

# **ESG and Different Stakeholders**

## Ziran Zuo

Department of Accounting and Finance

Lancaster University

Submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy in Finance

June 2025

### Abstract

This thesis contains three essays pertaining to the ESG and different stakeholders. In the first essay, we study the effects of insider horizon on firm-level CSR performance and find a positive relation between insider horizon and CSR performance. Further analysis supports the interpretation of good internal governance, rather than the agency problems, on this positive relation. To identify a causal link between insider horizon and CSR performance, we use reductions in managerial career horizons and the rejection of the inevitable disclosure doctrine as exogenous shocks to change the willingness of insiders to pursue long-term value. The heterogeneity analysis shows that the positive effects are more pronounced in firms with a higher proportion of long-term, socially responsible institutional investors, when insiders are on long-term compensation plans, and when firms are under less threat of takeovers. We also observe some real impacts of long-term oriented insiders on several raw CSR metrics, including toxic releases, CSR violations, employee satisfaction and negative ESG incidents. Overall, our findings suggest that insiders with a long-term focus can significantly enhance CSR outcomes.

In the second essay, we explore the portfolio rebalancing of mutual fund managers regarding the climate change exposure of their portfolio firms in response to the 2015 Paris Agreement. Relying on a difference-in-difference approach, we find that fund managers underweight the firms with high exposure to climate change following the Agreement. Furthermore, we show that the stringency of climate polices and the climate change exposure of the funds themselves significantly influences the divestment decisions. Our heterogeneity tests indicate that the divestment effects are stronger for portfolio firms in high-pollution industries and during the Trump administration. Lastly, we find that high-exposure firms respond to the divestments by improving their environmental scores and reducing carbon emissions post the Paris Agreement. Overall, our findings highlight the positive role that institutional investors play in driving the transition toward a green economy.

The third essay concentrates on the green transition in the supply chain. Since the voluntary disclosure policy regarding the supply chain does not mandate customer firms to disclose the information of supplier firms, these customer firms tend to strategically disclose their

associations with suppliers with good environmental performance while hiding the relationships with those with bad performance. We find that this selective, green-induced nondisclosure about unsustainable suppliers hampers the green transition within supply chains by limiting the positive influence that customer firms could have on their suppliers' environmental practices. Importantly, customer firms improve their own environmental performance at the cost of their suppliers' environmental outcomes. To establish causality, we use the introduction of greenhouse gas (GHG) emission targets in US states and the implementation of GHG emission trading systems in various regions and countries as exogenous regulatory shocks. Our cross-sectional analysis reveals that the impact of strategic disclosure varies depending on three factors: the involvement of common stakeholders in the supply chain, the environmental pressure on suppliers, and the financial constraints of customer firms. Additionally, we examine the real effects of such strategic disclosures, finding that customers outsource their carbon emissions to hidden unsustainable suppliers. Overall, our findings offer valuable insights into the consequences of strategic disclosure and its broader implications for managing sustainability within the supply chain.

## **Table of Contents**

| Declaration  | 7  |
|--|----|
| Acknowledgement  |    |
| Chapter 1: Thesis Introduction                                 | 9  |
| 1.1 Overview and Main Findings of the Study                    | 9  |
| 1.2 Contribution and Policy Implications of the Study          | 14 |
| 1.3 Limitations of the Study                                   |    |
| Chapter 2: Corporate Social Responsibility and Insider Horizon | 21 |
| 2.1 Introduction   |    |
| 2.2 Data, Variables, and Sample Description                    | 27 |
| 2.2.1 Data and Variables                                       |    |
| 2.2.2 Sample Description                                       |    |
| 2.3 Main Results   |    |
| 2.3.1 Baseline Results   |    |
| 2.3.2 Good internal corporate governance or agency problems?   |    |
| 2.3.3 Different insiders                                       |    |
| 2.3.4 Robustness tests   |    |
| 2.4 Identification Strategy                                    | 42 |
| 2.4.1 The effects of CEO career concerns                       | 43 |
| 2.4.2 The effects of Inevitable Disclosure Doctrine            | 46 |
| 2.5 Cross-sectional Analyses                                   |    |
| 2.5.1 Institutional investors                                  |    |
| 2.5.2 Compensation contracts                                   |    |
| 2.6 Real Effects   |    |
| 2.6.1 Toxic releases   |    |
| 2.6.2 Compliance violations                                    |    |
| 2.6.3 Employee satisfaction                                    |    |
| 2.6.4 RepRisk incidents and index                              |    |
| 2.7 Conclusion   |    |
| Chapter 2 - Appendix A: Variable Construction                  |    |

| Table 2.1 Summary Statistics   | 64 |
|--|----|
| Table 2.2 Insider Investment Horizon and CSR                                     | 65 |
| Table 2.3 Long-horizon buyers and sellers  | 67 |
| Table 2.4 Good internal corporate governance or agency problems                  | 68 |
| Table 2.5 Different Insiders   | 69 |
| Table 2.6 CEO Career Concern Effects   | 70 |
| Table 2.7 Inevitable Disclosure Doctrine Effects                                 | 71 |
| Table 2.8 Cross-Sectional Analyses Institutional Investors                       | 72 |
| Table 2.9 Cross-Sectional Analyses Compensation Contracts                        | 73 |
| Table 2.10 Real Effects — TRI Toxic Releases                                     | 74 |
| Table 2.11 Real Effects — CSR Compliance Violations                              | 76 |
| Table 2.12 Real Effects — Employee Satisfaction                                  | 77 |
| Table 2.13 Real Effects — RepRisk index and ESG incidents                        | 78 |
| Chapter 2 - Internet Appendix  | 79 |
| Table IA2.1 Alternative CSR measures from Refinitiv and Sustainalytics           | 79 |
| Table IA2.2 Alternative measures of insider investment horizon and KLD scores    |    |
| Table IA2.3 Firm-level analysis  |    |
| Table IA2.4 Subsample analysis   |    |
| Table IA2.5 CEO Career Concern Effects – Dynamic analysis                        |    |
| Table IA2.6 Inevitable Disclosure Doctrine Effects – Dynamic analysis            |    |
| Table IA2.7 The effects of IDD adoption  |    |
| Table IA2.8 Cross-sectional analysis Antitakeover law                            |    |
| Table IA2.9 Toxicity-weighted and harmful release                                |    |
| Chapter 3: How do Active Mutual Funds Respond to Firm's Climate Change Exposure? | 90 |
| 3.1 Introduction   | 91 |
| 3.2 Data, Sample and Summary Statistics  | 96 |
| 3.2.1 Firm-level Climate Change Exposure   | 96 |
| 3.2.2 Fund Portfolio Weights and Other Controls                                  | 97 |
| 3.2.3 Firm-level Controls  | 98 |
| 3.2.4 Sample and Summary Statistics  |    |
| 3.3 Identification strategy  |    |
| 3.3.1 Model Specification  |    |

| 3.3.2 Validity of Identifying Assumptions   | 100     |
|---|---------|
| 3.4 Results   |         |
| 3.4.1 Baseline results  |         |
| 3.4.2 The role of climate regulations   | 104     |
| 3.4.3 The role of funds pre-exposure  | 106     |
| 3.4.4 Heterogenous effects of salient industries  | 107     |
| 3.4.5 Heterogenous effects of beliefs on climate change                                 | 108     |
| 3.4.6 Heterogenous effects of Obama and Trump Administration                            | 110     |
| 3.4.7 How do firms respond to the reallocation of fund managers?                        | 111     |
| 3.5 Conclusion  | 113     |
| Chapter 3 - Appendix A: Variable Definitions  | 115     |
| Table 3.1 Summary statistics  | 117     |
| Table 3.2 High- and low-exposure sample: Parallel trends pre-Paris Agreement            | 118     |
| Table 3.3 Baseline results: Fund portfolio weights and firm climate change exposure     | 119     |
| Table 3.4 Baseline Results: Active versus Passive Funds                                 |         |
| Table 3.5 The effects of environmental regulation stringency of portfolio firms         | 121     |
| Table 3.6 The effects of fund-level climate risk exposure                               |         |
| Table 3.7 All-but-salient and salient industries  |         |
| Table 3.8 High and low climate change beliefs   | 124     |
| Table 3.9 Obama Administration and Trump Administration                                 |         |
| Table 3.10 Firm Response – Environmental Score  |         |
| Table 3.11 Firm Response – Carbon Emissions   | 127     |
| Chapter 4: The (Unintended) Consequences of Strategic Disclosure on Green Transition: E | vidence |
| from Supply Chain   |         |
| 4.1 Introduction  | 129     |
| 4.2 Data and Summary Statistics   |         |
| 4.2.1 Data and Variables  |         |
| 4.2.2 Summary Statistics  | 140     |
| 4.3 Green-induced Nondisclosure and Green Transition in Supply Chain                    | 142     |
| 4.3.1 Baseline Results  | 142     |
| 4.3.2 Changes in Environmental Performance  | 146     |
| 4.3.3 Termination Probability and Relationship Length                                   | 148     |

| 4.4 Identification Strategies  | 149 |
|--|-----|
| 4.4.1 The Enactment of US State-level GHG Emission Target                  |     |
| 4.4.2 The Implementation of Global GHG Emission Trading System             |     |
| 4.5 Cross-Sectional Heterogeneity  |     |
| 4.5.1 Common Stakeholders  | 154 |
| 4.5.2 Supplier Environmental Pressure                                      |     |
| 4.5.3 Customer Inability   | 157 |
| 4.6 Carbon Outsource   |     |
| 4.7 Conclusion   |     |
| Table 4.1 Summary Statistics   |     |
| Table 4.2 Supplier and Customer Firm Distribution by Country and Region    |     |
| Table 4.3 Baseline Results – The Effects of Green-induced Nondisclosure    | 164 |
| Table 4.4 The Effects of Green-induced Disclosure                          | 166 |
| Table 4.5 Changes in Environmental Scores                                  |     |
| Table 4.6 Relationship Length and Termination Probability                  |     |
| Table 4.7 US State-level GHG Emission Target                               | 169 |
| Table 4.8 Global Implementation of GHG Emission Trading System             | 170 |
| Table 4.9 Cross-sectional heterogeneity – Common Stakeholders              | 171 |
| Table 4.10 Cross-sectional heterogeneity – Supplier Environmental Pressure |     |
| Table 4.11 Cross-sectional heterogeneity – Customer Inability              | 174 |
| Table 4.12 Carbon Outsource  | 175 |
| Chapter 4 - Appendix A: Variable Definition                                | 176 |
| Chapter 5: Thesis Conclusion   |     |
| References   |     |

## Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university.

