion, 2016; Pastor & Veronesi, 2012; Zawadzki et al., 2020).

This paper introduces and examines the concept of Climate Political Leadership (CPL) as a determinant of financial market perception of climate regulatory exposure. I define CPL as the degree to which a country's highest political authority aligns with the scientific consensus on the anthropogenic cause of climate change and translates this belief into regulatory (or deregulatory) action. Drawing from the Political science and Socio-Psychology literature(Bomberg, 2017, 2021; De Pryck & Gemenne, 2017; Dunlap, 2013; Swinkels, 2020; Zawadzki et al., 2020), I distinguish between supportive climate political leadership (SCPL), which endorses science-based climate policy and promotes regulatory frameworks for decarbonisation, and climate sceptic political leadership (CSPL), which openly denies climate science and actively dismantles existing climate regulatory structures, undermining the green transition.

While the finance literature has made considerable progress in quantifying the impact of realised climate policies (Bartram et al., 2022; Gollop & Roberts, 1983), it has overlooked the symbolic influence of political leaders' climate ideologies. In contrast, political science literature emphasises the impact of Political leaders on belief systems, institutional priorities, and collective behaviour, even in the absence of immediate policy changes (Zawadzki et al., 2020; Parker & Karlsson, 2014). The stream of studies in this direction has focused on Political leaders' influence on public climate beliefs(Brulle et al., 2012; Zawadzki et al., 2020).

The climate change beliefs and ideological dispositions of political leaders can thus shape market expectations about future regulatory stringency, enforcement credibility, and long-term transition risk(Parker et al., 2017; Swinkels, 2020; Zawadzki et al., 2020). The literature suggests that climate change beliefs drive climate actions(Ceccarelli & Ramelli, 2024; Dowell & Lyon, 2024; Huang & Lin, 2022; O'Connor et al., 1999; Ziegler, 2017). Therefore, signals from political leaders' climate beliefs may, in turn, influence firm-level investment behaviour and market valuations.

The literature notes that economic agents revise beliefs and form new expectations in response to evolving political leadership and policy orientation (Kräussl et al., 2024; Pastor & Veronesi, 2012; Pástor & Veronesi, 2013). Accordingly, perceptions of regulatory exposure should reflect real-time attentional and interpretive processes shaped by the continuous flow of information and shifting expectations about climate-related risks, costs, and opportunities, subsequently influencing market behaviour (Hahnel & Brosch, 2016; Kräussl et al., 2024; Smith, 2001; Smith, 2016; Zawadzki et al., 2020).

A growing body of literature highlights substantial heterogeneity in expectations and risk perceptions among economic agents. Understanding how economic agents' expectations are formed and revised and how they shape perceptions that drive decision-making is central to economic theories of financial markets' behaviour and policy transmission (Francesco & Daniel, 2022; Gallemore et al., 2024; Gennaioli et al., 2016; Pastor & Veronesi, 2012).

To investigate how CPL shapes financial market perception, I draw on two complementary theoretical frameworks. First, the investor's belief updating framework of Pástor and Veronesi (2012, 2013) posits that investors revise their expectations in response to current information that alters the perceived probability of future policy outcomes. In this framework, a transition to a climate-sceptic political regime represents a salient exogenous signal that may reduce market expectations of regulatory stringency, thereby affecting firms' expected compliance costs and transition risks. This scenario, in turn, lowers the perception of market participants of firm-level climate regulatory exposure.

The Pastor and Veronesi (2012, 2013) framework provides a rational expectation model of how markets revise expectations in response to new policy signals, updating beliefs about future cash flows and discount rates. I argue that this framework is relevant in explaining the firm-level market perceptions of climate regulatory exposure (hereafter, FL-MPCRE), where forward-looking beliefs about climate regulation and associated transition influence firm-level market perceptions of climate regulatory exposure and, consequently, the pace of the green transition.

Second, I incorporate insights from Social Identity Theory (Tajfel & Turner, 1979; Akerlof & Kranton, 2000), which emphasises the behavioural and psychological pathways through which identity and group affiliations shape belief formation. The Social identity theory suggests that Political leaders are not only policy actors but also identity symbols for broader ideological coalitions(Huddy, 2001; Tajfel et al., 1979). The logic of the framework suggests that a political leader's ideological disposition on climate change can function as an identity-based cue, prompting market participants to re-categorize the regulatory environment and reassess climate-related risks and opportunities, even in the absence of immediate policy changes. This mechanism suggests that exogenous shock to supportive political leadership transitioning to sceptic political leadership can have symbolic effects that influence investor behaviour and corporate strategy.

This dual-theoretical approach enables a richer understanding of how market actors interpret political signals and integrate them into the formation of expectations, which leads to market participants updating their beliefs, which influences their perception and subsequent investment decision-making.

I assess the predictions of this framework in a rich market setting where key financial actors (firms, institutional investors, and analysts) interact in real time to interpret and discuss regulatory risk. Specifically, I provide the first empirical evidence of the impact of exogenous shifts in CPL(from SCPL to CSPL) on the market perception of firm-level climate regulatory exposure using market-based measures of climate regulatory exposure (i.e., FL-MPCRE).

To this end, I ask how an exogenous change in CPL alters financial markets' beliefs about firm-level climate regulatory risk. What mechanisms are market update expectations, and how are perceptions shaped? What are the downstream implications for capital markets? I hypothesise that an unexpected shift from an SCPL regime to a

CSPL reduces perceived regulatory pressure, as evidenced by a measurable decline in firm-level climate-related regulatory discourse. I formulate and test the climate sceptic political leadership hypothesis (CSPLH)[3] within the PV framework.

To assess the CSPLH, I exploit the quasi-natural experiment by employing the unexpected 2016 U.S. presidential election outcome. The election represents a well-defined, exogenous shock that shifts national climate policy from a pro-climate regulatory to a deregulatory stance, offering a unique setting to observe how financial markets revise beliefs, update expectations, and reprice regulatory risk[4] (Wagner et al.,2018; Child et al., 2020). I implement a propensity score matched difference-in-differences (PSM-DiD) empirical identification strategy, comparing U.S. firms (the treatment group) that exogenously migrated to a regime of CSPL with European firms (the control group) that remained under SCPL. The identification strategy allows me to credibly isolate the causal effect of a political regime change on market-based perceptions of regulatory risk.

I employ a novel, text-based, forward-looking measure of FL-MPCRE developed by Sautner et al. (2023). This measure quantifies the relative frequency of climate regulation–related bigrams used by market participants[5] during earnings conference calls. Specifically, I focus on the regulatory component of this measure,

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[3] See Section 3 for details on the logical formulation of the hypothesis.
[4] 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).
[5] Market participants refer to investors, analysts, and other actors in financial markets present at the company's earnings conference calls. 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).

which captures the tone and content of market participants' climate regulatory discussions with firm management. This market-based proxy offers a granular view of how investors, analysts, and corporate insiders perceive regulatory climate risk at the firm level under varying political leadership regimes.

First, I examine the parallel trend for our outcome variable (FL-MPCRE scores) over the sample period from 2013 to 2020. During the SCPL period (i.e., the pre-CSPL period from 2013 to 2016), the average FL-MPCRE scores of the treated group (U.S. firms) and the control group (E.U. firms) in our sample exhibit similar trends and are at the same 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 after the CSPL period, I 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[6]. 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 risk were much lower for U.S. firms than E.U firms. In conclusion, this suggests that while market participants perceived significant

[6] See Figure 2.2

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 U.S. firms compared to E.U. firms during the CSPL regime (i.e., 2017-2020). In quantitative terms, firms headquartered in the U.S. show a 0.307-unit (approximately 31%) decline in FL-MPCRE scores in the CSPL era compared to European firms. These findings suggest that the creation of a stringent climate regulatory environment by CPL (the EU from 2013 to 2020 and the US from 2013 to 2016) elevates analysts and investors to express their concerns about climate regulatory exposure by increasing the frequency of climate-related bigrams used in 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.

To summarise, my core results remain statistically and economically significant across all specifications of our robustness checks. Except for the gold standard of randomised controlled experiments, no empirical approach can eliminate every possible alternative explanation in a social science setting. However, the credibility of our quasi-natural experiment research design (the unexpected 2016 election results), the empirical identification strategy (PSM-DiD), and the consistency of our baseline results, which sustain across multiple robustness checks, strengthen confidence in the causal relationship between CPL and market-based perceptions of regulatory risk (i.e., FL-MPCRE).

I also undertake additional robustness checks to validate my findings. First, I conduct a placebo test to rule out the existence of pre-existing trends that may be driving the results. Second, I employ a complementary matching approach within the difference-in-differences framework, known as the entropy-balanced technique. Third, I employ an alternative proxy for the outcome variable by scaling individual FL-MPCRE scores for each year by the industry average of the FL-MPCRE scores for all firms operating in the same industry classification, following the Fama-French twelve industry classification code while excluding focal firms. Fourth, given the cross-country sample characteristics, I also rule out the possibility of alternative explanations driven by changes in politically induced firm-level tax and trade policies.

Finally, I examine cross-sectional differences based on a firm's level of carbon intensity and financial constraints. In line with expectation, my analysis reveals that the relationship is more substantial 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, I consider the moderating role of financial constraint. The analysis reveals a significantly effect on financially constrained firms, which I attribute to the market's expectation of lower future costs associated with CSPL deregulation policies (Bartram et al., 2022).

The outcomes of the 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 implications of my findings are stark yet straightforward: the climate-related beliefs of political leaders and their consequential regulatory regimes have a significant influence on the global decarbonisation effort.

Based on the earlier baseline results, I extend my analysis by evaluating the climate deregulatory mechanism. Aligned with existing literature, I use the country-level Environmental Policy Stringency Index (EPS) 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 scales from 0 to 6, where 0 indicates the lowest level of climate regulatory stringency, and 6 represents the highest. I find that compared to the E.U. countries in the post-SCPL era (2017-2020), the relatively lower level of EPS for the U.S. negatively mediates the link between CPL and FL-MPCRE, supporting the claim that climate regulatory stringency is a plausible mechanism that underpins the deregulatory channel as the mechanism through which CSPL institutes changes in FL-MPCRE.

Finally, I extend the analysis to firm-level financial implications of an adverse shock to CPL on FL-MPCRE. I investigate the effect of CPL and FL-MPCRE links on institutional investor ownership and capital market-based valuation. My empirical analysis reveals a significant differential increase in institutional investor ownership and firm market valuation for U.S. firms (treated group) compared to European firms (control group) in the post-shock period. The result suggests institutional investors increase their ownership when the market perceives lower climate regulatory exposure, rewarding firms operating in a lower regulatory risk environment with comparatively higher market valuation.

I make the following important contributions to the literature. First, I contribute to the growing literature on climate change beliefs, financial market expectations, perception formation, and regulatory risk pricing (e.g., Krueger et al., 2020; Ceccarelli & Ramelli, 2024; Barrios et al., 2024; Gallemore et al., 2024). Responding to the call by Hong et al. (2020) to better understand the climate beliefs of market participants for efficient climate finance, we are the first to examine how an exogenous but climate science-wise adverse shift in CPL reshapes the financial markets' perception of firm-level climate regulatory exposure (FL-MPCRE). While existing studies assume a steady increase in climate regulation, I introduce the CSPLH and test it within PV's model using a novel, market-based measure of regulatory risk.

Second, I contribute to the growing literature investigating the impact of the unexpected outcome of the 2016 U.S. presidential elections (Wagner et al., 2018a; Child et al., 2021). Prior studies document its effects on stock returns (Wagner et al., 2018a), climate-related corporate behaviour (Ramelli et al., 2021), pollution premia (Hsu et al., 2023), firm market valuation (see Berkman et al., 2019; Ramelli et al., .2021; Kundu, .2023) and tax policy expectations (Gallemore et al., 2024). We extend this literature by focusing on how climate-sceptic leadership reshapes market expectations of regulatory exposure at the firm level.

Third, I contribute to the literature on information production in earnings conference calls (ECCs). While prior studies document that ECCs reveal value-relevant climate information (Borochin et al., 2018; Rennekamp et al., 2022), we provide the first evidence that CPL systematically shapes the tone and discourse of these calls. I identify the deregulatory channel as the key mechanism through which changes in CPL influence how market participants interpret regulatory risk.

Fourth, this study is related to the literature on Politics and Finance. Marshall et al. (2018) document the impact of political changes on stock market liquidity, while Barrios and Hochberg (2021) show how politics affects Covid beliefs. Moving beyond stock return-based event studies (see Berkman et al., 2019; Ramelli et al., .2021; Kundu, .2023), I employ a PSM-DiD quasi-natural technique to demonstrate the impact of political changes on U.S firms' climate regulatory exposure, using European firms as a control group unexposed to U.S. regulatory shifts.

Fifth, I document an exogenous shift in climate political leadership, both as a rational signal and an identity-based cue based on the PV and Social Identity theories, into the analysis of the impact of climate political leadership on financial market perception of firm-level climate regulatory exposure. This study, therefore, contributes to a deeper understanding of the political economy of the green transition, bridging a critical gap between finance, political science, and behavioural economics, with implications for asset pricing, corporate governance, and environmental policy.

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

2.2 Background on 2016-US Presidential Elections

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-sceptic 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). Although the market was aware of the views of the Trump administration in advance, it never anticipated the election result with certainty, as poll results suggested a potential loss for Trump.[7] 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 U.S. presidential election outcome was unexpected, citing pre-election polling and betting market data that overwhelmingly favoured 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

[7] 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.

voting projections favouring 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.[8] 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"*.[9] 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.[10] 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, penalise, 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 the revaluation of the Clean Power Plan[11], among others.

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 denialist, as head of the EPA, which

[8]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).

[9] See https://twitter.com/realDonaldTrump/status/418542137899491328 (Assessed: 20 January 2024).

[10] Source: The New York Times: https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html. (Assessed: 2 November 2022).

[11]Source The New York Times: https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html (Assessed 2 November 2022).

demonstrated a U-turn in U.S. climate policy. As Attorney General of Oklahoma, Scott 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[12]. 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*".[13] 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-sceptic political leadership.

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

[13] 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).

Belton and Graham (2019) review the regulatory (deregulatory) actions of past Republican presidents and conclude that the Trump administration's deregulatory[14] actions were unique. They further argue that the Bush administration was relatively 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) analyses 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 that there were 60% fewer rules during the 2017-2019 period than during the 1981-2019 period, further supporting our empirical findings on why the era is the most climate-sceptic in U.S. history.

Considering the above discussion and for this investigation, I refer to the period from 2013 to 2016 as a regime of supportive climate political leadership (SCPL). Similarly, I refer to the period from 2017 to 2020 as a regime of climate sceptic political leadership (CSPL).

2.3 Hypotheses Development

2.3.1 Climate Sceptic Political Leadership Hypothesis

To better understand how climate political leadership influences firm-level perceptions of climate regulatory exposure, I draw on two complementary theoretical

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

frameworks: the investor belief-updating model proposed by Pástor and Veronesi (2012, 2013) and Social Identity Theory (Tajfel & Turner, 1979).

First, Pastor and Veronesi's (2012, 2013; referred to as PV hereafter) framework's mechanism emphasise information and incentives as key mechanisms through which cues from political leaders influence the formation of new expectations about the future regulatory environment, leading to updating prior beliefs and shift in climate regulatory perception. Based on the PV's framework, investors adjust their beliefs about government policies over time using Bayesian learning based on observed economic outcomes.

When political leaders introduce policy 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[15].

Research highlights the critical role of political leadership in creating and implementing policies that affect the expectations and behaviours 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 I 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, I expect CPL's climate change beliefs, statements, actions, and decisions to influence economic agents' (institutional investors, rating agencies, and financial analysts) beliefs and perceptions.[16]

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

[16] 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 behaviours of economic agents (Parker & Karlsson, 2014; Parker et al., 2017). In the context of climate governance, extensive

Given the above discussions, I examine how the regimes of SCPL and CSPL shape the insights into 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).

The second theoretical lens through which I examine the relationship between adverse shocks and supportive Climate Political Leadership (CPL) is Social Identity Theory(Tajfel & Turner, 1979). This framework posits that individuals categorise others into social groups and update their beliefs and behaviours based on expectations of actions they associate with that group. Applied to our empirical set-up, it implies that market participants categorise the emergence of a political leader with sceptic view of climate change into a social group of climate sceptic and accordingly update their beliefs and behaviour based on expectations of the actions associated with such ideological view. Furthermore, Social Identity theory portrays political leaders beyond being policy actors , but as identity symbols for broader ideological and policy coalition.

A new administration's climate stance is thus interpreted not only in terms of its immediate policy implications, but also as a social identity cue signalling alignment with a broader belief system. When a leader with climate-sceptic views assumes

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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). U.S. presidents hold significant authority, which enables them to implement substantial policies without the oversight of Congress or the judiciary power, market participants may re-categorise the policy environment into a lower regulatory threat group, leading to adjusted perceptions of climate risk and expected regulatory stringency. This identity-based signal influences not only investor expectations but also corporate strategic behaviour. Firms may anticipate relaxed enforcement and diminished climate-related compliance costs, affecting their incentives to invest in green transition.

Moreover, enforcement and compliance costs can adversely affect a company's production, profitability, corporate investment decisions, and cost of capital.[17] Matsumura et al. (2014) note that strict climate regulation may also increase the costs of lawsuits filed by the public or organisations, 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 investment costs in green technologies, and other indirect costs, it is logical to argue that under SCPL, investors perceive the climate regulatory exposure as 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

[17] 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.

mitigation costs under SCPL. With the new beliefs formed by investors, the perceived risks associated with climate change exposure are expected to decrease as investors may focus more on the positive impact of reduced operational constraints and the anticipated positive effect on shareholder wealth.

Literature notes that the CSPL deregulatory signals include dismantling climate regulations, scrapping government incentives for low-carbon investments, licensing and permitting carbon-intensive activities like coal and oil production, and the rollback of motor vehicle emission standard (Bomberg, 2017, 2021; De Pryck & Gemenne, 2017; Glicksman, 2017; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021). Consequently, this will reduce firms' compliance and abatement costs and diminish 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, I expect the exogenous shift to induce sustainability-related changes in firms' policies and strategies. Second, the expected corporate behavioural changes should influence financial markets' perception of climate regulatory exposure.

I illustrate the consequences using a simple example of two hypothetical firms, A (a U.S. firm) and B (an 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. Apriori, both firms have identical high environmental abatement costs during period 1. Following an exogenous shift in CPL (from SCPL to CSPL), firm A operates in period 2 (2017-2020) in a climate-deregulatory environment, where perceived regulatory compliance costs are reduced 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 it did 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 reflects the frequency of climate-related bigrams used during ECC. When investors update their beliefs in response to an exogenous shift from SCPL to CSPL, I expect a reduction in the 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. Consequently, 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, like 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 argument, as mentioned above, 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 regulatory exposure may significantly alter (Smith & Mayer, 2018).

Based on the arguments above, I 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, I formulate and test the following CSPL hypothesis.

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

(Figure 2.3 about here)

2.3.2 Climate Stringency Channel Hypothesis

The discussion above implies that the impact of CSPL on market perception is not purely rhetorical but operates through an observable shift in the regulatory environment. If market participants are forward-looking and rational, their perceptions of firm-level climate regulatory exposure should respond to actual policy stringency.

Therefore, I expect the measurable drop in the national climate regulatory stringency and abatement costs to drive the decline in FL-MPCRE under CSPL.

Based on the arguments above, I argue that CSPL modifies the financial markets' perceptions of climate regulatory exposure through its deregulatory policies, which lower regulatory burdens, climate compliance costs, and abatement costs. Hence, the strength of the macro-institutional climate stringency environment should determine the intensity of the link between CSPL and FL-MPCRE. In other orders, the strength of the expected adverse link between CSPL and FL-MPCRE is expected to be higher in a macro-institutional environment with a less stringent climate regulatory framework. Accordingly, I propose and test the following climate regulatory stringency channel hypothesis.

H_2: The lower the stringency of climate regulatory frameworks, the higher should be the strength of the inverse link between CSPL and FL-MRCRE.

(Figure 2.4 about here)

2.4 Data and Sample

The 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 American databases. Following the existing literature, I exclude financial firms (SIC 6000-6999) and utility firms (SIC 4900-4999) due to the distinct regulatory standards applicable to these industries. I further restrict the firms in our sample to those without missing asset values and those with an asset value of more than $10 million.

I exclude firms with a negative book value of equity and those with leverage greater than 100% of their asset value to avoid biasing our findings due to distress risk. The initial sample comprises a dataset of 22,803 firm-year observations, derived from 3,324 unique U.S. firms and 1,298 European-headquartered firms, spanning the period from 2013 to 2020. The treatment group consists of firms headquartered and listed in the United States, as well as 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. I also acquire firm-level political risks related to tax (*Prisk_Tax*), trade (*Prisk_Trade*) and economics (*Prisk_Economics*) from Hassan et al. (2019).

As discussed in Section 2, U.S. firms experienced an abrupt shift in climate-political leadership in 2017. In contrast, European firms remained subject to a consistent and stringent climate regulatory framework throughout the sample period. As such, European firms serve as a counterfactual, capturing the trajectory of FL-MPCRE without a shock to political leadership. This rich, multi-source dataset enables us to track firm-level climate regulatory exposure over time while controlling for firm and country characteristics that may confound the observed relationship between political leadership and climate-related risk perception. I describe each of the variables below and provide a brief definition in Table A1 of the Appendix.

2.4.1 Key Variables

2.4.1.1 Outcome Variable: FL-MPCRE

To capture the firm-level market perception of climate regulatory exposure (FL-MPCRE), I employ the novel dataset of Sautner et al. (2023a), constructed using textual information from participants' quarterly earnings conference call (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 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 utilising 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, and rating agencies) 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 provides valuable insights into discussing events and policies essential for informed 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 measure is a broad indicator of overall climate change exposure, and the other three reflect exposure related to physical threats, regulatory interventions, and technological opportunities. As a proxy for FL-MPCRE, I 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, I briefly define the measure using the model below[18].

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

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 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

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

figure, the greater the firm's perceived exposure to climate change. 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, like "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 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 specialised 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 like 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, like green innovation and differentiated financial risk profiles.

Estimation reveals that firms with higher climate change exposure scores are more likely to engage in green innovation and green hiring (Sautner et al., 2023a; von Schickfus, 2021), validating the practical relevance of these measures. Seventh, a snippet-based audit by trained coders evaluates the algorithm's accuracy in identifying regulatory discussions. Coders analyse text fragments around the identified bigrams, confirming that the algorithm reliably captures regulatory climate discussions. Finally, the authors compare the performance of the entire keyword discovery approach 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 the sample is at a yearly level, I average the quarterly transcripts to obtain annual measures of FL-MPCRE for the 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)

2.4.1.2 Key Independent Variable: CPL Shock

For this study, I 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 or designing climate-related regulatory frameworks. I 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 sceptic political leadership (CSPL), which rejects the scientific consensus on climate change science. CSPL, thus, engages in deregulatory activities, opposing stricter regulations and seeking to dismantle institutions that provide climate science information or support climate change mitigation and adaptation solutions.

As noted earlier, I test the hypothesis in a quasi-natural experiment that exploits the 2016 United States (U.S.) presidential election as a source of exogenous shocks to CPL. I 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. I 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 takes the value of one for the CSPL regime period (2017-2020) and zero for the SCPL regime period (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.

2.4.1.3 Covariates for PSM

Since I employ the PSM technique to ensure the credibility of our counterfactual, I obtain several covariates to create identical treated and control group firms at the baseline period, i.e., before the 2016 shock. Following climate finance literature (Azar et al., 2021; Balachandran & Nguyen, 2018), I 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 the public attention that 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, which hypothetically could crowd out climate mitigation investments (Azar et al., 2021). The covariate vector also includes 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 due to regulatory changes or physical destruction (Brown et al., 2022; Wang, 2023). Finally, I include the return on assets (RoA), which measures a firm's profitability, calculated as the ratio of earnings before interest and taxes 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.

Furthermore, I also include time-varying politically induced tax, trade, and economic factors (*PRisk_Tax, PRisk_Trade, and PRisk_Economic*) at the firm level using firm-level data from Hassan et al. (2019), which can also affect FLMPCRE as additional covariates. The argument is that 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 have confounded our results (Child et al., 2021). Similarly, in the post-2016 elections, both 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 setup. This is particularly relevant to the lower tax regime of the U.S. administration following the 2016 election.

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 like "*regulation*," "*legislation*," "*tariffs,"* and *"policy,"* analysed using machine learning and natural language processing (NLP). This 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.

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, like lobbying or geographic shifts. This approach offers a granular, firm-level, real-time measure of political risk, surpassing the traditional reliance on macroeconomic or survey-based indicators.

Hassan et al. (2019) construct separate sub-indices within their *PRisk* index framework to analyse the specific dimensions of political risk. Separate tax, trade, and economic indices are included, each focusing on different dimensions of political uncertainty. The tax index (*PRisk_Tax*) relates political risks to taxation policies and reforms. The keywords include "tax reform," "taxation," "corporate tax," and "tax policy." The *PRisk_Tax* index measures the impact of discussions about politically induced tax-related risks on firm decision-making. Similarly, the trade index (*PRisk_Trade*) measures the political risk of trade policies, tariffs, and international trade relationships. The keywords include "trade policy," "tariffs," "trade agreements," and "import/export barriers". The *PRisk_Trade* index highlights firms' exposure to geopolitical shifts in trade dynamics. Finally, the economic index (*PRisk_Economics*) captures broader macroeconomic risks associated with political uncertainty, like economic, monetary, and fiscal policy discussions. The keywords include "economic policy," "inflation," "recession," and "monetary policy." The *PRisk_Economics* index reflects concerns about the overarching economic conditions shaped by political factors. I winsorise all covariates at the 1st and 99th percentiles in both tails to exclude the influence of obvious outliers.

2.4.1.4 Time-varying Country-Level Controls

Although the firm-level covariates may nearly randomise the treated and control groups, there could still be country-level factors that drive our results. As such, I also include time-varying country-level variables reflecting differences in macroeconomic and institutional quality. First, I use each country's real gross domestic product growth rate (*Gdp_Grt*) to capture its macroeconomic performance (Kim et al., 2021a). As a result, we anticipate a favourable link between a country's *Gdp_Grt* and *FL-MPCRE*. Following Kim et al. (2021), I control for institutional quality by utilising the country's Rule of Law (RuleLaw) indicator from the World Bank Governance Indicators. The *RuleLaw* indicator measures a country's quality of state governance and institutions with a standardised scale of -2.5 to 2.5 (Kim et al., 2021a). 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).

In addition, we obtain a measure of climate regulatory stringency using the Environmental Policy Stringency (*EPS*) index published by the OECD as part of our mechanism tests in later sections.

2.4.2 Summary Statistics

Table 2.1 presents the summary statistics of the total sample from 2013 through 2020, which I employ to analyse 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. Regarding borrowing behaviour, 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.

The country-level time-varying *Gdp_Grt* 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, along with a significantly smaller standard deviation of approximately 0.17, indicates a relatively stable rule of law across our sample countries.

2.5 Empirical Identification Strategy: Propensity Scored Matched (PSM)

2.5.1 Difference in Differences Research Design

Following the literature on climate finance (Bartram et al., 2022; Bose et al., 2021; Kim et al., 2021a; Roy et al., 2022) and as noted earlier, I 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), I need to estimate a control set of firms unaffected by the shock. I 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, I need to ensure that before the shock of 2016, both groups are, on average, statistically similar.

2.5.2 *Justifying the PSM Technique*

Before applying the DiD, we need to ensure that both groups are, on average, statistically similar at the baseline of the 2016 shock.

Panel A of Table 2.2 reports the mean differences between the treated and control groups for 2013-2016, adjusted for the set of covariates, including *Size, Lev, RoA, Tang, PRisk_Tax, Prisk_Trade,* and *Prisk_Economics.* Except for *Lev* and *Tang*, the characteristics of the treated and control groups are fundamentally different when measured against all other covariates. These statistical differences validate our argument for employing the PSM technique.

(Table 2.2 about here)

To further justify our argument, we run a probit model, as stated in Equation (1), for the sample period 2013 -2016 to evaluate the validity of the PSM technique. $Treat_{it}$ is the dummy that takes the value of one if the firm is treated and zero otherwise. If both groups are similar, then none of the regression coefficients should be statistically significant.

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

As reported in column 1 (pre-PSM), almost all the covariates, except RoA, are statistically significant, which further justifies the employment of the PSM technique. PSM balancing ensures the comparability of observable firm characteristics before the shock, while the DiD framework accounts for unobservable time-invariant differences. This approach enables us to isolate the causal effect of the transition to the CSPL on the financial market perceptions of firm-level climate regulatory exposure.

2.5.3 Matching on Observed Covariates

We use nearest neighbour matching with common support, in which each treated unit matches with one closest control unit based on the propensity score within a calliper of 0.04, with replacement. $Treat_{it}$ 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, Cash, RoA, R&D, Tang, PRisk_Tax, PRisk_Trade, and PRisk_Economic,* 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 winsorise all covariates at the 1% and 99% levels. The pre-PSM sample comprises 10,552 observations and 3,460 firms (PSM Model 1), whereas the post-PSM sample consists of 8,858 firm-year observations from 3,233 firms.

Next, we validate our PSM results by employing two matching diagnostic tests. First, we re-estimate Equation (1) using probit regression with PSM-matched treated and control group firms for the period 2013-2016. We present the results in column 2 (Post-PSM) of Panel B. Compared to the results in Panel B (i.e., column 1 (pre-PSM), the outcomes in the Post-PSM Model imply that none of the covariates can statistically predict the treatment.

Second, we generate Rosenbaum and Rubin's (1985) standardized percentage bias (SPB) reduction measures between unmatched (pre-PSM) and matched (post-matched) covariates. The 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. Accordingly, we expect a higher variance in the covariates for the unmatched sample relative to the matched sample of firms. If the matching is effective, we should observe a significant reduction in the SPB for the covariates for the matched firms; that is, the variance should be close to zero for the matched firms and further away from zero for the unmatched firms. The standardised percentage bias variance measures for the covariates in the matched and unmatched samples are shown in Figure 3.

[Figure 2.1 about here]

As expected, Figure 2.1 illustrates that the SBS values for the covariates in the matched sample are all close to zero relative to those in the unmatched sample, ensuring, to a considerable extent, that pre-existing disparities do not influence the observed effects during the post-shock periods in the covariates.

Given the results of both diagnostic tests, we are confident that PSM addresses the methodological prerequisite of ensuring statistical similarity (on average) between the treatment and control groups before the shock.

(Insert Figure 2.1 here)

2.6 Empirical Results

2.6.1 Parallel Trend Analysis

Before estimating the PSM-DiD regression, I conduct a parallel trend test over the sample period of 2013-2020 to establish the credibility of our research design, ensuring consistency with the difference in the research design. I report the yearly visual trend inspection in Figure 2.2 and the statistical test for parallel trend yearly in Table 2.3.

(Figure 2.2 about here)

As shown in Figure 2.2, the yearly averages of FL-MPCRE for the treatment and control groups 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.

The result indicates that, during the pre-treatment period, the yearly average difference is not discernible from zero, suggesting no significant difference between the treatment and control firms FL-MPCRE in 2013-2016. However, from 2017 onwards, I begin to observe material differences. To further authenticate the graphical observations, I report the yearly difference in coefficients of the parallel trend test in Table 2.3. The results indicate 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.

2.6.2 CPL and FL-MPCRE: PSM-DiD

Following the PSM matching and the parallel trend tests, I 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 is due to the 2016 U.S. election shock, which unexpectedly altered the *CPL* regime from *SCPL* to *CSPL*.

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

I quantify the average treatment effect of CPL on FL-MPCRE by estimating a PSM-DiD regression specification using a PSM-matched firm for the eight years between 2013 and 2020, as specified 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 firms (i) in the treated group (i.e., 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, Tang, PRisk_Tax, PRisk_Trade* and *PRisk_Economics.* Furthermore, $\boldsymbol{X}_{it}$ includes time-varying country-level control variables *Gdp_Grt* and *Rule Law*. I 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. I winsorise 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.

(Insert Table 2.4 here)

Column (1) presents the univariate DiD regression, which includes 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 the FL-MPCRE score, i.e., by 0.31, compared to 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 European firms, market participants perceive a lower degree of climate regulatory exposure for U.S. firms during the Trump regime (i.e., the CSPL era, covering the period 2017-2020) relative to that of the SCPL era, covering the period 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 suggests that market participants in the treated group 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 indicates that CSPL has significantly reduced the source of regulatory risk exposure for investors and other financial market participants through deregulatory actions (or future expectations of such actions).

2.6.3 Robustness Checks

In this section, I undertake several robustness checks to validate the baseline results reported in Table 2.4. First, I administer a placebo test and then a complementary matching technique.

2.6.3.1 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, I conduct a placebo test using 2015 as the year of the shock. I 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). I present the results of the regressions in columns (1)to (3) of Table 2.5.

The results of my analysis show that the DiD coefficients are not statistically significant. The results further support the main findings shown in Table 2.4, which are unaffected by any other events and alleviate concerns about any pre-existing patterns in FL-MPCRE.

(Insert Table 2.5 here)

2.6.3.2 Robustness Check: Entropy Balancing Approach

Following existing literature (Cook et al., 2021; Hasan et al., 2021; Hossain et al., 2023; Çolak & Öztekin, 2021), I employ 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 between the treatment and control firms, reducing reliance on specific modelling assumptions and ensuring balance improvements across all included covariates, such that re-weighted observations have identical post-weighting distributional characteristics for both 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 distribution of the covariate. For more technical details, see Hainmueller (2012) and Chapman et al. (2019).

The incremental advantage of entropy balance is that it significantly enhances the efficiency of our regression estimations by exploiting information in a much greater number of observations than PSM matching. Additionally, unlike PSM matching, which relies solely on the mean, it can also balance covariates across variance and skewness in addition to the mean. I re-estimate DiD specification 2 using the entropy-balanced sample, considering mean, variance, and skewness moments. I report the results in Table 2.6, columns (1) to (9).

I use the three moments (mean, variance, and skewness) to estimate the entropy balance technique. First, I 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, as estimated and reported in Column (3), is approximately -0.27. Second, I re-estimate the entropy balance matching using the first and second moments and present the results in Table 2.6 columns (4-6). After adjusting for covariates and 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, I employ all three moments (mean skewness and kurtosis) in the entropy balance matching and present the results in Table 2.6 columns (7-8). Again, after considering all covariates, firm, and year-fixed effects, the results remain statistically significant at a 1% significance level but indicate a smaller effect size relative to the results using PSM-DiD and the first- and second-moment entropy balance estimation. Although the effect size reduces when I include other moments, the results remain consistent. Such non-trivial reduction in the size effect is due to the more conservative matching mechanism imposed by the entropy balance technique when we estimate using additional moments. In summary, the outputs of the entropy balancing technique align with our main findings, as reported in Table 2.3, and thus further validate the baseline results, supporting the CSPL hypothesis.

(Insert Table 2.6 here)

2.6.4 Robustness Check: Firm Heterogeneity

In this section, I further offer several other robustness checks in the form of cross-sectional heterogeneity tests. I 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, I 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.

2.6.4.1 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). Moreover, 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 of our study implies that firms' future profitability may depend on environmental regime changes since 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-sceptic political leadership, which institutes deregulatory policies characterised 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. In addition, 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 my argument, U.S. firms under climate-sceptic 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 Figure 2.2). Simultaneously, deregulatory policies characterise 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 markets reward high carbon-intensive firms more with higher market valuations than non-carbon-intensive firms after the U.S. 2016 Presidential elections. The result further 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-sceptic political leadership may favour carbon-intensive firms regarding market performance. Therefore, to the extent that CSPL deregulatory policies lower the regulatory burden, I 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. I classify a firm as carbon-intensive if it operates in a carbon-intensive industry. For the list, see Table A2 in the appendix.

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[19]), leading to disruption in the production process and an increase in the unit cost of output[20]. 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 &

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[19] Welsby et al. (2021) predicts that if the world limits global warming to 1.5oC by 2050, approximately 60% of oil and 90% of coal may need to remain buried and thus unexploited.

[20] 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

Nguyen, 2018; Burby & Paterson, 1993; Grewal et al., 2019; Wu et al., 2023; Xu & Kim, 2022).

To empirically test this conjecture, I 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). I 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 2.7, Columns (1) to (3).

As seen in columns 1 to 3 of Table 2.7, 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. This finding indicates that the average negative differential relationship between treated and control units is more pronounced among carbon-intensive firms. The result 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.

(Insert Table 2.8 here)

2.6.4.2 Robustness Check: Role of Financial Constraints

I 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 constraints for firms, given the high regulatory compliance costs and 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 can modify corporate behaviour 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) argue that environmental costs, specifically emissions taxes, increase the operational costs for firms with high pollution levels, making it financially burdensome for them to continue utilising 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, I 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). Further, 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 reduces under the SCPL, it 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, I expect financially constrained firms to experience reduced compliance and pollution abatement costs[21] in the CSPL regime relative to that of the SCPL era. I 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, like 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, I expect the differential negative effect size to be more pronounced in the CSPL era for financially constrained firms.[22]

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[21]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).

[22] 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

To empirically study the relationship between CSPL and FL-MPCRE conditioned on a firm's financial constraints, I proxy for financial constraints using the Kaplan-Zingales Index (*KZ_Index*). I follow prior literature in constructing the *KZ_Index*[23] 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, like 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 the sum of the 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, I winsorise the index at the 1st and 99th percentiles to exclude the effect of outliers.

I then construct a financial constraint dummy to analyse the effect of CSPL on FL-MPCRE 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, I run a triple interaction term ($Treat_i*Post_t*FinCon_{it}$) following the specification (4) and report the findings in Table

underlying climate risks these firms face in absolute terms. However, in this study, we only focus on the perception of markets on regulatory exposure.

[23] KZ Index = (-1.002*(cashflow/ppe $_{t-1}$)) + (-1.315*(cash / ppe $_{t-1}$)) + (-39.368*(div/ ppe $_{t-1}$)) + (3.139 *Lev) + ((0.285*TQ))

2.8. The coefficients of both triple interactions capture the differential impact of CSPL on FL-MPCRE, conditioned on their level of financial constraints.

(Insert Table 2.8 here)

The results are in columns (1) to (3); the coefficients are statistically significant at the 1% significance level (β = -0.0682,-0.0652,-0.0641), respectively, in columns (1) to (3), implying that financially constrained firms' FL-MPCRE is significantly lower in CSPL than in the SCPL regime in the CSPL era.

2.6.5 Mechanism Test: Climate Deregulatory Channel

In Section 2.3, I 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. Within our setup, I employ the EPS Index to show the deregulatory (climate stringency) mechanism through which CSPL influences FL-MPCRE. The EPS index scales from zero (0) to five (5). Zero represents the lowest level of environmental stringency, and five (5) reflects the highest level. The uniqueness of the index is that it shrinks a multidimensional set of policy instruments into a single index comparable across countries, thereby alleviating bias in evaluating individual nations' climate-policy stringency. Equal weighting is applied to the EPS market-based and EPS non-market-based indicators to form the final EPS index. Hence, the Index captures the strength of a country's regulatory stringency (Deregulation & Stringent Regulation).

The environmental policy stringency index(EPI) evaluates countries' progress in implementing policies that contribute to environmental mitigation. 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. I first examine whether there is any difference in the yearly trend of the *EPS* index between the treated and control group countries over the sample period. I plot the average trend of the yearly EPS 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). I present the graph in Figure 2.5.

As seen and expected, I observe that after 2017, there was a drastic drop in the EPS score for the U.S. In contrast, the EPS scores for the E.U. countries' scores increased after 2017, suggesting 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 climate stringency regulatory channel, I interact the DiD variable (*Treat*Post*) with the EPS Index (EPS_{ct}), creating a triple interaction ($Treat_i * Post * EPS_{ct}$), and run specification (4).

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

I estimate specification (4) and report our findings in Table 2.9, 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.

(Insert Table 2.9 here)

As reported, all the coefficients across the three model specifications of the triple interaction ($Treat_i$*$Post_t$*EPS_{ct}) estimates are negative and statistically significant at the conventional 1% significance level. The findings suggest that a lower stringency of regulation following the emergence of the CSPL increases the differential effect in the treatment group relative to the control units. These results suggest that the climate deregulatory channel is the mechanism through which CSPL influences FLMPCRE.

2.6.6 Market Implication Tests

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

2.6.6.1 *Market Implication Test: Institutional Investor's Ownership*

Institutional investors are crucial in shaping corporate behaviour and 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). It implies that, *ceteris paribus*, the higher the level of ownership, the higher the pressure and engagement of firms to decarbonise (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 crucial to effective climate mitigation strategies, like 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). Regarding 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 CSPL regime, which creates a deregulatory environment and reduces the cost of environmental abatement, should exhibit significantly 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 notion that investors' perceptions influence asset prices and investment decisions (Krueger, Sautner, & Starks, 2020; Pflueger et al., 2020) and *ceteris paribus*, I expect institutional investors to increase their differential ownership in U.S. firms compared to their European counterparts following an exogenous shift in CPL from SCPL to CSPL that lowers the FL-MPCRE. Consistent with deregulation lowering perceived climate regulatory and abatement costs, I 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 my conjecture, I 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*. I interact the difference-in-differences variable with the *FLMPCRE_Dummy* to create a triple interaction. I use it as the key independent variable for the regression investigating the impact of climate sceptic political leadership on institutional investor holdings ownership.

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

$\boldsymbol{X}_{it}$ includes the covariates (*Lev, Size, RoA,* and *Tang*) employed in PSM balancing. I 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), like benchmark allocation, corporate governance, liquidity, and internationalisation, which could be simultaneously associated with OWN_{it} and ($Treat_i{*}Post_t$) factors. Moreover, following Gelos and Wei (2005), I 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 (*Gdp_Grt* and *RuleLaw*). I report the results in Table 2.10, columns 1- 4.

(Insert Table 2.10 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 1.4 % 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 favourable to firms concerning climate regulatory exposure. I also provide a visual inspection of the institutional ownership trend by treatment group, which further supports our result in Figure 2.5

2.6.6.2 Market Implication Test: Capital Market-based Valuation

Within the investor belief framework of Pastor & Veronesi (2012), when political leaders 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 setup, the unexpected results of the 2016 Election revised the perceptions of market participants, whereby the expected higher carbon risk premium of the climate-supportive regime should be revised downward in the climate-sceptic 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), implying that investors and the market view those firms favourably due to the impact of the new lower-cost climate regulatory regime, then in our empirical set-up, I expect that the U.S. firms should experience differentially higher market valuation relative to their European counterparts.

Accordingly, I 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).

$$VALUE_{it} = \alpha_i + \beta. (Treat_i{*}Post_t * FLMPCRE\_Dummy) + \Upsilon. \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \quad (6)$$

As a proxy of market-based value, I employ Tobin's Q(*TQ*) following prior literature (Bardos et al., 2020; Berkman et al., 2024). *FLMPCRE_Dummy is* a dummy variable if the FLMPCRE of the firm is above the industry's median-by-year and zero otherwise. I interact the difference-in-differences variable with the *FLMPCRE_Dummy* to create a triple interaction. I use it as the key independent variable in the regression investigating the impact of climate-sceptic political leadership on market valuation. $\boldsymbol{X}_{it}$ 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 (*Gdp_Grt* and *RuleLaw*). I report our results in Table 2.11, columns (1) – (3).

As documented across all three specifications Columns (1)-(4), estimates of $(Treat_i{*}Post_t{*}\ FLMPCRE\_Dummy)$ 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 0.13% in market valuation for U.S. firms' column (4) relative to their European counterparts, attributable to the reward for a lower perception of future climate regulatory exposure. This result suggests that reduced perceived regulatory exposure following the exogenous CPL shock and the emergence of CSPL leads to higher market valuations for U.S. firms compared to their European counterparts. The result is consistent with prior studies on the market valuation implications of the regulatory shock of the 2016 U.S. presidential elections (Kundu, 2024; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021)

Our findings suggest that investors consider the reduced climate abatement costs under the CSPL regime, as indicated 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 favour deregulatory policies, consistent with similar findings by Kundu (2024). This finding suggests that investors prioritise firm-level climate risk exposure only when 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 decarbonisation efforts. Given that the perception of climate regulatory exposure is critical to fostering pro-environmental behaviour (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.

(Insert Table 2.11 here)

(Insert Figure 2.6 here)

2.7 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 decarbonise economies. Thus, science suggests that fostering a climate-friendly regulatory environment should expedite the transition to a low-carbon economy. Climate political leadership (CPL) refers to the conviction and disposition of the highest political leadership that reflects the approach to tackling climate change, encompassing the establishment of a climate agenda, the design of regulatory frameworks, and the fostering of 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 sceptic 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 decarbonising 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 a firm-level market perception of climate regulatory exposure (FL-MPCRE), incentivising 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 from RCPL to CSPL significantly dampens 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 incentivise businesses and their investors to promote greener business practices. However, I 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 result 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.

Appendix

Table A2.1 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. I term 2013-2016 as an era of supportive climate political leadership (*SCPL*) (i.e., *CPL* = 0) and 2017-2020 as climate sceptic 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".) 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)
Size	For firm *i* at the end of year *t*, *Size* is the natural logarithmic of the total assets measured in US$ Billions. 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 the book value of equity scaled by the total book value of the 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 it is headquartered and listed in a 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
Gdp_Grt	For country j at the end of year t, the real Gross Domestic Product growth rate (*Gdp_Grt*), 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, ranging between zero and five. This indicator measures the extent to which economic agents trust in and adhere to the norms and regulations of society, with a specific focus on the effectiveness of contract enforcement, property rights protection, law enforcement agencies, judicial systems, and the likelihood of criminal activities and violence. It ranks 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
EPS	For country *c* at the end of year *t*, the Environmental Policy Stringency Index (EPS) is a time-varying country-level score measuring climate policy stringency. It evaluates a country's environmental policy performance, indicating the country-level climate mitigation regulatory stringency and efforts. It is scaled from zero (0) to five (6). Zero (0) represents the lowest level of environmental policy stringency, and five (6) represents the highest. Source:
CarbonDummy	Carbon Intensive dummy (*CarbonDummy*) is an indicator variable that takes a value of one if firm i is in the high energy-intensive sector, as classified by the 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 A2.2: Table A2: List of carbon-intensive firms using Four-digit Standard Industry Classification Codes

S/N	Sic Code	Industry Name
1	$1000 \leq SIC \leq 1800$	Mining, Oil and Construction
2	$2000 \leq SIC \leq 2700$	Light Manufacturing
3	$2800 \leq SIC \leq 2999$	Energy
4	$3000 \leq SIC \leq 3999$	Heavy Manufacturing
5	$4000 \leq SIC \leq 4799$	Transportation
6	$5000 \leq SIC \leq 5999$	Wholesale and Retail trade

Table A2.3: Lists the distribution of countries in the 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 A2.4 Fama-French 12 Industry Classification

S/N	Sector Description	Obs	Percentage
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 2.1: Descriptive Statistics.

This table shows the descriptive statistics of our sample dataset. I 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. I define all these variables in the Table A1 of the Appendix. The variable *FL-MPCRE* is scaled to 10^4 for ease of interpretation. I winsorise all the firm- and country-level continuous variables 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
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					
Gdp_Grt	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 2.2: 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* indexes 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 zero otherwise. X_{it} is a vector of control variables consisting of *Size, Lev, RoA, Tang, Prisk_Trade, Prisk_Tax and Prisk_Economic*, as defined in Table A1 of the Appendix. δ_j is industry fixed-effects, and ε_{it} represents the error term. I winsorise all 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 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
Cash	0.195	0.212	0.133	-0.080***	-15.583	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
R&D	0.051	0.057	0.029	-0.028***	-12.070	0.000
Tang	0.239	0.239	0.240	0.000	0.039	0.969
PRisk_Trade	0.216	0.202	0.271	0.069***	8.832	0.000
PRisk_Tax	0.270	0.259	0.311	0.052***	6.458	0.000
PRisk_Economic	0.282	0.268	0.337	0.069***	8.800	0.000
Obs.	10,557	8,333	2,224			

Panel B: Pre and Post Propensity score diagnostic regression.
The dependent variable is Dummy = one for the treated and zero for the control group**.**

Variables	**Pre-PSM**	**Post-PSM**
Size	-0.3234***	-0.0148
	(-33.22)	(-0.55)
Lev	1.1917***	-0.3055
	(11.34)	(-1.07)
Cash	0.8849***	-0.3491
	(6.10)	(-1.01)
Tang	0.3621***	-0.0058
	(5.04)	(-0.03)
RoA	-0.1524	-0.1138
	(-0.90)	(-0.29)
RnD	-0.8379**	0.0573
	(-2.69)	(0.08)
PRisk_Tax	0.3330*	0.5412
	(2.57)	(1.83)
PRisk_Trade	-0.2199*	-0.3452
	(-2.33)	(-1.46)
PRisk_Economic	-0.5615***	-0.3092
	(-4.05)	(-1.00)
Constant	2.9598***	0.2760
	(34.92)	(1.10)
Pseudo R^2	0.1630	0.007238
Obs	10,552	8,858
#Firms	3,460	3,233

Table 2.3: 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 2.2.

Year	**Coefficient**	**t-stat**	**P value**
*Treat*post$_{2013}$*	0.047	0.77	0.439
*Treat*post$_{2014}$*	0.022	0.36	0.718
*Treat*post$_{-2015}$*	0.048	0.88	0.380
*Treat*post$_{2017}$*	-0.009	-0.15	0.879
*Treat*post$_{2018}$*	-0.1662***	-2.57	0.010
*Treat*post$_{2019}$*	-0.390***	-4.91	0.000
*Treat*post$_{2020}$*	-0.666 ***	-6.38	0.000

Table 2.4: 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* indexes 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, Cash, RoA, R&D, Tang, Prisk_Tax, PRisk_Trade, and PRisk_Economic). X*it also includes time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are 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. I winsorise all at 1% and 99%, respectively. 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	**(1)**	**(2)**	**(3)**
$Treat_i$ *$Post_t$	**-0.307***** **(0.055)**	**-0.302***** **(0.055)**	**-0.289***** **(0.055)**
Size		-0.012 (0.029)	-0.011 (0.029)
Lev		-0.134 (0.093)	-0.143 (0.093)
Cash		0.032 (0.086)	0.023 (0.086)
Roa		-0.120 (0.149)	-0.125 (0.149)
R&D		-0.329 (0.265)	-0.340 (0.264)
Tang		0.046 (0.199)	0.035 (0.199)
PRisk_Tax		0.050 (0.040)	0.049 (0.040)
PRisk_Trade		-0.048 (0.033)	-0.048 (0.033)
PRisk_Economic		0.026 (0.052)	0.031 (0.052)
GdpGrt			-0.027 (0.019)
RuleLaw			1.053*** (0.292)
Obs.	18,129	18,129	18,129
Adj. R^2	0.406	0.406	0.408
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Clustering-*Firm*	YES	YES	YES

Table 2.5: 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* indexes 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 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 it is 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, Cash, RoA, R&D, Tang, Prisk_Tax, PRisk_Trade,* and *PRisk_Economic*. All the variables reported in this table are 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. I winsorise 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	**(1)**	**(2)**	**(3)**
Treat$_i$ *Post$_t$	**-0.0547**	**-0.0567**	**-0.0340**
	(0.0484)	**(0.0481)**	**(0.0738)**
Size		0.0595*	0.0608*
		(0.0351)	(0.0351)
Lev		-0.0252	-0.0218
		(0.1073)	(0.1072)
Cash		0.1685	0.1676
		(0.1047)	(0.1047)
Roa		0.0471	0.0448
		(0.0999)	(0.0998)
R&D		-0.4828*	-0.4813
		(0.2933)	(0.2935)
Tang		0.3373	0.3374
		(0.2599)	(0.2599)
PRisk_Tax		0.0409	0.0413
		(0.0484)	(0.0483)
PRisk_Trade		-0.0216	-0.0208
		(0.0427)	(0.0426)
PRisk_Economic		0.0248	0.0231
		(0.0684)	(0.0684)
GdpGrt			0.0426*
			(0.0248)
RuleLaw			0.1079
			(0.3539)
Obs.	11,851	11,851	11,851
Adj. R^2	0.4420	0.4426	0.4427
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 2.6: 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.

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

i and *t* indexes 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 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*, *Cash*, *RoA*, *R&D*, *Tang*, *Prisk_Tax*, *PRisk_Trade*, and *PRisk_Economic).* All the variables reported in this table are 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. I winsorise 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 $\boldsymbol{Treat_i {*}Post_t}$	**-0.2798*****	**-0.2713*****	**-0.2450*****	**-0.2798*****	**-0.2660*****	**-0.2443*****	**-0.2633*****	**-0.2559*****	**-0.2357*****
	(0.0517)	**(0.0514)**	**(0.0522)**	**(0.0517)**	**(0.0481)**	**(0.0492)**	**(0.0472)**	**(0.0468)**	**(0.0484)**
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.	22,210	22,210	22,210	22,210	22,210	22,210	22,210	22,210	22,210
Adj. R^2	0.3860	0.3867	0.3895	0.3990	0.3997	0.4020	0.4079	0.4088	0.4106
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 2.7: 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* indexes 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, Cash, RoA, R&D, Tang, Prisk_Tax, PRisk_Trade,* and *PRisk_Economic).* All the variables reported in this table are 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 winsorise all the firm- and country-level continuous variables at the 1st and 99th percentiles. 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	**(1)**	**(2)**	**(3)**
$\boldsymbol{Treat_i * Post_t * CarbonDum_{it}}$	**-0.0831****	**-0.0806****	**-0.0737****
	(0.0346)	**(0.0346)**	**(0.0345)**
Size		-0.0191	-0.0174
		(0.0289)	(0.0288)
Lev		-0.1580*	-0.1675*
		(0.0934)	(0.0932)
Cash		0.0415	0.0306
		(0.0866)	(0.0864)
Roa		-0.1179	-0.1216
		(0.1489)	(0.1490)
R&D		-0.3475	-0.3587
		(0.2634)	(0.2634)
Tang		0.0263	0.0176
		(0.2040)	(0.2037)
PRisk_Tax		0.0540	0.0516
		(0.0399)	(0.0400)
PRisk_Trade		-0.0455	-0.0455
		(0.0335)	(0.0335)
PRisk_Economic		0.0227	0.0281
		(0.0519)	(0.0518)
GdpGrt			-0.0383**
			(0.0194)
RuleLaw			1.0084***
			(0.2916)
Obs.	18,129	18,129	18,129
Adj. R^2	0.4038	0.4040	0.4056
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 2.8: 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* indexes 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 it is 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, Cash, RoA, R&D, Tang, Prisk_Tax, PRisk_Trade*, and *PRisk_Economic)*. All the variables reported in this table are 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. I winsorise all the firm- and country-level continuous variables at the 1st and 99th percentiles. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) presents the univariate triple interaction regression, which includes 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	**(1)**	**(2)**	**(3)**
$\boldsymbol{Treat_i * Post_t * FinCon_{it}}$	**-0.0682****	**-0.0652****	**-0.0641****
	(0.0324)	**(0.0323)**	**(0.0323)**
Size		-0.0200	-0.0181
		(0.0290)	(0.0290)
Lev		-0.1535*	-0.1633*
		(0.0932)	(0.0930)
Cash		0.0410	0.0294
		(0.0867)	(0.0865)
Roa		-0.1163	-0.1203
		(0.1492)	(0.1493)
R&D		-0.3365	-0.3484
		(0.2643)	(0.2642)
Tang		0.0574	0.0468
		(0.2030)	(0.2025)
PRisk_Tax		0.0536	0.0511
		(0.0398)	(0.0399)
PRisk_Trade		-0.0502	-0.0499
		(0.0335)	(0.0335)
PRisk_Economic		0.0247	0.0301
		(0.0519)	(0.0519)
GdpGrt			-0.0391**
			(0.0194)
RuleLaw			1.0165***
			(0.2925)
Obs.	18,133	18,129	18,129
Adj. R^2	0.4037	0.4039	0.4055
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 2.9: Testing the Channels: Climate Stringency Regulatory Channel

This table reports the results of the climate stringency regulatory channel using PSM-DiD for the following general specifications.

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

i, *t*, and *c* indexes 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 it is 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). EPS_{ct} is the Environmental Policy Stringency Index. $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size*, *Lev, Cash, RoA, R&D, Tang, Prisk_Tax, PRisk_Trade,* and *PRisk_Economic).* All the variables reported in this table are 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 winsorise all the firm- and country-level continuous variables at the 1st and 99th percentiles. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) presents the univariate triple interaction regression, which includes 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	**(1)**	**(2)**	**(3)**
$Treat_i * Post_t * EPS_{ct}$	**-0.1033*****	**-0.1016*****	**-0.0972*****
	(0.0193)	**(0.0192)**	**(0.0192)**
Size		-0.0126	-0.0115
		(0.0289)	(0.0289)
Lev		-0.1324	-0.1420
		(0.0932)	(0.0931)
Cash		0.0298	0.0203
		(0.0866)	(0.0864)
Roa		-0.1212	-0.1257
		(0.1494)	(0.1494)
R&D		-0.3320	-0.3433
		(0.2649)	(0.2646)
Tang		0.0296	0.0197
		(0.2004)	(0.2003)
PRisk_Tax		0.0508	0.0491
		(0.0401)	(0.0401)
PRisk_Trade		-0.0472	-0.0468
		(0.0336)	(0.0336)
PRisk_Economic		0.0257	0.0296
		(0.0521)	(0.0521)
GdpGrt			-0.0284
			(0.0197)
RuleLaw			1.0220***
			(0.3009)
Obs.	18,043	18,039	18,039
Adj. R^2	0.4063	0.4064	0.4077
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 2.10   Implication Test: Institutional Ownership

This table reports the implications of the institutional ownership tests. Panel A shows the simple univariate difference in the average of the Own (%) variable by pre-and post-test for the treated and control groups. Panel B reports the regression results using the PSM-DiD of the following general specification.

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

i and *t* indexes as firm and time (years). The dependent variable, Ownit, is the proportion of institutional investors holding firm i in year *t*. *REG* is a dummy variable that takes a value of one if the regulatory exposure is less than the sample median by industry year and zero otherwise. All the other variables reported in this table are 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 it is headquartered and listed in any of the 16 European countries. $Post_t$ is a dummy variable that takes the value of one for the post-shock period (2016-2020) and zero for the pre-shock period (2013-2016). $\boldsymbol{X}_{it}$ is a vector of firm-level covariates (*Size, Lev, Cash, RoA, R&D, Tang, Prisk_Tax, PRisk_Trade,* and *PRisk_Economic).* $\boldsymbol{X}_{it}$ also includes time-varying country-level control variables *GdpGrt* and *RuleLaw.* All the variables reported in this table are 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. I winsorise all at 1% and 99%, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses. Column (1) presents the univariate DiD regression, which includes 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	**(1)**	**(2)**	**(3)**
$Treat_i$ *$Post_t$ *REG	**0.0161*** (0.0041)**	**0.0117*** (0.0040)**	**0.0115*** (0.0040)**
Firm Covariates	YES	YES	YES
Country Covariates	YES	YES	YES
Obs.	18,129	18,129	18,129
Adj. R^2	0.8711	0.8818	0.8818
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 2.11: Implication Test: Market Valuation

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

$$VALUE_{it} = \alpha_i + \beta. (Treat_i{*}Post_{t*}REG) + \Upsilon. \boldsymbol{X}_{it} + \delta i + \lambda_t + \varepsilon_{it}$$

i and *t* indexes as firm and time (years). The dependent variable $VALUE_{it}$ *i*s the firm market valuation of firm *i* in year *t* proxied by *TobinsQ*. All the other variables reported in this table are 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 it is 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, Cash, RoA, R&D, Tang, Prisk_Tax, Prisk_Trade,* and *Prisk_Economic).* All the variables reported in this table are 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. I winsorise 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. I present all 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, column(3) includes additional firm-level controls, and (4) includes the country-level controls.

Variables	**Col.1**	**Col.2**	**Col.3**
Treati *Postt *REG	**0.0717***	**0.1155*****	**0.1021*****
	(0.0375)	**(0.0365)**	**(0.0358)**
Firm Covariates	YES	YES	YES
Country Covariates	YES	YES	YES
Obs.	18,085	18,082	18,082
Adj. R^2	0.7425	0.7579	0.7583
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

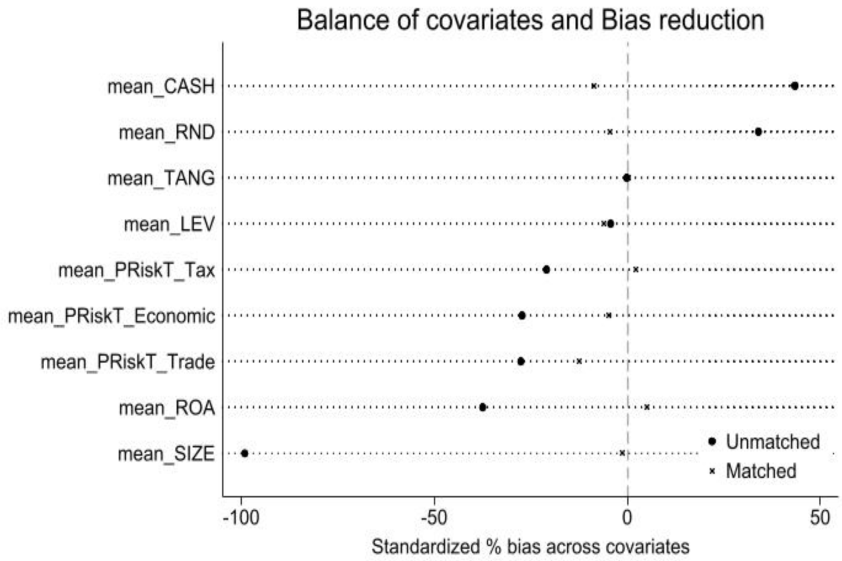

Figure 2.1 Bias Reduction

The figure shows the standardised percentage bias (SPB) measures of the variables *Size*, *Lev*, *RoA*, and *Tang* used in propensity score matching (PSM). I 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.

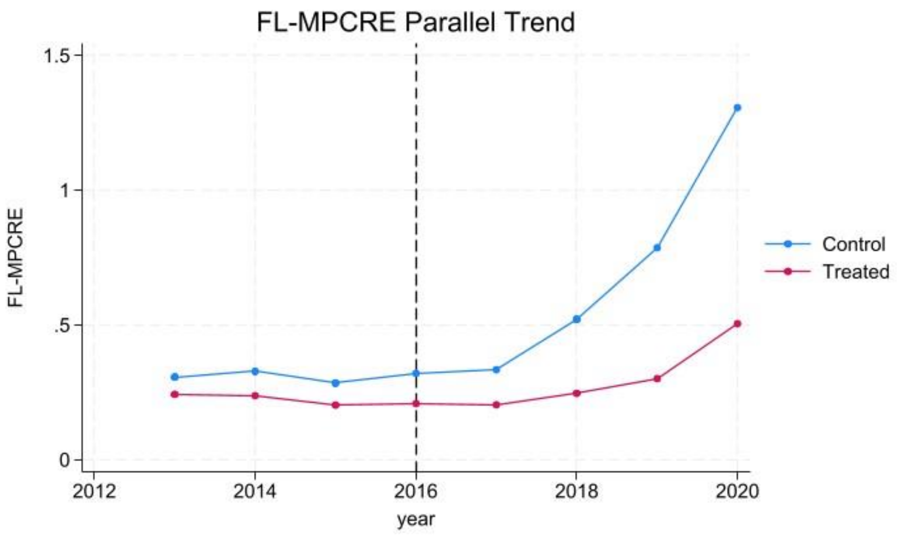

Figure 2.2 Parallel Trend of Yearly Average FL-MPCRE

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 A2.1 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 A2.3 of the Appendix.

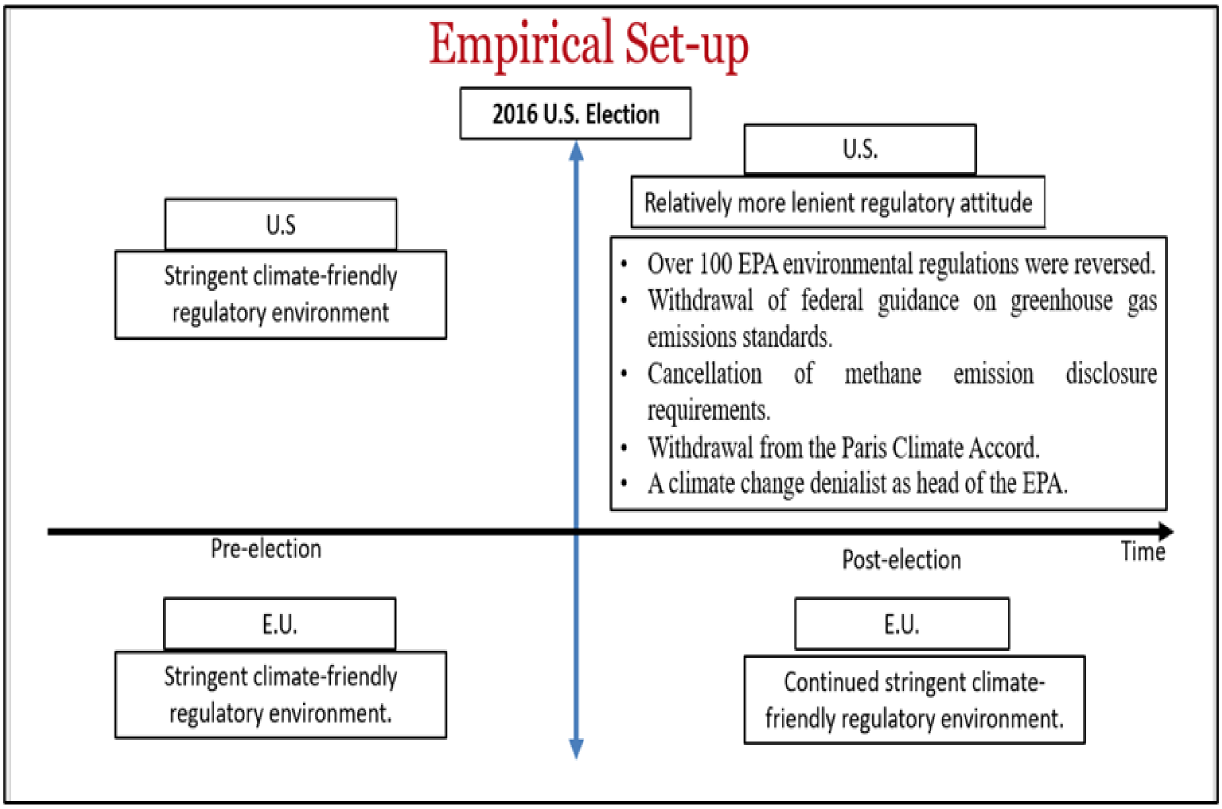

Figure 2.3: Empirical Setup

The figure shows the empirical setup used in this study.

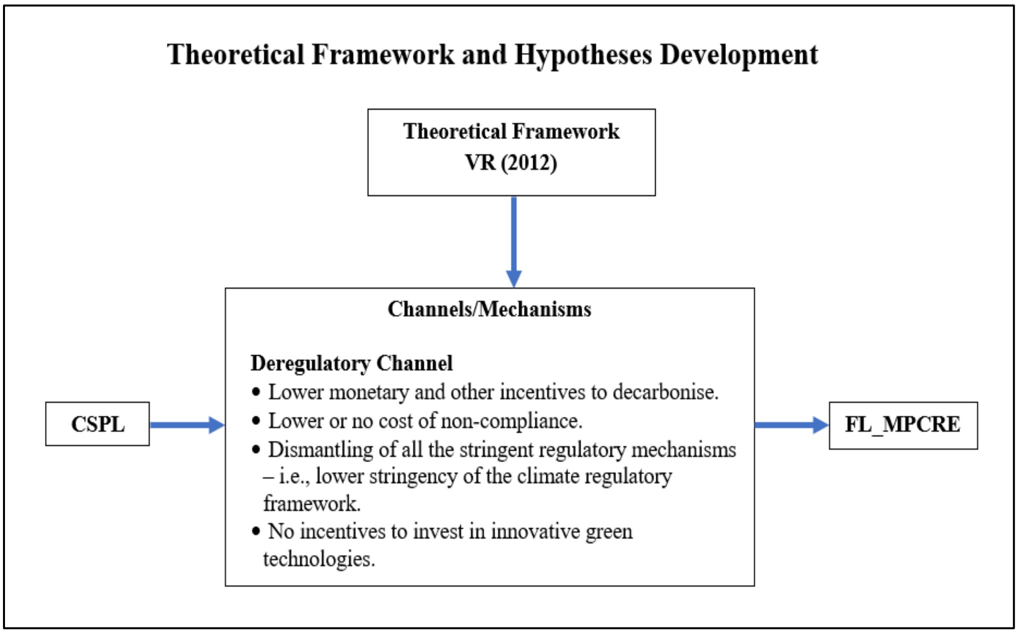

Figure 2.4: Theoretical Framework and Hypothesis

The figure shows the economic channels through which CPL influences FL_MPCRE.

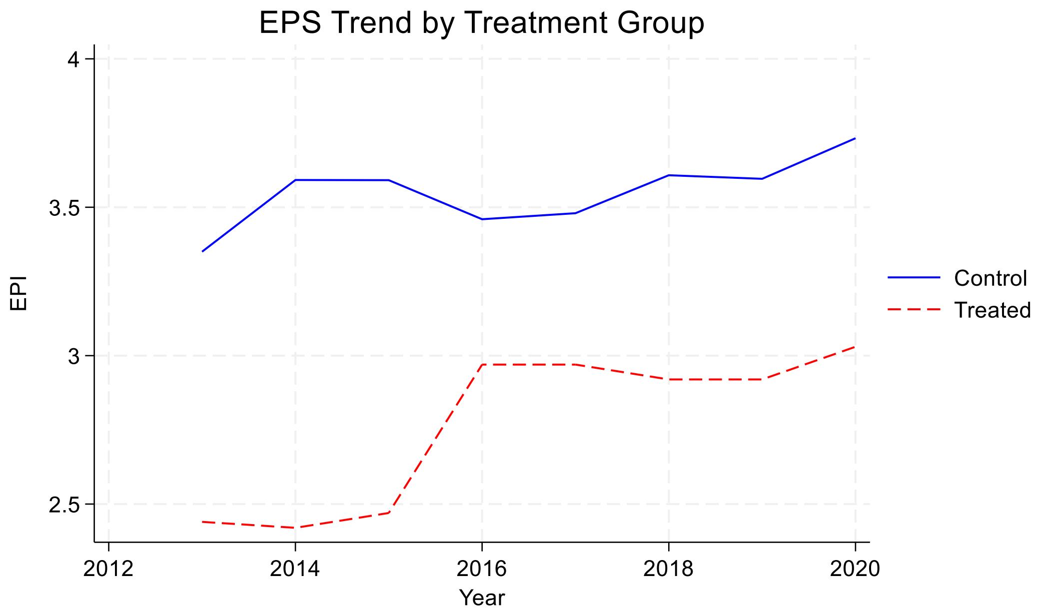

Figure 2.5:Country-level EPS Plots

This figure displays a graph of the yearly mean value of the country-level Environmental Policy Stringency Index (EPS) score for the sample period, comparing the treated group (the United States) with the control group (16 European Countries). The control group of 16 European countries is in Table A2.3 of the Appendix.