I further declare that the Chapter 2 of this thesis is co-authored with my PhD supervisor Professor Mark Shackleton and Chelsea Yao, a senior lecturer at Lancaster University. Chapter 3 is co-authored with Chelsea Yao. Chapter 4 is co-authored with Linxiang Ma, an assistant professor at University of Strathclyde, and Xiaoke Ye, an assistant professor at Liverpool University. For these chapters, I was responsible for developing research ideas and questions, designing and conducting empirical analyses, and writing the chapters. The contributions of the co-authors have been limited to the reasonable level expected in a doctoral thesis at a research university in the United Kingdom.

Ziran Zuo

June 2025

## Acknowledgement

The process of completing this PhD thesis has been both demanding and incredibly fulfilling. I am profoundly grateful to the many individuals and organizations whose support has been essential to this journey, and this thesis would not have been possible without their assistance.

First, I would like to extend my sincere thanks to my PhD supervisor, Professor Mark Shackleton. Your willingness to engage in detailed discussions on my research, as well as your help in navigating the challenges of revising papers, has shaped my academic experience.

I am also grateful to the academic and administrative staff at Lancaster University, especially Professor Sandra Nolte, Head of the Department, for her guidance and continued support throughout my studies.

Finally, I would like to express my deepest appreciation to my family and friends, particularly my father Qi Zuo, my mother Hui He and my wife Pu Tan for always understanding and supporting me during this academic journey. You all have made the PhD as a remarkable experience and one of the most joyful episodes of my life.

### **Chapter 1: Thesis Introduction**

#### 1.1 Overview and Main Findings of the Study

ESG has evolved from a niche subfield into a mainstream practice in recent years. Given the increasing importance of ESG, various stakeholders incorporate ESG into their decision-making processes. For example, ESG has significant impacts on corporate policies such as financial decisions (e.g., Dang, Gao and Yu, 2023), the design of executive compensation contracts (e.g., Cohen et al., 2023) and competitive strategies (e.g., Cao, Liang and Zhan, 2019). Investors also value ESG when making investment decisions (e.g., Krueger, Sautner and Starks, 2020). As of March 2024, 5,345 institutional investors managing total assets of 128.4 trillion US dollars had signed the Principles for Responsible Investment ("PRI"). In addition, ESG can influence the supply-chain contracting decisions (e.g., Darendeli et al., 2022) and the demands of retail customers (e.g., Meier et al., 2023). Analysts also revise their earnings forecasts depending on ESG issues of target firms (e.g., Derrien et al., 2024). On the regulatory side, regulators across the globe not only establish the mandatory disclosure policies for ESG information (e.g., Krueger et al., 2024) but also implement enforceable regulations such as carbon tax and emission trading system to limit carbon emissions (e.g., Bai and Ru, 2024).

This thesis focuses on three pivotal stakeholders of ESG and CSR issues: corporate insiders, institutional investors (mutual fund managers), and stakeholders in the supply chain (i.e., suppliers and customers). The aim of this thesis is to shed light on the antecedents and consequences of ESG and CSR in the context of these three different stakeholders and provide comprehensive understanding of these concepts. More specifically, the three chapters examine ESG and CSR issues from different perspectives.

It is worth clarifying the rationale for using the term "CSR" rather than "ESG" in Chapter 2, although many empirical studies use these terms interchangeably. Fundamentally, ESG has a slightly broader scope than CSR, as it explicitly encompasses environmental, social, and governance factors, whereas CSR typically focuses on environmental and social dimensions. More importantly, the key difference between ESG and CSR lies in their primary purposes and target audiences. CSR emphasizes whether and how firms voluntarily contribute to positive

social externalities—such as through corporate donations to local communities—and is generally value-driven and internally oriented. In contrast, ESG is a framework designed for external stakeholders, such as investors and regulators, to assess a firm's sustainability practices and related risks and opportunities. A typical example is the disclosure of firm-level carbon emissions, which helps investors evaluate carbon risks and regulators determine appropriate carbon taxes or allowances. Given these differences in purpose, CSR and ESG are directed at different groups. CSR, focusing on the social value created by firms from an internal perspective (e.g., firm reputation and culture), is mainly targeted at the public (e.g., local communities) and employees. By comparison, ESG primarily targets investors and regulators, who act as evaluators of firms' environmental and governance performance.

Understanding this distinction helps clarify the terminology used across the thesis chapters. Chapter 2 adopts the term CSR because it investigates whether and how the long-term orientation of corporate insiders (i.e., their investment horizon) influences their engagement in prosocial activities. In contrast, Chapters 3 and 4 focus on ESG: Chapter 3 explores how mutual fund managers make portfolio decisions based on firms' climate change exposure, and Chapter 4 examines the green transition in supply chains from the perspectives of suppliers and customers. Since both chapters focus on decision-making processes of external stakeholders, the term ESG is more appropriate in these contexts.

In Chapter 2, we investigate whether and how the horizon of insiders affects firm-level CSR performance. Based on the rationale that CSR is more likely to create long-term value rather than short-term profits, we expect that corporate insiders who are willing to pursue long-term value can lead to better firm-level CSR performance. The primary rationale for the focus on corporate insiders is that insiders (e.g., top manager and directors) can directly impact corporate strategies and steer the direction of firms compared to other external stakeholders (e.g., institutional investors). To measure the insider horizon, we construct a variable capturing the intrinsic desire of insiders to pursue long-term value based on the insider trading pattern, following Akbas, Jiang and Koch (2020). Those insiders with persistent trading behavior on the same direction (i.e., either buying or selling own-company stocks) are classified as long-horizon insiders, while insiders are labelled as short-horizon ones if they frequently switch between buying and selling. The appealing feature of this measure is the better ability to capture

insiders' intrinsic willingness to pursue long-term value compared to conventional horizon proxies relying on executive compensation, since insiders have more flexibility to conduct insider trading under legal guidance but less bargaining power on compensation contracts typically determined by a specialized committee.

Our baseline analysis reveals a positive relation between the insider horizon and firm-level CSR performance, which is consistent with the theories on managerial short-termism indicating the distinct attitudes of long-term and short-term insiders towards CSR. Further analysis distinguishes between two potential interpretations pertaining to the positive effects of insider horizon on CSR performance: the agency problem and good internal corporate governance. It is crucial to figure out the source of these positive effects since these two interpretations have opposite implications on shareholder value. Our empirical results based on decomposed CSR rating scores support the good internal governance interpretation for the prosocial activities of long-horizon insiders, which can benefit shareholders ultimately.

To identify a causal link between insider horizon and CSR performance, we consider two exogenous shocks to insider horizon. The first shock is the reductions in managerial career horizons driven by unforeseeable events such as the death or serious diseases of CEOs' close relatives. Alternatively, we employ the staggered rejection of the inevitable disclosure doctrine as another shock to insider horizon. Relying on a difference-in-difference-in-difference approach, we find consistent results using these two shocks and thus support a causal relationship between insider horizon and CSR performance.

Our empirical results regarding the heterogeneity tests show that the baseline results are stronger with more long-horizon and socially responsible institutional ownership, longer duration and higher Vega of insiders' compensation contracts and less takeover pressure. These findings reinforce the argument that our key measure, insider horizon, captures the intrinsic willingness of insiders to pursue long-term value. Finally, we provide further evidence by exploring the real effects of insider horizon using some raw CSR metrics. We find that longhorizon insider can reduce toxic releases, CSR compliance violations and negative ESG incidents, as well as improving employee satisfaction.

Different from Chapter 2, Chapter 3 and 4 narrow the scope to the environmental issues ("E") in "ESG" given the urgent need to combat climate change and global warming as

documented in the 2015 Paris Agreement. More explicitly, Chapter 3 concentrates on the institutional investors as they can manage climate change risks of their portfolios through the exit of threat (e.g., Gibson et al., 2022; Atta-Darkua et al., 2023, Huynh, Li and Xia, 2025) and engagement (e.g., Azar et al., 2021; Dimson, Karakas and Li, 2015; Naaraayanan, Sachdeva, and Sharma, 2021). The focus of this chapter is the mutual fund managers' portfolio rebalancing behavior depending on the climate change exposure of portfolio firms by adopting the Paris Agreement signed on December 2015 as a potential shock to fund managers' awareness and perceptions of climate change. We establish three competing hypotheses with respect to the potential investment behavior of fund managers. First, they may underweight firms with high climate change exposure following the Paris Agreement to cater to the demands of investors, thereby attracting more fund flows and expanding fund size. Second, they may overweight high-exposure firms after the Paris Agreement to pursue financial rewards stemming from risk premiums. Third, fund managers may not change their portfolio holdings based on firms' exposure to climate change.

We employ the measures of firm-level climate change exposure developed by Sautner et al. (2023) based on the textual information extracted from earnings conference calls. We define firms with above-median average climate change exposure prior to the Paris Agreement as high-exposure firms while the other firms are defined as low-exposure firms. Adopting a difference-in-difference approach, we reveal that mutual fund managers reduce 2.42% (0.415 million US dollars) of holdings for a high-exposure firms on average. Since the average number of portfolio firms for each fund is 61.9, the total reductions in the investments on firms with high climate change exposure are approximately 25.69 million US dollars for each fund. As a result, our baseline results indicate that mutual fund managers divest high-exposure firms and thus direct funds to a green economy.

Furthermore, we investigate the roles that climate regulation and fund-level climate change exposure plays on the investment decisions of fund managers depending on the climate change exposure of portfolio firms following the Paris Agreement. Using the US state-level enactment of greenhouse gas (GHG) emission targets aimed at reducing carbon emissions as a proxy for the stringency of climate regulations, we find that fund managers divest high-exposure firms after the Agreement only if these firms are located in states with GHG emission targets, reflecting that the effects of regulatory enforcement related to climate issues on fund managers' investment decisions. In addition, we show that divestment effects are concentrated on funds with lower climate change exposure. In contrast, funds with higher exposure increase the weights for highly exposed firms. Collectively, these findings suggest that the investment decisions of fund managers do not solely hinge on the portfolio firms' climate change exposure. Next, we conduct various heterogeneity tests regarding whether the portfolio firms belong to salient industries that are susceptible to climate change, whether fund managers are located in the states with high public views on climate change, and the different presidential administrations of Obama and Trump.

We also examine the real effects of fund managers' divestments on high-exposure firms, as divested firms may take measures to promote their environmental performance to avoid the negative consequences of divestments. Consistent with this notion, we document that highexposure firms indeed improve their environmental scores and reduce carbon emission following the Paris Agreement, indicating the discipline effects of divestments on corporate environmental outcomes.

The focus shifts to the green transition in the supply chain as supply chain management plays a crucial role in green transition of major corporations. A classic study of Dai, Liang and Ng (2021) demonstrates the unilateral propagation of environmental practices from customers to suppliers. In other words, the environmental performance of customer firms has discipline effects on the suppliers' environmental performance, which is beneficial to the green transition of the whole supply chain. Nevertheless, this beneficial propagation of green practices may be challenged by a disclosure policy regarding suppliers and customers.

Specifically, existing supply chain disclosure regulations do not mandate customer firms to disclose suppliers. Due to this voluntary disclosure requirement, customer firms can strategically disclose supplier firms with good environmental performance while withholding those performing poorly in environmental issues (Shi et al., 2023). Customer firms may be less incentivized to monitor and support the green practices of suppliers, since they can avoid investigations of regulators and other stakeholders by concealing the information of their suppliers. To explore this, we first construct a novel indicator for green-induced nondisclosure

to represent whether a supplier firm is hidden by the customer firm due to its poor environmental performance. Our baseline results reveal that this green-induced nondisclosure reverses the positive unilateral impacts of customers on suppliers' environmental performance. Put differently, the relation between customers' and suppliers' environmental performance become negative. Further analysis shows that the green-induced nondisclosure is negatively related to the annual change of suppliers' environmental scores but positively related to that of customers' environmental scores, indicating that customers achieve improved environmental performance at the expense of hidden unsustainable suppliers. These findings thus support the view that customer firms transfer environmental risks to hidden unsustainable suppliers, which is detrimental to the green transition of the supply chain.

To establish a causal link regarding our baseline results, we exploit two regulatory shocks to the incentives of customer firms to transfer environmental risks through the supply chain. The intuition is that customer firms tend to have stronger incentives to transfer environmental risks when they experience more stringent environmental regulations. Consistent with this rationale, we find that the reversing effects of green-induced nondisclosure on the relation between the environmental performance of customers and suppliers are stronger with higher stringency of environmental regulations in the places where customers are located.

The tests with respect to the heterogeneity of our main results indicate that the reversing effects of green-induced nondisclosure vary with information transparency stemming from common stakeholders in the supply chain, the environmental pressure of suppliers, and the financial constraints of customers. In the final part of this chapter, we document the real consequences of green-induced nondisclosure on supplier firms by showing that customer firms outsource part of their carbon emissions to those hidden unsustainable suppliers.

#### 1.2 Contribution and Policy Implications of the Study

Overall, this study generally contributes to the broad literature on the determinants and consequences of CSR and ESG from both internal and external perspectives. More explicitly, Chapter 2 primarily contributes to three strands of literature. First, it advances the growing body of research on the determinants of CSR, especially factors related to horizons. While prior studies have primarily focused on the impact of institutional investors' horizons—showing that

longer investment horizons tend to enhance firm-level CSR performance (e.g., Kim et al., 2019; Glossner, 2019; Krueger, Sautner, and Starks, 2020; Starks, Venkat, and Zhu, 2023)-less attention has been paid to how other critical stakeholders' time horizons, such as those of corporate insiders, influence CSR outcomes. Our study addresses this gap by demonstrating a positive relationship between insider investment horizon and CSR, supporting the notion that long-term perspective promotes CSR engagement. Unlike earlier works that proxy insider horizon using features of executive compensation contracts (e.g., Flammer and Bansal, 2017; Fu, Shen, Tang, and Yan, 2021), we rely on insiders' trading behavior to capture their intrinsic commitment to long-term value creation. This approach complements existing literature by highlighting a direct, behavior-based measure of insiders' long-term orientation and its connection to CSR. Second, our study contributes to the extensive literature on the conflicts between short-term and long-term managerial objectives, particularly the consequences of managerial short-termism. Theoretical frameworks suggest that shorter horizons may negatively impact CSR performance. Empirical findings support this concern, showing that short-term oriented managerial decisions-such as those involving opportunistic buybacks, mergers, or acquisitions-can harm firms' long-term performance (e.g., Edmans, Fang, and Huang, 2022). We add to this literature by empirically linking insider investment horizon to CSR outcomes, providing further evidence that short-termism among insiders can undermine long-term corporate value, including through weakened CSR engagement. Third, this paper builds on the work of Akbas, Jiang, and Koch (2020) and contributes to the relatively scant research focusing on the relation between insider trading and CSR. While Akbas et al. (2020) explore how insider investment horizon affects the informativeness of insider trades, we extend their work by examining how insiders' trading persistence relates to a major corporate strategy—CSR. This perspective is particularly relevant given findings by Gao, Lisic, and Zhang (2014), who show that insider trades in firms with stronger CSR performance tend to be less profitable and informative, suggesting that CSR can curb managerial opportunism by fostering a culture of altruism and increasing the costs of informed trading. Our study adds a new dimension by examining whether consistent insider trading behavior reflects a long-term orientation that contributes to stronger CSR engagement. To the best of our knowledge, we are among the first to empirically explore the relationship between insider trading behavior and

CSR performance.

Chapter 3 is related to various studies, ranging from the responses of institutional investors to climate change to the effects of these investors on firms' green practices. Most importantly, this chapter contributes to the growing body of research examining how institutional investors respond to climate change risks. While prior evidence-both survey-based (e.g., Krueger, Sautner, and Starks, 2020; Ilhan et al., 2023) and empirical (e.g., Alok, Kumar, and Wermers, 2020; Gibson et al., 2022; Atta-Darkua et al., 2023; Huynh, Li, and Xia, 2025)-document that institutional investors tend to divest from firms with elevated climate risk, our study offers three novel contributions that distinguish it from existing literature. First, while previous studies typically rely on various forms of "hard" climate risk indicators, we approach the issue from a different perspective by utilizing "soft" information derived from firms' earnings conference calls as constructed by Sautner et al. (2023), which enables us to assess investor responses to distinct dimensions of climate risk-such as technological opportunities, regulatory pressures, and physical risks. Hence, we can offer new insights regarding how institutional investors react to nuanced types of climate-related concerns. Second, our research highlights the role of regulatory enforcement in shaping investor behavior. We show that institutional investors' divestments in firms with high climate exposure are more pronounced in jurisdictions with stricter climate regulations. This underscores the importance of the regulatory environment in influencing sustainable investment practices. Third, unlike most prior work that focuses solely on firm-level climate risk, we also consider the climate risk exposure of institutional investors. Our results suggest that divestment decisions can be also driven by the climate change exposure of these institutional investors. This chapter is also related to the literature on the real effects of institutional investors on corporate environmental practices. Regarding the two primary channels that institutional investors can influence portfolio firms' green practices (i.e., screening and engagement), a debate concentrates on which of these two strategies is more effective. Heinkel et al. (2001), for example, argue that divestment can depress the stock prices of polluting firms by limiting risk-sharing. In contrast, Berk and van Binsbergen (2025) propose a theoretical model suggesting that divestment has little impact on firms' cost of capital and instead advocate for engagement as a more effective approach for socially responsible investors. Our study contributes to this debate by providing

empirical evidence that firms with high climate exposure improve their environmental scores and reduced carbon emissions in response to divestment by mutual fund managers. These findings support the view that divestment can be an effective mechanism for promoting green corporate outcomes.