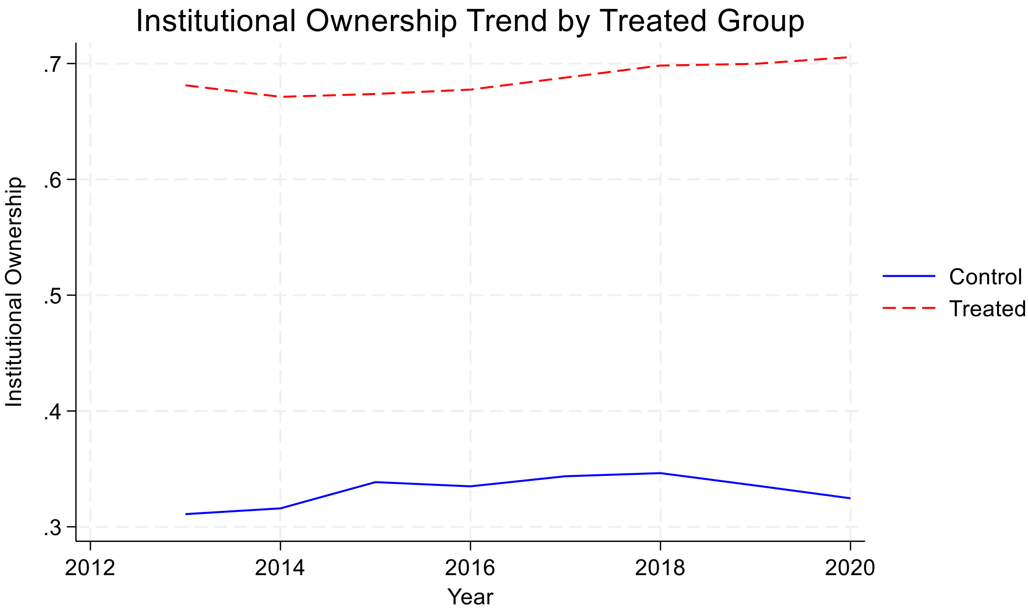

Figure 2.6:Institutional Investors Ownership Trend Plots
This figure displays institutional investor ownership between the treated group (the United States) and the control group (16 European Countries). The control group of 16 European countries is in Table A2.3 of the Appendix.

Chapter 3 Race to the Bottom: Effect of Climate Political Leadership on Corporate Green Innovation.

Abstract: I document the causal effect of climate political leadership on corporate green innovation. Exploiting a quasi-natural experimental setup that leads to an unexpected but adverse shock to supportive climate political leadership, I show that the emergence of a climate-sceptic political leader impedes corporate green innovation. I document the climate deregulatory channel as an economic mechanism for the result. Moreover, the headwind effects are notably stronger for firms in energy-intensive industries, financially constrained firms and those with higher institutional investors and analyst coverage.

JEL Classifications: *Q34*, *G38*, *Q55*

Keywords: *climate-political leadership, climate sceptic political leadership, corporate green innovation, climate deregulation.*

3.1 Introduction

"It is horrifying to see politicians sacrifice the lives of future generations just to protect the profits of the car industry or, I could not help suspecting at times, for their financial advantage. I hope that perspective helps explain why our action on the most dangerous crisis we have ever threatened as a species has been shockingly slow." (Molly Scott Cato (2022), Sustainable Finance: Using the Power of Money to Change the World, 2022, page ix)

Europe stands "ready to lead the fight" for global emissions reductions even if Donald Trump undercuts the bloc's efforts to tackle the issue………… Europe is "clearly ready to continue the global leadership on the fight against climate change"(Maros Sefcovic, European Commission's energy VP, FT February 1, 2017)

Climate change is associated with significant risk to the sustainable performance of firms, institutional investors' portfolios, and the real economy (Benlemlih et al., 2022; Currie et al., 2014; Garel & Petit-Romec, 2021; Giglio et al., 2021; Ilhan, Sautner, Vilkov, et al., 2021; IPCC, 2014; Krueger, Sautner, Starks, et al., 2020; Ramadorai & Zeni, 2021; Stroebel & Wurgler, 2021b). Not only are investors[24] expressing concerns about the costs associated with corporate climate risk exposure, like climate-related litigation, regulatory penalties, reputational damage, and the loss of shareholder wealth (Karpoff et al., 2005; Liu, 2020), but they also demand more green innovation as a risk management strategy(Berrone, Fosfuri, Gelabert, & Gomez-Mejia, 2013; Garel & Petit-Romec, 2021; Ramelli, Wagner, Zeckhauser, Ziegler, et al., 2021; Wagner, 2015)

[24] Larry Frink, CEO and Chairman of the world's largest asset manager, Blackrock, **notes**, "*Getting to net zero carbon emissions by 2050 is going to require a revolution in the production of everything we produce and a revolution in everything we consume. The process of creating fuel, food and construction materials, with all the needs that we have as humanity, it all has to be reinvented,*" "*And that's going to require a large amount of investment, a large amount of ingenuity and a large amount of innovation*." He further says, "*I believe that the next 1,000 unicorns — companies that have a market valuation over a billion dollars — won't be a search engine, won't be a media company, they'll be businesses developing green hydrogen, green agriculture, green steel and green cement*," (Source: **Middle East Green Initiative Summit in Riyadh, Saudi Arabia**, 25 October 2021, **https://www.cnbc.com/2021/10/25/blackrock-ceo-larry-fink-next-1000-unicorns-will-be-in-climate-tech.html**, accessed 26 April 2023, 08.11 BST).

Corporate Green Innovation[25] (CGI, thereafter) is a climate mitigation and adaptation strategy that involves designing low-carbon technologies and innovative climate-friendly products and processes that mitigate the negative externalities of climate change(Cheng et al., 2024; Rennings 2000; Schiederig et al., 2012). In addition, innovative green technologies may retrofit existing assets to extend their lifetime, lower their carbon footprint, and minimise transition risk(Acemoglu et al., 2016; Jagarajan et al., 2017; Takalo & Tooranloo, 2021). Besides directly contributing to mitigating and managing the planet's ever-urgent environmental and climate risks, identifying the factors driving CGI strategies is vital for firms' financial sustainability.[26]

There has been an expanding body of literature on the determinants of CGI(Aghion et al., 2016; Amore & Bennedsen, 2016; Bennedsen, 2015; Berrone, Fosfuri, Gelabert, & Gomez-Mejia, 2013; Chen, 2008). Ley et al. (2016) document the impact of energy prices on CGI, while Bennedsen (2015) uses the enactment of anti-takeover laws in the US to document the role of corporate governance in CGI. While the literature focuses on the impact of climate regulation and policy instruments on innovation, I depart from these studies and focus on how a shock to supportive climate political leadership (SCPL) influences corporate green innovation at the national level[27].

[25] The importance of various forms of green innovation is often referred to as eco-innovation in prior management literature. We assume the usage of both words as synonyms in literature See Xie et al., 2019; Rennings., 2000; Rennings and Zwick,2002; Chen, 2007; Carrión-Flores & Innes, 2010; Abdullah et al., 2015; Berrone et al., 2013; Albort-Morant et al., 2016; Rennings et al.,2016 ; Kim et al., 2021). Furthermore, see Takalo & Tooranloo, 2021, for an extensive literature review on Gereen Innovation

[26] To explore more details on the factors driving green innovation, see (del Río González, 2009; Horbach, 2008; Horbach et al., 2012)

[27] Political leaders can influence the economic environment through moral disposition, climate beliefs on anthropogenic causes of climate change, support for climate-related litigations, open rhetorics,

Climate political leadership is the perspective and belief held by the highest-ranking political figures regarding the credibility of climate change science, policies implemented, attitudes towards fundamental principles, trust, adherence to norms about climate change matters, and the measures undertaken by these leaders to mitigate the risks associated with climate and environmental changes. The literature suggests that leadership can use power and associated resources to implement actions that create incentives, costs, and benefits that can influence the behaviour of economic agents(Parker and Karlsson, 2014; Parker et al., 2017).

Given the foundational role of CPL in climate governance (Petri & Biedenkopf, 2020), supportive CPL addresses the existential threat of climate change through pro-climate policy formulation, implementation, and coordination of climate-focused activities, including supporting pro-climate-related litigation cases[28], formulation of climate mitigation framework, supporting institutional framework to advance climate mitigation, providing incentives for research and development, positively projecting environmental values, and urging public support for transition to low carbon economy via positive communication and persuasion(Gilligan & Vandenbergh, 2020; Thapa & Hillier, 2022; Zawadzki et al., 2020). What happens to the CGI in response to a sudden adverse shock to the Supportive CPL?

This study attempts to answer this question by exploiting the 2016 U.S. Presidential elections as a source of exogenous shock to the supportive CPL. A better

climate policies and other climate action initiatives, including enforcement, climate action coordination, and creating incentives to encourage

[28]A recent example of climate political leadership is the Supreme Court verdict supporting the Biden administration's argument that all major oil companies face litigation at the state level instead of at the federal level contradicts Trump's administration position.
https://www.theguardian.com/environment/2023/apr/25/experts-hail-decision-us-climate-lawsuits-advance, assessed April 30th, 2023, 12.15 GMT.

understanding of a firm’s green innovation activities and connection to regulatory settings under an exogenous shock to supportive CPL will aid informed decisions in climate-mitigation discussions. Neoclassical Economics argues that stringent regulatory intervention is to correct the failure of market mechanisms to ensure firms internalise the full social cost of pollution (Ambec & Ehlers, 2016; Besley & Persson, 2023; Gray & Shadbegian, 1998). Despite the increasing attention paid to climate regulation to mitigate climate change risks and the recognition of the significance of CGI as a mitigating and adapting strategy (Borghesi et al., 2015; Jiang et al., 2020; Veugelers, 2012), there is a lack of credible empirical evidence on the effects of the unexpected emergence of climate sceptic political leadership (CSPL) on CGI.

The literature suggests that Climate Political Leaders, through their regulatory policies, have the potential to significantly reduce carbon emissions and global atmospheric temperatures below the Paris Climate Accord target through appropriate incentives and implementing an optimal set of policies to facilitate a seamless transition toward a low-carbon economy(Acemoglu et al., 2016; Rennings & Rammer, 2011; Stern, 2008; Stolbova et al., 2018). Moreover, the Economic literature has long argued that, given that environmental technologies primarily benefit society rather than individual inventors or adopters, market forces offer minimal motivation for their development, making environmental regulations the primary incentive driver of innovation(Popp, 2010; Popp et al., 2009; Porter & Van der Linde, 1995; Porter & Linde, 1995).

Furthermore, Castellacci and Lie (2017) suggest that CGI requires supportive policies due to the double externality problem identified by Rennings (2000). Rennings et al. (2006) and Jaffe et al. (2005) suggest that CGI addresses two market failures: the positive externality in knowledge creation, justifying R&D and innovation policy support of supportive CPL(Castellacci & Lie, 2015), and the negative externality of pollution necessitates CPL's supportive environmental regulatory interventions, like environmental taxes(Aghion et al., 2016; Martinsson et al., 2024b).In addition, Popp (2006) and Popp (2010) argue that all private-sector-led green innovations suffer from market failure and that addressing innovative technical change requires understanding its key drivers. Thus, without supportive CPL environmental, taxes, subsidies and innovation policies to support innovative firms capturing a significant share of return from their innovation, incentives to innovative, superior environmental technologies for future applications diminish considerably (Ambec & Ehlers, 2016; Bai et al., 2021; Brown et al., 2022; Popp, 2010; Zhang et al., 2024).

In the absence of supportive climate political leaders' climate-friendly policies which generate optimal incentives to invest in CGI, firms may find it less economically viable to invest in CGI, which can slow down the transition process (Acemoglu et al., 2016; Jaffe et al., 2002; Popp et al., 2009). Moreover, economic theory suggests that climate deregulation can affect the dynamics of technology transitions by disincentivising investment in green innovation and altering the profitability and attractiveness of green technologies.(Besley & Persson, 2023; Popp, 2010).

Corporations face significant climate change-related transition risks, particularly when adapting to regulatory and policy changes with capital market implications (Semieniuk et al., 2020; Stroebel & Wurgler, 2021b). For instance, Lee Seltzer (2021) demonstrates how credit rating analysts include estimates of future climate regulation changes in their analyses of the impact of climate exposure on corporate default risk. Hsu et al. (2015) and Safiullah et al. (2024) show corporate innovation lowers corporate default risk. Hence, CGI could demonstrate a firm's commitment to tackling the existential threat of climate risk, mitigating future stringent climate regulatory changes (Benlemlih et al., 2022), and improving the firm's credit risk profile(Hsu et al., 2015; Safiullah et al., 2024). However, incentives to engage in environment-related innovations are multifaceted and intricate, contingent upon economic benefits, peer-firm compliance with laws and regulations, potential access to new markets, market appreciation of reputational green capital, and product market competition(Chen, 2008; Henriques & Sadorsky, 1996; Kim et al., 2021b; Popp, 2010).

This study focuses on the role of unexpected shocks to responsible climate political leadership and the resulting deregulatory policies on the direction and magnitude of green technological innovation quantified by green patent filling. This study refers to the 2016 U.S. Presidential post-election period as a shock to the CPL. Current literature argues that this period signals a rollback of the previous administration's pro-climate regulations[29], inducing uncertainty around the future climate regulatory environment and a period of radical regulatory decay(Bomberg, 2021; Glicksman, 2017; Ramelli, Wagner, Zeckhauser, Ziegler, et al., 2021; Wagner

[29] According to the NY Times, the Environmental Protection Agency(EPA) has implemented changes to regulations previously established during the Obama administration. These changes include the relaxation of limitations on carbon dioxide emissions from power plants and vehicles, the elimination of protections for over 50% of wetlands across the United States, and the retraction of legal justifications for restricting mercury emissions from power plants. Concurrently, the Department of the Interior made efforts to increase land accessibility for oil and gas leasing by implementing restrictions on wildlife conservation measures and easing environmental requirements for ventures. The Department of Energy also relaxed efficiency standards for a wide range of products. Source; https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html. assessed April 30th, 2023, 12.15 GMT.

et al., 2018). For example, the Trump (45)[30] administration made landmark changes in EPA[31] rules and emission reporting standards, and the possibility of withdrawing from the Paris Climate Agreement could discourage climate-friendly corporate behaviour (Ilhan, Sautner, Vilkov, et al., 2021) and negatively impact environmental enforcement[32]

Transitioning towards a low-carbon economy is intricately linked to political processes and political actors' policy decisions (Besley & Persson, 2023; Dolšak & Prakash, 2018; Hsu, 2013; Wurzel et al., 2021a). The literature suggests that government policies significantly change corporate attitudes toward green behaviour by generating incentives that alter a firm's operational environment (Gulen and Ion, 2016; Buchanan et al., 2017; Cao et al., 2019; Matousek et al., 2020). However, government policies are subject to the beliefs and ideological disposition of the political leader in power. Therefore, I argue that an exogenous shift in supportive CPL influences CGI.

When supportive CPL pursues stringent carbon regulations, it should positively influence the perceived benefits of investing in green technology. In this case, the cost of not investing or underinvesting would be higher, encouraging investment in green innovation. Similarly, providing subsidies for green investment can lower corporate

[30] This refers to the first election of President Donald Trump in 2016. Given that he has won another election as at the time of writing this thesis, the second presidency is referred to as Trump(47)

[31] EPA refer to the U.S. Environmental Protection Agency. It is the authority tasked with enforcing environmental-related policies and government legislation, monitoring the externalities of firms' pollution, and providing guidelines on environmental-related issues in the United States. See https://www.epa.gov/aboutepa/our-mission-and-what-we-do for further details. Summary of changes to EPA rules and other deregulatory policies of President Trump(45) administration can be found here: https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html

[32] For example, Knickmeyer (2019) reports a 30-year low in the rate of criminal pursuit of polluters by the EPA under the Trump presidency. https://www.inquirer.com/wires/ap/epa-pollution-cases-sent-prosecutors-hits-year-low-20190115.html
Assessed July 15th, 2023

capital costs and shift firms' investment preferences towards CGI(Bai et al., 2021; Popp, 2006; Zhang et al., 2024). Therefore, the threat of stringent climate regulations coupled with state incentives should encourage green innovation.[33]

On the other hand, when CPL policy preferences actively promote environmental deregulation, firms would be reluctant to internalise environmental abatement costs and rationally underinvest since mitigating climate change transfers the cost borne by society to the firm through the internalisation of carbon costs (Ambec & Ehlers, 2016; Brown et al., 2022; Popp, 2010; Popp et al., 2009). Ramelli et al. (2021) show that the capital market rewards firms are likely to benefit from climate-deregulatory policies (high-polluting firms) with a higher market value than cleaner firms following Trump's 2016 election. Economic intuition suggests that a firm's investment incentive is linked to the financial market valuation feedback mechanism, suggesting underinvesting in CGI under CPL, which promotes deregulatory climate policies.

Furthermore, using several economic theories-Race to the Bottom, Dynamic complementarity, Signalling, and Utility maximisation framework, I develop and test the corporate *climate irresponsibility hypothesis* within the setting of an exogenous shift in CPL prompted by climate-sceptic leader Donald Trump's(45) unexpected election win to support the argument that climate-sceptical political leadership negatively affects corporate investment in green innovation. First, the Race

[33] For example, the recently passed Inflation Reduction Act of the Biden Administration provides subsidies for green investments such as climate pollution reduction grants of $5 Billion, the methane emissions reduction Program of $1.55 Billion, implemented through numerous mechanisms including grants and loans, contracts, rebates, and technical assistance. Further, the American Innovation and Manufacturing (AIM) Act Implementation of $38.5 Million will be administered via compliance. competitive grants, and monitoring. Renewable Fuels Standards (RFS) Program of $15 Million is being administered through further investment in biofuels to support renewable energy generation. See https://www.epa.gov/inflation-reduction-act/tackling-climate-pollution for more details on all the programmes.

to the bottom theory argues that firms actively trade climate responsibility activities for other profitable investments in a deregulatory environment.

Second, the Dynamic complementarity theory (Besley & Persson, 2023) suggests that climate sceptic political leaders' climate actions negatively impact CGI by disrupting the alignment between corporate incentives, climate policies, and green values. Further, Wilson (1996) suggests that suboptimal regulatory standards waste resources and distort the economy's prudent and efficient resource allocation. Therefore, I characterise climate sceptic political leaders through their deregulatory policies as suboptimal and a form of political and institutional failure in addressing climate change risks. Consequently, climate deregulatory policies compound the future economic cost of climate mitigation and adaptation, , complicating the transition process and passing the social cost to society (Porter, 1999; Wentz, 2017). Hence, a combination of existing market failure in producing green innovative technology and political and institutional failure provides a compelling argument for investigating the impact of climate sceptic political leadership on CGI.

In addition, the signalling argument suggests that climate-sceptic political leaders' beliefs, rhetoric, and disposition signal the expected level of future regulatory stringency. Therefore, climate-sceptic political leader's deregulatory policy conveys a lower future regulatory environment that substantially diminishes the incentive for firms to engage in CGI. Furthermore, the literature suggests that firms may choose green or brown investment options under conditions of uncertainty(Kemp-Benedict, 2014, 2018). I employ firms' environmental decision-making within a utility-maximization framework grounded in net present value (NPV) principles and a discrete choice framework. This framework suggests that to optimise environmental strategies; firms actively trade off the value of CGI against the present value of anticipated consequences of environmental liabilities, like enforcement penalties, regulatory penalties, and reputational damage.

For a given level of production output, firms incur a fixed amount of environmental externality borne by society in the absence of regulation(Ambec & Ehlers, 2016; Brown et al., 2022; Henriques & Sadorsky, 1996). However, firms invest in abatement efforts in a stringent regulatory environment, reducing pollution emission intensity and other environmental externalities (Ambec & Ehlers, 2016; Brown et al., 2022; Gollop & Roberts, 1983). Therefore, in this framework, firms determine their optimal abatement expenditure by equating the marginal cost of abatement with the marginal reduction in expected environmental liabilities(Shapira & Zingales, 2017; Xu & Kim, 2022).

The equilibrium framework ensures that firms allocate resources efficiently to minimise environmental risks, like investments in green innovation while maximising stakeholder value. Therefore, supportive CPLs that formulate carbon restriction policies like Pigouvian taxes raise future environmental liability costs for polluting firms and incentivise firms to change their behaviour towards increasing green innovation to mitigate the risk of future environmental liabilities(Acemoglu et al., 2016; Aghion et al., 2016; Brown et al., 2022; Calel & Dechezleprêtre, 2016).

Furthermore, supportive CPL may pursue policies that lower the investment cost of CGI through subsidies, direct investment, and the deployment of infrastructure supporting CGI(Bai et al., 2021; Brown et al., 2022; Van Oijstaeijen et al., 2022). Green subsidies alongside Pigouvian carbon taxes shift firms' production equilibrium from brown to green production, mitigating the impact of climate change and increasing the future welfare of the next generation (Bai et al., 2021; Besley & Persson, 2023; Popp, 2006).In contrast, climate-sceptic CPL pursues deregulatory policies that lower climate compliance and legal liabilities, reducing the utility of firms' CGI relative to other non-green alternatives.

I test the *corporate climate irresponsibility* hypothesis within a quasi-natural experimental setup using the propensity score-matched difference-in-differences (PSM-DiD) technique. I follow prior literature in exploiting the 2016 U.S. presidential election as a source of an exogenous shock to CPL (Child et al., 2021; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021). I employ several patent measures as a proxy for CGI, drawing on the literature on innovation[34] . The treatment group consists of non-financial firms domiciled and listed in the United States. I also use the PSM approach to identify statistically similar European firms that were not subject to the shock. I conduct a parallel trend test to confirm the suitability of the empirical methodology. My investigation reports the following outcomes.

I show that exogenous shock to responsible CPL leads to lower green innovation. In economic terms and within our sample, I find that in the post-2016 CPL shock period, there is a considerable differential decline of 2.53% in the green patent count and 6.5% in green patent citations in treated firms relative to the control group firms in the post-shock period. This baseline result is statistically and economically significant across all green innovation measures and persists after accounting for all known cofounders and across multiple regression specifications. Furthermore, the results are robust to several other tests, including using alternative measures of the CGI, entropy balance technique, Poisson regression technique, altered measures of

[34] See Hall et al., 2000; He & Tian., 2013; Aghion et al., 2013; Hsu et al., 2015.

CGI and placebo tests. These empirical results support the corporate climate irresponsibility hypothesis, indicating that an adverse shock to supportive CPL dampens CGI investment.

I delve into the economic mechanism for this result by testing the climate deregulatory channel. Using the country-level climate regulatory stringency index from GermanWatch, which provides time-varying data on national stringency of climate policy, I find that a decrease in the stringency of climate regulation in the treated group significantly reduces the intensity of green innovation in the treated group compared to the control group in the post-shock period, supporting the climate deregulatory channel. The result is consistent with the notion that firms will only internalise the cost of pollution when mandated through stringent climate regulation by political leadership(Acemoglu et al., 2016; Besley & Persson, 2023; Brown et al., 2022)

I undertake three cross-sectional heterogeneity tests. First, I explore whether financial constraint's role is in the established link between climate sceptic political leadership and CGI. Environmental mitigation and abatement technical change require significant capital resources with associated long-term returns (Dang et al., 2022; Xu & Kim, 2022; Xu et al., 2022). Hence, I expect financially constrained firms under lax climate regulation to reduce CGI due to the lack of mandated incentives to pressure the reallocation of capital to CGI. Consistent with theoretical prediction, financially constrained firms experience significant differential declines in green patent filling and citations. This result is consistent with prior literature that shows that financial constraints significantly influence corporate environmental policies (Dang et al., 2022; Xu & Kim, 2022)

I explore whether energy intensity moderates the link between climate sceptic political leadership and underinvestment in corporate green innovation. Consistent with theoretical conjecture, I find that firms in energy-intensive industries experience stronger differential declines in green patent filling and patent count, respectively, consistent with the notion that firms in the energy-intensive industries benefit more from lax climate regulation due to associated high costs under stricter climate regulation. Hence, in the absence of supportive CPL climate actions, firms would be unwilling to internalise the cost of their pollution through CGI investment (Acemoglu et al., 2016; Ambec & Ehlers, 2016; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021)

This study contributes to several strands of literature. First, it expands a stream of literature on the determinants of corporate environmental policies, specifically corporate green innovation(Amore & Bennedsen, 2016; Bennedsen, 2015; Chen, 2007; Kim et al., 2021a; Ley et al., 2016; Lin et al., 2024). Several studies document the effect of drivers of green innovation, like corporate governance structure (Aggarwal & Dow, 2012; Kock et al., 2012; O'Connor & Rafferty, 2012), Analyst coverage(Fiorillo et al., 2022; Guo et al., 2019), energy prices (Ley et al., 2016), asset redeployability (Do, 2024), institutional investors (Jiang & Yuan, 2018; Sakaki & Jory, 2019; von Schickfus, 2021; Xu et al., 2023), stringent regulatory drivers(Ambec et al., 2013; Brown et al., 2022; Fabrizi et al., 2018; Lin et al., 2024; Ren et al., 2022; Xing & Kolstad, 2002), national culture. Xing and Kolstad (2002) investigate the role of lax environmental regulation in the host country as a determinant of US firms' foreign direct investment. Kim et al. (2021a) show that firms with higher sales in foreign markets that enforce stricter environmental regulations encourage multinational corporations to increase their green patent filings. However, the literature has not yet documented the role of climate sceptic political leadership in corporate environmental policies like CGI. I contribute to this literature by documenting the impact of the emergence of climate sceptic political leadership that introduces climate deregulatory policies on the magnitude and direction of CGI.

Second, more specifically, I expand the literature on modelling macroeconomic consequences of climate political leadership and their consequential climate policies on the economy. Given that, in the absence of supportive regulation by CPL, firms are unwilling to internalise the cost of pollution and are borne by society(Acemoglu et al., 2016; Ambec et al., 2013; Brown et al., 2018, 2022; Calel & Dechezleprêtre, 2016; Greenstone et al., 2012; Ley et al., 2016; Rennings & Rammer, 2011; Ryan, 2012). Aghion et al. (2016) and Brown et al. (2022) show that environmental regulation induces technical change, increasing firms' transition towards generating low-carbon green patents. I distinguish my study from the literature in this direction by investigating the effect of climate sceptic political leadership, which introduces climate deregulatory policies on the direction of CGI.

Third, this study contributes to the literature investigating the effect of climate policies on firms (Johnstone et al., 2010; Nguyen et al., 2022; Ramadorai & Zeni, 2021; Seltzer et al., 2022). Prior literature documents that climate regulation has a heterogeneous effect on firms(Kim et al., 2021a; Ouyang et al., 2020). Bartram et al. (2022) document the impact of the California cap-and-trade initiative on the financial constraint, Brown et al. (2022) show that pollution taxes increase firms' utility for increasing environmental abatement expenditure, Dang et al. (2023) show that firms adopted a more conservative capital structure after introducing the Nitrogen Oxides (NOx) Budget Trading Program (NBP) of 2004 in the U.S. Dang et al. (2024) show that climate regulation reduces a firm's access to credit. Martinsson et al. (2024b) document the effect of carbon tax regulation on carbon emission reduction. I contribute to this strand of the literature by documenting the emergence of climate sceptic leadership's deregulatory policies and firms' underinvestment in corporate green innovation, which has a more substantial effect on financially constrained firms and firms in energy-intensive industries.

I organise the rest of the paper as follows: Section 2 discusses the relevant literature that leads to the formulation of the central hypothesis. Section 3 describes the dataset, summary statistics and empirical strategy. Section 4 reports and discusses the empirical results, and Section 5 concludes the study.

3.2 Relevant Literature and Hypotheses Development

In this section, I discuss relevant political leadership and CGI literature and develop hypotheses grounded in race-to-the-bottom theory, dynamic complementarity theory, signalling theory, and Utility maximisation framework. These theoretical frameworks explain how climate-sceptic political leadership (CPL) influences corporate green innovation (CGI) investments.

3.2.1 Climate Political Leadership and Green Innovation

3.2.1.1 Review of Literature

Political science literature suggests that Political leadership involves leveraging power and resources to implement policies that shape the incentives, costs, and benefits influencing economic agents' behaviours(Parker & Karlsson, 2014; Parker et al., 2017). Studies note that climate change, with its socioeconomic and geopolitical consequences, represents one of the political leaders' most pressing global policy challenges (Dolšak & Prakash, 2018; Stern, 2007). Therefore, Political Leadership is critical in addressing complex collective action problems like climate change (Thapa & Hillier, 2022; Wurzel et al., 2017; Young, 1991).

The leadership literature suggests that the policy preferences of political leaders directly impact corporate behaviour (Ahlquist & Levi, 2011; Harrison & Sundstrom, 2010; Wurzel & Connelly, 2011). While CPL's global and transnational aspects are well-documented, the research underscores its significance at the national level in shaping climate policies and enforcement.(Christmann, 2004; Wurzel et al., 2021b). Given that domestic government climate regulatory policies design aims to influence corporate environmental behaviour (Christmann, 2004; Henriques & Sadorsky, 1996), the intensity of the CPL's climate regulatory push will significantly impact corporate incentives to address climate change through CGI investments.

Empirical studies demonstrate the effects of political leadership ideology on national policy preferences (Blyth et al., 2007; Pastor & Veronesi, 2012). Gulen and Ion (2016) document the impact of political leadership decisions on the firm's operating environment, while Fowlie (2014) notes that the executive branch of the U.S. government substantially impacts U.S. climate policy. Unexpected shocks to supportive CPL often translate into weakened climate-related policies, like emission curbs or toxic waste disposal regulations, disposal permits, and drilling and mining permits[35]. Bomberg (2021) suggests that the Trump(45) administration's deregulatory

[35] For example, according to Bomberg (2021), the Trump administration initiated the process of revoking or climate deregulatory policies aimed at reducing emissions, safeguarding wildlife, prohibiting hazardous pesticides, and mitigating the pollution of water, land, and air. In contravention of the prevailing scientific consensus regarding the factors contributing to climate change, the Trump Administration authorised the exploration of previously untapped territories for the extraction of oil and gas resources while also granting permissions for the construction of contentious oil pipelines coupled.

approach significantly undermined the objectives of federal environmental agencies, thereby altering corporate incentives for CGI.

The literature suggests that market forces, like consumer and investor demand, pressure firms to act responsibly regarding climate issues (Dimson et al., 2015; Dyck et al., 2019; Ramelli, Wagner, Zeckhauser, Ziegler, et al., 2021). Nevertheless, stringent regulatory pressure is required to substantially influence CGI magnitude and direction (Popp, 2010; Rugman & Verbeke, 1998). Amber and Ehlers (2016) and Besley and Persson (2023) argue that a sufficiently high carbon tax(stringent regulation that raises the cost for polluting firms) on environmentally harmful activities (brown tax) can drive a green transition, even if there are few or no environmentally conscious consumers. Without such a carbon tax, a successful transition requires a critical mass of green consumers, implying that effective climate policy reduces reliance on consumer preferences for a sustainable transition(Besley & Persson, 2023). Owing to market failures, the literature argues that such regulatory intervention is necessary to generate sufficient incentives to encourage CGI(Johnstone et al., 2010; Popp, 2006, 2010; Popp et al., 2009).

When CPL creates a deregulatory environment, firms are more likely to engage in environmentally degrading activities due to the absence of constraining climate policies. For example, Xu et al. (2022) document an increase in toxic waste emissions by publicly listed US firms under climate deregulation and weaker enforcement. The Trump(45) Administration's aggressive deregulatory policies exemplify such

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Additionally, with a commitment to terminate the perceived antagonism towards coal, the Trump Administration endeavoured to dismantle the Clean Power Plan implemented by the Obama administration which was specifically formulated to establish regulations for controlling carbon emissions from power plants. (Bomberg, 2021) dynamics(Aldy, 2017; Bomberg, 2021), reinforcing the expectation that firms underinvest in greener technologies when regulatory incentives are weak.

One of the channels through which climate political leaders influence corporate environmental behaviour is altering the stringency of climate regulation. Climate regulation can induce environmental innovation, which can be costly and leads to higher production costs for both ends of pipes and cleaner production technologies (Acemoglu et al., 2016; Frondel et al., 2008; Popp et al., 2009; Rennings & Rammer, 2011).

Despite CGI's high cost, it contributes significantly to overall firm performance and enhances knowledge spillovers and clean technology adoption(Bennedsen, 2015). For example, it contributes significantly to overall innovation (Aghion et al., 2013), pollution abatement (Carrión-Flores & Innes, 2010), higher efficiency (Abdullah et al., 2015), core competencies (Albort-Morant et al., 2016), and superior financial performance (Hao et al., 2022; Xie et al., 2019). Furthermore, it facilitates firms to meet the increasing demand for their products without endangering the environment(Albort-Morant et al., 2016; Takalo & Tooranloo, 2021). Albort-Morant et al. (2016) further argue that investment in green innovation provides economic incentives for generating environmentally sustainable products and boosts competitiveness.

CGI also significantly alleviates environmental burdens (e.g., greenhouse gas emissions) through pollution abatement and modernising the economy(Rennings 2000; Rennings & Rammer, 2011). Furthermore, CGI can alleviate the associated costs of environmental regulation and enhance corporate brand equity and consumer perceptions of greenness (Chen, 2010; Rennings 2000). It can enhance financial performance through increased sales and margins from new green product development, especially among environmentally conscious clients and new market entries (Cheng et al., 2014; Hao et al., 2022; Xie et al., 2019). The existing research indicates that green patenting enhances a firm's value and competitive position(Chen, 2008; Kim et al., 2021a; Porter & Van der Linde, 1995).In addition, CGI enhances green reputation, which benefits numerous firm stakeholders (Chen, 2007; Hart, 1995; Sharma & Vredenburg, 1998)

Henriques and Sadorsky (1996), Ilhan, Sautner, Vilkov, et al. (2021), and Brown et al. (2022) argue that regulatory actions are required to combat climate change and address its existential threat. Bennedsen (2015) examines US firms using the enactment of anti-takeover laws and shows that firms with poor corporate governance generate lower green patents. Kim et al. (2021b) document lower CGI activities among firms with high foreign sales in countries with weaker climate regulations by CPL.

3.2.1.2 Hypothesis Development: Climate Political Leadership and Green Innovation

I draw on three theoretical views to support my central hypothesis. First, the *Race to the bottom* theory[36] , also called the "*regulatory meltdown hypothesis*"(Charny, 1991; Warren III, 1990), posits that weakened climate regulations reduce firms' incentives

[36] The term "race to the bottom" emphasizes that environmental standards are reduced below the optimal level rather than literally falling to the lowest possible level. First received legal attention in the 1933 Supreme Court judgement Liggett vs Lee. In his opinion, Judge Louise Brandeis claimed that corporations are encouraged to undercut each other and governments to deregulate to seek a competitive advantage. It is a philosophy in environmental politics that helps governments thrive economically but harms their environment. It has since been widely applied in Economic, Tax, Trade, Environmental Economics and Finance literature on the consequences of government deregulatory policies and corporate competition. See Chan, 2003; Olney, 2013; Abbas, S. A., & Klemm, A., 2013.

for CGI, leading to increased environmental degradation (Chan, 2003; Olney, 2013; Abbas & Klemm, 2013).

Multiple factors often constrain CGI, especially the allocation of resources to corporate climate-responsible activities subject to firms’ utility maximisation. Mohr (2002) suggests that innovation is endogenous, and firms rationally underinvest without stringent external regulatory pressure. I argue that the push for stringent climate regulation depends on Climate Political leaders' climate beliefs and ideological disposition regarding the anthropogenic cause of climate change science. Therefore, climate political leadership's beliefs in climate science drive the stringency of Climate regulation, which influences corporate behaviour (Christmann, 2004; Johnstone et al., 2010; Popp et al., 2009)

Empirical evidence supports this view, indicating that stringent climate policies by Political leaders impose future liabilities on polluting firms through legal and reputational penalties (Bhagat et al., 1998; Karpoff et al., 2005; Liu, 2020).In contrast, political leader’s deregulatory policies often justify reductions in compliance costs necessary for economic growth and industrial competitiveness (Madsen, 2009; Porter, 1999). Such policy preferences could negatively impact climate mitigation strategies, increasing environmental degradation.

Clark (1995) argues that lax or inadequately enforced environmental standards can be a form of economic subsidy provided to companies through reduced environmental compliance costs and mitigation strategies, like CGI. Applying the race-to-the-bottom theory links climate sceptic political leadership deregulatory policies to financial markets and corporate behaviour. Rugman and Verbeke (1998) note that firms typically respond to stringent climate regulation by adopting strategies like green innovation. However, political leaders’ deregulatory policies weaken incentives for proactive climate-mitigating activities, significantly reducing firms' engagement in green innovation. Therefore, if firms revise their beliefs following adverse shocks to CPL, the *race to the bottom* theory posits that they should underinvest in CGI. In the climate-sceptic political leadership regime, the possibility of more stringent climate regulatory pressure was comparatively lower among U.S. firms than their European counterparts[37].

Second, the Dynamic Complementarity Theory(Besley & Persson, 2023) posits that climate sceptic political leader’s deregulation disrupts the alignment between CGI, climate policies, and green values, negatively impacting CGI intensity. This view implies that climate policy decisions influence the market and provide value-based incentives for firms necessary for transitioning to sustainable practices. Climate deregulation undermines the alignment of policy, values, and market incentives, removing mechanisms that support green technology development (Besley & Persson, 2023).

In addition, climate sceptic leaders’ deregulation reduces the perceived value and urgency of transitioning to greener practices, misaligning incentives necessary for fostering innovation. This misalignment undermines the dynamic complementarity between climate policies, market incentives to invest in green innovation and corporate values, creating obstacles to a successful green transition (Besley & Persson, 2023). Furthermore, deregulation shifts societal and market values towards polluting

[37] According to the European Union’s Energy Chief, Europe stands “ready to lead the fight” for global emissions reductions even if Donald Trump undercuts the bloc’s efforts to tackle the issue. Europe is “clearly ready to continue the global leadership on the fight against climate change.”. Source Financial Times; https://www.ft.com/content/64e5388a-e70f-11e6-967b-c88452263daf. Assessed April 30th, 2023, 12.15 GMT.

technologies, creating a feedback loop where diminished regulatory support further weakens incentives for CGI.

Climate deregulation indicates political failure, exacerbating unaddressed market failures like underinvestment in CGI. The absence of stable climate policies weakens market signals and policy commitments, disrupting the equilibrium of green values and technological change, consequently undermining long-term incentives for CGI(Besley & Persson, 2023; Brown et al., 2022; Jaffe & Stavins, 1995). Consequently, it constrains the dynamic complementarity needed to address the climate crisis.(Besley & Persson, 2023).Without consistent, supportive, long-term political leadership policy commitment, the alignment between market, technological, and societal forces would dislocate, hindering the transition to a greener economy and worsening the climate change crisis(Besley & Persson, 2023; Ramiah et al., 2013).

Third, stringent environmental policies typically signal the high costs associated with environmental externalities of firms(Botta & Koźluk, 2014; Haščič & Migotto, 2015). Therefore, I draw on the signalling theory(Spence, 1978, 2002), which suggests that CPL policy preferences signal the direction and strength of the future regulatory regime. Under climate-sceptic political leaders, firms will underinvest in CGI if regulatory incentives are weak. Therefore, signals from CPL through proposed policy changes can affect a company's investment decisions, diversification strategies, and business model adaptations. For example, studies suggest that policy uncertainty that emanates from external shocks may undercut investors' and firms' confidence in long-term climate mitigation and adaptation strategies(Fuss et al., 2009; Helm et al., 2003; Ilhan, Sautner, & Vilkov, 2021). Within this context, the signalling framework, as noted by Ramelli, Wagner, Zeckhauser, Ziegler, et al. (2021), implies that

Trump(45) decision to withdraw the U.S. from the Paris Climate Accord signals an era of climate deregulation and scepticism.

Fourth, firms always choose the investment option that maximises their utility(Kemp-Benedict, 2014; Xu & Kim, 2022). Their investment decisions are guided by utility maximisation(Boneva & Linton, 2017; de Palma et al., 2008; Van Oijstaeijen et al., 2022; Xu & Kim, 2022). Following Xu et al. (2022), I adopt a utility maximisation framework of optimal climate investment decisions to gain insight into the relationship between CSPL and CGI investment. The framework provides intuition on how firms incorporate the influence of risk, utility maximisation, and preferences in comprehending the decision-making processes involved in CGI under climate-sceptic political leadership. CGI involves significant risks, uncertain outcomes and high costs (Gray, 1987; Ren et al., 2022; Rennings 2000).

The idea is that supportive climate political leadership creates a climate mitigation-focused environment that increases the utility of firms in investing in environmental abatement and mitigating expenditures like CGI by raising the cost of pollution externalities. For example, Brown et al. (2022) show that introducing pollution taxes by supportive CPL increases the production costs for polluting firms using dirty technologies, which should generate financial incentives for them to invest in green innovation on the assumption that the stringency of climate regulation will continue upwards.

I use a simple economic intuition to explain the utility maximisation framework: the utility of choosing CGI (UCGI) compared with alternative investment options (UA_{lt}), like traditional or no investment, after accounting for relevant deterministic factors. The utility is a function of deterministic[38] components, characteristics like regulatory environment, financial constraint, and error terms. Under this framework[39], a firm will choose a CGI if its utility is greater than the alternative brown investment or no investment. Blundell (2020) argues that firms actively weigh the costs of installing pollution abatement devices against the anticipated costs of environmental regulations to determine the timing and feasibility of investing in clean technologies. Brown et al. (2022) show that pollution increases a firm's utility from environmental abatement expenditure. The absence of such regulatory pressures, like the institution of climate deregulatory policies, leads to lower utility in such climate mitigating expenditure, leading to underinvestment in green innovation.

Therefore, unexpected shocks to supportive climate policies, like deregulation or weakened enforcement, reduce the external regulatory pressure, incentivising firms to engage in CGI. Without stringent CPL, the expected cost of non-compliance or the benefit of a green reputation diminishes., further decreasing the relative utility of the CGI (U_{CGI}) compared with the alternative uses of resources (U_{Alt}). Managers are risk-averse and prefer a quiet life(Bertrand & Mullainathan, 2003). It implies managers may invest in safer, more familiar non-green options without external regulatory pressure rather than exploring innovative but riskier green innovations.

The expected benefits of CGI include an impact on market value, potential gains in production efficiency, lower default risk, alleviation of future environmental

[38] . A simple model of Utility maximization framework for the discussion is

$U_{CGI}=V_{CGI}+\varepsilon_{it}$ $U_{Alt}=V_{Alt}+\varepsilon_{it}$

Where U represents utility, V represents Value which are deterministic components of the model and ε is the error term

[39] It suggests a trade-off of CGI for economic benefit and the future cost of legal and climate regulatory liabilities within a wealth maximisation framework. The literature shows that climate-related litigation incurs significant financial costs and reputational damage to firms, coupled with significant erosion of shareholder wealth (Bhagat et al., 1998; Karpoff et al., 2005)

burden, access to government subsidies, and stakeholders' positive perceptions of green and reputational capital (Cohen et al., 2020; Kim et al., 2021a; Rugman & Verbeke, 1998; Safiullah et al., 2022; Vasileiou et al., 2022; Xie et al., 2019). However, suppose the relative costs like capital investments, alternative investments forgone, and the risks associated with research and development in green innovation activities are higher. In that case, the utility from green investment is comparatively lower than that of other investments, leading to underinvestment in corporate green innovation.

Consequently, if the market expects a future climate deregulatory environment by climate sceptic political leadership, it may diminish or lower the expected utility from green projects relative to other investments, coupled with a managerial preference for a quiet life(Bertrand & Mullainathan, 2003), the utility maximisation framework predicts a lower CGI under climate-sceptic political leadership.

Based on the above theoretical and empirical argument, adverse shocks to climate political leadership (CPL) reduce the perceived benefits relative to the costs, dislocating required dynamic complementarity critical to advancing transformation, prompting firms to underinvest in CGI. Deregulatory policies signal weaker future regulatory enforcement and diminishing incentives[40] for green innovation. Given the contrasting CPL regimes in the U.S. and Europe, firms operating under climate-sceptic regulatory environments will likely reduce CGI. Thus, we propose that an exogenous shock to supportive CPL (SCPL) significantly disincentivises CGI.

[40] One is implied subsidies from lax climate regulation and weak institutions responsible for climate enforcement. We should expect firms to exhibit less propensity to invest in green and environmentally friendly innovation activities.

H_1: An unexpected shock to supportive CPL dampens a firm's CGI investments.

In our experimental setup, this implies that the CGI levels of U.S. firms after the 2016 election should have been lower than those of their European counterparts in the post-shock period.

3.2.1.3 Hypothesis Development: Climate Deregulatory Channel

In the previous section, I argue that climate sceptic political leadership institutes deregulatory policies that disincentivise economic agents from pursuing investment in CGI. I formally propose the *Climate Deregulatory channel,"* for the relationship between climate sceptic political leadership and CGI strategy. The hypothesis proposes that lax environmental regulations diminish incentives for companies to adopt greener practices. Such deregulatory policies may result in higher corporate environmental misbehaviour. For example, Xu et al. (2022) document an increase in toxic waste emissions by publicly listed US firms under climate deregulation and weaker enforcement.

Since the Trump(45) presidency aggressively pursued deregulatory climate policies(Aldy, 2017; Bomberg, 2021), I conjecture that a weakened climate regulatory environment(deregulation) is the channel through which climate sceptic political leadership influences CGI investment, I hypothesise as follows:

H2: Climate deregulation mediates the relationship between adverse shocks to responsible climate political leadership and CGI strategy.

3.3 Data and Empirical Strategy

3.3.1 Data

I draw data from several sources. First, I obtained patent count and citation data from the European Patent Office (EPO)'s Worldwide Patent Statistical Database (PATSAT), which provides bibliographic patent information from over 100 patent offices. From this dataset and following the Organization for Economic Cooperation and Development (OECD's) International Patent Classification (IPC) guideline (Haščič & Migotto, 2015)[41], I identify "green patents" as those that are directly attributable to technologies associated with environmental management, water-related adaptation technologies, biodiversity protection, ecosystem health, climate change mitigation technologies related to energy generation, transmission, or distribution, transportation, buildings, waste-water treatment or waste management, and the production or processing of goods.

I obtain firm-level accounting and financial data on publicly traded firms from S&P's Compustat database (Dass et al., 2017). I obtain institutional investor ownership data and analyst coverage data from the Standards and Poor's Capital I.Q. database, similar to prior literature on institutional ownership (Marshall et al., 2022). Following the literature, I set the missing values for institutional investors to zero (Bena et al., 2017; Ferreira & Matos, 2008; Guan et al., 2021).

I apply standard filters and eliminate firms with negative or missing sales figures (see (Acharya & Xu, 2017). Second, following Bartram et al. (2022) and Mukherjee et al. (2017), I exclude firms with Standard Industry Classification (SIC) codes belonging to financial institutions (6000-6999) and utility firms (4900-4999. Third, I

[41] See the OECD patent website: https://www.oecd.org/env/indicators-modelling-outlooks/green-patents.htm

exclude companies without SIC codes and firms with missing control variables for any of the years. Fourth, I include only companies with a positive book equity value in our sample (Bennedsen, 2015). Furthermore, I exclude firms with negative returns on assets and firms with assets of less than ten million dollars. Finally, following Atanassov (2013) and Acharya and Xu (2017), I set missing patent values and Research and Development variables to zero if missing.

After merging the accounting and financial data from Compustat and the patent dataset from PATSTAT using S & P Capital company identification and applying the filters, the sample includes 31,740 firm-year observations for 5,161 unique firms between 2013 and 2020 from major stock exchanges in the United States and 15 developed European markets. Below, I briefly discuss all the variables used in this study.

3.3.1.1 Corporate Green Innovation

The primary dependent variable is the number of green patents filed by firm *i* in year *t* (green patent count) and eventually granted (granted patents) and the number of citations received. Studies overwhelmingly argue that patents and their associated citations are credible proxies for firm innovation (Bloom, 2002). I follow the literature in the field of corporate innovation[42] using the number of patents filed by firms in year *t* (patent count) and eventually granted to measure green innovation (Bena et al., 2017; Biggerstaff et al., 2019; Boubakri et al., 2021; David Hirshleifer, 2012).

The key explanatory variable in this analysis, green innovation, is from the World Patent Statistical Database (PATSTAT), maintained by the European Patent

[42] See Hall et al., 2005; Fang et al.,2014; Bena et al.,2017; Cumming et al.,2020a and Kim et al., 2021.

Office (EPO). PATSTAT, maintained by the European Patent Office (EPO), serves as the primary data source for patent-based innovation measures in this study. I measure Innovation using patent data from the World Patent Statistical Database (PATSTAT), maintained by the European Patent Office (EPO). PATSTAT provides comprehensive coverage of global patent filings from over 90 authorities, including USPTO, EPO, JPO, and WIPO, and widely recognised as a reliable source for innovation metrics (He & Qiu, 2025).

To isolate environmentally focused patents, I follow the OECD framework developed by Haščič and Migotto (2015), which classifies green technologies based on International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes. I refer to Haščič and Migotto (2015), who outline a detailed taxonomy for measuring environmental innovation using patent data . Their classification spans approximately 80 distinct technological domains relevant to environmental and climate-related policy priorities. A representative subset of these classifications can be found in Haščič and Migotto (2015). These codes allow for detailed categorisation of innovations aligned with four key environmental objectives: pollution mitigation, water resource management, ecosystem resilience, and climate change adaptation. This taxonomy spans approximately 80 distinct technological domains relevant to environmental policy.

Green patents are identified using algorithmic filters developed under this OECD framework, capturing both traditional environmental technologies (e.g., emission control, waste treatment) and emerging areas (e.g., biodiversity conservation). The analysis relies on patent application dates (rather than grant dates) to address truncation bias from time lags in patent processing (Bena et al., 2017;

Biggerstaff et al., 2019; Boubakri et al., 2021; David Hirshleifer, 2012).Because PATSTAT lacks standardised firm identifiers, I employ fuzzy matching based on legal names, locations, and ISO/IMF country codes to link patent assignees with firm-level data from S&P Capital. I supplement by manual verification to ensure matching accuracy. Furthermore, I construct alternative measures of adjusted green patents by scaling green patent counts and citations by total assets, allowing me to capture a firm's green patent activities relative to its size (Kim et al., 2021a; Mukherjee et al., 2017).

Next, I address salient issues often encountered in empirical studies that use patent data. The literature has two truncation challenges with using patent measures. (Boubakri et al., 2021). The first is the lag between the application-filling date in the patent registry and the grant date. The patent application grant date appears only when a patent is granted in the patent database. In exceptional cases, it may take an average of 18–24 months after filling and as long as three to four years. The second truncation issue arises when accounting for forward citations. The citation count continues after the sample period for a patent. To address truncation issues, I ended our sample in 2020 for approved patents to appear in the database.

3.3.1.2 Key Independent Variable

The key independent variable of interest is the interaction variable between the treatment dummy ($Treat_i$) and year dummy ($Post_t$); *that is*, ($Treat_i$*$Post_t$), known as the difference-in-differences (*DiD*) estimator, which captures the causal effect of CPL on CGI. $Treat_i$ is an indicator variable equal to one if firm i is in the treatment group and zero otherwise. The variable $Post_t$ equals one for the periods after the shock (i.e., post-2016) and zero otherwise.

3.3.1.3 Covariates for PSM

Following the existing literature, I include several covariates in the PSM techniques to create a statistically balanced treated and control group before the 2016 shock. For each firm *i* and year *t*, these covariates include firm size (Size) the natural logarithm of the asset's total book value, which is positively related to CGI. Large firms innovate more than smaller firms (Chang et al., 2015). Leverage (*Lev*) and the total book value of debt, scaled by the book value of total assets. *Lev* is negatively associated with firm innovation. (Hsu et al., 2014). *Cash* is the sum of cash holdings and cash equivalents scaled by total assets(Balsmeier et al., 2017; Kim et al., 2021a) I scale research and development expenses using the book value of assets*(R&D)* as input for innovation, which is positively related to innovation. (Tian & Wang, 2014). Firm profitability *(RoA*) is earnings before interest and tax scaled by the book value of assets, and tangibility (*Tang*) is tangible assets divided by the total book value of assets.

3.3.1.4 Time-varying country-level controls

In line with extant literature on corporate innovation, I also consider time-varying country-level macroeconomic and institutional quality. First, I employ the GDP growth rate of the country of domicile of firms to control for macroeconomic performance (Benlemlih et al., 2022). In addition, following Kim et al. (2021), I control for institutional quality using the country's Rule of law indicator obtained from the World Bank Governance Indicator[43] (WBGI). The rule of law, a measure of a nation's level of governance, is stated in standard normal units with a range of -2.5 to 2.5 with a zero mean and unit standard deviation. A higher value reflects a higher institutional quality. It demonstrates how confident economic agents are in the effectiveness of enforcement of property rights, contract enforcement, the legal system, and the likelihood of crimes and violent acts (Mundial et al., 2010).

3.3.2 Descriptive Statistics

Table 1 presents the summary statistics for all firm-level variables employed in our empirical analysis (see Appendix 3.1 for detailed variable definitions). The statistics are based on raw values, winsorised at the 1st and 99th percentiles to mitigate the influence of extreme outliers.

Regarding patent characteristics, the average firm in our sample generates 0.06 green-granted patents annually (Gp), with each green patent receiving an average of 0.36 citations per year(Gc). On average, firms report a book value of assets of $6.6 billion and maintain borrowing levels(Lev) equivalent to 23.2% of total assets. Cash holdings (Cash) average 14.5% of total assets, while profitability (RoA) is 12%. Firms allocate 2.2% of total assets to research and development (R&D) expenditure, and tangible assets(Tang) comprise 23% of total assets. In addition, firms attract an

[43] Source; http://info.worldbank.org/governance/wgi/. For detailed methodology, see Kaufmann, Daniel, Aart Kraay and Massimo Mastruzzi (2010). "The Worldwide Governance Indicators: Methodology and Analytical Issues". World Bank Policy Research Working Paper No. 5430

average of seven analysts (Analysts) following their activities, and institutional investors hold an average of 38.98% of firm equity. These statistics provide a comprehensive overview of the firms' key financial and operational characteristics included in our analysis.

(Insert Table 3.1)

In this section, I discuss the identification strategy, an empirical methodology I employ in investigating the relationship between exogenous shock to responsible climate political leadership and corporate green innovation. I discuss various pre-requisite tests validating my identification strategy and the procedures for addressing endogeneity in the analysis.

3.3.3 Empirical Methodology and Identification Strategy

In this sub-section, I discuss the identification strategy and the empirical methodology I employ in investigating the relationship between exogenous shock to responsible climate political leadership and corporate green innovation. I discuss various pre-requisite tests validating my identification strategy and the procedures for addressing endogeneity in the analysis.

3.3.3.1 Test of Mean differences in covariates.

First, I conduct a t-test of the mean difference of the covariates of firms within the treatment and control groups to establish differences in covariate characteristics that may bias our findings post-shock period. Table 3.2a reports the t-test for firm-level covariates in the pre-shock period(2013-2016). The results indicate a significant difference between the controls in the two groups at 1% significance, suggesting the need for covariates balancing using the matching technique. I justify the use of highly credible propensity score matching technique in line with prior empirical studies(Marshall et al., 2022; Roy et al., 2020)

3.3.3.2 Propensity Score Matched Randomization

As noted earlier, I exploit the outcome of the 2016 U.S. presidential election as a source of an exogenous shock to the CPL. However, since this adverse shock to supportive CPL affects all U.S. firms (treated group), I identify an estimate of the counterfactual: a control group of firms unaffected by the shock. I use European firms as a possible control group, similar to the method in prior literature (Benlemlih et al., 2022; Thapa & Hillier, 2022). However, I need to apply some form of balancing technique to generate statistically identical groups conditional on the factors (covariates) the literature identifies to explain variations in CGI.

Matching highly comparable firms in the treated and control groups is critical for reliable causal inferences to address the issue of selection bias (Rubin, 1997). Following the literature, I apply the propensity score matching (PSM) technique to generate a matched sample of highly comparable treated (U.S. firms) and control groups (European firms) based on observable characteristics (covariates) before the 2016 shock(Austin, 2011). Furthermore, using PSM in the difference-in-differences (PSM-DiD) framework ensures that time-varying factors have homogeneous effects on the treatment and control groups in the post-2016 climate regulation shock period. However, in our regression framework, I also control for time-varying country-level factors, time-invariant fixed effects, and time-varying industry trends (Heider and Ljungqvist (2015), which helps us create a near-perfect randomisation empirical setup (Donald B. Rubin & Richard P. Waterman, 2006).

The expectation for using PSM in the DiD framework is to ensure that our shock-based quasi-experiment utilises highly comparable treated and untreated firms, with the prospect that in the post-shock *period*, the outcomes will be of equal expectations (Atanasov & Black, 2021). To this end, |I first examine whether significant differences exist between the covariates' average figures for the treated and control groups of firms before matching by running a probit model, as shown in equation (1).

$$Treat_t \quad = \alpha_i + \beta.\boldsymbol{X}_{it} + \delta_j + \varepsilon_{it} \tag{1}$$

Treat$_i$ 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 treatment group or zero otherwise. X_{it} is a vector of covariates consisting of Size, *Lev, Cash, R&D, RoA,* and *Tang,* all defined in Appendix A1. δ_j represents firm fixed effects and ε_{it} represents the error term. All covariates are winsorised at the 1% and 99% levels. Following the standard procedure outlined in the literature(Marshall et al., 2022; Roy et al., 2022). I address this empirical challenge by first generating the propensity scores. Using data from 2013 to 2016 (pre-shock), I estimate the probit regression and present the results before and after PSM (Table 3.2).

(Insert Figure 3.1 here)

The probit regression results in the model (1) indicate that the treatment and control groups of firms are not comparable, at least in statistical terms, before the matching, as evidenced by statistically significant differences in the arithmetic means of the covariates. However, PSM generates 7,326 unique firm-year observations of 1,087 unique firms out of 15,068 firm-year observations of 1,823 unique firms from the initial pre-treatment sample. More importantly, in the post-matching sample, the results show that the differences in the mean of the covariates are statistically indistinguishable. This indicates that the treated group and the control pair firms are statistically identical in the post-matched sample.

(Insert Table 3.2 here)

I supplement the PSM outcomes with diagnostics to validate the results. I examine the potential reduction of observable differences between the treated and control firms before the shock by reanalysing specification (1) on the matched subsample using propensity score matching (PSM). Table 3.2, panel 3.2b, shows the outcomes of the probit estimations for both the pre- and post-matched samples. I generate graphs showing the standardised percentage bias between the unmatched and matched covariates (Rosenbaum & Rubin 1985). Standardised percentage bias assesses the disparity between the treatment and control groups based on propensity scores after matching. It indicates the degree of variation in the distribution of covariates between the treatment and control groups. It measures the covariate distribution differences between groups after matching. Figure 3.1 shows the *standardised percentage bias* variation between the treated and control firms' covariates in the pre- and post-matching samples.

The interpretation is that the closer the value of the standardised percentage bias to zero, the better the balance between the treated and control groups. As expected, Figure 3.1 shows that the standardised percentage bias for the covariates of the matched sample is close to zero. By contrast, those unmatched are significantly far from the ideal zero figure. PSM matching satisfies the methodological requirement that the treatment and control groups be statistically similar before the shock. The PSM-DiD estimation approach ensures that changes observed post-2016 between the treatment and control firms are attributable to the shock and not to common trends that impact both treatment and control firms or by their cross-sectional heterogeneity.

3.3.3.3 Parallel Trend test.

Following the PSM matching, I conduct a parallel trend test to confirm that the treatment and control firms share similar green revenue trends in the pre-treatment period, conditioned on the covariates. I report the trend analysis in Table 3.3 and show the graphical illustration in Figure 3.2. As shown in Table 3, the yearly difference in differences estimate coefficient is insignificant in the pre-treatment period, confirming the conditions required for using the difference in differences estimate.

(Insert Table 3.3 here)

This result shows that the treatment and control groups had a downward trend pre-2016 but at different levels. However, I observed relatively sharper decline in the treatment group than in the control group in the post-shock period. In the following sections, I argue and empirically establish that the observed relative differences in green patents/citations of the treated group in the post-shock period are potentially associated with unexpected adverse shock in supportive CPL.

3.4 Empirical Results

3.4.1 Baseline results

After successfully demonstrating the econometric requirement to conduct a difference-n-differences estimate, I quantify the average treatment effect of CPL on CGI. I estimate the following standard PSM-based difference-in-differences (DiD) regression:

$$Ln(1+CGI_{it}) = \alpha_i + \beta.(Treat_i*Post_t) + \Upsilon.\, \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \quad (2)$$

Where i and t are indexed as firm and time (year), respectively, throughout the analysis, the dependent variable is the natural logarithm of one plus the measures of CGI for firm i in year t $Ln(1+CGI)$. The CGI measures are proxied by the number of green patents and citations. $Treat_i$ is an indicator variable equal to one if firm i is in the treatment group and zero otherwise. $Post_i$ is an indicator variable equal that takes the value of one for the year after the adverse shock to CPL (post-2016, i.e., from 2017-2020) and zero otherwise. ƛ sub t, wise. λ_t *and* δ_j represents the year and firm fixed effects. Our key variable of interest is the interaction between $Treat_i$ and $Post_t$ ($Treat_i*Post_i$). The sign and magnitude of the coefficient β of the DiD factor ($Treat_i*Post_i$) reflect the causal effect of the adverse shock to supportive CPL on CGI. Clearly, in the absence of treatment (shock to supportive CPL in our case), the magnitude of the coefficient should be zero (He & Tian, 2013).

However, a non-zero and significant β represents the differential change in the mean value of CGI for the treated firms relative to the matched group of control firms in the post-CPL period. $\mathbf{X}_{it}$ is a set of firm-level covariates used in PSM estimation and time-varying country-level control variables. I address the impact of apparent outliers by winsorising all continuous variables at the 1st and 99th percentiles, except for the time-varying country-level control variables. I cluster standard errors at the firm level. Table 3.4 presents the regression results for the different specifications of Equation 2.

(Insert Table 3.4 here)

The dependent variables (*CGI*) in columns (1) and (2) represent the natural logarithm of one plus green patent Ln(1+Gp)$_{it}$ and green patent citations Ln(1+Gc)$_{it}$ for firm *i* in year *t*, respectively. The results in columns (1) to (4) show that the *DiD* coefficients are all negative and statistically significant at a significance level of 1 %. This evidence implies that in the aftermath of an adverse shock to supportive CPL, the treated group firms' (i.e., the U.S. firms) CGI is differentially lower than the control group firms (that is, European firms).

In the multivariate regression models (2) and (4), I include firm-level covariates (*Size, Lev, Cash, R&D, RoA,* and Tang) and time-varying country-level control variables (*Gdp_Grt* and *Re*). I define all the variables in the Appendix. Given the robust PSM-based DiD experimental setup, I expect stability in the size of DiD coefficients. I investigate hypothesis H1 by observing the coefficient of the DiD estimates in Table 3.4, columns (1) to (4). As expected, the *DiD* coefficients are negative and statistically significant across the four models. I focus on the full models with the covariates to interpret the findings. As shown in the full multivariate model in columns (2) and (4), the DiD coefficient is (β= =–0.025; -0.063). These results suggest that, on average, treated firms experienced a differential decline of 2.53%[44] in the green patent count and 6.5% citations in the post-shock period relative to the control group, respectively. These economic and statistically significant results support the H1 and corporate climate irresponsibility hypotheses. All four regression outcomes suggest an adverse shock to the supportive CPL dampens CGI.

3.4.2 Robustness Checks

I further validate the preliminary results by employing a variety of robustness checks. First, I undertake an alternative matching technique using entropy balancing. Second, I follow the current debate in analysing count data in empirical corporate finance by estimating the regression using the Poisson regression technique. Third, I undertake a placebo test using an alternative year as the onset of CPL shock and re-analysed the sample. Fourth, I employ alternative CGI measures in the regression specification.

3.4.2.1 Robustness check: Entropy Balance Regression

I employ an alternative matching approach incorporating higher-order distributional moments (mean, Skewness, and Kurtosis) to further address potential endogeneity issues. These issues may arise when a variable correlates with the error term, possibly due to omitted variables, measurement errors, selection bias, or reverse causality. To mitigate this, I follow previous research by implementing the entropy balancing

[44] Since our outcome variable is log-linear(ln(1+GC), we employ the transformation to interpret the coefficient of the regression: $(e^{0.047}-1)*100 = 4.92\%$

technique to create a balanced sample of firms between treated and control groups(Arifin et al., 2020; Cook et al., 2021; Hasan et al., 2021; Hossain et al., 2023) This quasi-matching method employs maximum entropy to ensure balance across all covariates by assigning appropriate weights to each observation in the sample.

The mean entropy weights reflect the average of the covariates, ensuring balanced averages between treatment and control groups. Skewness weights address potential bias caused by imbalances in distribution shape by balancing both averages and distributional asymmetry. This approach tackles disparities in covariate representation between treatment and control units, reducing dependence on specific modelling assumptions and ensuring improved balance across all included covariates. As a result, reweighted observations exhibit identical post-weighting distributional characteristics for both treatment and control units. Concurrently, entropy balancing computes precise weights for control observations, maintaining sample integrity and covariate balance (Chapman et al., 2019). The reweighing procedure eliminates endogeneity bias caused by latent variables that distort covariate distribution.

The entropy balance offers an incremental advantage because it can significantly improve the efficiency of regression estimations by utilising information from a larger number of observations compared to PSM matching. In contrast to PSM matching, which depends exclusively on the mean, this method can balance covariates through variance and skewness as well as the mean. I re-estimate the Difference-in-Differences specification (2) utilising the entropy-balanced sample, applying mean weight only like matching with PSM matching technique in the first regression model; a combination of mean and skewness in the second regression; and combination of mean, skewness and kurtosis moments in their set of regression. I present the results in Table 3.5, columns (1) through (6).

(Insert Table 3.5 here)

I utilise the three moments to estimate the entropy balance technique: mean, variance, and skewness. Initially, I estimate the matching by utilising the mean in the entropy balance matching. The findings in columns (1) and (2) align with my primary PSM-DiD estimation results and maintain statistical significance at the 1% level. The estimated coefficient of the DiD, as indicated in Columns (1) and (2), is approximately (β =-0.19 and -0.49) for green patent count and green patent citation, respectively. I re-estimate the entropy balance matching utilising the first, second and third moments(Mean and Variance). I present the results in Table 3.5, columns (3-4). The results continue to be significant at the 1% level. However, they demonstrate a reduced effect size compared to the PSM-DiD regression outcomes.

Finally, I utilise all three moments (mean, variance and skewness) in the entropy balance matching and present the findings in Table 3.5 columns (5-6). After accounting for all covariates, firm, and year-fixed effects, the results remain statistically significant at the 1% level. However, they demonstrate a reduced effect size compared to the findings obtained through PSM-DiD and first and second-moment entropy balance estimation. The effect size diminishes with the inclusion of additional higher-order moments; however, the results maintain their consistency. I anticipate a significant reduction in the size effect due to the conservative matching mechanism enforced by the entropy balance technique when I incorporate additional moments into the estimation. The outputs of the entropy balancing technique corroborate the primary findings presented in Table 3.4, reinforcing the baseline results and supporting the *H1 Corporate Climate irresponsibility hypothesis.*

3.4.2.2 Alternative Measures of CGI

As an additional robustness check, I run specification 3, including alternative CGI proxies.

$$Ln(1+Alt\_CGI_{it})_{it} = \alpha_i + \beta.(Treat_i * Post) + \Upsilon . \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \quad (3)$$

The dependent variable $Ln(1+Alt\_CGI_{it})$ represents the natural logarithm of one plus green patents *(Gp)* and citations (*Gpc*) scaled by total assets in billions of dollars (that is, $Ln(1+Gp/Asset)_{it}$ and $Ln(1+Gpc/Asset)_{it}$. All other variables and specifications are identical to those in Specification 2. I report the results in Table 3.6. The result is consistent with our main finding on CPL's impact on CGI, indicating a statistically significant decline in green patents across the alternative green patent measures.

(Insert Table 3.6 here)

3.4.2.3 Placebo test

I exploit the 2016 U.S. presidential election as a source of exogenous variation in the CPL. Since I assumed the shock was unexpected, the findings may capture trends in green patenting or other unobservable factors or shocks that occurred earlier than 2016. To test the possibility of such a confounding effect, I designed a placebo test by running the following placebo regression specification, whereby $Post_t$ assumes that the shocks differ from the 2016 shock period, specifically, 2015 and estimates regression specification (4)

$$Ln(1+ CGI_{it})_{it} = \alpha_i + \beta.(Treat_i * Post_{2015t}) + \Upsilon.\, \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \qquad (4)$$

Like our earlier baseline test, I use pre- and post-shock periods within a 3-year pre-shock (2013-2015) and post-shock (2016-2018). However, in Specification 4, I assume that the shock occurred in 2015 (false shock) instead of 2016. If the results of specification 2 capture the effect of an earlier shock, I expect the coefficient β to be negative in sign and statistically significant. Table 3.7 presents the results.

(Insert Table 3.7 here)

The results show no significant decline across the green patent measures, with and without covariates. This result indicates that the 2016 shock is credible. The estimates of the regressions obtained post-2016 reflect the impact of the shock on CPL and are consistent with our main findings in the magnitude and direction of the relationship.

3.4.2.4 Poisson Regression Specification

I follow Cameron and Prattico (2022) using the Poisson regression approach to address potential bias in OLS regression for patent analysis. If the results from the Poisson regression are consistent with findings using PSM-DID ordinary least square(OLS) regression, it would further strengthen our inferences and assure that our results are not biased by the OLS regression technique. I estimate the Poisson regression specification (5) and present the result in Table 3.8.

$$(CGI_{it}\,|X) = e^{(\,\alpha i + \beta.(Treati\ *Post) + \Upsilon.\ Xit + \delta j + \lambda t + \varepsilon it\ )} \qquad (5)$$

As shown in Table 8, columns 1-4, the coefficient of the DiD regression is significant and negative, consistent with prior OLS regression specification in Table 4. The results confirm the earlier results presented in Table 4 and alleviate concerns that our OLS regression results are biased, further strengthening our claim on the negative effect of climate sceptic political leadership on corporate green innovation.

(Insert Table 3.8 here)

3.4.3 Economic Mechanism Test: Deregulatory Channel

Consistent with previous research, this study employs the country-level climate change performance index (CCPI) from Germanwatch[45] to indicate climate regulatory stringency (Bose et al., 2021; Kim et al., 2021a). This independent national measure aims to enhance transparency in global climate politics and enable the assessment of individual countries' efforts and progress in addressing climate change (Bose et al., 2021). The index is developed by tracking and evaluating the actions taken by individual nations to mitigate climate change, allowing for comparisons of their climate protection initiatives.

For this study, I utilise the specific index that reflects a country's climate policy assessment, constituting a distinct component of the CCPI that evaluates nations' progress in implementing policies that contribute to achieving the Paris Agreement objectives. This index

[45] 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/

is henceforth called the climate regulatory stringency index (CRSI). The CRSI scales from zero (0) to five (5), where zero (0) represents the lowest level of climate regulatory stringency, and five (5) represents the highest.

To examine the deregulatory channel empirically, I construct a dummy variable that takes a value of one if the CSRI score is below the median and zero otherwise. I 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:

$$Ln(1+CGI)_{it} = \alpha_i + \beta.(Treat_i * Post_t * CRSI\_Dummy) + \Upsilon.\boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \qquad (6)$$

I report the findings in Table 3.9, columns (1) to (4). Columns (1) and (2) show the regression of the triple difference in differences (DiDiD) regression with patent count as the outcome variable, while Columns (3) and (4) report the outputs for patent citations. All regressions are clustered at the firm level to account for errors due to autocorrelation. I investigate the deregulatory channel by observing the coefficient of the triple interaction term. A significant and more substantial magnitude of the coefficient would confirm our conjecture. As reported, all the coefficients of the triple interaction ($Treat_i$*$Post_t$**CRSI_Dummy)* estimates are negative and statistically significant at the conventional 1% significance level. The coefficients for the patent count and (β= -0.035, -0.031) for the CSPL are (β= -0.08 and -0.074), respectively. The results suggest that the climate deregulatory channel is the mechanism through which CSPL influences CGI.