Chapter 4 makes contributions to various literature, particularly the studies concentrating on the determinants of green transition. Prior studies document that government interventions, such as environmental disclosure and carbon trading schemes, play important roles in curbing firm-level pollution and promoting the shift toward a green economy (e.g., Downar et al., 2021; Bai and Ru, 2024; Martinsson et al., 2024). However, some scholars challenge this optimistic view, showing that firms may respond to stricter regulations by offshoring pollution-intensive activities to regions with weaker environmental policies (e.g., Ben-David et al., 2021; Bartram, Hou, and Kim, 2022). Our study contributes to this strand of literature by exploring the unintended impacts of non-environmental policies (i.e., disclosure policies for supply chain) on the green transition in the supply chain. This study also adds to the literature on the real effects of voluntary disclosure. A well-established theoretical body of work suggests that firms may selectively withhold information to maintain competitive advantage (e.g., Verrecchia, 1983; Darrough and Stoughton, 1990). Empirical evidence has shown that voluntary disclosure can significantly influence various corporate strategies and outcomes. Most notably, Shi et al. (2023) document that firms tend to selectively disclose environmentally responsible suppliers while concealing ties to those with poor environmental records. Such green-motivated strategic disclosure not only enhances firms' market valuation and operational performance but also allows them to maintain a favorable public image. We build upon Shi et al. (2023) by examining the impact of this selective disclosure on the green transition of supply chains. Our findings suggest that such disclosure may actually impede environmental progress, as firms become less inclined to support the sustainability efforts of concealed, high-risk suppliers. More broadly, we provide novel evidence that voluntary disclosure can serve as a mechanism for firms to evade environmental responsibilities and shift risks onto other stakeholders. To our knowledge, we are among the first to explore how firms may strategically disclose information to evade accountability and reallocate environmental risk. Lastly, this study enhances the understanding of how green practices propagate among economically connected stakeholders—particularly within supply chains. Prior studies of Dai, Liang, and Ng (2021) and Schiller (2018) show that customer firms positively influence the environmental performance of their suppliers. Similarly, Homroy and Rauf (2024) find that suppliers often adopt emission reduction goals in response to similar initiatives by their customer firms, even though such commitments are not fully implemented. Our study extends this strand of research by identifying key factors that obstruct the diffusion of green practices along the supply chain, highlighting how these barriers can undermine the broader green transition within industries.

In addition to literature contribution, this thesis also provides various implications for internal corporate policies and external government regulations. Specifically, as illustrated in Chapter 2, firms should shape long-term perspectives for their executives and thus facilitate the alignment of shareholder value and ESG performance over the long run. Chapter 3 reinforces the effectiveness of climate regulations on facilitating the transition to a green economy as these regulations have real impacts on the investment decisions of fund managers. Chater 4 may motivate policymakers to re-evaluate the efficiency of voluntary disclosure requirement in the supply chain as it poses threats to green transition along the supply chain.

#### 1.3 Limitations of the Study

Similar to other social science research, this thesis is subject to several limitations that cannot be fully resolved at the current stage. First, this thesis adopts the perspective of ESG proponents, assuming that stakeholders should engage in ESG activities to create long-term value. However, there is an ongoing debate over whether ESG actually enhances shareholder value. Some studies argue that ESG activities may reflect agency problems, where managers use prosocial initiatives to entrench themselves and build a positive image (e.g., Masulis and Reza, 2015; Cheng, Hong, and Shue, 2023). Moreover, it remains uncertain whether stakeholders prioritize ESG concerns when making key decisions. For example, Edmans, Gosling, and Jenter (2025) survey hundreds of portfolio managers and find that ESG performance is generally regarded as an inferior concern, especially when compared to financial returns and investment constraints. To partially address these concerns, we conduct robustness tests and include relevant discussions. Specifically, in Chapter 2, we rule out the possibility that the positive association between insider investment horizon and CSR performance is driven by agency problems. In Chapter 3, we mitigate the concern that mutual fund managers' divestment in response to firms' climate exposure is merely a form of greenwashing.

Second, the primary ESG performance measures used in this thesis are ESG scores constructed by rating agencies. However, such scores are often subject to disagreement due to differences in methodology, weighting schemes, and scope (Berg, Koelbel, and Rigobon, 2022). As a result, ESG scores may not accurately reflect firms' actual ESG practices. To address this limitation, we incorporate ESG data from multiple sources and include raw ESG indicators (e.g., carbon emissions and employee satisfaction) to ensure that our main findings are robust to alternative measurement approaches.

Third, the causal relationships proposed in this study may not be fully or effectively identified. Because both the drivers and outcomes of ESG engagement relate to various aspects of firm behavior-such as stock performance, executive compensation, risk exposure, and institutional ownership-our results may be affected by omitted variable bias, as it is difficult to control for all relevant factors. In Chapter 2, we attempt to establish causality by using two exogenous shocks for insider investment horizons. However, the second shock (i.e., the rejection of the Inevitable Disclosure Doctrine) may not be truly exogenous, as it is arguably linked to CSR activity (Flammer and Kacperczyk, 2019). In Chapter 3, we use the Paris Agreement as an exogenous shock to fund managers' awareness of climate risk. However, as discussed in that chapter, institutional investors' responses to ESG may also be influenced by political differences across US states. In Chapter 4, we exploit two regulatory shocks that increase pressure on customer firms to adopt green practices, which in turn increase the likelihood of these firms shifting environmental responsibility to their suppliers. Nevertheless, firms' motivations for transferring environmental risk may vary. Apart from stricter environmental regulations on the customer side, more lenient regulations on the supplier side may also encourage these shifting activities.

Fourth, this thesis is limited to examining three primary types of stakeholders in the ESG context: corporate insiders, institutional investors, and supply chain participants. As ESG issues gain increasing prominence, a broader range of stakeholders—including bondholders, consumers, and retail investors among others—are incorporating ESG considerations into their

decision-making. These stakeholders, however, fall outside the scope of this study.

Finally, Chapters 3 and 4 may suffer from the issue of partial optimization with respect to ESG dimensions. Edmans (2023) argues that firms may improve performance in one ESG dimension (e.g., environment) at the expense of another (e.g., social). Farzamfar, Foroughi, and Ng (2022) provide empirical evidence supporting this view, showing that improvements in environmental performance coincide with declines in social performance. Hence, we caution that the environmental improvements (or deteriorations) documented in Chapters 3 and 4 may be associated with corresponding trade-offs in social outcomes.

## **Chapter 2: Corporate Social Responsibility and Insider Horizon**

Abstract: We show a positive relation between insider horizon and a firm's corporate social responsibility (CSR) performance. This positive relation is likely driven by good internal governance rather than agency problems. To support a causal interpretation, we adopt managerial career horizon reductions and the rejection of inevitable disclosure doctrine as exogenous shocks to insider horizon. We find that the observed positive effects are stronger when firms have higher ownership of long-term and socially responsible institutional investors, when insiders sign long-term compensation contracts, and when firms face less takeover pressure. We document the real effects of long-horizon insiders using various raw CSR metrics. Overall, our results indicate that insiders' long-term orientation can promote CSR.

#### 2.1 Introduction

Many academics and practitioners believe corporate social responsibility (CSR) activities are more likely to create long-term value than near-term profits<sup>2</sup> because of substantial up-front investments (e.g., Martin and Moser, 2016) and the underreactions of investors (e.g., Edmans, 2011; Duan, Li, and Wen, 2023). In his recent annual letters to the CEOs of Blackrock's portfolio firms, Larry Fink, Chairman and CEO of Blackrock, emphasized the positive effects of CSR on firm value over the long run and encouraged the firms to make long-term strategies to improve CSR<sup>3</sup>. Edmans (2020) argues that CSR and shareholder value align in the long term (i.e., the "pie-growing mentality"), and thus a long-term perspective is required when stakeholders commit to CSR.

In this paper, we study whether and how the horizon of insiders primarily including top managers and directors influences firm-level CSR performance. That is, does the longer horizon of insiders lead to better CSR performance? We focus on insider horizon for three reasons. First, insiders can directly affect corporate strategies and steer the direction of firms compared to institutional investors and other shareholders, who usually express their views through voting and trading. Second, CSR may depend on insiders' desire to engage in prosocial activities rather than other stakeholders' demands or willingness to pursue social value (Benabou and Tirole, 2010). In this case, insiders' preferences play an important role in CSR activities. Third, insiders tend to cut long-term investments when they can personally profit from boosting short-term performance.<sup>4</sup> Because the effects of CSR may not be realized immediately, myopic insiders may reduce CSR investments and activities when pressured by short-term targets.

We construct an insider horizon measure based on an insider's trading behavior with owncompany stocks, aiming to capture the insider's intrinsic desire to pursue long-term value. Edmans, Gosling, and Jenter (2023) find that insiders' intrinsic motivations may have a greater

<sup>&</sup>lt;sup>2</sup> Long-term value created by CSR may stem from mitigated risk, especially downside risk (e.g., Albuquerque, Yrjo, and Zhang, 2019; Hoepner et al., 2019), higher employee satisfaction and productivity (e.g., Edmans, 2011; Flammer, 2015), better customer attraction (e.g., Baron, 2008), or reduced labor costs and higher talent retention (e.g., Krueger, Metzger, and Wu, 2024).

<sup>&</sup>lt;sup>3</sup> See, for example, https://www.blackrock.com/corporate/investor-relations/2016-larry-fink-ceo-letter; https://www.blackrock.com/corporate/investor-relations/2019-larry-fink-ceo-letter.

<sup>&</sup>lt;sup>4</sup> See, for example, Edmans, Fang, and Lewellen, 2017; Kraft, Vashishtha, and Venkatachalam, 2018; Ladika and Sautner, 2020.

impact on decision making than incentive pay, though the intrinsic motivations can be influenced by financial incentives. Compared to the conventional insider horizon measures based on insider incentive pay (e.g., Gopalan et al., 2014), ours appears better able to capture insiders' intrinsic willingness to pursue long-term value, as insiders can decide their own trades within legal guidelines while their compensation contracts are typically approved by a committee.

We adopt the insider investment horizon used by Akbas, Jiang, and Koch (2020) as our proxy for insider horizon. Intuitively, an insider's persistent trading behavior of either buying or selling suggests a lower probability of realizing profits using private information frequently and thus a longer investment horizon. Conversely, if insiders often switch between selling and buying, they are more likely to realize profits in a timely manner, suggesting a shorter investment horizon.<sup>5</sup> Accordingly, we postulate that insiders who exhibit persistent trading behaviors are more likely to enhance CSR because the longer investment horizon reflects a willingness to remain with their firms and pursue long-term value. Indeed, we find this prediction to be borne out in the data.

The positive relation between insider investment horizon and CSR performance is consistent with theories on managerial short-termism, suggesting attitudes toward CSR could differ between long-term and short-term insiders. Narayanan (1985) argues that insiders are likely to boost short-term performance at the expense of long-term value when they possess private information that informs their decisions. Applied in our context, an insider tends to have a longer investment horizon, as reflected by a persistent trading behavior, when they rarely take advantage of private information. Thus, insiders with a longer investment horizon are less likely to sacrifice long-term value for short-term gain, thereby engaging in CSR activities and promoting CSR performance.

We investigate whether long-horizon buyers and sellers make identical impacts on CSR. Intuitively, both long-term buyers and sellers may have similarly positive impacts on CSR as they exhibit less tendency to engage in opportunistic trading to realize profits<sup>6</sup>, though their

<sup>&</sup>lt;sup>5</sup> Akbas, Jiang, and Koch (2020) document that insiders with shorter investment horizons engage more in myopic activities such as earnings management.

<sup>&</sup>lt;sup>6</sup> Akbas, Jiang, and Koch (2020) show that trades executed by both long-horizon buyers and sellers contain less information content, suggesting that these traders do not engage in opportunistic traders.

persistent trading behavior may stem from various factors. For example, long-horizon buyers may trade because of the need to increase corporate control, while long-horizon sellers persistently sell to satisfy liquidity or diversification needs. Consistent with the conjecture, we do not find any difference between long-horizon buyers and sellers' effects on CSR, suggesting that insiders with persistent buying and selling behavior should be treated identically. Therefore, they make similarly positive impacts on CSR.

We then disentangle whether the positive effects of insider investment horizon on CSR performance stem from agency problems of insiders to entrench themselves or from good internal corporate governance, the latter of which can benefit shareholders. To this end, we first distinguish CSR scores into strengths (i.e., positive indicators) and concerns (i.e., negative indicators) and demonstrate that the positive effects of long-horizon insiders on CSR are driven primarily by CSR concerns, to which shareholders are more responsive compared to CSR strengths (Krueger, 2015). Second, having separately assessed financially material and immaterial CSR issues, we show that the positive relation between insider investment horizon and CSR is attributed mainly to financially material CSR issues, which can generate positive financial returns for shareholders (Khan, Serafeim, and Yoon, 2016). These evidence support the view that good internal corporate governance motivates insiders to engage in CSR, which can potentially benefit shareholders.

We consider all types of insiders in the baseline analysis and find a positive relation between insider investment horizon and CSR in general. However, due to different personal attributes and insiders' power, different insiders' influence on CSR may vary. Thus, we explore how insider investment horizon affects CSR, considering different types of insiders. First, we find that both top directors' and managers' investment horizon exhibit positive effects on CSR. Second, when examining the CEO, chairman of the board, and CFO individually, we discern that the CEO's investment horizon exerts the most pronounced effects on CSR.

Despite various precautions, we may be unable to identify a documented positive relation between insider investment horizon and CSR performance as a causal link. To support a causal interpretation, we adopt two types of potential shocks to insider investment horizon. First, we focus on reductions in managerial career horizons driven by exogenous events, such as CEOs or their close relatives being diagnosed with serious diseases, as Aktas, Boone, Croci, and Signori (2021) demonstrated. The rationale is that when CEOs experience such events, which can reduce their career horizons, they are likely to become myopic and, thus, reduce long-term investments, such as CSR. If a causal link exists between insider investment horizon and CSR, the positive relation between insider investment horizon and CSR would be attenuated after the events reduced managerial horizon. Having adopted a difference-in-difference-in-difference-in-difference approach, we find that CSR performance deteriorates in response to events that reduce managerial career horizon, which can lend support for a causal interpretation of our main findings. Second, we facilitate the causal interpretation by relying on the staggered rejection of the inevitable disclosure doctrine that prohibits employees with trade secrets from working for rival firms. In the case of such rejection, insiders may have more outside opportunities and fewer career concerns (Li, Shevlin, and Zhang, 2022). Thus, they may focus more on long-term value and tend to have a longer investment horizon, which may boost the positive relation between insider investment horizon and CSR. Indeed, we find this to be the case in the data, relying on a difference-in-difference-in-difference-in-difference approach.

Next, we examine the cross-sectional heterogeneity of our main results from different perspectives to better understand the mechanisms through which insider investment horizon can influence CSR performance. First, we test a variation of our results using two characteristics of institutional investors that may affect insiders' long-term perspectives. We show that the positive effects of insider investment horizon on CSR performance are stronger when one firm's long-term and socially responsible institutional (SRI) ownership is higher. Second, we explore whether insiders' compensation contracts alter our main results, as they may affect insiders' desire to pursue long-term value. We find that the sensitivity of insiders' wealth to stock volatility (Vega) and pay duration can enhance the positive effects of insider investment horizon on CSR performance. Third, we show a stronger relation between insider investment horizon and CSR performance under less takeover pressure, as takeover pressure may constrain insiders to pursue long-term value according to Stein (1998). Taken together, these findings corroborate the argument that insider investment horizon can capture insiders' desire to pursue long-term value for Stein (1998). Taken together, these findings corroborate the argument that insider investment horizon can capture insiders' desire to pursue long-term value according to Stein (1998).

Finally, we conduct a series of tests to add evidence of the real effects of our findings. First, we focus on the level of toxic releases and explore whether firms with long-horizon insiders

report a lower level of toxic releases. We find that insider investment horizon is associated with a lower level of toxic releases. Second, we examine the relation between insider investment horizon and CSR compliance violations, documenting that firms with long-horizon insiders are less likely to commit CSR violations and receive fewer CSR violation penalties. Third, we test whether insider investment horizon positively affects employee satisfaction, as long-term insiders can promote overall CSR performance by improving employee satisfaction. We find that firms with long-horizon insiders are more likely to be listed in "100 Best Companies to Work for in America," which indicates higher employee satisfaction. Finally, we find that firms with long-horizon insiders tend to have a lower level of risk exposure to ESG issues and fewer ESG incidents, as captured by RepRisk database. Collectively, the above results complement our main findings by focusing on raw CSR metrics. These findings shed light on how longhorizon insiders can promote overall CSR performance by testing the real effects of insider investment horizon.

This study makes three contributions to the literature. First, our study contributes to the burgeoning research investigating CSR determinants, particularly factors related to horizon issues. Prior studies have investigated whether horizon influences CSR performance, paying particular attention to institutional investors' horizons, and have demonstrated that longer institutional investor horizons lead to better firm-level CSR performance (e.g., Kim et al., 2019; Glossner, 2019; Krueger, Sautner, and Starks, 2020; Starks, Venkat, and Zhu, 2023). However, relatively little is known about whether and how other key stakeholders' horizons affect CSR. Our paper fills this gap by establishing a positive link between insider investment horizon and CSR, thereby reinforcing the argument that a long-term perspective is beneficial to CSR. By comparing existing literature using compensation contracts' characteristics (e.g., Flammer and Bansal, 2017; Fu, Shen, Tang, and Yan, 2021) to measure insider horizon, we adopt a stand-alone and intrinsic measure of insiders' willingness to pursue long-term value based on their trading behavior, rather than incentives. Thus, our paper complements this strand of literature by establishing a link between insiders' intrinsic desire for long-term value and CSR.

Second, our study contributes to a large literature investigating the conflicts about corporate policies between short-horizon and long-horizon insiders, namely the consequences of managerial short-termism. Theories on managerial short-termism suggest a negative relation between insider horizon and CSR performance. Prior empirical studies indicate that managerial short-termism results in various detrimental short-term actions that harm firms' long-term value.<sup>7</sup> Notably, Edmans, Fang, and Huang (2022) find long-term negative returns following strategic repurchases, mergers, or acquisitions driven by managerial short-termism. Our study extends this strand of literature by building a link between insider investment horizon and CSR performance. Our empirical evidence supports the view that managerial short-termism tends to harm long-term value.

Third, our paper extends the study of Akbas, Jiang, and Koch (2020) and adds to the scarce literature that focuses on CSR and insider trading. We investigate the effects of insider investment horizon on one important corporate strategy (i.e., CSR), building on Akbas et al. (2020), who primarily examine whether insider investment horizon affects the information content of insider trades.<sup>8</sup> Furthermore, our study fills the void in the literature focusing on CSR and insider trading. Gao, Lisic, and Zhang (2014) conclude that insider trades in firms with better CSR performance exhibit less profitability and generate less information content, which indicates that CSR can alleviate managers' egotism by building a positive culture of altruism and increasing the costs of informed insider trading. In comparison, our paper sheds new light on whether the persistency of insider trading influences CSR. To our knowledge, we are among the first to explore the relation between CSR and insider trading behaviors.

The remainder of this paper proceeds as follows. Section 2.2 introduces the data and describes the summary statistics. The main empirical results are presented in Section 2.3, while identification strategies are discussed in Section 2.4. Section 2.5 shows the cross-sectional analyses, and Section 2.6 reveals the real effects of insider investment horizon. Section 2.7 concludes.

#### 2.2 Data, Variables, and Sample Description

In this section, we show the data source of our key variables as well as a battery of control

<sup>&</sup>lt;sup>7</sup> For example, managerial myopia leads to more earnings management (e.g., Brochet, Loumioti and Serafeim, 2015; Ernstberger et al., 2017), reduced long-term capital and R&D investments (e.g., Edmans et al., 2017; Ladika and Sautner, 2020), more strategic information disclosure (e.g., Edmans et al. 2018) and lower long-term productivity (e.g., Almeida et al., 2019).