In the alternative specification, I interact the CSRI scores directly with the difference in different variables. I report the findings in Table 3.9, columns (5) to (8). Columns (5) and (6) show the regression of the triple difference in differences (DiDiD) regression with patent count as the outcome variable, while Columns (7) and (8) report the outputs for patent citations. All regressions are clustered at the firm level to account for errors due to autocorrelation.

The coefficient of the triple interaction is negative and significant at 1%, which is consistent with the prior result using the deregulatory dummy in the triple interaction.

(Insert Table 3.9 here)

3.4.4 Robustness Test: Cross-sectional Tests

In this section, I conduct several cross-sectional examinations to strengthen the empirical results of the core hypothesis. Specifically, I explore how the effects of an adverse shock to supportive CPL on CGI vary depending on the firm-level attributes. Accordingly, drawing on the literature examining their importance in influencing firm-level environmentally sustainable practices. I identify two critical firm-level attributes that might moderate the link between CPL and CGI. These firm-level characteristics include whether we classify a firm as being in the energy-intensive sector and their level of financial constraints.

3.4.4.1 Moderating Effect of Financial Constraints

Corporate resources are inherently limited, requiring managers to prioritise internal capital allocation and R&D budgets to optimise firm value(Custódio et al., 2014; Custódio et al., 2019). Financial constraints play a significant role in corporate climate strategy and strategic investment decision-making. Hong et al. (2012) find that CGI activities decline under financial constraints. Bennedsen (2015) suggests that, owing to the radical and novel nature of CGI investment, it may demand higher capital requirements.

Financial constraints also restrict firms' ability to innovate and adapt to market demands. Almeida and Campello (2010) document that financially constrained firms are less willing to invest and innovate, which limits their potential to adapt to market dynamics and growth opportunities. Hubbard (1994) argues that firms facing capital constraints in the equity market are likely to face double-binding constraints in the debt market. Similarly, Xu et al. (2022) use a sample of U.S. firms' establishment-level microdata on toxic waste release, and the study shows that financially constrained firms significantly increase toxic waste release when climate regulations weaken. In addition, the results suggest that financially constrained firms underinvest in environmental innovation, thereby increasing poisonous waste pollution emissions.

Conversely, a contrasting body of literature explores the potential for financial constraints to drive innovation. Bloom et al. (2013) find that financial constraints can encourage risk-taking behaviour, arguing that firms are more willing to take risks while financially constrained. As financial constraints become more stringent, firms exhibit a decreased propensity to allocate resources to CGI, as such investments' perceived utility or feasibility diminishes. Financial constraints exacerbate the negative impact of CPL shocks on CGI investment decisions. Therefore, firms facing financial constraints possess reduced financial flexibility to mitigate regulatory uncertainty or prioritise long-term environmental objectives over short-term profitability. Consequently, the probability of selecting CGI decreases more precipitously for financially constrained firms following a negative CPL shock than for their unconstrained counterparts.

However, without stringent climate regulation, financially constrained firms will sacrifice green innovation development as a self-preservation strategy in a race to the bottom. As a result, I expect financial constraints to intensify underinvestment in CGI following the shock to responsible CPL. Given this dynamic, I conjecture that financial constraints amplify firms' underinvestment in CGI in response to shocks to responsible CPL.

Following Chen and Wang (2012), I adopt Kaplan-Zingales Index[46] (Kaplan and Zingales,1997; Lamont et al., 2001) as a measure of financial constraint. First, I create K.Z. Index financial constraint score for firm *i* in year *t*. Firms' financial constraints increase with a high KZ. Index score (Chen & Wang, 2012). This index measures the difference between the internal and external costs of funds. The index considers operating cash flow, cash balances, and dividends as negative, while Tobin's Q and leverage are positive. I compute the KZ. Index for each firm's year by combining cash flow over lagged net property plant and equipment (Cashflow/ppe_{t-1}), cash balances over lagged property plant and equipment (Cash/ ppe_{t-1}), cash dividends over lagged book assets (DIV/$Asset_{-1}$), total debt over book assets (Lev), and Tobin's Q (*TQ*) .To reduce the influence of outliers, I winsorise at the 1st and 99th percentiles before computation.

I then create a financial constraints dummy (*FinCon*), representing one if the firm's financial constraint scores in year *t* are greater than the sample median score and zero otherwise. Firms with lower *FinCon* scores represent firms with low financial constraints, whereas firms with high scores are financially constrained. Finally, I interact *the FinCon* variable with the DiD variable in a triple interaction to estimate

[46] We compute following as follows KZ= -1.002*(cashflow/ ppe_{t-1}) + (3.139 *Lev) + (0.285*TQ) + -39.368*(DIV/ ppe_{t-1}) + (-1.315*(Cash/ ppe_{t-1}))

the role of financial constraints in the relationship between climate sceptic political leadership and corporate green innovation.

In the empirical setup, I interact *FinCon* with the DiD variable to form a triple-difference-in-difference variable. First, I regress the green patent measures on the triple interaction term. Financial constraints directly reduce the value of CGI, and the interaction term captures the moderating effect of financial constraints under climate-sceptic political leadership.

$$Ln(1+CGI_{it})= \alpha_i + \beta.(Treat_i * Post_t * Fincon) + \Upsilon. \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \qquad (7)$$

Table 3.10 presents the regression estimates. These results indicate that this effect is more substantial for firms with higher financial constraints. Models (1) to (2) show the coefficient of the triple-interaction term, which is negative and consistent across all innovation measures. The results imply that, on average, firms in our treated group with higher financial constraints have differential underinvestment in CGI compared to their unconstrained counterparts in the post-shock period. They also received fewer citations, as shown in models (3) and (4). This result is consistent with the literature, which documents that financial constraints impede innovation (Jiang & Yuan, 2018). The economic argument hinges on the trade-off between immediate resource constraints and the long-term benefits of CGI investment. Financial constraints skew firms' choices away from CGI, particularly when regulatory pressure weakens, reinforcing the notion that financial constraints intensify underinvestment in CGI following an adverse shock to supportive CPL.

(Insert Table 3.10 here)

3.4.4.2 Effect on Energy-Intensive Firms

Literature suggests that carbon-intensive firms are more sensitive to climate policy (Ilhan, Sautner, Vilkov, et al., 2021; Ramelli, Wagner, Zeckhauser, & Ziegler, 2021). The 2016 U.S. presidential election shock demonstrates the deregulatory and reversal of earlier stringent regulations (Ramelli, Wagner, Zeckhauser, Ziegler, et al. (2021); Wagner et al. (2018). Furthermore, in the aftermath of the 2016 Trump election, the literature documents a higher capital market valuation of carbon-sensitive firms than their less carbon-sensitive counterparts (Ramelli et al., 2021). Using a sample of publicly listed U.S. firms, Xu et al. (2022) show that toxic waste emissions increase under a weakened regulatory environment and enforcement.

Prior literature shows that firms update their beliefs in response to climate policy shocks(Pastor & Veronesi, 2012; Pástor & Veronesi, 2013; Pflueger et al., 2020; Thapa & Hillier, 2022). Similarly, Ramadorai and Zeni (2024) show that firms' emission abatement actions depend substantially on their beliefs about climate regulation. Suppose managers revise their beliefs in response to climate policy shocks; in this case, I expect firms, especially those in energy-intensive sectors, likely to benefit from such deregulatory policies, to show a stronger effect. Accordingly, I conduct an additional test on the energy intensity of firms in our sample.

First, I follow Kim et al. (2021b) and classify the firms in our sample based on the energy intensity of their 4-digit SIC code. Then, I construct a dummy variable HEI_i equal to one if the firm is in the high energy-intensive sector based on a four-digit SIC code and zero otherwise. In our empirical setup, as shown in the specification

(8), I construct a triple *DiDiD* estimation by interacting the HEI_i variable with the *DiD* variable to uncover the differential impact of CPL on CGI along the energy intensity dimension. Table 3.11 presents the results of the regression estimation.

$$Ln(1+CGI)_{it} = \alpha_i + \beta.(Treat_i * Post_t * HEI_i) + \Upsilon. \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it} \quad (8)$$

Table 11 reports the results of the regressions. The findings indicate that the effect is more significant in highly energy-intensive firms. The coefficients of the regression, as shown in columns (1) and (2) for the green patent count, are (β=- 0.063, $p<0.01$;β=- 0.061) for the green patent count and (β=- 0.156, $p<0.01$;β=- 0.152) green patent citations, respectively. The finding is statistically and economically significant at 1%, implying that energy-sensitive firms expected to benefit from the Trump administration's deregulation policies underinvest more in green innovation. Green patent generation is lower because of the disincentives and absence of regulatory forces to drive green innovation among the energy-sensitive firms in our treatment group, consistent with the economic prediction(Besley & Persson, 2023). This finding is unsurprising, given that state incentives and regulations are critical to stimulating green innovation investment(Acemoglu et al., 2016; Popp, 2010; Rugman & Verbeke, 1998). Since innovation is endogenous, it supports the notion that regulatory pressure is one of the primary reasons firms invest in green technologies.

(Insert Table 3.11 here)

3.5 Conclusion

Given the importance of innovation in managing climate and environmental risk, this study examines the relationship between climate political leadership (CPL) and corporate green innovation (CGI). I argue that the motivations and drivers of business to invest in green innovations that help tackle the growing environmental and climate risk, to a considerable extent, depend on the climate change philosophy, beliefs and views of the highest political leadership. Empirically, I answer this question in a quasi-natural experimental setup by exploring the 2016 United States presidential election as a source of an exogenous shock to the CPL. I argue that the unexpected election results of the 2016 U.S. election, the emergence of climate-sceptic executive political leaders and the ensuing lax regulatory regime did not incentivise U.S. firms to invest in environmentally friendly and climate-change-mitigating innovations.

I test the hypothesis using US-headquartered and listed firms as the treated group and their developed-market European-headquartered contemporaries as our control group between 2013 and 2020. Employing credible measures of CGI (green patents, citations, and their derivatives), the results indicate that a shock to supportive CPL results in relative underinvestment in CGI by U.S. firms compared to European firms. Finally, different cross-sectional examinations show that the negative effect of sceptic CPL on CGI is more substantial for firms with financial constraints and those in energy-intensive industries.

The findings complement the nascent literature on climate-political leadership, corporate green innovation strategy, and climate policy by providing helpful insights into corporate green innovation investment decisions under a change in climate-political leadership. In addition, the evidence highlights the negative consequences of the race to the bottom notion of government deregulatory policies and their effects on climate change mitigation and adaptation strategies.

Appendix

Table A3.1 Variable Definitions

Variable	Description
CGI	Corporate Green Innovations (*CGI*) is an investment in green innovation proxied by the number of green patents filed and granted or the number of citations received by green patents filed for firm *i* in year *t*.
Gp	Green patent count (*Gp*) is the sum of the number of green patents filled by a firm *i* (and eventually granted) in year *t*. Source: PATSAT.
Gc	Green Patent Citation (*Gc) is* the sum of citations received by each green patent filed by firm *i* and granted patents in year *t*. Source: PATSAT.
Gpa	The green patent count per billion of the assets *(Gpa*) is the sum of the number of green patents filled by a firm *i* (and eventually granted) in year *t* scaled by the book value of its assets in billions of dollars ($Gpa = Gp/Asset$).
Gca	Green Patent Citation per billion of the assets (Gca*)* is the sum of citations received by each green patent filed(and eventually granted) by firm *i* and granted patents in year *t* scaled by the book value of assets in billions of U.S. dollars. ($Gca = Gc/Asset$).
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. I term 2013-2016 as an era of supportive climate political leadership (*SCPL*) (i.e., *CPL* = 0) and 2017-2020 as climate sceptic political leadership (*CSPL*) (i.e., *CPL* = 1)
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	Leverage (*Lev*)is the ratio of the total book value of debt of firm *i* in year t over the total book value of the asset of firm *i* at the end of year *t. Source: Compustat*
R&D	Research and development intensity *(R&D)* is the ratio of research and development expenditure of firm *i* in year *t* to the total book value of assets at the end of year *t. Source: Compustat*
RoA	Return on asset (RoA) is a proxy of profitability, defined as operating earnings (EBITDA) scaled by the book value of total assets of firm i in year t. Source: Compustat
Tang	Tangibility(*Tang)* It is measured by scaling the net property and plant if firm *i* in year t by the book value of total assets at the end of year t. Source: Compustat.
Cash	Cash and cash equivalence (*Cash)* is cash and cash equivalent scaled by the total book value of the asset of the firm *i* at the end of year *t. Source:* Compustat
Analyst	Analyst Coverage(Analyst) is the number of financial Analysts providing earnings per share estimates for a firm I in year t. Source: S & P Capital IQ

InstO	Institutional ownership (*InstO*) is the percentage of institutional holding in firm *i* in the year *t. S & P Capital IQ Database*
KZ_Index	The proxy for financial constraint. It reflects the degree to which a firm is financially constrained. Kaplan and Zingales(1997).
$Treat_i$	Treat is a dummy variable equal to one if firm *i* is in the treated group (U.S.-headquartered and listed firm) and zero (European-headquartered and listed firm) otherwise.
$Post_s$	The dummy variable ($Post_t$) is an indicator variable that equals one for observations in years after the 2016 U.S. Presidential election period (2017-2020) and zero otherwise.
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
Gdp_Grt	For country j at the end of year t, the real Gross Domestic Product growth rate (*Gdp_Grt*), 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
Re	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

Table A3.2 Data Trimming Process Year 2013 to 2020

Data Trimming	**#Firms**	**Obs**
Financial Dataset from WRDS for US and Developed Market Europe Firms(Compustat North America and Global)	20,617	126, 119
Drop Utility firms and Financial Films (sic>4900 & sic<=4999) and (sic>5999 & sic<=6999)	12,696	73,928
Drop if asset =0 or asset ==.	12,450	72,189
Drop if the book value of equity is zero or missing	12, 435	72,036
Drop in total liabilities, research and development, capital expenditure and cash and cash equivalence are negative	12,432	71,986
Merge capital IQ ID	12,090	71,031
Merge with patent Data	7,824	52,421
Drop if asset <$10m	7,079	45,490
Drop missing Book value of equity is negative or equal to Zero	6,876	42,514
Replace missing RND with Zero((18,453 observations Missing)		
Drop missing covariates	6,827	42,280
Drop if Return on Asset (ROA) is negative	5,161	31,745
Total Data for the Analysis	**5,161**	**31,745**
Missing Institutional investors		5,238

Table 3.1: Descriptive Statistics.

The table provides descriptive statistics for the overall sample period. I report the corresponding number of observations, mean, standard deviation (*Std.Dev*), and maximum values. The sample period is from fiscal year 2014 to 2020. A full description of all the variables reported in this table *(Gp*, *Gc, Size*, *Lev, Cash*, *Lev*, *R&D*, *RoA*, *Tang*, *InsO*, *KZ_Index, Analyst*, *Gdp_Grt*, and *Re*) is in Appendix A1. Except at the country level, I winsorise all the firm-level variables at the 1st and 99th percentiles.

Variable	Obs	Mean	Min	Max	Std.Dev
Key Dependent					
Gp	31,745	0.059	0.000	3.000	0.385
Gc	31,745	0.355	0.000	23.000	2.649
Covariates					
Asset'$Bn	31,745	6.180	0.123	12.408	2.146
Lev	31,745	0.232	0.000	0.706	0.177
Cash	31,745	0.145	0.001	0.962	0.145
R&D	31,745	0.022	0.000	0.770	0.046
RoA	31,745	0.120	0.000	0.374	0.072
Tang	31,745	0.232	0.000	0.897	0.216
Others					
InsO	31,745	38.979	0.000	98.310	33.632
Analyst	31,745	5.886	0.000	31.000	7.364
KZ_Index	28,905	-8.709	-718.292	34.859	46.468
ESIncidence	31,745	2.917	0.000	78.00	10.700
Country-level					
Gdp_Grt (%)	31,745	1.237	-10.360	4.490	2.583
Re	31,745	1.539	0.240	2.020	0.339

Table 3.2:Mean difference in covariates and propensity score matching

Panel 3.1a Mean Difference in covariates between control and treatment groups pre-2016 period (2013-2016)

Variable	Control	Treatment	coefficient	t-test	p-value
Size	6.208	6.985	-0.777***	-22.201	0.000
Lev	0.209	0.224	-0.015***	-5.141	0.000
Cash	0.135	0.155	-0.019***	-8.133	0.000
RoA	0.118	0.133	-0.015***	-12.607	0.000
RnD	0.020	0.024	-0.004***	-5.048	0.000
Tang	0.216	0.249	-0.033***	-9.323	0.000
Observations	8,828	6,240	15,068		

Panel 3.2b: Propensity Score Matching (PSM)

The table shows the result of the probit regression model for propensity score-matched treated and control firms following the specification.

$$Treat_{it} = \alpha_i + \beta.\boldsymbol{X_{it}} + \delta_j + \varepsilon_{it}$$

i and *t* indexes as firm and time (year). The dependent variable, *Treat,* is a dummy variable that takes a value of one if the firm is in the treatment group or zero otherwise. $\boldsymbol{X}_{it}$ is a vector of firm-level covariates consisting of *Size, Lev, Cash, R&D, RoA,* and *Tang.,* defined in Appendix A1. δ_j are firm fixed effects and ε_{it} represents the error term. All covariates are winsorised at 1% and 99%, respectively.

Panel A: Pre and Post Propensity score diagnostic regression.

	Pre-PSM	Post-PSM
Size	0.1123***	-0.0066
	(21.50)	(-0.48)
Cash	1.2005***	-0.1626
	(12.88)	(-0.82)
Lev	0.3424***	-0.0533
	(4.62)	(-0.32)
R&D	0.8749***	-0.3456
	(3.42)	(-0.57)
RoA	1.8098***	0.5717
	(11.24)	(1.47)
Tang	0.4656***	0.0719
	(8.85)	(0.58)
Constant	-1.5577***	-0.0001
	(-33.44)	(-0.00)
Pseudo-r2	0.04569	0.001373
Obs	15,068	7,326
# Firms	1,823	1,087

Table 3.3: Parallel Trend Test

The table shows the result of the parallel test as the yearly difference in the mean treatment effect of the effect of CPL on CGI between the treated and the control, between 2013 and 2020 for the parallel trend test graph shown in Figure 3.1

Variable	Coefficient	t-Stat	p-value
$Treat*Post_{2013}$	0.006	-0.91	0.365
$Treat*Post_{2014}$	0.004	-0.66	0.511
$Treat*Post_{2015}$	0.000	-0,07	0.942
$Treat*Post_{2016}$	0.000	0.000	0.000
$Treat*Post_{2017}$	-0.024	-0.41	0.685
$Treat*Post_{2018}$	-0.016**	-2.780	0.006
$Treat*Post_{2019}$	-0.040***	-5.08	0.000
$Treat*Post_{2020}$	-0.057***	-6.090	0.000

Table 3.4: Climate Political Leadership and Corporate Green Innovations: PSM-DiD regression

This table reports the results of the PSM-matched difference in differences (DiD) regression examining the effect of CPL on CGI following the specification below.

$$Ln(1+CGI)_{it} = \alpha_i + \beta.(Treat_i * Post_t) + \Upsilon.\,\boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it}$$

i and *t* indexes as firm and time (year). The dependent variable *Ln(1+CGI*) represents corporate green innovations (CGI) proxied by either the natural logarithm of one plus patent green patent or green patent citations and their derivatives). $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in 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, Cash, RoA, R&D,* and *Tang.* $\boldsymbol{X}_{it}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re.* I define all variables in Appendix A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses. The dependent variable in Models (1) and (2) represents the natural logarithm of one plus green patent counts Ln(1+Gp). In models (3) and (4), the dependent variable represents the natural logarithm of one plus green patent citation $Ln(1+Gc)_{It}$

	Dep. Var =CGI			
	(1)	(2)	(3)	(4)
DiD(Treat$_i$*Post$_t$)	**-0.026*** **	**-0.025*** **	**-0.065*** **	**-0.063*** **
	(0.006)	**(0.005)**	**(0.013)**	**(0.013)**
Size		0.008		0.013
		(0.005)		(0.013)
Lev		0.011		0.019
		(0.018)		(0.044)
Cash		0.026		0.061
		(0.019)		(0.051)
RoA		-0.069**		-0.120*
		(0.028)		(0.064)
R&D		0.217**		0.512*
		(0.100)		(0.277)
Tang		0.075***		0.154***
		(0.025)		(0.057)
Gdp_Grt (%)		-0.002*		-0.004
		(0.001)		(0.002)
Re		0.106***		0.217***
		(0.023)		(0.048)
Obs	19,942	19,942	19,942	19,942
Adj-R^2	0.5962	0.5975	0.5638	0,5649
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 3.5:PSM-DiD regression using Entropy Balance weights

The table reports the results of the multivariate PSM-matched DiD robustness test using entropy balance weight in the regression specification below.

$$Ln(1+Green)_{it} = \alpha_i + \beta.(Treat_i * Post_t) + \Upsilon.\, \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it}$$

i and t indexes as firm and time (year). The dependent variable *Ln(1+CGI)* represents corporate green innovations (CGI) proxied by either the natural logarithm of one plus patent green patent or green patent citations and their derivatives). $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in 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*, *Cash*, *RoA*, *R&D*, and *Tang*. $\boldsymbol{X}_{it}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re.* I define all variables in Appendix A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses.

	Dep. Var =CGI					
	Entropy Balance Weights					
	Mean		Mean and Skewness		Mean, Skewness & Kurtosis	
	(1)	(2)	(3)	(4)	(5)	(6)
DiD(Treat$_i$*Post$_t$)	**-0.019*** **	**-0.049*** **	**-0.025*** **	**-0.061*** **	**-0.026*** **	**-0.061*** **
	(0.005)	**(0.013)**	**(0.005)**	**(0.012)**	**(0.005)**	**(0.012)**
Size	0.010**	0.017	0.009**	0.015	0.009**	0.014
	(0.005)	(0.011)	(0.004)	(0.010)	(0.004)	(0.010)
Lev	0.009	0.032	0.014	0.035	0.013	0.034
	(0.015)	(0.038)	(0.015)	(0.036)	(0.015)	(0.036)
Cash	0.023	0.060	0.027*	0.064	0.025	0.060
	(0.016)	(0.043)	(0.016)	(0.042)	(0.015)	(0.041)
RoA	-0.054**	-0.084	-0.040*	-0.058	-0.044**	-0.070
	(0.024)	(0.056)	(0.022)	(0.052)	(0.022)	(0.053)
R&D	0.184**	0.441**	0.246***	0.595**	0.247***	0.641***
	(0.075)	(0.212)	(0.085)	(0.244)	(0.082)	(0.246)
Tang	0.072***	0.146***	0.069***	0.137***	0.070***	0.140***
	(0.021)	(0.048)	(0.020)	(0.045)	(0.020)	(0.045)
Gdp_Grt (%)	-0.001	-0.000	-0.001	-0.002	-0.002*	-0.002
	(0.002)	(0.005)	(0.001)	(0.002)	(0.001)	(0.002)
Re	0.073***	0.183***	0.104***	0.231***	0.102***	0.233***
	(0.021)	(0.047)	(0.019)	(0.042)	(0.019)	(0.042)
Obs	31,365	31,365	31,365	31,365	31,365	31,365
Adj-R^2	0.6086	0.5687	0.5941	0.5575	0.6076	0.5701
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 3.6: PSM DiD regression using Altered Measures of Green Patent

The table reports the results of the multivariate PSM-matched DiD robustness test using alternative measures of the green patent in the regression analysis following the specification below.

$$Ln(1+Green)_{it} = \alpha_i + \beta.(Treat_i * Post_t) + \Upsilon.\, \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it}$$

i and t indexes as firm and time (year). The dependent variable *Ln(1+CGI)* represents corporate green innovations (CGI) proxied by either the natural logarithm of one plus green patent or green patent citations scaled by total assets. $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in 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, Cash, RoA, R&D,* and *Tang.* $\boldsymbol{X}_{it}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re.* I define all variables in Appendix A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses. The dependent variable in Models (1) and (2) represents the natural logarithm of one plus green patent counts scaled by total assets Ln(1+Gp/Asset). In models (3) &(4), the dependent variable represents the natural logarithm of one plus green patent citation-scaled by total assets $Ln(1+Gc/Asset)_{it}$.

	Dep. Var =CGI			
	(1)	(2)	(3)	(4)
DiD(Treat*$_i$Post*$_t$**)***	**-0.019*****	**-0.019*****	**-0.055*****	**-0.054*****
	(0.004)	**(0.004)**	**(0.010)**	**(0.009)**
Size		-0.002		-0.001
		(0.003)		(0.008)
Lev		0.005		0.008
		(0.013)		(0.031)
Cash		0.016		0.041
		(0.017)		(0.044)
RoA		-0.056**		-0.095*
		(0.022)		(0.050)
R&D		0.198**		0.405*
		(0.090)		(0.231)
Tang		0.047***		0.106***
		(0.016)		(0.040)
Gdp_Grt (%)		-0.001		-0.001
		(0.001)		(0.002)
Re		0.061***		0.139***
		(0.015)		(0.031)
Obs	19,942	19,942	19,942	19,942
Adj-R^2	0.5100	0.5113	0.5048	0.5058
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 3.7:PSM DiD regression placebo test.

The table reports the results of the univariate and multivariate PSM-matched DiD regression analysis of the effect of CPL on CGI presented in panels A and B, respectively, following the specification below.

$$Ln(1+CGI_{it}) = \alpha_i + \beta.(Treat_i * Post_t) + \Upsilon. \boldsymbol{X_{it}} + \delta_j + \lambda_t + \varepsilon_{it}$$

i and t indexes as firm and time (year). The dependent variable *Ln(1+CGI)* represents corporate green innovations (CGI) proxied by either the natural logarithm of one plus patent green patent or green patent citations and their derivatives). $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in the post-shock (2016-2018) period and zero for the pre-shock period (2013-2015). $\boldsymbol{X_{it}}$ is a vector of firm-level covariates: *Size, Lev, Cash, RoA, R&D,* and *Tang.* $\boldsymbol{X_{it}}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re.* I define all variables in Appendix A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses. The dependent variable in Models (1) and (2) represents the natural logarithm of one plus green patent counts $Ln(1+Gp)_{it}$. In models (3) &(4), the dependent variable represents the natural logarithm of one plus green patent citation $Ln(1+Gc)_{it}$

	Dep. Var =CGI			
	(1)	(2)	(3)	(4)
DiD($Treat_i$*$Post_{t2015}$)	-0.002	-0.004	-0.016	-0.020
	(0.004)	(0.005)	(0.011)	(0.013)
Size		0.001		-0.001
		(0.005)		(0.012)
Lev		-0.006		-0.021
		(0.019)		(0.048)
Cash		-0.018		-0.035
		(0.017)		(0.046)
RoA		-0.042		-0.024
		(0.030)		(0.068)
R&D		0.032		0.091
		(0.080)		(0.264)
Tang		0.027		0.051
		(0.020)		(0.049)
Gdp_Grt (%)		-0.001		-0.001
		(0.002)		(0.004)
Re		0.020		0.047
		(0.023)		(0.052)
Obs	15,131	15,131	15,131	15,131
Adj-R^2	0.7560	0.7560	0.7289	0.7288
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 3.8: Poisson Regression

This table reports the results of the univariate and multivariate PSM-matched DiD regression examining the effect of CPL on CGI following the specification below.

$$CGI_{it} = e^{(\alpha i + \beta\beta.(Treati *Postt) + \Upsilon.\, \boldsymbol{X}it + \delta j + \lambda t + \varepsilon it)}$$

i and t indexes as firm and time (year). The dependent variable *CGI* represents corporate green innovations (CGI) proxied by green patent count or citations. $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in 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, Cash, RoA, R&D,* and *Tang.* $\boldsymbol{X}_{it}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re.* I define all variables in Appendix A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses. The dependent variable in Models (1) and (2) represents the green patent counts In Models (3) &(4), the dependent variable represents a green patent citation.

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	Dep. Var =CGI			
	(1)	(2)	(3)	(4)
DiD($Treat_i$*$Post_t$)	**-0.808*****	**-0.362*****	**-1.032*****	**-0.512*****
	(0.059)	**(0.068)**	**(0.025)**	**(0.029)**
Size		-0.323***		-0.500***
		(0.115)		(0.047)
Lev		-0.155		-0.175
		(0.376)		(0.151)
Cash		-0.790*		-0.762***
		(0.451)		(0.181)
RoA		-0.931		0.370
		(0.869)		(0.354)
R&D		-0.987		-2.895***
		(2.245)		(0.891)
Tang		-0.331		-0.239
		(0.771)		(0.327)
Gdp_Grt (%)		0.253***		0.209***
		(0.030)		(0.013)
Re		3.437***		4.142***
		(0.365)		(0.155)
Obs	2,083	2,083	1,939	1,939
FE	YES	YES	YES	YES

Table 3.9: Channel Test: Climate Regulatory Stringency (CRSI)

This table reports the triple interaction of propensity-matched pairs of treated and control firms per the specification below.

$$Ln(1+CGI)_{it} = \alpha_i + \beta.(Treat_i * Post_t * CRSI\_Dummy) + \Upsilon.\, \boldsymbol{X}_{it} + \delta_j + \lambda_t + \varepsilon_{it}$$

i and t indexes as firm and time (year). The dependent variable *Ln(1+CGI*) represents corporate green innovations (CGI) proxied by either the natural logarithm of one plus patent green patent or green patent citations and their derivatives). $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in the post-shock (2017-2020) period and zero for the pre-shock period (2013-2016). *CRSI_Dummy* takes a value of one if the country-level stringency of climate regulation is above the sample's median and zero; otherwise, $\boldsymbol{X}_{it}$ is a vector of firm-level covariates: *Size, Lev, Cash, RoA, R&D,* and *Tang.* $\boldsymbol{X}_{it}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re*. I define all variables in Appendix A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses. The dependent variable in Models (1) & (2),(5) & (6) is the natural logarithm of one plus green patent counts $Ln(1+Gp)_{it}$. In models (3) &(4), the dependent variable represents the natural logarithm of one plus green patent citation $Ln(1+Gc)_{it.}$ DiDiD represents either ***$Treat_i$*$Post_t$*CRSI_Dummy*** *for columns (1) to (4) and* ***Treati*Postt*CSRI*** *for columns (5) to (8)*

	Dep. Var =CGI							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DiDiD	**-0.035*** (0.006)**	**-0.031*** (0.006)**	**-0.080*** (0.014)**	**-0.074*** (0.016)**	**-0.007*** (0.002)**	**-0.009*** (0.002)**	**-0.020*** (0.005)**	**-0.025*** (0.006)**
Firm Control	YES	YES	YES	YES	YES	YES	YES	YES
Country Control	YES	YES	YES	YES	YES	YES	YES	YES
Obs	19,942	19,942	19,942	19,942	19,942	19,942	19,942	19,942
Adj-R^2	0.5969	0.5976	0.5643	0.5649	0.653	0.655	0.625	0.627
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.10: Role of Financial Constraints

This table reports the triple interaction regression of propensity-matched pairs of treated and control firms per the specification below.

$$Ln\ (1+CGI)_{it} = \alpha_i + \beta.(Treat_i * Post_t * FinCon) + \Upsilon.\ X_{it} + \delta_j + \lambda_t + \varepsilon_{it}$$

i and t indexes as firm and time (year). The dependent variable *Ln(1+CGI*) represents corporate green innovations (CGI) proxied by either the natural logarithm of one plus patent green patent or green patent citations and their derivatives). $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in the post-shock (2017-2020) period and zero for the pre-shock period (2013-2016). The financial constraints dummy (*FinCon*) is an indicator variable with a value of one if the *KZ_Index* is above the median value and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of firm-level covariates: *Size*, *Lev*, *Cash*, *RoA*, *R&D*, and *Tang*. $\boldsymbol{X}_{it}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re*. I define all variables in Appendix .A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses. The dependent variable in Models (1) and (2) represents the natural logarithm of one plus green patent counts $Ln(1+Gp)_{it}$. In models (3) &(4), the dependent variable represents the natural logarithm of one plus green patent citation $Ln(1+Gc)_{It}$

	Dep. Var =CGI			
	(1)	(2)	(3)	(4)
DiDiD(Treat$_i$*Post$_t$*FinCon)	**-0.013****	**-0.013****	**-0.029****	**-0.029****
	(0.006)	**(0.006)**	**(0.014)**	**(0.014)**
Size		0.007		0.011
		(0.005)		(0.013)
Lev		0.009		0.013
		(0.018)		(0.045)
Cash		0.026		0.062
		(0.019)		(0.052)
RoA		-0.068**		-0.117*
		(0.028)		(0.064)
R&D		0.222**		0.523*
		(0.101)		(0.278)
Tang		0.079***		0.164***
		(0.025)		(0.057)
Gdp_Grt (%)		-0.003**		-0.006**
		(0.001)		(0.003)
Re		0.104***		0.213***
		(0.022)		(0.048)
Obs	19,942	19,942	19,942	19,942
Adj-R^2	0.5956	0.5969	0.5628	0.5640
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 3.11: Role of Energy Intensity

This table reports the triple interaction regression of propensity-matched pairs of treated and control firms per the specification below:

$$Ln(1+CGI)_{it} = \alpha_i + \beta.(Treat_i * Post_t * HEI) + \Upsilon. X_{it} + \delta_j + \lambda_t + \varepsilon_i$$

i and t indexes as firm and time (year). The dependent variable *Ln(1+CGI*) represents corporate green innovations (CGI) proxied by either the natural logarithm of one plus patent green patent or green patent citations and their derivatives). $Treat_i$ is an indicator variable that takes a value of one if the firm *i* is in the treated group (i.e., US-headquartered and listed) and zero otherwise. $Post_t$ is a dummy variable that takes a value of one if the period is in the post-shock (2017-2020) period and zero for the pre-shock period (2013-2016). High Energy Intensive dummy (*HE*) is an indicator variable that takes a value of one if the firm i is in the high energy-intensive sector or zero otherwise. $\boldsymbol{X_{it}}$ is a vector of firm-level covariates: *Size, Lev, Cash, RoA, R&D,* and *Tang.* $\boldsymbol{X_{it}}$ also includes time-varying country-level control variables *Gdp_Grt* and *Re.* I define all variables in Appendix .A1. δ_j *and* λ_t represent the firm and year-fixed effects, while ε_i represents the error term. The symbols *, **, and *** indicate statistical significance levels at 10%, 5%, and 1 %, respectively. I winsorise all dependent variables and covariates at 1% and 99%, except for the country-level controls. The standard errors are corrected for clustering at the firm level and presented in parentheses. The dependent variable in Models (1) and (2) represents the natural logarithm of one plus green patent counts $Ln(1+Gp)_{it}$. In models (3) & (4), the dependent variable represents the natural logarithm of one plus green patent citation $Ln(1+Gc)_{it}$

	Dep. Var =CGI			
	(1)	(2)	(3)	(4)
DiDiD($Treat_i$*$Post_t$*HEI)	**-0.063***** **(0.008)**	**-0.061***** **(0.008)**	**-0.156***** **(0.019)**	**-0.152***** **(0.018)**
Size		0.006 (0.005)		0.007 (0.012)
Lev		0.008 (0.018)		0.011 (0.044)
Cash		0.016 (0.019)		0.037 (0.050)
RoA		-0.064** (0.027)		-0.107* (0.063)
R&D		0.180* (0.098)		0.420 (0.274)
Tang		0.059** (0.024)		0.116** (0.055)
Gdp_Grt (%)		-0.002 (0.001)		-0.003 (0.002)
Re		0.107*** (0.023)		0.219*** (0.048)
Obs	19,942	19,942	19,942	19,942
Adj-R^2	0.6004	0.6013	0.5691	0.5699
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

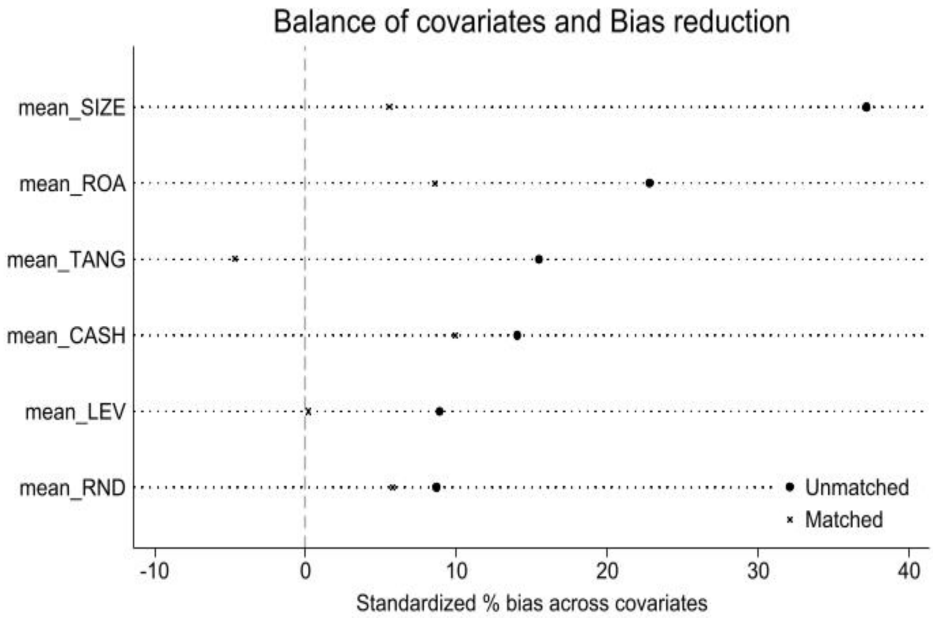

Figure3.1 Standardised Percentage Bias

The figure shows the standardised percentage bias of covariates before and after the PSM Matching. The round dark cycles indicate the dispersion of the mean differences between the covariates of the treated and control group of firms in the pre-2016 shock (unmatched). The diagram shows vast differences because the farther the indicators are away from zero, the more the mean differences in the covariates before the PSM matching. After the PSM matching, the star indicators show the mean difference and standardised percentage bias. It shows that there has been a significant reduction in bias, as demonstrated by the mean differences in the covariates closer to zero.