<sup>&</sup>lt;sup>8</sup> The authors provide abundant evidence to show the trades of short-horizon insiders are more unexpected and informed about future stock returns compared to long-horizon investors.

variables and how we construct them. We also present the summary statistics of our sample.

#### 2.2.1 Data and Variables

Our firm-level CSR performance measures are from the KLD database, which has a longest history of available ESG rating data since 1991<sup>9</sup> and has been the most frequently used by prior studies measuring firm-level CSR performance<sup>10</sup>. The KLD database processes and evaluates ESG-related information from different sources (e.g., company disclosures and government databases) each year and generates a set of positive (i.e., ESG strengths) and negative (i.e., ESG concerns) indicators within eight categories: environment, community, employee relations, diversity, product, human right, corporate governance, and controversial business involvement (i.e., whether a firm's main operations is related to "sin" sectors such as alcohol and tobacco). A firm is given one (zero) for each indicator when it satisfies (fails to satisfy) the evaluation criteria for the corresponding indicator. In our study, we only consider KLD rating scores for five dimensions: environment, community, employee relation, diversity, and product. The reasons we exclude the human right category are that it is only applicable to a small number of firms and the variation of human right rating is negligible across firms (Chen, Dong, and Lin, 2020). We also exclude corporate governance, because insider investment horizon is related to corporate governance.<sup>11</sup> Finally, we remove the controversial business involvement rating, as firms can do little to change their primary business operations.

Following Deng, Kang, and Low (2013), we calculate the strength (concern) score as strengths (concerns) divided by maximum number of strengths (concerns) for each category in a given year, in order to mitigate the concern of inconsistent total number of ESG indicators across years. Next, we take the difference between strength score and concern score as the index for each category and aggregate the indexes for all five categories to produce our ultimate measure of CSR performance. The measure ranges from -5 to +5.

We extract insider trades data from the Thomson Reuters insider filings database. Corporate insiders, including officers, directors, and beneficial owners who hold more than 10%

<sup>&</sup>lt;sup>9</sup> Starting in 1991, the KLD ESG dataset covers S&P 500 firms before 2001. In 2001 and 2003, the KLD database began to extend its coverage to firms included in the Russell 1000 and Russell 3000, respectively.

<sup>&</sup>lt;sup>10</sup> See for example, Hong, Kubik and Scheinkman (2012), Deng, Kang and Lou (2013), Giuli and Kostovetsky (2014), Khan, Serafeim and Yoon (2016), Chen, Dong, Lin (2020), Berg, Kolbel and Rigobon (2022).

<sup>&</sup>lt;sup>11</sup> Abkas, Jiang and Koch (2020) show that short-term insiders tend to work for those firms with weaker corporate governance.

of a firm's stock, are required to report their open market trades to the Securities and Exchange Commission (SEC).<sup>12</sup> We only consider open market trades of common shares and exclude small trades of less than 100 shares (see Akbas et al., 2020). We then calculate net shares bought or sold by each insider in a given year and match these with the yearly CSR performance measure. For each insider, we construct the insider investment horizon based on their previous ten-year trading pattern for each year *t* as follows:

$$HOR_{i,j,t} = \frac{\sum_{T=9}^{T} IOF_{i,j,y}}{N}$$

Where  $IOF_{i,j,y}$ , the annual net order flow of insider *i* at firm *j* in year *y*, is calculated as  $\frac{P_{i,j,y} - S_{i,j,y}}{P_{i,j,y} + S_{i,j,y}}$ . *P*(*S*) is the total number of shares that an insider purchases (sells) during a given year. *N* is the number of years an insider traded from year *t*-9 to year *t*. The ultimate measure of insider investment horizon (*HOR*) ranges from zero to one, indicating that insiders with long (short) investment horizon tend to have an *HOR* close to one (zero).<sup>13</sup>

We also construct a series of firm-level and insider-level control variables using the financial data from Compustat, stock price data from CRSP, institutional holding data from the Thomson Reuters Institutional Holdings (13F) database (formerly known as CDA/Spectrum), and insider characteristic data from BoardEx. We define firm size (*Size*) as the natural logarithm of total assets for each fiscal year. *Cash ratio* is cash and short-term investments deflated by total assets. *Capex ratio* is the ratio of capital expenditures over total assets. *Tangibility* is defined as net property, plants, and equipment deflated by total assets. We measure *Tobin's Q* as the ratio of market value over total assets. *Leverage* is measured as the sum of long-term and current debt deflated by total assets. *ROA* is the operating income before depreciation scaled by total assets. *R&D intensity* is calculated as annual research and development (R&D) expenses divided by total assets. *Blue* is equal to one if the headquarter of a firm locates in a state

<sup>&</sup>lt;sup>12</sup> In the beginning, insiders were required to report their trades to the SEC no later than ten days after the end of each trading month, after which the deadline was reduced to two days.

<sup>&</sup>lt;sup>13</sup> Unlike Akbas et al. (2020), we do not multiply the ultimate measure by -1, which makes the HOR range lie between -1 to 0, because we expect a positive regression coefficient between insider investment horizon and CSR performance to facilitate the interpretation of our results.

supporting the Democratic Party during the previous US presidential election (i.e., blue state) and zero otherwise. *Prior-year return* is the stock return over the past year. *IO* is defined as the percentage of outstanding shares held by institutional shareholders. Insider-level control variables include an insider's ager (*Age*), their tenure in the firm (*Tenure*), and their gender (*Gender*). We provide details about how to construct all variables used in this study in Appendix A.

#### 2.2.2 Sample Description

Our final sample consists of 30,545 observations of 9,449 insiders in 2,095 unique firms from 1996 to 2015.<sup>14</sup> The summary statistics of all variables used for primary results are reported in Table 1. Panel A reports the statistics of firm-level variables. The average CSR score is -0.06, indicating that concerns (0.30) exceed strengths (0.24). Comparing firms in our sample with the whole universe of Compustat firms, we find the average CSR performance of our sample firms is better than that of Compustat firms (*CSR* mean value is -0.11), implying that firms with insider trades do better in CSR. Furthermore, our sample firms are bigger, less leveraged, more profitable, and held by more institutional investors compared to Compustat firms.

#### [Insert Table 2.1 here]

Panel B shows the summary statistics of insider-level variables. The mean and median values of *HOR* are 0.82 and 1.00, respectively, suggesting over half of insider-years in our sample have only bought or sold over the past ten years.<sup>15</sup> The negative trading strength (*STR*) reveals insiders sell more than purchase.<sup>16</sup> Meanwhile, the majority of insider-years are officer-years and director-years, which comprise over 85% of the sample. CEO-years, Chairman of board-years, and CFO-years account for 16%, 9%, and 8% of our sample, respectively.

<sup>&</sup>lt;sup>14</sup> We begin our sample in 1996 because insider data become available in 1986, and we calculate the insider investment horizon based on the past ten-year trading behavior of each insider.

<sup>&</sup>lt;sup>15</sup> Our sample shows 62% of insiders have engaged in persistent trading behavior over the past ten years. Following Akbas et al. (2020), we also generate a dummy equal to one if the *HOR* is one to define long-horizon insiders. Replacing *HOR* with the dummy, we find that our main results hold, as shown in next section.

<sup>&</sup>lt;sup>16</sup> These results are comparable to Akbas et al.'s (2020) summary statistics. Their average monthly HOR is 0.79 and the standard deviation is 0.30. Meanwhile, they also find the measure of trading strength is negative, suggesting that insiders sell more often than they purchase.

#### 2.3 Main Results

In this section, we test whether insider investment horizon affects firm-level CSR performance and discuss the primary empirical results. Section 2.3.1 introduces the baseline model and presents the baseline empirical results. To shed light on the reasons why insiders are motivated to affect CSR performance, we outline the results of tests created in Section 2.3.2. In Section 2.3.3, we explore whether the investment horizon of different insiders affects CSR performance. Finally, we conduct a set of robustness tests by using alternative measures of insider investment horizon and CSR performance in Section 2.3.4.

#### 2.3.1 Baseline Results

To examine the relation between CSR performance and insider investment horizon, we establish the baseline regression model as follows:

$$CSR_{j,t+1} = \beta_0 + \beta_1 HOR_{i,j,t} + \gamma_1 X_{j,t} + \gamma_2 Y_{i,j,t} + \delta Industry_k + \theta Year_t + \varepsilon_{i,j,t},$$
(1)

Where *i* indexes insiders, *j* indexes firms, and *t* indexes years. The dependent variable,  $CSR_{j,t+1}$ , is the CSR rating score for firm *j* in year *t*+1, while the primary independent variable,  $HOR_{i,j,t}$ , is the investment horizon for insider *i* in firm *j* in year *t*. The firm-level control variables described in Section 2.2.1 are represented by  $X_{j,t}$  and  $Y_{i,j,t}$  includes a set of insider-level control variables such as age, tenure, and gender of each insider. To control for time-invariant industrial characteristics and the variation of CSR performance across years, we include industry-fixed effects ( $\delta Industry_k$ )<sup>17</sup> and year-fixed effects ( $\theta Year_t$ ) in the baseline regression model.<sup>18</sup> To treat insiders heterogeneously and capture their unique individual attributes (e.g., Hiller, Korczak and Korczak, 2015), we introduce insider-level investment horizon in the baseline model. Meanwhile, we analyze the horizon's effects on firm-level CSR performance

<sup>&</sup>lt;sup>17</sup> We use the two-digit Standard Industrial Classification (SIC2) code to define industries. Our main results are robust to the three-digit Standard Industrial Classification (SIC3) code and Fama-French 48-industry classification for industries.

<sup>&</sup>lt;sup>18</sup> We incorporate year and industry fixed effects following prior studies (e.g., Deng, Kang and Low, 2013; Giuli and Kostovetsky, 2014; Chen, Dong, and Lin, 2020). We do not incorporate firm or insider fixed effects for two reasons. First, firm and insider fixed effects could absorb the variation of interest pertaining to our research question, which focuses on cross-sectional variations at the firm and insider levels. Second, most of the variation on CSR ratings stems from between-firm variation, given the time-series stickiness of these ratings, and therefore firm and insider fixed effects may absorb much of the variation in CSR ratings.

by considering single primary insiders such as the CEO and chairman of the board (see Section 2.3.3). In the robustness tests, we also aggregate investment horizon into a firm-level indicator and repeat our baseline analysis, which do not alter our primary findings (see Table IA2.3 of the Internet Appendix).

We first estimate the baseline model without fixed effects. As presented in Column (1) of Table 2.2, the coefficient of HOR, 0.071, with a t-statistic of 5.59, is positive and significant at the 1% level after controlling for firm-level variables. In Column (3), we add three insiderlevel controls and find that the coefficient of HOR remains positive and significant at the 1% level (t-statistic of 4.30). These results suggest a positive relation between insider investment horizon and firm-level CSR performance. We then control for industry and year fixed effects to examine whether insider investment horizon remains a key determinant of CSR performance. In Column (2), we only include firm-level controls and find that the coefficient of HOR, 0.038, with a *t*-statistic of 3.16, is positive and significant at the 1% level. Ultimately, we include all firm- and insider-level controls, as well as fixed effects in the baseline model, and the results are presented in Column (4). The coefficient of HOR, 0.026, with a t-statistic of 2.19, is positive and significant at the 5% level, indicating that adding controls and fixed effects does not qualitatively affect our results. Apart from statistical significance, our baseline results are also economically significant since a one-standard-deviation increase in insider investment horizon (0.29) leads to a 0.01 ( $0.29 \times 0.026$ ) increase in CSR rating score, which is about one-sixth of the magnitude of sample mean (-0.06), after considering both firm-level and insider-level controls.

#### [Insert Table 2.2 here]

Moreover, the coefficients of other control variables echo the findings of prior literature exploring the determinants of CSR. Specifically, the significantly positive coefficients of *Size* and *ROA* indicate bigger and more profitable firms perform better in CSR, which implies the view "Doing good by doing well" (e.g., Hong, Kubik, and Schinkman, 2012). The positive association between cash ratio and CSR, as well as the negative association between leverage and CSR, is in line with the findings of Xu and Kim (2022), which demonstrate that financial constraints negatively affect CSR. Consistent with the study emphasizing the importance of

customer awareness on CSR (Servaes and Tamayo, 2013), the loading on *A&D intensity* is positive. The negative coefficient of prior-year return is line with the main findings of Mark, Yan and Yao (2022) documenting improved CSR performance following negative past stock returns as managers tend to adopt CSR as a tool to entrench their positions when experiencing poor stock market performance. The positive coefficient of *Blue* indicates that firms headquartered in states that support the Democratic Party have better CSR performance, echoing findings showing CSR is related to political affiliation (e.g., Giuli and Kostovetsky, 2014). In line with existing evidence that female managers are more likely to engage in CSR activities than other managers (Borghesi et al., 2014), the loading on *Gender* is negative.

There may be several alternative explanations for the positive relation between CSR performance and insider horizon. First, the positive relation can be explained by the deep link between insiders' human capital, personal wealth, and their firms. Therefore, these longhorizon insiders tend to reduce long-term risk by investing in CSR. To rule out this explanation, we control for delta and insiders' related wealth and find that our baseline results remain qualitatively unchanged in an unreported analysis. These results can also enable us to mitigate the concerns regarding the effects of managerial overconfidence on the baseline results since insiders who persistently buy their own company shares can be regarded as overconfident ones (e.g., Malmendier and Tate, 2005)<sup>19</sup>. Another potential explanation could be the firms' investment opportunity set. More explicitly, growth firms with more investment opportunities may focus more on long-term value and make relatively long-term compensation contracts for their executives (e.g., Smith and Watts, 1992). Thus, these firms may have more long-horizon insiders who are more willing to engage in CSR activities. To ensure the positive effects of insider horizon on CSR are not absorbed by the investment opportunity set, we construct various proxies for investment opportunities such as market-to-book equity ratio, earnings-toprice ratio, and stock return volatility and include them in the baseline analysis. We do not find altered results after adding these controls in an unreported analysis.

We distinguish between persistent buyers and sellers to investigate whether they impact CSR differently. Intuitively, both long-term sellers and buyers can be viewed as long-horizon

<sup>&</sup>lt;sup>19</sup> Overconfident insiders may underestimate firm risks and thus undertake less hedging such as CSR activities (e.g., McCarthy, Oliver and Song, 2017).

insiders; they both aim to pursue long-term value, refraining from opportunistic trading, albeit for different reasons (Akbas, Jiang and Koch, 2020). While long-term sellers might frequently sell due to liquidity or diversification needs, long-term buyers might trade with an intention to enhance corporate control. Consequently, both groups are likely to have comparably positive effects on CSR.

#### [Insert Table 2.3 here]

To distinguish between long-term buyers and sellers, and to explore whether the positive relation between insider investment horizon and CSR varies between these two groups, we add three variables and their interaction terms with insider investment horizon (*HOR*) and repeat our baseline analysis. The results are presented in Table 2.3. In Column (1), we construct the variable *STR\_RK* as the rank of the ratio between one insider's net purchase and her firm's total trading volume in each year. It measures one insider's trading strength; thus, a higher value of *STR\_RK* indicates more purchases for one insider. If long-horizon buyers are really more willing to engage in CSR, then the interaction term (*HOR*×*STR\_RK*) needs to be positive and significant. However, the coefficient on the interaction term is not significant, albeit with a positive sign, suggesting that long-term buyers do not exert stronger positive effects on CSR than sellers. More directly, we construct the *Netbuyer* and *Netbuyer*10 to proxy for buyers in a similar vein. *Netbuyer* is defined as a dummy taking the value of one when net purchase of one insider is positive (i.e., the amount of insider purchases is more than sales) in a given year. *Netbuyer*10 has a similar definition, but the net purchase is aggregated over the past 10 years.

According to Columns (2) and (3), the coefficients on the interaction terms between buyer proxy and insider investment horizon remain insignificant, indicating no difference between long-horizon buyers and sellers' impacts on CSR. Collectively, these results corroborate the view that both long-term buyers and sellers exert equivalent positive effects on CSR, as they all pursue long-term investment goals, which is consistent with Akbas, Jiang, and Koch's (2020) argument. In unreported analysis, we calculate the algebraic value of insider investment horizon (*HOR*) and repeat our baseline analysis by replacing the insider investment horizon with its algebraic value. Under these conditions, long-term sellers have an *HOR* nearing -1, while buyers approach an *HOR* of 1. We do not find a significant coefficient for the algebraic

value of *HOR*, indicating that long-horizon buyers and sellers do not have differing effects on CSR.

Overall, our baseline results suggest that an insider investment horizon exerts positive effects on firm-level CSR performance, which is consistent with the view that CSR requires long-term commitment. When distinguishing between long-term buyers and sellers, we do not find our main results to be stronger with respect to a certain type of long-term insider, supporting the view that both long-horizon buyers and sellers focus on long-term investment goals and, thus, should be treated equally.

#### 2.3.2 Good internal corporate governance or agency problems?

There might be two distinct explanations for the positive relation between insider investment horizon and CSR performance, given the debate on whether CSR can create shareholder value. On the one hand, CSR can be regarded as an intangible asset that drives long-term value (e.g., Edmans, 2023). Thus, long-horizon insiders promote CSR performance to pursue long-term value, indicating the alignment between insiders' interests and shareholder value. In other words, the positive effects of insider investment horizon on CSR performance can be interpreted as good internal corporate governance. On the other hand, CSR might be detrimental to shareholder value since insiders may improve CSR performance for selfish purposes, such as building a socially friendly image to entrench their positions, at the expense of shareholder value. In this case, there is a conflict between insiders' interests and shareholder value, reflecting the agency problems between insiders and shareholders (e.g., Krueger, 2015; Masulis and Reza, 2015; Cheng, Hong, and Shue, 2023). In our context, agency problems refer to insiders' propaganda detailing their efforts to engage in CSR activities and promote CSR performance but not benefiting shareholders ultimately. Put differently, the positive relation between insider investment horizon and CSR performance can be interpreted as agency problems. To discriminate between good internal corporate governance and agency problems, we conduct the following tests.

2.3.2.1 Strengths and concerns. We examine the effects of insider investment horizon on CSR strengths and concerns separately. As CSR performance equals CSR strengths minus CSR
concerns, the baseline results can be driven by either a positive relation with CSR strengths and/or a negative relation with CSR concerns. Krueger (2015) documents that investor responses to negative CSR events are strong, while investors respond weakly to positive CSR events. Thus, if long-horizon insiders really care about shareholder value, they may aim to reduce the downside of CSR, which investors concentrate on relative to CSR's strengths. In this case, the positive relation between CSR performance and insider investment horizon may be attributed to a lower level of CSR concerns. Conversely, if the goal of long-horizon insiders is to entrench themselves by building a socially friendly image without creating value for shareholders, they may engage more in promoting CSR strengths. In this case, the positive relation may stem from a higher level of CSR strengths.

## [Insert Table 2.4 here]

To explore, we repeat the exercise but replace the dependent variables in the baseline model with CSR strengths and concerns. Panel A of Table 2.4 tabulates the results. Column (1) indicates there is no significant relation between insider investment horizon and CSR strengths, as the *t*-statistic of loading on *HOR* is 0.16. In comparison, Column (2) shows the loading on *HOR* is -0.025, with a *t*-statistic of -2.92, revealing a negative relation between insider investment horizon and CSR concerns. Thus, we demonstrate that the positive relation between insider investment horizon and CSR performance primarily arises from a lower level of CSR concerns rather than a higher level of CSR strengths. These evidence support the view that the positive effects of insider investment horizon on CSR reflect good internal corporate governance rather than agency problems, since long-horizon insiders focus on reducing the downside of CSR that shareholders care about.