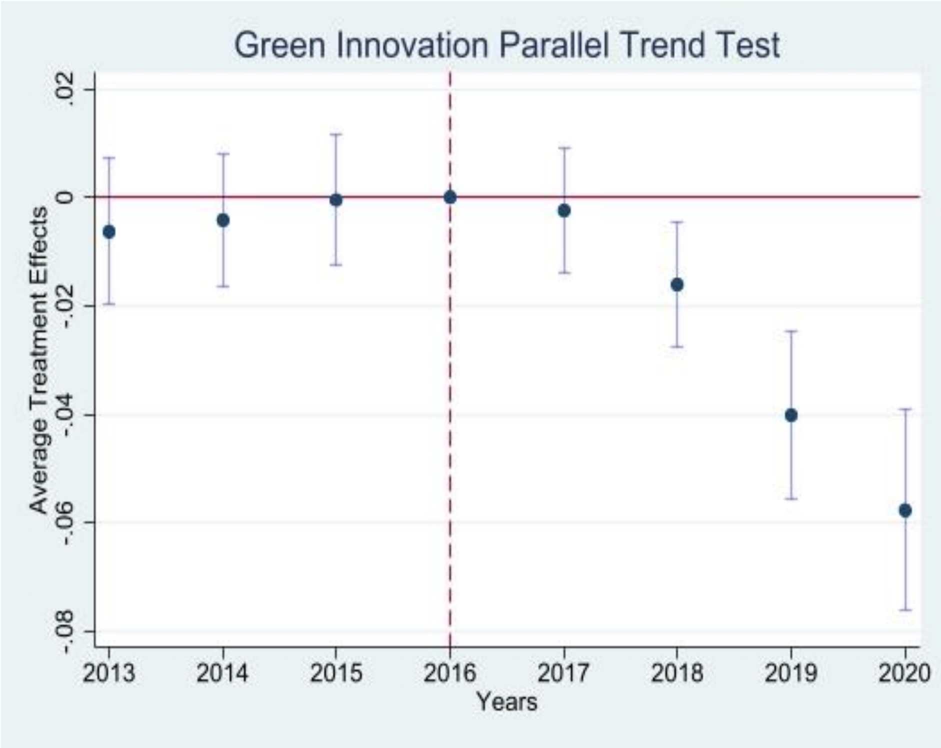

Figure3.2 Parallel trend test of Green Patent Count

This figure shows a time-series plot of the mean of treated and control firms. Analysis of green patent filling trends before the 2016 climate regulatory uncertainty shock shows that US-headquartered and European firms have similar trends using mean yearly filling for green patents. However, following the 2016 U.S. Presidential Election, a period of Unexpected change in climate political leadership, I observe a sharper and more significant decline in the patent filing by U.S. firms than in the control firms (non-US firms).

Chapter 4 Green Taxonomy and Corporate Green Revenue

Abstract: Political constraints arising from a lack of commitment to long-term policy pathways for green transit have been a long-standing problem in addressing the climate change crisis. In this study, I investigate the impact of the Green Taxonomy initiative of the European Union climate political leadership on corporate green revenue. Using a global dataset of corporate green revenue between 2016 and 2022 and exploiting a quasi-natural experimental setting in which firms' green revenue is exogenously affected in a difference-in-differences framework, I find that green taxonomy regulation promotes corporate green revenue performance. I document environmental innovation as a plausible economic mechanism. The effect is stronger for firms with higher analyst coverage, higher stock liquidity, and lower financial constraints. This study highlights the importance of political leadership's climate regulation in driving the shift towards a green transition.

GEL Classifications: *034, G38, Q55*
Keywords*:* *climate responsibility, corporate green revenue, climate policy, stock liquidity, corporate reputation*

4.1 Introduction.

Climate change risk poses a challenge for firms owing to the effects on corporate revenues, capital costs, and productivity while exacerbating environmental and public health crises(Currie et al., 2014; Huynh & Xia, 2021; Krueger, Sautner, & Starks, 2020). The externalities of climate change present a significant market failure, demanding immediate policy intervention for a structural transformation of production and consumption patterns to facilitate a green transition (Besley & Persson, 2023; Brown et al., 2022; Carattini et al., 2023; Hombach & Sellhorn, 2019; Ilhan, Sautner, & Vilkov, 2021; Martinsson et al., 2024b; Ramadorai & Zeni, 2024; Stern, 2008). Climate Political leadership's regulatory intervention to address externalities of climate change may take several dimensions, like Pigovian[47] taxes and subsidies, emission trading schemes, and renewable energy policies(Andreou & Kellard, 2021; Besley & Persson, 2023; Brown et al., 2022; Nicolli & Vona, 2016). For example, Jaffe et al. (2002) and Brown et al. (2022) suggest that emission taxes cause polluting firms' production costs to increase, thereby encouraging cleaner production investment.

Firms' response to climate regulatory pressure may take several dimensions(Backman et al., 2017). They may adopt diverse strategies, ranging from actions like lobbying[48] , asset divestment[49] , and pollution export [50] or engaging in substantive efforts like green innovation, clean energy adoption, resource efficiency, and production of green products and services(Ben-David et al., 2021; He & Qiu, 2025; Laeven & Popov, 2023; Orazalin et al., 2024; Rahman et al., 2024; Rugman & Verbeke, 1998). The literature notes that substantive climate-responsible actions are

[47] The concept of Pigouvian taxes stems from Arthur Pigou's economic theory, which advocates imposing a tax equal to the external cost of negative externalities to achieve optimal resource allocation. This principle finds significant application in environmental policies, where it seeks to mitigate pollution and other detrimental environmental effects by increasing the financial burden associated with such activities.

[48] Those facing a higher probability of future climate-related incidents tend to be significant anti-climate lobbyists. See further literature on lobbying and environmental risk management(Meng & Rode, 2019; Rahman et al., 2024)

[49] See Duchin et al., 2022; Ecker & Keeve, 2023

[50] Firms may transfer pollution to factories located in less regulated environments or engage in offshoring activities referred to as "carbon leakage" or "pollution export." (Babiker, 2005; Ben-David et al., 2021; Li & Zhou, 2017). .

required to achieve the green transition in response to climate regulation (Orazalin et al., 2024). An example of substantive action is transforming a firm's production strategy to create green products and services that generate revenue.

Corporate green revenue(after that, CGR) is a dimension of a firm’s climate responsibility that focuses on addressing the negative externalities of climate change at both the production and the consumption levels[51] by developing and offering products and services[52] that lower environmental externalities while generating green revenue(Klausmann et al., 2024; Kruse et al., 2024). Literature notes that firms' products and services can contribute to combating global climate change by improving consumers' energy efficiency (Acemoglu et al., 2016; Kruse et al., 2020). Such green practices create long-run value by improving stakeholder trust while serving as a product differentiation strategy that commands higher price premiums[53] and improves corporate green reputation(Berrone, Fosfuri, Gelabert, & Gomez-Mejia, 2013; Dangelico & Pontrandolfo, 2010; Drozdenko et al., 2011; Hart & Milstein, 2003).

[51] Greenhouse gas emissions are primarily driven by household consumption, which accounts for 72% of the total. Government consumption and investments contribute 10% and 18% to these emissions. Food consumption is the largest contributor to household activities, responsible for 20% of GHG emissions. Close behind are the operation and upkeep of homes at 19%, while transportation-related activities generate 17% of emissions(see : Hertwich & Peters, 2009).The literature suggests that significant greenhouse gas emissions are attributable to households(Hertwich & Peters, 2009; Ivanova et al., 2016). Given that greenhouse gas (GHG) emissions are a significant cause of global warming(Martinsson et al., 2024a; Stern, 2008), addressing these sources is critical for the transition race. For the EU green taxonomy, see: https://finance.ec.europa.eu/sustainable-finance/tools-and-standards/eu-taxonomy-sustainable-activities_en .Assessed Dec 10th 2023

[52] The US Department of Energy (1997a, b) demonstrates that lighting in industrial and commercial settings is responsible for 13% of the total power demand in the United States. This significant contribution to electricity consumption produces carbon dioxide, nitrogen oxides, and other pollutants involved in generating electricity. Hence, companies that produce lower energy consumption contribute positively to reducing the impact of consumer lightening on the environment while equally generating green revenue in the process.

[53] Green products command higher premiums in the product market than non-green products(Drozdenko et al., 2011)

Furthermore, it reduces firms' use of non-renewable resources, eliminating harmful inputs and preventing resource waste(Albino et al., 2009).

Motivated by growing concerns over the impact of climate change and the extent and magnitude to which firms change their behaviour, I examine whether and how climate regulation proxied by green taxonomy regulation impacts corporate green revenue. Green Taxonomy is part of the European Union's sustainable finance Action Plan, which provides a structured framework for classifying economic activities as environmentally sustainable if they significantly contribute to one or more objectives, particularly climate-change mitigation or adaptation(Alessi et al., 2024; Sautner et al., 2024). It is a classification tool that helps companies and investors make informed investment decisions on environmentally friendly economic activities to accelerate green transitions (Alessi et al., 2024).

The European Union's sustainable finance framework has a 'double materiality' approach, which places equal importance on evaluating the risks arising from sustainability factors and assessing the impact of corporate activities on society and the environment(Alessi et al., 2024). Understanding how firms' green revenue practices align with green taxonomy regulations is essential for advancing the debate on the pace and effectiveness of green transition. Consequently, examining this relationship is timely and crucial for several reasons.

First, the different dimensions and scales of environmental risks, like carbon emissions, toxic waste release, biodiversity, and air pollution, imply the possibility of asymmetric effects of climate policies in addressing these environmental issues. (Bowen et al., 2018). Second, policy formulation and implementation differ across countries across target dimensions and policy designs.(Ben-David et al., 2021; Botta

& Koźluk, 2014; Nachtigall et al., 2022). Third, firms may develop a competitive advantage in response to regulatory pressure.(Porter & Van der Linde, 1995; Porter & Linde, 1995). Rugman and Verbeke (1998) develop a framework of corporate strategic response to regulatory pressure in which a firm's strong response to regulatory pressure should lead to the development of green competitive resources that are proprietary to the firm, even though it could be from external regulatory pressure. Fourth, the classification of firms based on greenness varies across scholars(Pedersen et al., 2021), complicating the assessment of a firm's actual environmental footprint across all dimensions. Moreover, identifying and assessing what constitutes green business activities is challenging for investors and firms, creating friction in the green transition process.

Furthermore, economic theory suggests that greener firms should benefit from lower costs of capital and higher market valuations(Chava, 2014; Heinkel et al., 2001; Pástor et al., 2021; Pedersen et al., 2021; Zerbib, 2022)[54]. Therefore, if firms increase their green revenue share by default in response to green regulations, it is rational to assume that firms should increase their corporate green revenue performance. Nonetheless, the impact of climate regulation on the CGR may vary for several reasons.

On the one hand, firms may choose between green and brown investments (Kemp-Benedict, 2014). Therefore, firms may not adopt green revenue strategies if the cost of CGR practices outweighs the expected utility of generating green revenue. Thus, firms may favour greener investments only when the expected returns, influenced by the

[54] Pastor et al. (2021) propose that some investors harbour social preferences and seek positive utility from holding green stocks, thereby affecting returns through their willingness to pay higher prices. Sauzet and Zerbib (2022) suggest that a green premium is important, especially for investors who want to change corporate practices and can incentivize companies to minimize their environmental footprints and thereby decrease their capital costs.

anticipated stringency of climate policies, exceed those of carbon-intensive options(Popp, 2010; Xu & Kim, 2022). In addition, investment in climate mitigation strategies requires exorbitant corporate resources coupled with financial friction, which reduces a firm's capacity to invest in greener production (Ambec & Ehlers, 2016; Dang et al., 2022; Ramadorai & Zeni, 2024; Xu & Kim, 2022).On the other hand, firms may engage in green revenue practices to demonstrate better climate responsibility, build green reputational capital, expand into new markets, and avoid environmental controversies(Ambec & Lanoie, 2008; Dangelico, 2016; Dangelico & Pontrandolfo, 2015; Hart & Milstein, 2003).

I develop testable hypotheses based on sound economic theories and relevant empirical literature to investigate whether the Green Taxonomy regulation under the European Sustainable Action Plan influences green revenue performance. The hypotheses, based on the Dynamic Complementarity theory, which suggests that in equilibrium, climate regulation serves as a catalyst that facilitates a structural shift towards corporate production of green products and services, creating a bidirectional complementarity of production and consumption patterns that converges to facilitate the transition to a greener economy(Besley & Persson, 2023). Therefore, green taxonomy policies that facilitate consumption-level structural change by fostering the corporate production of green products and encouraging the transformation of firms' business production activities to meet green consumption demand are critical to the green transition.

Next, I employ two complementary theories: signalling and legitimacy theories(Bansal & Clelland, 2004; Connelly et al., 2011), which suggest that a firm may increase its green revenue performance following the introduction of green regulations to signal better climate responsibility to its stakeholders and improve its legitimacy with stakeholders. Consequently, this reduces information asymmetry, enhances corporate reputation, and improves green legitimacy(Connelly et al., 2011; Hart & Milstein, 2003). Literature shows that firms partly engage in green practices to navigate environmental and reputational risks, benefiting them, especially during periods of salient environmental risk(Brammer & Pavelin, 2006).

I employ a quasi-natural setting in which firms' green revenue performance is exogenously affected. I exploit the 2018 European Commission adoption of a set of policy frameworks in the European Union Action Plan on sustainable growth[55], including the "Green Taxonomy Policy" as a source of exogenous variation in firm-level green revenue performance. The European Union is a leader in green climate policy, and the green taxonomy policy is a highly ambitious plan to address the net-zero transition(Alessi & Battiston, 2022; Wurzel & Connelly, 2011). Hence, I consider firms listed and headquartered in the European Union with publicly available green revenue data as the treatment group and firms in the rest of the world as the control group. I employ the entropy balance technique to address potential endogeneity issues following prior literature to strengthen my empirical strategy.

The quasi-natural experiment and subsequent analysis yield the following findings. I find a 1.4% differential increase in the treated firms' green revenue activities relative to their counterparts in the control group. This evidence is consistent with the role of climate regulatory pressure in fostering better climate responsibility by modifying corporate behaviour (Boamah, 2022; Hombach & Sellhorn, 2019; Lin

[55] See section 2.1 for the details of the Green Taxonomy

et al., 2024). These results are robust to the parallel trend test, placebo test, entropy balance test, and alternative CGR measures.

I extend my investigation to uncover the plausible economic channels of the result. The literature argues that green innovation practices are required for firms to make significant progress in addressing climate change(Cheng et al., 2024; Cohen et al., 2020). Consistent with theoretical argument and empirical evidence suggesting well-crafted environmental regulation can induce environmental innovation(Kemp, 2000; Lin et al., 2024; Popp, 2010; Rennings & Rammer, 2011), I expect environmental innovation to positively mediate the link between Green Taxonomy policy and corporate green revenue performance. I find strong support for the environmental innovation channel, consistent with the literature on the relationship between climate policy and green revenue performance(He & Qiu, 2025; Lin et al., 2024; Popp, 2010).

Next, I explore cross-sectional variations in which the main findings hold. First, I investigate whether stock market liquidity moderates the relationship between green taxonomy regulation and corporate green revenue performance. I employ the Amihud illiquidity measure as a proxy for stock market liquidity and analyse whether it is a plausible economic channel for the observed effect. Consistent with the notion that stock liquidity conveys information to managers that may influence corporate policies(Amihud & Levi, 2023), I find that stock liquidity positively mediates the relationship.

Next, I examine whether firm-level information asymmetry proxied by analyst coverage moderates this link. The literature notes that Financial Analysts act as an external governance mechanism and influence corporate environmental policies through monitoring functions(Benlemlih et al., 2024; Jing et al., 2023). The findings indicate that higher analyst coverage reduces the level of information asymmetry, leading to an increase in green revenue practices, consistent with the role of financial analysts in corporate environmental performance(Benlemlih et al., 2024; Jing et al., 2023).

This study contributes to the literature in several ways. First, it is a part of the growing literature on corporate green revenue (Bassen et al., 2025; Bassen et al., 2023; Guo & Zhong, 2023; Klausmann et al., 2024; Kruse et al., 2020; Lel, 2024a; Quaye et al., 2024; Yan & Yin, 2023). Kruse et al. (2020) document the effect of green revenue on corporate profitability, Bassen et al. (2023) investigate the link between green revenue and stock returns, and Quaye et al. (2024) document asset pricing implications of green revenue factors. Yan and Yin (2023) examine the relationship between green revenue and syndicated loan pricing and show that banks offer lower spreads on syndicated loans to firms that generate green revenues. Additionally, this study shows that firms with green revenues tend to file more green patents after loan origination despite banks often viewing green innovations as riskier and demanding higher spreads. Guo and Zhong (2023) use green revenue data from Chinese firms to document the relationship between green revenue practices and corporate cash holdings. Klausmann et al. (2024) use the imputation of green factors to generate firms' green revenue share, documenting that institutional investors' presence before the Paris Climate Accord increased green. Lel (2024a) show the impact of green revenue on corporate profits. This study differs from the other studies in that it documents the role of the Green Taxonomy policy as a critical driver of firms' green revenue behaviour.

Second, this study contributes to the literature on the determinants of corporate environmental policies. Akey and Appel (2021) show that moral hazard issues, evidenced by parent companies' limited liability laws, influence subsidiaries' environmental policies, as evidenced by higher pollution levels. Brown et al. (2022) show that higher pollution taxes increase a firm's utility from environmental abatement expenditures, leading to improved investment in climate responsibility. Benlemlih et al. (2024) document that more analyst coverage leads to better quality and quantity of environmental information disclosures. Azar et al. (2021) document the influence of institutional ownership on corporate environmental performance. Other studies investigate the role of financial constraints in corporate environmental policies(Bartram et al., 2022; Dang et al., 2022; Xu & Kim, 2022). I contribute to this growing strand of literature by documenting the role of green taxonomy policy in enhancing corporate environmental performance through improved green revenue generation.

This study also contributes to the broader literature on the effects of climate regulation on corporate outcomes(Bartram et al., 2022; Dang et al., 2024; Dechezleprêtre, 2017; Fard et al., 2020; Hombach & Sellhorn, 2019; Kundu, 2024; Lin et al., 2024; Lopez et al., 2017; Ramadorai & Zeni, 2024; Shapiro & Walker, 2018). Fard et al. (2020) use international data showing the effect of climate regulation on the cost of credit. Bartram et al. (2022) use the California cap-and-trade bill to document higher financial constraints for firms subject to complying with the regulation. Martinsson et al. (2024b) use the introduction of the first carbon tax in Sweden to document a reduction in carbon emissions. Exploiting California's cap-and-trade bill, Ivanov et al. (2024) investigate the impact of carbon regulations on bank credit to carbon-intensive firms. It shows that high-carbon-intensive firms face shorter loan maturity and higher interest rates. Dang et al. (2024) use the implementation of the Nox Trading Program to show that climate regulation significantly impacts a firm's access to credit. I contribute to this growing literature by documenting the role of green taxonomy policy on a firm's corporate climate responsibility outcome, specifically green revenue performance.

Finally, this study contributes to the literature on the intersection between climate regulation and corporate environmental performance. Previous studies have mainly focused on the impact of climate regulation on the operational dimensions of climate responsibility, like carbon emissions, toxic waste release, air pollution, and biodiversity destruction(Bartram et al., 2022; Ivanov et al., 2024; Martinsson et al., 2024a; Tomar, 2023). Despite the significance of addressing consumption-level emissions, this study is the first to empirically examine the impact of green policies on corporate green revenue performance using global green revenue data.

The remainder of this paper is as follows: Section Two deals with the Institutional background, relevant literature and hypothesis development; Section Three addresses the data and empirical strategy; Section Four presents the results and discussion; and Section Five presents the conclusion.

4.2 Institutional Background, Literature Review and Hypothesis Development

4.2.1 Institutional Background

The European Commission issued a press release[56] in 2018 introducing a comprehensive package of legislative measures as part of its sustainable finance action

[56]https://ec.europa.eu/commission/presscorner/api/files/document/print/en/ip_18_1404/IP_18_1404_EN.pdf.Assessed December 18th, 2013

plan[57]. The Action Plan was published by the European Commission in March 2018, followed by the formation of the Technical Expert Group (TEG) two months later (Alessi & Battiston, 2022; Kooroshy et al., 2020). The TEG, consisting of 35 representatives from diverse sectors, like civil society, academia, business, and finance, was commissioned to develop recommendations for taxonomy.

At the core of this legislative measure lies the proposal for a regulation to establish a unified classification system, or taxonomy, for environmentally sustainable economic activities referred to as "Green Taxonomy."[58]. These regulatory measures set out the criteria and conditions for defining activities that contribute meaningfully to environmental objectives referred to as "Green Taxonomy", which clarifies which revenue and associated business activity is eligible as "Green revenue." Green Taxonomy supports firms' investments in green activities and encourages investors to make green investments(Alessi & Battiston, 2022; Plan, 2018).

Widely regarded as a foundational step[59], the EU Taxonomy is a comprehensive framework outlining economic activities and the criteria to be considered environmentally sustainable(Kooroshy et al., 2020). It provides harmonised terminologies and standardised benchmarks to measure green economic activities across businesses and sectors. Almeida et al. (2023) suggest that the Green Taxonomy framework legislative proposal is viable for investigating green performance.

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[57] See:https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52018PC0353&from=EN Assessed December 18th, 2013

[58] "A Taxonomy is a classification tool to help investors and companies make informed investment decisions on environmentally friendly economic activities. It can help to grow the clean economy of the future and substantially improve the environmental performance of industries we have today." (Plan, 2018)

[59] Subsequently, several regulatory frameworks have since been developed from the EU Action Plan for sustainable finance growth

At its core, the taxonomy identifies economic activities[60] that contribute to six key environmental objectives: mitigating climate change, adapting to its impacts, promoting sustainable use and protection of water and marine resources, advancing circular economy practices through waste prevention and recycling, preventing and controlling pollution, and safeguarding healthy ecosystems(Alessi & Battiston, 2022). Through this structured approach, the EU Green Taxonomy provides a transparent and adaptable tool for guiding investments toward sustainable outcomes.

Beyond risk management, taxonomy fosters meaningful discussions on corporate sustainability strategies by focusing on economic activities rather than broad corporate-level metrics. This detailed approach reveals inconsistencies and highlights opportunities within business models. For companies, the Taxonomy offers a science-based framework to guide environmentally sustainable practices. It may unlock financial support for research and development while rewarding those committed to sustainability-driven initiatives.

Green taxonomy aims to provide investors with clarity and consistency, enabling effective capital channelling into sustainable projects(Alessi & Battiston, 2022). Complementing this, a proposed regulation on sustainability disclosures mandates that institutional investors and asset managers transparently integrate environmental, social, and governance (ESG) factors into their risk management and investment decision-making processes. Through delegated acts, these obligations ensure accountability and alignment with long-term sustainability goals.

[60] https://www.unepfi.org/industries/investment/teg-reports/

Additionally, the legislative package includes amendments to the benchmark regulation, introducing new categories, like low-carbon and positive-carbon impact benchmarks(Alessi & Battiston, 2022). These benchmarks offer investors greater transparency regarding the carbon intensity of their portfolios, supporting informed decision-making in aligning investments with climate objectives(Plan, 2018).

4.2.2 Theoretical Framework and Hypothesis Development

This section describes the theoretical framework employed and the formulation of a testable hypothesis. First, I briefly describe the Dynamic Complementarity theoretical framework (Besley & Persson, 2023). Drawing on the logic and predictions of the theoretical framework, I explain the channels through which Green Taxonomy regulation causally influences green revenue. In formulating the hypotheses based on the theoretical view of Dynamic Complementarity and two other related theories, Signalling and Legitimacy Theories

4.2.2.1 Theoretical Framework: Green Taxonomy Policy and Corporate Green Revenue Performance

The dynamic complementarity theory(Besley & Persson, 2023) proposes a dynamic model for analysing green transitions. It suggests that a transition in firm production technology and consumer demand(values)[61] for green products interact in a mutually reinforcing loop. The interaction leads to dynamics that converge to either a "green steady state" (sustainable practices dominate) or a "brown steady state" (traditional practices persist). The DCT framework suggests that green practices are endogenous

[61] Besley & Persson, 2023 describes green values as Intrinsic consumer preferences for environmentally friendly choices.

and exogenous climate regulatory shocks to green practices, like introducing regulations, incentivising green technologies, and reinforcing the interaction with shifting values(consumer demand) in a two-way complementarity similar to that observed in platform technologies(Besley & Persson, 2023; Tirole & Rochet, 2003), and ensuring convergence toward a green, steady state. Otherwise, the firms persist in their brown state.

The DCT framework suggests that the share of consumers holding green value evolves, partly in response to the economic incentives generated by climate regulation. It assumes consumers' green preferences, incorporating more concerns about green values, based on the assumption that consumers derive additional utility related to the pollution level of their consumption. Utility increases if consumers know that buying environmentally friendly goods and services reduces pollution. The framework further suggests that firms adopting green technologies may reduce the marginal cost of innovative green technologies through learning-by-doing, in which the cost of green technologies progressively decreases as more firms engage in the green transition of their production technologies to green innovative ones. Consequently, green products are more accessible and encourage consumers to embrace green value. Similarly, increasing consumer demand for green products incentivises firms to adopt green technologies.

The framework captures how value and technology interdependent co-evolution underpin green transitions, emphasising the pivotal role of regulation in overcoming coordination failures and achieving sustainability goals. The framework argues that a lack of incentive to invest in green technologies to produce green goods and services and inadequate consumer demand(values) for green goods could lead to "*a green trap*[62]". Based on the notion that climate policies shape both production and consumption choices while also impacting their dynamic interdependence and complementarity, the DCT framework suggests that exogenous regulatory intervention incentivises the firms to adopt greener technologies to produce greener goods and simultaneously create consumer awareness, reinforcing the green transition.

The lack of political commitment to long-term climate regulations represents a constraint that can hinder optimal green transition (Besley & Persson, 2023; Hsu, 2013). The DCT incorporates such political constraints in its model, highlighting the interplay between the market and political processes. It posits that market and government failures can interact, hindering welfare-improving green transition. The framework advances a more holistic approach to environmental regulation, considering the market and political dynamics in the green transition process. Therefore, the DCT argues that optimal exogenous regulation should generate sufficient corporate incentives and value transitions to accelerate green transition.

4.2.2.2 Hypothesis Development

I draw on the prediction and logic of Dynamic Complementarity Theory(Besley & Persson, 2023) discussed in the earlier section to explain the relationship between green taxonomy regulation and corporate green revenue performance. Dynamic Complementarity Theory(Thereafter DCT) suggests that climate regulation creates a

[62] Besley & Persson, 2023 describes a "*green trap* "as the state where an economy remains stuck in an environmentally unfriendly state due to various factors such as initial conditions, market dynamics, political constraints, or the interaction between these elements, thus preventing the economy from realising the potential benefits of a greener economic structure, even though such a transition would improve overall welfare.

dynamic interaction between firms' production and green product consumption patterns, leading to mutual reinforcement and market growth during the green transition. Economic literature argues that climate regulation may significantly promote green consumption, shifting the economy towards green products(Nyborg et al., 2006). Specifically, government regulatory commitments can act as a coordination mechanism, shifting the economy from a low-adoption to a high-adoption equilibrium state for green products(Nyborg et al., 2006).

Introducing our empirical setup into the DCT theoretical framework implies that green taxonomy regulation should encourage firms to adopt innovative environmental technologies to produce eco-friendly goods that boost consumer demand for green products. This positive feedback loop, where increased consumption of green products promotes further adoption of innovative green practices and expansion of green production, enhances corporate green revenue and reduces carbon footprints at both the production and the consumer level.

Hence, based on the prediction of the DCT theory, exogenous climate regulation shifts production and consumption patterns from a brown to a green(sustainable) state, increasing market share for green firms and influencing consumer behaviour. Climate regulation strengthens this mechanism by aligning firm incentives with consumer preferences and promoting interconnectedness between regulatory tools, market dynamics, and value transitions.(Besley & Persson, 2023). Consequently, green taxonomy regulation catalyses sustainable economic performance in addressing environmental externalities at both the production and consumption levels.

Moreover, stricter climate regulations create greater stakeholder awareness (Alok et al., 2020; Fahmy, 2022; Krueger, Sautner, & Starks, 2020). Therefore, firms should increase their green revenue in response to green taxonomy regulations. The literature notes that consumer and investor preferences have increasingly shifted towards sustainable consumption and investment driven by growing concerns about climate change (Ceccarelli et al., 2024; Finance, 2018; Gibson Brandon et al., 2022; Pástor et al., 2021, 2022; Zerbib, 2022). Therefore, given that green products command price premium (Drozdenko et al., 2011) and consumers derive a self-image benefit from choosing green products, which increases with both the perceived environmental impact and popularity of green choices(Brekke et al., 2003; Nyborg et al., 2006), I argue that green taxonomy regulation should strengthen the moral preferences of green consumers by providing clear environmental standards, increasing willingness to pay for green products, leading to higher corporate green revenue.

Furthermore, green taxonomy regulation could empower activists, increasing pressure on firms to transform their production and products into greener choices, thus indirectly boosting green revenue performance. I expect firms to demonstrate better corporate climate responsibility by engaging in more green business activities and offering customers green products and services, leading to revenue generation.

Firms' response to climate regulatory pressure may take several dimensions(Backman et al., 2017). One could argue that firms may engage in greenwashing activities rather than green-oriented business models in response to regulation. Further, compliance costs, especially for small and medium-sized firms, may outweigh the green revenue gains, exacerbating financial constraints and impairing the ability to invest in green business models, eventually lowering green revenue. Some companies might divert funds from green investment to comply with reporting requirements instead of expanding their green business activities. At the same time, some may reclassify their current activities to fit green taxonomy standards without significant investments in green business activities.

Therefore, the direction of the relationship between the EU taxonomy initiative and corporate green revenue remains an empirical question. To examine this relationship, I propose the following hypothesis :

H1: Ceteres Paribus, treated firms increase (increase) their green revenue performance in response to the European Union Green Taxonomy initiative.

4.2.2.3 Economic Channel: Environmental Innovation Channel

DCT predicts that green taxonomy regulation influences corporate green revenue generation through corporate environmental innovation channels by adopting innovative technologies to produce green products that generate revenue. Environmental innovation encompasses the modification and design of processes, techniques, systems, and development of environmentally sustainable products to replace inefficient and wasteful energy-intensive production processes with clean energy, energy efficiency, and conservation strategies, thereby mitigating environmental degradation(Cheng et al., 2024; Kemp, 2000; Rennings & Rammer, 2011).

Climate regulation can also induce green innovation practices(Kemp, 2000; Porter & Van der Linde, 1995; Porter & Linde, 1995; Rennings & Rammer, 2011). The Literature suggests that green innovation encompasses the modification and design of processes, techniques, systems, and development of environmentally sustainable products to supplant inefficient and wasteful energy practices with clean energy,

energy efficiency, and conservation strategies, thereby mitigating environmental degradation(Cheng et al., 2024; Kemp, 2000; Rennings & Rammer, 2011). Therefore, Green or Environmental innovation practices are strategic corporate resources and serve a market differentiation strategy, contributing to firm performance (Cheng et al., 2024; Khanra et al., 2022; Lin et al., 2024)

According to the "strong" version of Porter's hypothesis, stringent environmental regulations compel firms to reevaluate their products and processes, necessitating innovation to comply with established market norms that induce green innovation practices in firms.(Porter & Van der Linde, 1995; Porter & Linde, 1995; Rubashkina et al., 2015).Significant archival studies document the positive impact of regulation on innovation(Cheng et al., 2024; Lin et al., 2024; Rennings & Rammer, 2011). Moreover, the literature argues that if compliance costs outweigh the cost of developing innovation activities, firms may engage in green innovation practices(Cohen et al., 2020; Dangelico, 2016; Khanra et al., 2022; Kim et al., 2021a; Lin et al., 2024; Rugman & Verbeke, 1998). I argue that the EU Action Plan for Sustainable Growth's Green Taxonomy policy measure, which highlights the taxonomy of green practices as a core policy measure, should positively influence green innovation, leading to green revenue activities.

Meanwhile, the literature notes that market forces can encourage innovation and promote a profit-oriented approach to address environmental issues if private rewards exist for green practices through capital market recognition and rewards of green firms (Kruse et al., 2020; Zerbib, 2022). Moreover, environmental regulations may encourage better competition by designing and implementing green innovation practices, leading to diverse product offerings to meet the demands of green-conscious customers and better access to them(Berrone, Fosfuri, Gelabert, & Gomez-Mejia, 2013; Eichholtz et al., 2010; Rugman & Verbeke, 1998). Therefore, environmental regulation may induce green innovation practices and positively reposition firms into a competitive advantage in the product market through the acquisition of new environmentally conscious customers (Dechezleprêtre, 2017; Leiter et al., 2011; Popp, 2010; Porter & Van der Linde, 1995; Porter & Linde, 1995; Rennings & Rammer, 2011; Rubashkina et al., 2015). Therefore, I propose the following hypothesis :

H2: Green innovation positively mediates the relationship between green taxonomy policies and corporate green revenue performance.

4.3 Data, Summary and Variable Measurement

4.3.1 Data

I draw data for empirical analysis from several sources. First, I obtain global green revenue data from the FTSE Russel Green Revenue Database, which consisted of firms with green revenue data from 2016 to 2022. Financial and accounting data come from Compustat fundamental annual databases(I combine North America and Global) and Datastream. I follow prior literature in excluding financial firms (SIC 6000-6999) and utility firms (SIC4900-4999) owing to the different nature of their financial statements (Edmans et al., 2012). I exclude firms with a negative book equity value to avoid confounding effects arising from financial distress(Gilchrist et al., 2014).To mitigate biases in the findings, I restrict the firms in the sample to those without missing key variables. I obtain data on environmental innovation scores from ASSET4G and the climate regulatory stringency index from Germanwatch. Furthermore, I obtain time-varying country-level data on gross domestic product (GDP) and governance from the World Bank group. The initial sample consists of global firms across 37 countries with firm-level green revenue data between 2016 and 2022, consisting of 20,851 firm-year observations derived from 3,689 unique firms present in the FTSE green revenue database. In the empirical set-up, I consider European firms the treated group, while the rest of the green firms in the database from other countries are in the control group.

4.3.2 Key Variable Measurement

4.3.2.1 Corporate Green Revenue

Green revenue is classified as green using the European Union Taxonomy for the classification of green activities relative to the total revenue generated by the firm in a specific year(Kruse et al., 2020). I follow Kruse et al. (2024), Klausmann et al. (2024), and Quaye et al. (2024) in using the FTSE Green Revenue database. Kooroshy et al. (2020) suggest that it offers in-depth insights into the climate responsibility of publicly traded companies' operations, thereby revealing their shift towards a low-carbon economy over time.

4.3.2.2 Firm-level Control Variables

Drawing on prior literature, I incorporate a vector of firm- and country-level control variables, described in Appendix A4.1, which may predict a firm's green revenue performance. The variables consist of firm size *(Size),* defined as the natural logarithm of the total assets. I include book leverage (*Lev*), defined as the ratio of the total book value of debt to that of total assets, because debt holders may demand better disclosure from firms (Leftwich et al., 1981). Furthermore, I include cash holdings (*cash),* the cash and cash equivalence scaled by the book value of assets. Improved disclosure practices may require more financial resources. (Kim et al., 2020). I include a measure of firm profitability, namely Return on Assets (*RoA*), calculated by dividing earnings before interest and tax by the book value of assets.

I include Tangibility (*Tang*), the net property plant, and equipment scaled by the total book value of assets. I also include R&D expenses(*RnD*), which are R&D expenses scaled by the total book value of assets. All covariates are winsorised at one and ninety-ninth percentile in both tails to exclude the influence of outliers. I further cluster the standard errors in our regression analysis at the firm level.

4.3.2.3 Time-varying country-level Macroeconomic Variables

I include time-varying country-level macroeconomic and institutional quality in line with existing literature(Kim et al., 2021a). First, I use the GDP growth rate of the headquartered country for each firm to account for macroeconomic performance. I control for institutional quality by utilising the country's Rule of Law indicator from the World Bank Governance Indicator (WBGI). The rule of law measures a country's quality of governance. A higher rating indicates higher institutional quality, indicating 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).

4.3.3 Summary Statistics

I present summary statistics of the sample from 2016 to 2022 in Table 4.1. An average firm generates 27.2 % of revenue classified as green. Regarding firm-level control variables, a typical firm in the sample has an average book value of assets of $7.7bn. Regarding borrowing behaviour, an average firm in our sample borrows 19.6% of its total assets. The average firm exhibited 4.1% profitability in terms of return on assets. Firms hold approximately 20.4% of their cash relative to their total assets. Also, the average firm invests 1.6 % of its assets in Research and Development(R&D) and has 27.5 % of Tangible assets.

The country-level time-varying variables consist of the Gross Domestic Product growth rate (*Gdp_Grt*), with a mean of 2.56% and a standard deviation of 3.38, reflecting the variation in economic growth rates across different countries in our sample. Concerning the rule of law, an average score of 0.97 for a typical country in our sample and a standard deviation of 0.78 indicates a relatively stable rule of law across countries. The Climate Change Regulatory Stringency Index (*CRSI*) measures countries' climate regulation stringency, averaging 2.41, indicating moderate stringency. However, there are significant variations, with some countries having minimal or stringent regulations.

4.4 Empirical Strategy and Results

This section describes the empirical strategy, examines whether national climate policy is associated with CGR performance, and presents the results. Following the literature, I employ a difference-in-differences technique with entropy balance weights to further address endogeneity concerns. I also present the robustness and cross-sectional heterogeneity tests.

4.4.1 Empirical Strategy: Difference in Differences

4.4.1.1 Empirical strategy

I introduce the EU sustainable finance action plan as an exogenous shock that causes variation in firm-level green revenue. I adopt 2018 as the shock year when the EU Commission announced the action plan to ensure no anticipation of the treatment effect. I consider firms headquartered in Europe to be the treated group, while the rest are the control group. The European Union is considered a climate leader at the forefront of greening the global economy and formulating ambitious policies to foster green practices(Wurzel & Connelly, 2011).

I employ the following regression model using high dimensional fixed effects regression.

$$CGR_{it} = \alpha_i + \beta.\ Treat_i * Post_t + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_{c,t} + \varepsilon_{it} \qquad (1)$$

Where i and *t* indexes as firm and time (year), respectively, the dependent variable is CGR_{it}, which is the revenue derived from green activities scaled by the total revenue, expressed as a percentage. The key independent variable is $treat_i$* $post_t$, the difference-in-differences variable. Treat takes a value of one if the firm is a European firm and zero otherwise. Post takes a value of one if the year is after 2018 and zero if before 2018. $\boldsymbol{X}_{it}$ represents a vector of firm-level control variables *(Size, Lev, Cash, RoA, RnD, and Tang)* and country-level variables *Gdp_Grt and RuleLaw, as* described in Appendix A1. δ_j represents the firm-fixed effect, while $\lambda_{c,t}$ denotes the country-year fixed effects. While ε_{it} denotes the error term, I winsorise all firm- and country-level control variables at the 1st and 99th percentiles.

(Insert Table 4.2 here)

4.4.1.2 Parallel Trend Test

To employ difference-in-differences regression, I conduct parallel trend analysis to confirm that the empirical strategy meets the methodological requirement in the pre-shock period. I present the statistical tests of the parallel trend analysis in Table 4.3. panel A. Figure 4.1 shows a graphical illustration of the estimate. Both results indicate that in the pre-shock period 2016-2018, the difference in the level of the green revenue trend between the treatment and control groups is statistically insignificant at all levels. This result meets the requirement for using the difference-in-differences as my empirical setup.

(Insert Table 4.3 here)

4.4.1.3 Green Taxonomy and Corporate Green Revenue: Difference-in Differences OLS Regression. (Unmatched)

Following the favourable result of the parallel trend test, I estimate the difference-in-differences regression following specification (2) to establish a causal relationship between the Green Taxonomy and corporate green revenue .

$$CGRi_t = \alpha_i + \beta.\ Treat*Post_t + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_{c,t} + \varepsilon_{it} \qquad (2)$$

Where i and *t* are indexed as firm and time (year), respectively, the key independent variable is the difference in differences variable(*Treat*$Post_t$ *)*. The dependent variable is CGR_t, which is the revenue derived from green activities scaled by the total revenue, expressed as a percentage. $\boldsymbol{X_{it}}$ represents a vector of firm-level controls *Size, Lev, Cash RoA, RnD, and Tang* and country-level variables *(Gdp_Grt, RuleLaw), as* described in Appendix A1. δ_j represents the firm-fixed effect, while $\lambda_{c,t}$ denotes the country-year fixed effects. Where ε_{it} denotes the error term, I winsorise all firm- and country-level control variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses.

I present the results of the regression in Table 4.4. 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 and country-level covariates, and column (3) includes country-fixed effect. The coefficient of the difference-in-differences estimation suggests that green climate policies positively influence corporate green revenue practices. In economic terms, this results in a 1.4% differential increase in treated firms in the post-regulatory period relative to the control unit. This result is consistent with the role of regulation in fostering a transition to a low-carbon economy and addressing the impact of climate change externalities (Lin et al., 2024; Ramadorai & Zeni, 2024)

(Insert Table 4.4 here)

4.4.1.4 *Green Taxonomy and Corporate Green Revenue Performance: (Entropy Matched sample)*

I recognize that the difference-indifferences estimation may suffer from omitted variable bias and that pre-trend characteristics may bias our findings. I address these concerns using the entropy balance technique. In line with prior research(Cook et al., 2021; Hasan et al., 2021; Hossain et al., 2023), I employ the entropy balancing method to create a balanced sample of treated and control firms. Entropy balancing is a quasi-matching approach that ensures equilibrium across all covariates by generating a set of matching weights that satisfies the specified balancing constraints for each sample observation. This method tackles disparities in covariate representation between treatment and control firms, reducing dependence on specific modelling assumptions and guaranteeing balance improvements across all included covariates.

As a result, the reweighted observations exhibit identical post-weighting distributional characteristics for both treatment and control units. Concurrently, entropy balancing computes precise weights for control observations, preserving sample integrity and covariate balance (Chapman et al., 2019). The reweighing process eliminates the endogeneity bias caused by latent variables that distort the covariate distribution[63]. This technique adjusts the weights of control sample observations, resulting in matched covariate distributions that show no significant differences between the treatment and reweighted control groups (Hainmueller, 2012). The aim is to equilibrate the predetermined distribution moments (mean, variance, and skewness) of the covariates between the treatment and reweighted control groups.

[63] . For more technical details, refer to Hainmueller, 2012 and Chapman et al., 2019

The added benefit of entropy balancing is the significant enhancement of regression estimation efficiency by utilising information from a much larger number of observations than propensity score matching (PSM) matching, which often disproportionately reduces the sample size, leading to a significant loss of information within the dataset. Furthermore, the PSM matching technique considers only the mean distribution in its matching procedures, whereas the entropy balance technique provides the option of matching the three distribution moments. It considers only the mean and uses iterations with different callipers. However, entropy balancing can equilibrate covariates across variance and skewness in addition to the mean. I present the entropy balance test result in Table 4.3, panels 4.3b and 4.3c.

I re-estimate DiD specification (2) using the entropy-balanced sample. I present the result in Table 4.4, columns (1) to (3). The column indicates a differential 1.4% increase in green revenue performance in the treated group in the post-shock. Subsequent empirical analyses are based on entropy-balanced weights unless otherwise stated.

(Insert Table 4. 4 here)

4.4.2 Robustness Test

This subsection provides a series of robustness tests to validate the main findings of this paper. I conduct a series of tests to rule out alternative explanations for the results I document.

4.4.2.1 Robustness Test: Alternative measure of green revenue

I re-estimate specification (2) with the dependent variable CGR_{it} scaled by the average green revenue of all firms in the Fama and French industry classification for the same year(Ind_CGR_{it}). I report the findings in Columns (1) to (3) of Table 4.5. Column (1) is a univariate regression, while column (2) adjusts for firm-level covariates, firm- and year-fixed effects, and column (3) adjusts for country-level time-varying covariates and indicates a 1% significance level. These results are consistent with my main findings and validate the baseline results, supporting the *green inducement hypothesis.*

(Insert Table 4.5 here)

4.4.2.2 Robustness Test: Alternative sampling

I recognize the choice of all firms outside Europe as the control group for the empirical set-up may raise concerns. To alleviate this concern, I exclude firms from the United States due to significant and dramatic changes in the regulatory trajectory from 2016 to 2020, which could bias the findings I document. Second, I exclude firms headquartered in China due to prior initiatives on green revenue policies, which can also bias the findings I document. Lastly, I excluded firms headquartered in the United States and China and re-estimated the difference-in-differences specification. I re-estimate specification 2 using alternative treatment and control firms using entropy balance scores and report the results of the estimations in Table 4.6, column (1) to (3).

First, I estimate a fully saturated regression equation (2) excluding firms from the United States due to significant and dramatic changes in the regulatory trajectory from 2016 to 2020 and report in Columns (1). Next, I estimate regression equation (2) excluding firms from China and report in Columns (2). Last, I estimate regression equation (2) excluding firms from the United States and China from the sample and report in Columns (3).

The estimates show that the coefficient of the variable of DiD is significant at the 1% level and economically meaningful, consistent with our prior findings in Table 2. These results are consistent with my main findings and validate the baseline results, supporting the *green inducement hypothesis.*

(Insert Table 4.6 here)

4.4.3 Economic Channels

This subsection presents the economic channel for the main results. I identify environmental innovation as the main mechanism for the results.

4.4.3.1 Economic Mechanism test. : Environmental Innovation Channel

Hypothesis H2 posits that green innovation mediates the relationship between climate policy and green revenue performance. Following prior studies, I employ the green innovation score from ASSET4G as a reasonable proxy for environmental innovation(Safiullah et al., 2024). I create a dummy variable (*Env_Inv*) that takes a value of one if the firm's score is above the median and zero otherwise. I interact *Env_Inv with the* difference in differences variable to create a triple interaction variable *(Treat*Post*Env_Inv)* and estimate regression specification 5.

$$CGR_{it} = \alpha_i + \beta.\ Treat_i{*}Post_t{*}Env\_Inv + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_{c,t} + \varepsilon_{it} \quad (5)$$

Where i and t are indexed as firm and time (years), respectively, and CGR_t is the revenue derived from green activities scaled by total revenue, expressed as a percentage. The key dependent variable is the triple difference in differences estimator*(Treat*Post*Env_Inv)*. $Treat_i$ takes a value of one if the firm's headquarters is in Europe and zero otherwise in year *t*. $Post_i$ represents a time dummy that takes a value of one if the observation is in the pretreatment period(2016-2018) and zero otherwise. *Env_Inv* is a binary variable that takes the value of one if the firm's environmental innovation score is above the sample's median and zero otherwise. $\boldsymbol{X}_{it}$ represents a vector of firm-level control variables *(Size, Lev, Cash RoA, RnD, and Tang)* and country-level variables *(Gdp_Grt, Re), as* shown in Appendix A1. δ_j represents the firm-fixed effect, while $\lambda_{c,t}$ denotes the country-year fixed effects. Where ε_{it} is the error term, I winsorise all firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses.

I present the results in Table 4.7, columns (1) to (3). The coefficient of the triple interaction variable ($Treat{*}Post_t\ {*}Env\_Inv$) is significant at the 1% level, supporting the environmental innovation channel as a plausible mechanism for the result I document results, which is consistent with the role of environmental innovation in enhancing firms' corporate environmental performance (Cheng et al., 2024; Lin et al., 2024).

(Insert Table 4.7 here)

4.4.4 Cross-Sectional Heterogeneity Tests

This subsection shows the cross-sectional heterogeneity tests to add further robustness to the main findings. For this batch of tests, I identify three firm-level characteristics: stock market liquidity, Analyst coverage, and financial constraints.

4.4.4.1 Cross-Sectional Heterogeneity Tests: Stock Liquidity Channel

Stock liquidity refers to the ease with which investors sell stocks without adverse price effects.(Hanselaar et al., 2019).Stock liquidity is a first-order firm security attribute.(Krueger et al., 2024) , which serves as a channel for managers to obtain financial market feedback regarding their corporate strategy (Amihud & Levi, 2023). Prior studies note that stock liquidity is associated with firm value(Cheung et al., 2015; Fang et al., 2009), dividend policy(Banerjee et al., 2007), provision of trade credit (Shang, 2020), and investment and production capabilities (Amihud & Levi, 2023; Becker-Blease & Paul, 2006).

Further, Stock market liquidity is a disciplinary channel for monitoring managerial behaviour (Holmström & Tirole, 1993). Becker-Blease and Paul (2006) investigate the relationship between capital expenditure and stock liquidity and show that the level of a firm's stock liquidity positively relates to its corporate investment decisions through the expansion of the investment opportunity set. Similarly, Amihud and Levi (2023) show that market liquidity is the economic mechanism through which the capital market influences corporate investments. Hence, stock liquidity is important for firms and institutional investors.

Higher stock liquidity may facilitate better green revenue performance for several reasons. First, it may attract stockholder trading and instil monitoring and governance, fostering long-term corporate investment (Edmans, 2009; Edmans et al., 2013) in green business activities and improving a firm's revenue generation. Second, Stock liquidity is an important factor for firms and investors as it correlates with the capital cost. Theoretical evidence shows that investors demand higher returns for stock illiquidity(Amihud & Mendelson, 1986; Brennan & Subrahmanyam, 1996). Corwin (2003) and Butler et al. (2005) find evidence that lower market liquidity is associated with higher costs of equity. Similarly, Amihud and Levi (2023) show that higher market liquidity positively influences corporate investments.

Moreover, Economic theory also suggests that greener firms should benefit from lower capital costs and higher market valuations (Chava, 2014; Heinkel et al., 2001; Pástor et al., 2021; Zerbib, 2022)[64]. Hence, higher stock market liquidity should lower the cost of capital and expand investment opportunities necessary to increase corporate green revenue.

Furthermore, climate policy is an external governance mechanism that should reduce agency issues between a firm and its shareholders, thereby lowering the monitoring cost for institutional investors. Roy et al. (2022) show that stock market liquidity is a channel through which mandatory CSR expenditure regulation influences

[64] Pastor et al. (2021) propose that some investors harbour social preferences and seek positive utility from holding green stocks, thereby affecting returns through their willingness to pay higher prices. Sauzet and Zerbib (2022) suggest that a green premium is important, especially for investors who want to change corporate practices and can incentivize companies to minimise their environmental footprints and thereby decrease their capital costs.

firm market valuation. Consistent with the notion that the transition to a low-carbon economy requires significant external capital investment (Kemp-Benedict, 2014) and that higher stock liquidity is associated with a lower cost of capital(Butler et al., 2005; Fang et al., 2009), firms with higher stock liquidity should increase green revenue performance.

I test the hypothesis that stock market liquidity positively mediates the link between climate policy and the CGR. I follow prior empirical studies(Roy et al., 2022; Shang, 2020) using the price impact measure of Amihud liquidity as a proxy for stock market liquidity because of its superior performance in capturing high-frequency liquidity measures (Fong et al., 2017; Hasbrouck, 2009). Computing the Amihud measure involves dividing the absolute stock return by the stock's trading volume (Hanselaar et al., 2019).

$$AmihudIlliquid_{it} = \frac{1}{D_{i,t}} * \sum_{d=1}^{D} \frac{|Ret_{id}|}{Dollar\ Volume_{id}}$$

Ret_{it} and $Dollar\ volume_{id}$ represent the return and dollar volume of firm *i* on a day *d*, while D is the total number of trading days during firm *i'* fiscal year t. I discard firms with greater than 7 days non-trading days a month during the year.

To test this conjecture, I construct a dummy variable (*Amihud*) that takes a value of one if the firm's Amihud illiquidity value is below the median of the sample distribution and zero otherwise. I interact Amihud with the difference in differences variable to create a triple interaction variable*(Treat*Post*Amihud)* and estimate regression specification (6)

$$CGRi_t = \alpha_i + \beta.\ Treat*Post_t\ *Amihud + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_{c,t} + \varepsilon_{it} \qquad (6)$$

Where *i* and *t* are indexed as firm and time (years), respectively, the dependent variable CGR_t is the revenue derived from green activities scaled to the total revenue, expressed as a percentage. The key independent variable is the triple difference in differences estimator *(Treat*Post*Amihud). Treat*$_i$ takes a value of one if the firm headquarters are in Europe and zero otherwise, in year t. $Post_t$ represents a time dummy that takes a value of one if the observation is in the pre-treatment period(2016-2018) and zero otherwise. $\boldsymbol{X}_{it}$ represents a vector of firm-level control variables *(Size, Lev, Cash, RoA, RnD and Tang)* and country-level variables *Gdp_Grt and RuleLaw, as* shown in Appendix A1. δ_j *represents* the firm-fixed effect, while $\lambda_{c\ t}$ denotes the country-year fixed effects. ε_{it} represents the error ter*m.* I winsorise all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses.

I present the results in Table 4.8, columns (1) to (3). The coefficient of the triple interaction variable (*Treat*Post$_t$ *Amihud*) is significant at the 1% level, thus supporting H2. The result is consistent with the role of stock liquidity in corporate investment and corporate social responsibility and the role of the financial market in the transition to a sustainable economy(Amihud & Levi, 2023)

(Insert Table 4.8 here)

4.4.4.2 Cross-Sectional Heterogeneity Test: Analyst Coverage

Analysts act as crucial external monitors for institutional investors (Borochin et al., 2018; Chen et al., 2015; Derrien & Kecskés, 2013; Jung et al., 2018; Yu, 2008). A high level of analyst coverage serves as a crucial external governance mechanism. Analyst coverage reduces earnings management and agency costs through lower managerial compensation, improving corporate governance practices(Irani & Oesch, 2013; Yu, 2008). Analyst coverage directly and indirectly influences corporate policies, including corporate environmental disclosure. (Benlemlih et al., 2024; Chang et al., 2006; Derrien & Kecskés, 2013; Jing et al., 2023; Jo & Harjoto, 2014; Yu, 2008).

Analyst coverage is related to a firm’s level of information asymmetry (Brauer & Wiersema, 2018; Brown et al., 2004; Chang et al., 2006). Information asymmetry affects corporate product market outcomes(Billett et al., 2017). Analysts improve a firm’s information environment and reduce agency conflicts between shareholders and management(Benlemlih et al., 2024; Chang et al., 2006; Jing et al., 2023). Derrien and Kecskés (2013) use broker closures and mergers in a quasi-natural experiment to demonstrate that analyst coverage has an inverse causal relationship with information asymmetry. Their study shows that firms with reduced analyst coverage after brokerage closures experience higher information asymmetry and capital costs.

Thus, more analyst coverage should signify more information production and lower information asymmetry. Hansen (2015) suggests lower information asymmetry results from the analyst's persistent pursuit of publicly available information (like firms' green growth opportunities, facilitating a more equitable distribution across markets). Lower information asymmetry through analysts enriching the firm’s information environment decreases the firm's cost of capital(Derrien et al., 2016), better perception of the firm and improve access to capital(Derrien & Kecskés, 2013; To et al., 2018).

Luo et al. (2015) show that analysts connect a firm’s corporate social responsibility (CSR) performance to stock returns, acting as an information pathway for investors. Using a toxic waste inventory dataset, Jing et al. (2023) show that firms with lower analyst coverage emit more pollution, highlighting the role of financial analysts in corporate environmental performance. Analysts’ monitoring activities during earnings conference calls include raising important environmental issues and questioning managers on corporate environmental performance.

In addition, analysts are crucial to the transition to a green economy through their information intermediary role in the financial market(Fiorillo et al., 2022). Furthermore, analysts' direct monitoring efforts incentivise managers to enhance corporate environmental performance (Jing et al., 2023). Consistent with the external monitoring hypothesis(Jing et al., 2023), I expect firms with higher analyst coverage to demonstrate better green revenue practices.

However, I recognise the emerging literature on the dark side of analyst coverage. A stream of literature suggests analysts pressure firms and increase managerial myopia (Graham et al., 2006). Firms covered by larger analysts generate fewer patents(He & Tian, 2013). Therefore, higher analyst coverage can improve or dampen corporate green revenue performance.

I test these competing views in the relationship between the EU Green Taxonomy and corporate green revenue performance. To test this conjecture, I construct a dummy variable (*Analyst*) that takes the value one if the number of analysts following a firm is above the sample's median and zero otherwise. I interact the *Analyst* dummy with the difference-in-differences variable in a triple interaction (Treat*Post**Analyst*).

$$CGR_{it} = \alpha_i + \beta.\ Treat{*}Post_t{*}Analyst + \Upsilon.\ \boldsymbol{X}_{it} + \delta_j + \lambda_{c,t} + \varepsilon_{it} \qquad (7)$$

Where i and t are indexed as firm and time (*year*), respectively, and CGR_t is the revenue derived from green activities scaled by the total revenue, expressed as a percentage. The key dependent variable is the triple difference in differences estimator*(Treat*Post*Analyst).* Treat takes a value of one if the firm headquarters is in the European Union and zero otherwise in year *t.* $Post_t$ represents a time dummy that takes a value of one if the observation is in the pre-treatment period*(2016-2018)* and zero otherwise. *Analyst* is a binary variable that takes the value one if the number of analysts covering a firm is above the sample's median and zero otherwise. $\boldsymbol{X}_{it}$ represents a vector of firm-level controls *(Size, Lev, Cash, RoA RnD, and Tang) and country-level variables Gdp_Grt and RuleLaw, as* Appendix A1 shows. δ_j *represents* the firm-fixed effect, while $\lambda_{c,t}$ denotes the country-year fixed effects. Where ε_{it} is the error term, I winsorise all firm- and country-level continuous variables at the 1st and 99th percentiles. Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses.

I present the result in Table 4.9. Columns (1) to (3). The coefficient of the triple interaction variable is significant at the 1% level. The evidence supports the bright side of the analyst coverage and a channel through which EU Taxonomy regulation influences CGR practices consistent with the notion that a higher analyst monitoring role reduces information asymmetry and influences corporate policies, including environmental policies (Chan, 2022; Chang et al., 2006; Jing et al., 2023; Jo & Harjoto, 2014).

(Insert Table 4.9 here)

4.4.4.3 Cross-Sectional Heterogeneity Tests: Financial constraints

I investigate the role of financial constraint in shaping the effect of the Green Taxonomy policy on corporate performance. Financial constraints significantly influence corporate investment and firm environmental policies(Almeida & Campello, 2007; Hong et al., 2012; Xu & Kim, 2022). Therefore, it can limit firms' engagement in climate-responsible activities like green revenue generation. Moreover, resources required to engage in climate-responsible activities like generating green revenue are non-trivial.

Literature shows the acquisition of environmentally compliant production facilities, design, testing, and approval of green products, product compliance with green labelling, and the acquisition of intangible capital to generate green revenue requires significant capital commitment(He & Qiu, 2025; Hong et al., 2012; Xu & Kim, 2022). Given that generating green revenue requires significant investment in translating green product design and modernising processes and infrastructure to meet the green taxonomy standard for accounting for green revenue, I expect that firms that are less financially constrained will have more capacity to engage in green business activities, giving rise to higher green revenue.

To test this conjecture, I proxy financial constraints using two indicators: the HP Index (Hadlock & Pierce, 2010) and the KZ Index following prior literature (Bartram et al., 2022; Lin et al., 2024). For each indicator, I create a dummy variable which takes a value of one if the firm's score is below the median of the sample score and zero otherwise. I interact *FinCon,* a dummy variable for each of the indicators as described above, with the difference in different variables to create a triple interaction variable*(Treat*Post*Fincon)* and estimate regression specification 8.

$$CGRi_t = \alpha_i + \beta .\ Treat*Post_t *FinCon + \Upsilon .\ \boldsymbol{X}_{it} + \delta_j + \lambda_{c,t} + \varepsilon_{it} \qquad (8)$$

Where i and *t* indexes as firm and time (years). The dependent variable CGR_t is the revenue derived from green activities scaled to the total revenue, expressed as a percentage. *FinCon* represents a dummy variable equal to one if the financial constraint proxy is below the sample's median and zero otherwise. The key independent variable is the triple difference in differences estimator*(Treat*Post*FinCon). Treat*$_{it}$ takes a value of one if the firm headquarters is in Europe and zero otherwise, in year *t*. $Post_t$ represents a time dummy that takes a value of one if the observation is in the pre-treatment period(2016-2018) and zero otherwise. $\boldsymbol{X}_{it}$ represents a vector of firm-level control variables *(Size, Lev, Cash, RoA, RnD and Tang)* and country-level variables *Gdp_Grt and RuleLaw, as* shown in Appendix A1. δ_j represents the firm-fixed effect, while $\lambda_{c,t}$ denotes the country-year fixed effects. ε_{it} is the error term.

I winsorise all the firm- and country-level continuous variables at the 1st and 99th percentiles. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are corrected for clustering at the firm level and are presented in parentheses.

I present the result in Table 4.10, columns (1) to (6). The coefficient of the triple interaction variable (*Treat*Post*FinCon)* for all the models and proxies is significant at 5%, supporting the conjecture that a low level of financial constraint positively moderates the link between green taxonomy policies and corporate green revenue performance. This result suggests that the effect is more significant for firms that face fewer financial constraints, consistent with the notion that the transition to a green economy requires huge capital investment.

(Insert Table 4.10 here)

4.5 Conclusion

The long-standing challenge in addressing the climate change crisis has been the political limitation stemming from a lack of dedication to long-term green transition strategies. Using a global dataset of green revenue companies from the FTSE Green Revenue Database, I investigate the impact of the Green Taxonomy Policy on corporate green revenue performance. Climate responsibility is important to firms' performance because climate change risks affect corporate outcomes. Most climate regulations have focused only on reducing carbon emissions and releasing toxic waste. Meanwhile, the EU Green Taxonomy regulations address the core economic dimension to measure a firm's climate-friendly activities.

I delve into how the EU Green Taxonomy policy impacts a firm's climate-friendly activities through its green revenue performance. Using the Dynamic Complementarity Theory to explain the link between Green Taxonomy and corporate Green Revenue performance as a dynamic interaction that aligns climate policy, customer values and corporate production in a dynamic feedback loop that shifts firms' production and investors' green values toward a better sustainable pathway. My investigation reveals that the Green Taxonomy regulations lead to an increase in green performance. I show that green revenue performance increases through higher stock. The result is relevant to policymakers, investors, and firms regarding the significance of well-crafted climate regulation in transitioning to a zero-zero economy. It is also useful in informing consumers and investors about firms that address climate change at both the production and consumption levels.

Appendix

Table A4.1 Variable Definitions

Variable	Description
CGR	For firm *i* at the end of year *t,* Corporate green revenue *(CGR)* is the share of revenue classified as green scaled by total revenue in year *t*. Source: FTSE Russel Greem Revenue database.
Ind_CGR	For firm *i* at the end of year *t*, Industry-adjusted *green revenue* for firm *i* at the end of year *t, is the share of revenue classified* as green scaled by industry average based on Fama and French 12 industry classification with the focal firm excluded from the industry average computation. Source: FTSE Russel Greem Revenue Database.
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
Cash	For firm *i* at the end of year *t,* Cash holding (*Cash*) is the ratio of the cash and cash equivalence 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
RnD	Research and development expenditure (*RnD)* of firm *i* in year *t* , scaled by the total book value of the asset. Source: Compustat
Analyst	Analyst Coverage (*Analyst)* is the number of financial analysts providing earnings per share estimate for firm *i* in year *t.* Source: S&P Capital IQ
Env_Inv	*E*nvironmental innovation (*Env_Inv) is a dummy variable that* takes a value of one if the firm-year observation is above the median of the Environmental Innovation score of the sample and zero otherwise. Source ASSET4G

Amihud	Amihud illiquidity *(Amihud)* measures stock market liquidity for firm *i* at the end of year t. This dummy variable takes a value of one if the firm-year observation is above the sample's median and zero otherwise. Source: Author
KZ_index	The proxy for financial constraint(*KZ_index)*. It reflects the degree to which a firm is financially constrained.). Higher values of the *KZ_index* indicate that a firm is more financially constrained. Computed as follows: KZ Index = (-1.002*(cashflow/ppe $_{t-1}$)) + (-1.315*(cash / ppe $_{t-1}$)) + (-39.368*(div/ ppe $_{t-1}$)) + (3.139 *Lev) + ((0.285*TQ)) Source: (Kaplan & Zingales, 1997)
HP_Index	The proxy for financial constraint *(HP_Index*) calculated as follows: HP_Index = − 0.737 * Size +0:043 * Size2–0:040 * Age. Higher values of the HP index indicate that a firm is more financially constrained. *Source:(Hadlock & Pierce, 2010)*
FinCon	*FinCon* represents a dummy variable equal to one if the financial constraint proxy is below the sample's median and zero otherwise.
$Treat_i$	*Treat* is a dummy. *$Treat_i$* is equal to one if the firm headquarters is in the Europe countries and zero otherwise.
$Post_t$	*$Post_t$* is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. Source: Author constructed

Country-level

Gdp_Grt	For country *j*, at the end of year t, the real gross domestic product growth rate (Gdp_Grt) measures the percentage annual growth rate of each country's gross domestic product. Source: World Bank Group. 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 ranks 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

Table A4.2 Firm country of headquarters

Firm Country Headquarters	Code	Freq.	Per cent	Cum.
Argentina	ARG	52	0.26	0.26
Australia	AUS	352	1.77	2.03
Austria	AUT	96	0.48	2.51
Belgium	BEL	108	0.54	3.05
Brazil	BRA	315	1.58	4.63
Canada	CAN	453	2.27	6.91
Switzerland	CHE	235	1.18	8.09
Chile	CHL	56	0.28	8.37
China	CHN	3,779	18.97	27.33
Germany	DEU	483	2.42	29.76
Denmark	DNK	81	0.41	30.16
Spain	ESP	173	0.87	31.03
Finland	FIN	135	0.68	31.71
France	FRA	417	2.09	33.80
United Kingdom	GBR	1,087	5.46	39.26
Indonesia	IDN	136	0.68	39.94
India	IND	874	4.39	44.33
Italy	ITA	213	1.07	45.40
Japan	JPN	3,575	17.94	63.34
South Korea	KOR	835	4.19	67.53
Mexico	MEX	66	0.33	67.86
Malaysia	MYS	387	1.94	69.81
Netherland	NLD	125	0.63	70.43
Norway	NOR	168	0.84	71.28
New Zealand	NZL	60	0.30	71.58
Philippines	PHL	12	0.06	71.64
Poland	POL	80	0.40	72.04
Russia	RUS	51	0.26	72.29
Saudi Arabia	SAU	68	0.34	72.64
Singapore	SGP	57	0.29	72.92
Sweden	SWE	338	1.70	74.62
Thailand	THA	315	1.58	76.20
Turkey	TUR	73	0.37	76.57
United States	USA	4,471	22.44	99.01
South Africa	ZAF	198	0.99	100.00
	Total	19,924	100.00	

Table 4.1: Summary Statistics

Table 1a presents descriptive statistics of the main variables in the sample dataset. This table presents the distribution of the main variables of interest with non-missing advertising values for 2016–2022. I report the corresponding number of observations (*Obs*), Mean, Standard Deviation (*S.D.*), minimum(min), median (p50), and maximum (max) values. I define all variables in Table A1 in the Appendix and winsorise all firm-level continuous at the 1st and 99th percentiles and described in Appendix A1.

Variables	**Obs**	***Mean***	***SD***	***Min***	***Median***	***Max***
Dependent						
CGR	19,924	0.272	0.317	0.001	0.131	100.00
Ind_CGR	19,924	0.999	1.163	0.002	0.477	3.882
Key Independent						
Size	19,924	7.712	3.053	0.399	7.700	15.326
Lev	19,924	0.196	0.180	0.000	0.159	0.919
Cash	19,924	0.204	0.190	0.001	0.151	0.873
RoA	19,924	0.040	0.186	-1.304	0.068	0.365
RnD	19,924	0.016	0.041	0.000	0.000	0.304
Tang	19,924	0.274	0.222	0.000	0.230	0.889
Others						
Env_Inv	19,924	26.741	32.872	0.000	0.000	98.53
Amihud	18,540	0.001	0.002	0.000	0.000	0.013
Analyst	19,924	0.863	2.277	0.000	0.000	14.000
KZ Index	18,162	-8.366	36.024	-276.904	-0.070	23.832
SA_Index	19,924	-3.030	0.625	-3.510	-3.293	-0.597
Country-Level						
CSRI	19,924	2.430	0.729	1.250	2.400	3.600
Gdp_Grt	19,924	2.519	3.397	-9.520	2.460	8.670
RuleLaw	19,924	0.967	0.771	-0.490	1.39	1.950

Table 4.2: Eu Taxonomy and Corporate Green Revenue: OLS regression Unmatched DiD regression

This table presents the results of the difference-in-differences ordinary least square regression based on the specifications below.

$$CGR_{it} = \alpha_i + \beta.(Treat_i * Post_t) + \Upsilon. \boldsymbol{X}_{it} + \delta_j + \lambda_t + \phi_{ct} + \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is CGR_{it}, which measures the corporate green revenue. $Treat_i$ equals one if the firm headquarters is in Europe and zero otherwise. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. δ_j, λ_t, *and* ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 multivariate regression outputs, including firm-level and country-level covariates, and column (3) additional country fixed effect.

	Dept. Var=CGR		
	(1)	(2)	(3)
DiD($Treat_i$*$Post_t$)	**0.0135***** **(0.0042)**	**0.0145***** **(0.0041)**	**0.0150***** **(0.0041)**
Size		-0.0015 (0.0019)	-0.0015 (0.0019)
Lev		0.0144 (0.0098)	0.0144 (0.0098)
Cash		0.0041 (0.0072)	0.0042 (0.0072)
RoA		0.0069 (0.0063)	0.0069 (0.0063)
RnD		0.0488 (0.0300)	0.0492 (0.0300)
Tang		-0.0031 (0.0097)	-0.0029 (0.0097)
Gdp_Grt		0.0001 (0.0004)	0.0002 (0.0004)
RuleLaw		0.0116 (0.0094)	0.0166* (0.0096)
Obs	19,775	19,775	19,775
Adj_r^2	0.9702	0.9703	0.9703
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	NO	NO	YES

Table 4.3: Parallel Trend Test and Entropy Balance Tests

Panel 4.3a The table shows the Parallel trend test of yearly difference in the mean of the *Green Revenue* variable between the treated and the control, including 95% confidence firms between 2016 and 2022 for the parallel trend test shown in Figure 4.1

Year	**Coefficient**	**t-stat**	**P value**
*Treat*post*$_{2016}$	-0.638	-1.54	0.105
*Treat*post*$_{2017}$	-0.466	-1.52	0.144
*Treat*post*$_{-2018}$	0.000	0.00	1.00
*Treat*post*$_{2019}$	0.344*	1.35	0.083
*Treat*post*$_{2020}$	0.912**	2.36	0.018
*Treat*post*$_{2021}$	1.662***	3.39	0.001
*Treat*post*$_{2022}$	1.476 ***	2.58	0.000

Panel 4.3b reports the t-test of mean differences in covariates between treated firms and control from 2016 to 2022The Symbols *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	Treat	Control	Diff	t-stat	p-value
Size	7.728	7.708	-0.038	-0.447	0.655
Lev	0.191	0.197	0.003	0.523	0.601
Cash	0.204	0.204	0.001	0.108	0.914
RoA	0.037	0.041	0.003	0.568	0.570
RnD	0.016	0.016	-0.001	-0.692	0.489
Tang	0.275	0.274	0.003	0.542	0.588
Gdp_Grt	1.596	2.732	1.396***	22.706	0.000
RuleLaw	1.478	0.849	-0.659***	-30.640	0.000
Obs	3,739	16,185			

Panel 4.3c. Presents the mean difference between treated and control firms post entropy score matching. All covariates are winsorised at the 1% and 99% levels.

	Treat	Control
Variable	Mean	Mean
Size	7.728	7.728
Lev	0.191	0.191
Cash	0.204	0.204
RoA	0.037	0.041
RnD	0.016	0.016
Tang	0.275	0.275
Gdp_Grt	1.596	1.595
RuleLaw	1.478	1.478

Table 4.4: Entropy balance Matched DiD Regression.

This table presents the results of the ordinary least square regression with entropy weight scores based on the specifications below.

$$CGR_{it} = \alpha_i + \beta.(Treat_i * Post_t) + \Upsilon.\, \boldsymbol{X}_{it} + \delta_j + \lambda_t + \phi_{ct} + \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is $CGR_{it,}$ which measures the corporate green revenue. $Treat_i$ equals one if the firm headquarters is in Europe and zero otherwise. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. $\delta_{j,}$ $\lambda_{t,}$ *and* ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 multivariate regression outputs, including firm-level and country-level covariates, and column (3) additional country fixed effect.

	Dept. Var=CGR		
Variables	(1)	(2)	(3)
DiD($Treat_i$*$Post_t$)	**0.0134*** **	**0.0135*** **	**0.0135*** **
	(0.0043)	**(0.0042)**	**(0.0042)**
Size		-0.0026	-0.0026
		(0.0029)	(0.0029)
Lev		-0.0096	-0.0096
		(0.0158)	(0.0158)
Cash		0.0090	0.0090
		(0.0100)	(0.0101)
RoA		0.0075	0.0075
		(0.0075)	(0.0075)
RnD		0.0342	0.0342
		(0.0330)	(0.0330)
Tang		0.0023	0.0023
		(0.0115)	(0.0115)
Gdp_Grt		0.0012	0.0012*
		(0.0007)	(0.0007)
RuleLaw		0.0226	0.0230
		(0.0156)	(0.0158)
Obs	19,775	19,775	19,775
Adj_r^2	0.9698	0.9699	0.9699
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	NO	NO	YES

Table 4.5: Robustness Test: Altered measures of green revenue

This table presents the results of the ordinary least square regression with entropy weight based on the specifications below.

$$Ind\_CGR_{it} = \alpha_i + \beta.(Treat_i * Post_t) + \Upsilon . \boldsymbol{X}_{it} + \delta_j + \lambda_t + \phi_{ct} + \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is $CGR_{it,}$ which measures the corporate green revenue. $Treat_i$ equals one if the firm headquarters is in Europe and zero otherwise. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. $\delta_{j,}$ $\lambda_{t,}$ *and* ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 multivariate regression outputs, including firm-level and country-level covariates, and column (3) additional country fixed effect.

	Dept. Var=Ind_CGR		
Variables	(1)	(2)	(3)
DiD(Treat*i**Post*t*)	**0.0004*****	**0.0004*****	**0.0004*****
	(0.0002)	**(0.0002)**	**(0.0002)**
Size		-0.0001	-0.0001
		(0.0001)	(0.0001)
Lev		-0.0003	-0.0003
		(0.0006)	(0.0006)
Cash		0.0004	0.0004
		(0.0004)	(0.0004)
RoA		0.0002	0.0002
		(0.0003)	(0.0003)
RnD		0.0014	0.0014
		(0.0014)	(0.0014)
Tang		0.0000	0.0000
		(0.0004)	(0.0004)
Gdp_Grt		0.0000	0.0000
		(0.0000)	(0.0000)
RuleLaw		0.0012**	0.0012**
		(0.0006)	(0.0006)
Obs	19,775	19,775	19,775
Adj_r^2	0.9688	0.9688	0.9688
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	NO	NO	YES

Table 4.6: Robustness Test: Placebo Test: Alternative Sample Regression

This table presents the difference-in-differences ordinary least square regression results with entropy scores based on the specifications below.

$$CGR_{it} = \alpha_i + \beta.(Treat_i *Post_t)+ \Upsilon. \boldsymbol{X}_{it} + \delta_j + \lambda_t +\phi_{ct}+ \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is $CGR_{it,}$ which measures the corporate green revenue. $Treat_i$ equals one if the firm headquarters is in Europe and zero otherwise(excluding U.S firms)from the sample. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. δ_j, λ_t, *and* ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 full DiD regression results excluding U.S firms. Column (2) reports full DiD regression excluding Chinese firms from the sample, and column (3) reports full DiD regression excluding both U.S and Chinese firms.

	Dept. Var=Ind_CGR		
Variables	(1)	(2)	(3)
DiD(Treat*$_i$*Post*$_t$***)***	**0.0104****	**0.0135*****	**0.0104****
	(0.0045)	**(0.0042)**	**(0.0046)**
Size	-0.0031	-0.0026	-0.0031
	(0.0036)	(0.0029)	(0.0036)
Lev	-0.0174	-0.0098	-0.0177
	(0.0193)	(0.0159)	(0.0195)
Cash	0.0085	0.0091	0.0085
	(0.0123)	(0.0101)	(0.0124)
RoA	0.0032	0.0075	0.0031
	(0.0086)	(0.0075)	(0.0087)
RnD	0.0503	0.0342	0.0504
	(0.0381)	(0.0332)	(0.0383)
Tang	0.0055	0.0023	0.0055
	(0.0131)	(0.0115)	(0.0131)
Gdp_Grt	0.0011	0.0012*	0.0012
	(0.0007)	(0.0007)	(0.0007)
RuleLaw	0.0097	0.0235	0.0101
	(0.0221)	(0.0163)	(0.0228)
Obs	15,341	16,026	11,592
Adj_r^2	0.9668	0.9699	0.9668
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	YES	YES	YES

Table 4.7 Economic Mechanism Test: Environmental Innovation Channel

This table presents the results of the *triple Difference-in-differences regression* with entropy weight scores based on the specifications below.

$$CGR_{it} = \alpha_i + \beta.Treat_i *Post_t *Env\_Inv + \Upsilon. \boldsymbol{X}_{it} + \delta_j + \lambda_t + \phi_{st} + \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is $CGR_{it,}$ which measures the corporate green revenue. $Treat_i$ equals one if the firm headquarters is in Europe and zero otherwise. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. *Env_Inv* measures environmental innovation, a dummy variable that takes a value of one if the firm-year observation is above the sample's median and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. $\delta_{j,}$ $\lambda_{t,}$ *and* ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 multivariate regression outputs, including firm-level and country-level covariates, and column (3) additional country fixed effect.

	Dept. Var=CGR		
Variables	(1)	(2)	(3)
DiDiD($Treat_i$*$Post_t$ *Env_Inv_i)	**0.0104****	**0.0111*****	**0.0114*****
	(0.0042)	**(0.0042)**	**(0.0042)**
Size		-0.0017	-0.0016
		(0.0019)	(0.0019)
Lev		0.0145	0.0144
		(0.0099)	(0.0099)
Cash		0.0041	0.0042
		(0.0072)	(0.0072)
RoA		0.0071	0.0071
		(0.0063)	(0.0063)
RnD		0.0476	0.0479
		(0.0300)	(0.0300)
Tang		-0.0028	-0.0026
		(0.0097)	(0.0097)
Gdp_Grt		0.0001	0.0002
		(0.0004)	(0.0004)
RuleLaw		0.0087	0.0130
		(0.0095)	(0.0098)
Obs	19,775	19,775	19,775
Adj_r^2	0.9636	0.9636	0.9635
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	NO	NO	YES

Table 4.8: Cross-Sectional Heterogeneity Test: Stock Market Liquidity

This table presents the results of the *triple Difference-in-differences regression* with entropy weight scores based on the specifications below. Amihud is a dummy variable that takes a value of one if the firm-year observation is above the sample's median of Amihud liquidity and zero otherwise.

$$CGR_{it} = \alpha_i + \beta.Treat_i *Post_t *Amihud + \Upsilon. \boldsymbol{X}_{it} + \delta_j + \lambda_t + \phi_{ct} + \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is $CGR_{it,}$ which measures the corporate green revenue. $Treat_i$ equals one if the firm headquarters is in Europe and zero otherwise. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. Amihud is a dummy variable that takes a value of one if the firm-year observation is above the sample's median and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. δ_j, λ_t, *and* ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 multivariate regression outputs, including firm-level and country-level covariates, and column (3) additional country fixed effect.

	Dept. Var=CGR		
Variables	(1)	(2)	(3)
DiDiD(Treat$_i$*Post$_t$ *Amihud)	**0.0240*** **	**0.0239*** **	**0.0239*** **
	(0.0066)	**(0.0065)**	**(0.0065)**
Size		-0.0047	-0.0047
		(0.0032)	(0.0032)
Lev		-0.0044	-0.0044
		(0.0170)	(0.0171)
Cash		0.0070	0.0069
		(0.0104)	(0.0104)
RoA		0.0064	0.0063
		(0.0078)	(0.0079)
RnD		0.0258	0.0258
		(0.0352)	(0.0353)
Tang		0.0002	0.0002
		(0.0122)	(0.0122)
Gdp_Grt		0.0008	0.0008
		(0.0006)	(0.0006)
RuleLaw		0.0176	0.0173
		(0.0160)	(0.0161)
Obs	18,366	18,366	18,366
Adj_r^2	18,366	18,366	18,366
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	NO	NO	YES

Table 4.9: Cross-Sectional Heterogeneity Test: Analyst Coverage

This table presents the results of the triple *Difference-in-differences regression* with entropy weight scores based on the specifications below.

$$CGR_{it} = \alpha_i + \beta.Treat_i *Post_t*Analyst + \Upsilon.\boldsymbol{X}_{it} + \delta_j + \lambda_t + \phi_{ct} + \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is $CGR_{it,}$ which measures the corporate green revenue. $Treat_i$ is equal to one if the firm headquarters is in the European Union countries, and zero is for companies with headquarters in the United States. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. *Analyst* measures analyst following a dummy variable that takes a value of one if the firm-year observation is above the sample's median and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. δ_j, λ_t, and ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 multivariate regression outputs, including firm-level and country-level covariates, and column (3) additional country fixed effect.

	Dept. Var=CGR		
Variables	(1)	(2)	(3)
DiDiD($Treat_i$*$Post_t$ *Analyst)	**0.0133***	**0.0136***	**0.0171****
	(0.0077)	**(0.0075)**	**(0.0076)**
Size		-0.0035	-0.0020
		(0.0029)	(0.0019)
Lev		-0.0087	0.0146
		(0.0155)	(0.0098)
Cash		0.0098	0.0046
		(0.0100)	(0.0072)
RoA		0.0076	0.0068
		(0.0075)	(0.0063)
RnD		0.0335	0.0483
		(0.0328)	(0.0301)
Tang		0.0022	-0.0028
		(0.0114)	(0.0097)
Gdp_Grt		0.0012	0.0002
		(0.0007)	(0.0004)
RuleLaw		0.0181	0.0110
		(0.0157)	(0.0097)
Obs	19,775	19,775	19,775
Adj_r^2	0.9698	0.9699	0.9702
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	NO	NO	YES

Table 4.10: Cross-Sectional Heterogeneity Test: Financial Constraint

This table presents the results of the triple *Difference-in-differences regression* with entropy weight scores based on the specifications below.

$$CGR_{it} = \alpha_i + \beta.(Treat_i *Post_t *Fincon) + \Upsilon.\, \boldsymbol{X}_{it} + \delta_j + \lambda_t + \phi_{st} + \varepsilon_{it}$$

i and *t* indexes as the firm and time (years). The dependent variable is $CGR_{it,}$ which measures the corporate green revenue. $Treat_i$ is equal to one if the firm headquarters is in the European Union countries, and zero is for companies with headquarters in the United States. $Post_t$ is a dummy variable that takes the value one for the period after the introduction of the Green Taxonomy policy and zero otherwise. *Fincon* is a dummy variable that takes a value of one if the firm-year observation is above the sample's median and zero otherwise. $\boldsymbol{X}_{it}$ is a vector of the firm-level covariates *Size, Lev, Cash RoA, RnD, and Tang, as well as country-level variables (Gdp_Grt, RuleLaw).* I list all the variables reported in Table A1 of the Appendix. δ_j, λ_t, *and* ϕ_{ct} represent the firm, year, and country fixed effects, respectively, and ε_i represents the error term. I winsorise all the 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 multivariate regression outputs, including firm-level and country-level covariates, and column (3) additional country fixed effect.

	Dept. Var=CGR		
Variables	(1)	(2)	(3)
DiDiD($\boldsymbol{Treat_i}$ ******* $\boldsymbol{Post_t}$ **** Fincon)***	**0.0181*** **	**0.0184*** **	**0.0184*** **
	(0.0058)	**(0.0058)**	**(0.0058)**
Size		-0.0036	-0.0036
		(0.0029)	(0.0029)
Lev		-0.0098	-0.0098
		(0.0156)	(0.0156)
Cash		0.0085	0.0085
		(0.0101)	(0.0101)
RoA		0.0081	0.0081
		(0.0074)	(0.0074)
RnD		0.0300	0.0300
		(0.0330)	(0.0330)
Tang		0.0027	0.0027
		(0.0115)	(0.0115)
Gdp_Grt		0.0011	0.0011
		(0.0007)	(0.0007)
RuleLaw		0.0212	0.0216
		(0.0155)	(0.0157)
Obs	19,775	19,775	19,775
Adj_r^2	0.9699	0.9700	0.9700
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Country FE	NO	NO	YES

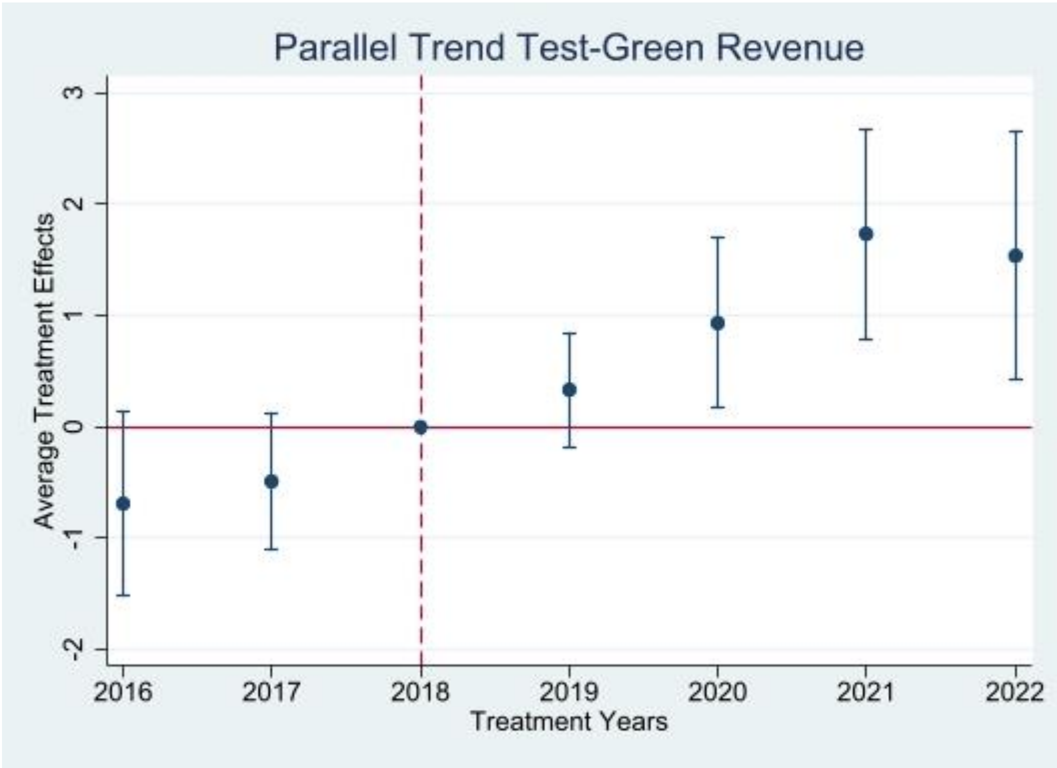

Figure 4.1 Parallel trend test of Green Revenue

This figure shows a time-series plot of the coefficient of the yearly mean difference between treated and control firms.

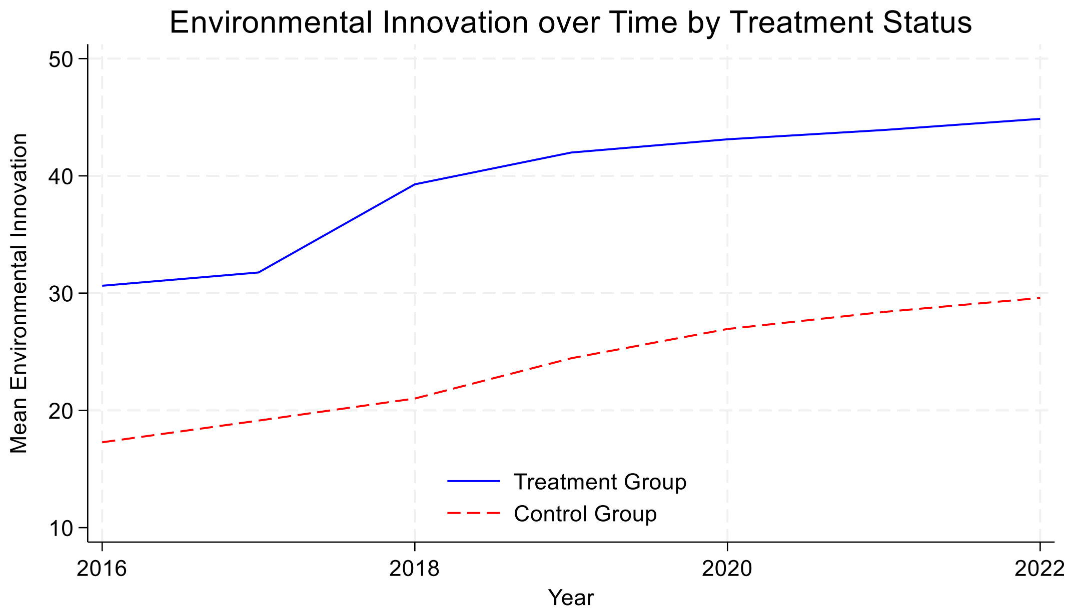

Figure 4.2 Parallel trend test of Green Revenue
This figure shows a time-series plot of the trend of the yearly mean Environmental innovation scores of treated and control firms.

Chapter 5 Conclusion

5.1 Thesis Summary

Political constraints from a lack of commitment to long-term policy pathways for green transition have been a long-standing problem in addressing the climate change crisis (Besley & Persson, 2023). This thesis comprises three empirical essays that explore the political economy of the green transition through the lenses of climate political leadership beliefs, policy decisions, and their consequential impacts on financial markets and corporate green innovation and revenue.

The first essay investigates the effects of adverse exogenous shocks to supportive climate political leadership on market perceptions of firm-level regulatory exposure to climate change. Establishing that climate political leadership as an upstream driver of both cross-sectional and temporal variations in market participants' perceptions of climate regulatory exposure. The study further examines the real consequences of this effect on corporate green innovation. Predictably, climate-sceptic political leadership's deregulatory policies and actions dampen corporate investment in green technological innovations. The study extends existing research on climate beliefs (Ceccarelli & Ramelli, 2024; Giglio et al., 2023; Kräussl et al., 2024; Lel, 2024b) , by empirically linking political leaders' climate beliefs and resulting regulatory frameworks with financial market participants' behaviour. It aligns with findings that institutional investors demand carbon premiums and adjust portfolios based on perceived regulatory risks(Giglio et al., 2023; Kräussl et al., 2024)

In the second essay, I build on the findings of the first essay, exploring a similar empirical setting; I investigate the effect of climate sceptic political leadership on corporate green innovation activities. I document a negative causal relationship between the climate sceptic political leadership regime and corporate green innovation generation. The study further highlights financial constraints and lower institutional ownership as key moderating factors for the finding, demonstrating the complementary governance role of institutional ownership in supporting the green transition and the role of access to external finance in corporate climate responsibility(Dang et al., 2022; Xu & Kim, 2022).

In the third essay, I extend my investigation into the political economy of green transition by employing a setting where supportive climate political leadership attempts to address an important problem long identified by economists: the need for long-term policy commitment pathways to achieve a green transition. I employ a setting in which a firm's green revenue performance is exogenously affected by the introduction of green taxonomy policies under the Sustainable Finance Action Plan of the European Union supportive climate political leadership.

In the following section, I discuss the implications of the findings of this thesis.

5.2 Implications

5.2.1 Financial Market Perception and Climate Political Leadership

5.2.1.1 Implication for Political Economy of Green Transition

This chapter's findings have numerous implications for the Political Economy of green transition. Specifically, it highlights that CPL significantly influences market participants' perceptions of firm-level climate regulatory exposure. This relationship demonstrates how political leadership alter financial market dynamics by reshaping the perception of beliefs, expectations, and perceptions of firms' climate regulatory exposure. I introduce a market-based measure constructed by (Sautner et al., 2023a), demonstrating that climate political leadership influences cross-sectional and temporal variations. By implication, I offer a novel lens for analysing and interpreting firm-level regulatory risk and the factors driving it, which can be employed to assess market participants' behaviour.

I foresee the following implications of my findings. First, at the micro level, firms that face weaker climate regulations or lax enforcement should experience reduced regulatory costs. In an economic sense, such firms may experience a short-term boost in their valuation. I also expect affected firms to significantly delay strategic investments in climate and environment-friendly innovations, misaligning themselves with future regimes and market expectations. Delayed and under-investments in greener technologies may also erode firms' prospects for sustaining long-term global competitive advantage. Consequently, I contend that firms that fail to internalise political signals as a core component of their regulatory climate risk management and sustainability strategies will likely incur significant long-term strategic and financial vulnerabilities.

Second, at the macro level, global decarbonisation progress may become volatile or reversible, being materially conditioned on political orientation rather than following the scientific consensus. Financial markets may convey weaker price signals for businesses to prioritise decarbonisation, thus retarding the capital reallocation towards greener firms. If businesses anticipate weaker climate regulation and lower associated costs, their underinvestment in low-carbon technologies might undermine global technological progress toward a low-carbon economy. To conclude, lax regulatory pressure, lower social cost of carbon, and weaker financial market pricing incentives may lead to higher emissions, making it even more challenging to achieve global climate targets, particularly those agreed upon in the Paris Agreement.

5.2.1.2 Implications for Green Transition Beliefs

This chapter's findings advance a better understanding of Climate Beliefs by empirically characterising the climate beliefs of climate-sceptic political leadership and their effects on market participants. This contribution enriches the literature on how political beliefs and ideological dispositions influence regulatory frameworks, market behaviour, and corporate decision-making(Ceccarelli & Ramelli, 2024; Fritz et al., 2024; Huang & Lin, 2022). The study shows the interconnectedness of climate political leadership, regulatory frameworks, and financial market dynamics. It shows that CPL influences institutional investor behaviour and firm valuation, providing intuition into how leveraging capital markets for climate governance and advancing the transition to a low carbon economy.

5.2.1.3 Implications for firms' and institutional investors' behaviour.

This chapter's findings have significant implications for institutional investor behaviour. The finding of empirical chapter one shows that Institutional investors adjust their ownership stakes based on perceived climate regulatory risk. When CPL introduces a lax regulatory regime, institutional investors increase their ownership in firms under a lax regulatory regime and reward them with a higher market valuation, signalling a preference for firms in a lower regulatory risk environment. Such behaviour shows the importance of climate regulatory perceptions in shaping economic agents' behaviour and the need for long-term sustainable green policies to mitigate investor misbehaviour under climate sceptic political leadership.

5.2.1.4 Implication for Market Pricing of Climate Risk:

This chapter's findings have stark implications for the pricing of climate risk. Firms exposed to lax climate regulatory risks under a climate sceptic political leadership lax regulatory regime experience higher market valuation. This finding suggests the market’s favourable response to lax climate regulation, similar to findings by (Ramelli, Wagner, Zeckhauser, & Ziegler, 2021). While Ramelli, Wagner, Zeckhauser and Ziegler (2021) investigate the valuation implications of introducing deregulation from the perspective of energy-intensive firms in the U.S., I employ a quasi-natural experimental set-up, which presumably identified an unaffected counterfactual in our analysis.

I further show the effect and underlying economic and market mechanism, providing valuable insight to market participants, investors and policy analysts. Contrary to the established belief that institutional investors and market mechanisms can solely facilitate the Green Transition(Azar et al., 2021; Dyck et al., 2019), this essay offers a compelling insight into how long-term regulatory commitment to the Green Transition can stimulate market incentives on an upward trajectory to sustain the necessary market mechanisms effective in addressing climate change.

5.2.1.5 Implication for Corporate Behaviour

This chapter's findings have implications for capital market mechanisms supporting the Green Transition. It provides empirical support for the Economic theory of Dynamic complementarity(Besley & Persson, 2023). My findings show the complementarity of Capital market mechanisms and political leadership Regulation policies. Effective regulatory environments, shaped by CPL, can leverage capital market mechanisms to accelerate the transition to a low-carbon economy(Popp, 2010; Semieniuk et al., 2021). For example, I show that capital markets reward firms with lower perceived regulatory risk through increased valuation and institutional investor ownership. This finding suggests that regulatory stability and clarity are critical for aligning financial incentives with climate mitigation goals. Without these, we have a dislocated green transition, which might have a consequential escalating multiplier effect for future generations.

5.2.1.6 Implication for Macroeconomic modelling of Political leadership regulatory actions

These findings affect how macroeconomic policy models address green transition. It bridges gaps between political economy and climate governance by showing how CPL beliefs and ideology shape regulatory frameworks and, in turn, financial market perceptions of climate regulatory risk. It emphasises the role of political ideology and leadership in driving firm-level responses to climate change, expanding on the literature that examines corporate and investor behaviours under climate regulation (Dyck et al., 2019; Lopez-de-Silanes et al., 2024; Roy et al., 2022). It opens a transparent policy debate on the need for complementary frameworks where capital market participants and society can catalyse green transitions. It highlights the potential of market-based solutions to support climate governance objectives through long-term green transition policy commitments that are not subject to adverse political changes.

5.2.1.7 Implications for Future Research

The study’s findings on U.S. and European firms suggest that international variations in Political leadership preference and regulatory environments offer opportunities for comparative studies. Very few studies explore such empirical settings due to a lack of credible exogenous shock besides Benlemlih et al. (2023) attempts to investigate a comparative analysis of the United Kingdom and the US greenhouse gas emission and institutional ownership. Given evidence that institutional investors drive firms toward greener practices(Cohen et al., 2023; Dyck et al., 2019; Nofsinger et al., 2019), future research could explore mechanisms to enhance investor influence in jurisdictions with weaker climate governance.

Also, examining heterogeneity in institutional investors' behaviour under climate-sceptic political leadership will enrich the findings of this thesis. It would identify which institutional investors drive the observed empirical pattern and their motive for such behaviour. This evidence will help create incentives and regulatory restrictions to mitigate such misbehaviour and facilitate optimal capital allocation.

5.2.1.8 Concluding Remarks

In Conclusion, this chapter delves into the dynamic complementarity of climate political leadership’s regulatory frameworks with the financial market mechanism, highlighting how CPL influences institutional investor behaviour and firm valuation; it provides an understanding of how climate political leadership beliefs and the direction of climate actions accentuate capital markets mechanism climate governance role. This understanding is necessary to solve the long-standing policy commitment problem, as current Political leaders cannot commit to maintaining a supportive climate regulatory trajectory according to economic theory. Therefore, for an effective and frictionless green transition, solving the long-term Political commitment problem is the required catalyst in advancing the transition to a low-carbon economy.

In terms of practical applications of my findings, it provides valuable insights into how CPL impacts financial markets and can guide the design of policies that harness market mechanisms to support green transitions. It also provides evidence to support the notion that long-term supportive regulatory predictability and clarity are key levers to attract institutional investment and foster corporate sustainability (Acemoglu et al., 2016; Aghion et al., 2016; Besley & Persson, 2023). Institutional investors can use climate regulatory exposure metrics to optimise portfolio decisions, and firms can align their strategies with evolving regulatory risks to attract capital and enhance valuation.

5.2.2 Race to the Bottom: The Effects of Climate Political Leadership on Corporate Green Innovation

5.2.2.1 Implication for Corporate Green Innovation Investment

The findings show that exogenous political leadership shifts toward climate scepticism can significantly suppress green innovation activities. This indicates the critical role of supportive climate political leadership in encouraging firms to invest in green technology. Without the implementation of stringent regulation by supportive climate political leaders, firms may prioritise short-term cost savings over long-term environmental benefits, leading to societal costs like higher pollution levels. The findings underline the importance of supportive climate political leadership as an upstream driver of green revenue through the creation of incentives and stringent climate regulatory environment in driving firms to internalise pollution costs (Acemoglu, 2003; Acemoglu et al., 2016; Aghion et al., 2016; Ivanov et al., 2024). In contrast, climate-sceptic political leadership create weaker regulatory environments that dampen the market incentives necessary for firms, particularly in energy-intensive industries. The weakened incentives disincentivise market participants, negatively impacting the optimal allocation of resources to green innovation, and exacerbating environmental degradation.(Choy et al., 2024; Dasgupta et al., 2023; He & Qiu, 2025; Wu et al., 2023)

5.2.2.2 Implications for Corporate Access to Finance

Regarding access to finance, my findings reveal that financially constrained firms are disproportionately affected by the lack of mandated incentives, further widening the gap in green innovation between well-capitalized and capital-constrained firms. I also show that firms in energy-intensive industries benefit more from lax regulation due to cost reductions, highlighting a sector-specific resistance to voluntary green investment without regulatory incentives.

5.2.2.3 Implications for Intergenerational Cost of Carbon

This chapter's findings also demonstrate that climate-sceptic political leadership introduces macroeconomic risks by delaying technological progress in green innovation, undermining efforts to mitigate climate change, and potentially increasing societal costs from pollution, exacerbating the intergenerational cost of future climate mitigation on the economy and society.

5.2.2.4 Limitations and Recommendations for Future Research

First, while this study explores the cross-sectional variation in only carbon-intensive sectors based on the CDP classifications, future research could explore how different industries respond to climate deregulatory policies beyond energy-intensive sectors to identify nuanced patterns of green innovation investment. Second, further studies could extend the analysis to different geopolitical contexts, focusing on climate regulation stringency variations and the resulting global impact on green innovation. Third, further investigation is needed to determine the long-term effects of climate sceptic leadership on corporate green innovation, particularly how sustained deregulatory policies influence technological stagnation or eventual shifts in corporate behaviour. In addition, more analysis of patents as a measure of innovation, including patents without assigns, could lead to innovation leakage in patent research.

Furthermore, future research can examine the role of institutional investors, consumers, and advocacy groups jointly in counteracting the negative effects of lax climate regulations on corporate green innovation. It can also examine how alternative financing mechanisms, like green bonds or sustainability-linked loans, might mitigate firms' financial constraints under weak climate regulatory regimes.

5.2.2.5 Concluding Remarks

The study advances the understanding of how climate sceptic political leadership influences corporate environmental strategies, emphasising the role of climate policies as a key determinant of corporate green innovation.

5.2.3 Green Taxonomy and Corporate Green Revenue

5.2.3.1 Implications for the overall Political Economy of Green Transition

This chapter's findings demonstrate that green taxonomy policies significantly increase corporate green revenue activities, emphasising the effectiveness of regulatory frameworks in fostering environmentally responsible corporate behaviour. These findings show climate political leadership’s regulatory pressure as a critical driver of green revenue generation. The findings confirm that green innovation is a key mechanism linking green taxonomy policies to improved green revenue performance., reinforcing the importance of policies incentivising innovation in addressing climate change challenges and the notion of dynamic complementarity in Green Transition.

This essay advances the understanding of corporate green revenue drivers, the mediating role of environmental innovation, and the broader implications of climate policies for corporate outcomes. It provides empirical support for new economic thought on the Dynamic complementarity of political leadership regulatory policies, structural transformation of corporate production and shifts in consumer preferences in the Green transition race (Besley & Persson, 2023). It fills an important gap by connecting green taxonomy policies with corporate green revenue generation, offering empirical evidence of their effectiveness. It further highlights the transformative potential of green taxonomy policies in driving corporate green revenue activities and lays a robust foundation for both policymaking and further academic exploration.

5.2.3.2 Financial Market Implication

Analyst coverage and information Asymmetry Reduction mediate the green taxonomy effect by reducing information asymmetry, further validating the role of external governance mechanisms in enhancing corporate environmental performance. The essay also highlights that higher stock liquidity facilitates the transmission of green taxonomy policies to green revenue generation, highlighting the role of financial markets in shaping corporate environmental strategies.

The study reveals that financially unconstrained firms benefit more from green taxonomy policies, suggesting that access to internal capital is a critical determinant of a firm's ability to respond effectively to climate policies(Xu & Kim, 2022).

5.2.3.3 Policy Implications

This chapter's findings show that Policymakers should focus on designing and implementing green taxonomies to incentivise corporate green revenue practices. It also highlights complementary mechanisms, like improving financial market efficiency, enhancing analyst coverage, and fostering innovation ecosystems that can amplify the impact of green taxonomy policies. Therefore, targeted support for financially constrained firms can reduce disparities in green revenue outcomes and promote more equitable environmental progress.

5.2.3.4 Limitations and Recommendations for Future Research

Extend the analysis to compare the impact of green taxonomy policies across different regions or countries with varying regulatory environments and market dynamics and explore how the green taxonomy effect varies across industries, particularly between high-emission and less environmentally intensive sectors. Further studies examining the long-term effects of green taxonomy policies on corporate green revenue performance, including potential lag effects or cumulative benefits, will be beneficial and provide more evidence for future regulatory design and implementation.

Further studies can Investigate how stakeholders like institutional investors, consumers, and advocacy groups influence firms' responses to green taxonomy policies. Studies can also explore the combined impact of green taxonomies and carbon pricing mechanisms on corporate green revenue and innovation practices.

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