2.3.2.2 Material and immaterial issues. We conduct a more straightforward analysis to determine whether long-horizon insiders benefit shareholders by engaging in CSR activities. More specifically, we investigate whether the insider investment horizon is related to financially material CSR performance and immaterial CSR performance. From the perspective of shareholders who pursue the maximization of financial return, financially material CSR issues are much more important than immaterial ones. Khan, Serafeim and Yoon (2016)

document that better performance on financially material CSR issues can significantly predict higher future stock returns, but this is not the case for immaterial CSR issues. If better CSR performance driven by long-horizon insiders aligns with the interests of shareholders, we would find a positive relation between insider investment horizon and financially material CSR issues.

Because there is a wide variation of material CSR issues across industries, we refer to the Sustainability Accounting Standards Board (SASB) Materiality Map to discriminate between material and immaterial CSR categories for different industries.<sup>20</sup> Founded in 2011, the SASB aims to establish a connection between CSR issues and their financial impact and create standards for companies to disclose financially material CSR information for 11 sectors that consist of 77 industries.<sup>21</sup> One typical example is that greenhouse gas (GHC) emissions matter to the extractive and mineral processing sector, but not the consumer goods sector. Data security, a social issue, is material for the technology and communications sector but immaterial for the food and beverage sector. To determine whether a CSR indicator is material or immaterial for firms within different industries, we hand-map firm-level CSR indictors from the KLD database with the SASB sector-specific guidelines.<sup>22</sup> We then calculate the material strengths (concerns) under the subcategory scaled by the maximum number of indicators within the subcategory. The material (immaterial) CSR rating score is constructed by subtracting material (immaterial) concerns from material) strengths.

After constructing material and immaterial CSR scores, we repeat the baseline model, replacing the dependent variable with the financially material and immaterial CSR score. Panel B of Table 2.4 presents the results. As shown in Column (1), the coefficient of *HOR* is positive and significant at the 5% level (*t*-statistic of 2.31), suggesting that insider investment horizon is positively related to material CSR performance. In comparison, Column (2) shows an

<sup>&</sup>lt;sup>20</sup> For more information, see https://materiality.sasb.org/

<sup>&</sup>lt;sup>21</sup> The 11 sectors are consumer goods, extractives and minerals processing, financials, food and beverage, health care, infrastructure, renewable resources and alternative energy, resource transformation, services, technology and communications, and transportation.

<sup>&</sup>lt;sup>22</sup> Khan, Serafeim, and Yoon (2016) provide details of their hand-map of material CSR ratings in Appendix D, which includes only 6 sectors and 45 industries because the coverage of the SASB Materiality Map was smaller in early years. We extend their classification to all 11 sectors and 77 industries currently covered by the SASB.

insignificant loading on *HOR*, with a *t*-statistic of 1.37, indicating long-horizon insiders do not have significant effects on immaterial CSR performance.

The evidence suggests that long-term insiders are more likely to promote CSR performance by engaging in a greater number of financially material CSR activities compared to immaterial ones, which benefits shareholders by increasing potential financial returns. Thus, the positive relation between insider investment horizon and CSR performance may not be subject to agency problems.

# 2.3.3 Different insiders

In the baseline model, we construct the investment horizon measure at the inside level and include all types of insiders. We find that generally, insider investment horizon is related positively to firm-level CSR performance. However, little is known about whether and how various insiders' investment horizons influence CSR. This question needs to be answered for two reasons. First, given the increasing importance of CSR in recent years, all types of insiders may consider CSR factors when making decisions. Second, the influence of insiders can vary. For example, a CEO is typically more influential than an independent director when it comes to a firm's operations and decision-making in most cases.

To this end, we repeat the baseline model but consider the results for different insiders separately. The results are shown in Table 2.5. We first consider directors and managers, who account for over 85% of our sample. While directors and managers may have distinct roles and responsibilities, achieving CSR may be a shared objective, as it can create long-term value for the firm. Given this, we expect that both long-horizon directors and managers may have positive effects on CSR performance. Consistent with this expectation, we find that the loadings on *HOR* are positive and significant for both directors and managers, as shown in Column (1) and Column (2)<sup>23</sup>.

## [Insert Table 2.5 here]

 $<sup>^{23}</sup>$  It is noteworthy that the loading on *HOR* is larger and more significant for directors than that for managers. However, drawing a conclusion that directors have a stronger positive influence than managers is not straightforward. This is because many insiders simultaneously serve as both director and managers. In our sample, over 20% of insiders hold these dual roles.

Next, we individually test the relation between investment horizon and CSR performance of specific insiders who may make critical corporate decisions. Column (3) shows that long-horizon CEOs have much stronger effects on CSR performance compared to other insiders. The coefficient of *HOR* is 0.086, approximately three times than that of the baseline results (0.026), echoing the findings of literature emphasizing the materiality of CEOs in corporate policies (e.g., Bennedsen, Perez-Gonzales, and Wolfenzon, 2020). Column (4) reveals the loading on *HOR* is 0.064, with a *t*-statistic of 1.78, indicating the chairman's investment horizon has positive but weaker effects on CSR performance compared to CEOs. As evidenced in Column (5), CFOs' investment horizons exert no significant effect on CSR. This is surprising because CFOs have needed to play an important role in handling increasing demand for CSR disclosures in recent years. Therefore, one implication is that firms may need to provide more relevant training for CFOs and help them better realize CSR's importance.

#### 2.3.4 Robustness tests

To ensure our primary results are robust to alternative measures of CSR performance and insider investment horizon, firm-level analysis and subsample analysis, we conduct a variety of robustness checks.

Alterative ESG ratings. We repeat the baseline analysis by using alternative CSR scores due to the concern about ESG rating divergence across various data providers<sup>24</sup>. Following the suggestion of Berg, Kolbel and Rigobon (2022), we incorporate ESG rating data from other providers besides the KLD to ensure that our conclusion can be generalized with respect to other ESG ratings. Specifically, we construct a CSR score using the ESG rating data from Refinitiv and Sustainalytics. We then replace the dependent variable in the baseline results with these alternative CSR measures. The results are presented in Table IA2.1 of the Internet Appendix. We find that the insider investment horizon is positively related to the Refinitiv CSR score, as evidenced in Column (1). Similarly, we document a positive relation between *HOR* and Sustainlytics CSR score in Column (2). Taken together, the evidence based on alternative CSR measures may mitigate the concern that our baseline analysis is subject to the well-

<sup>&</sup>lt;sup>24</sup> Berg, Kolbel and Rigobon (2022) document the low correlation across six prominent ESG rating data providers and attribute the ESG rating divergence primarily to measurement methodology, weight and scope.

documented ESG rating divergence and enhance the generalizability of our results.

Alterative measures of insider horizon. We consider alternative measures of insider investment horizon, including 7-year HOR, 5-year HOR, and LH. Compared with the baseline measure, 7-year HOR (5-year HOR) is constructed based on the average annual net order flows of insider trading over the past seven years (five years). LH is a dummy equaling one if the HOR is one, and zero if the HOR is between zero and one (excluding). We estimate the baseline model but replace the independent variable of interest (HOR) with these alternative measures of insider investment horizon. Panel A of Table IA2.2 of the Internet Appendix presents the results. We find the results of the robustness tests do not alter regarding two of the three alternative insider investment horizon measures. The only exception is 5-year HOR, as the loading on HOR is not statistically significant despite the positive sign (t-statistic of 1.19). One possible explanation may be that the term is too short to define the insider investment horizon, as various incentives can motivate insiders to trade (e.g., vesting policy of restricted equity) in the short term.

Alternative KLD CSR measures. We perform various tests to check whether alternative KLD CSR performance measures change our baseline results. We repeat the baseline model using these alternative CSR performance measures as dependent variables. We first consider the raw CSR score, which is calculated by taking the difference between CSR strengths and concerns without being divided by the maximum number of strengths and concerns in each year. Columns (1) in Panel B of Table IA2.2 of the Internet Appendix tabulates the results. Though the coefficient of HOR is positive, it is not statistically significant (t-statistic of 1.60). The statistical insignificance may be driven by the biased raw CSR score. As the KLD database updates positive and negative indicators under each subcategory every year, the number of indicators in each subcategory varies considerably across years. This may lead to biased measures of CSR performance when not considering the available number of indicators in each year. Next, to mitigate the concern that our results are biased by zero rating scores that may stem from missing CSR information, we exclude zero CSR rating scores from the sample. Columns (2) in Panel B of Table IA2.2 presents the results, which do not change compared to the baseline results and thus indicate that our main results are not biased by zero rating scores. We then consider the rank of CSR performance by dividing firms into deciles based on their

CSR performance in each year to rule out the concern of universal changes in CSR performance. Columns (3) in Panel B of Table IA2.2 shows the results remain unchanged when using the rank of CSR performance as the dependent variable.

**Firm-level analysis**. Unlike our baseline analysis that treat insiders heterogeneously and use insider-level investment horizons, we aggregate insider investment horizon at the firm level and conduct robustness checks using firm-level measures. First, we construct two firm-level measures by calculating the average investment horizon for all insiders within a firm in each year (*average horizon*) and the ratio of the number of insiders with an insider investment horizon (*HOR*) equaling one on the number of all insiders for each firm in each year (*Frac\_LH*). These results are presented in Table IA2.3 of the Internet Appendix. As presented in Column (1) of Table IA2.3, the coefficient on *average horizon* is positive and significant, indicating that average investment horizon still is associated positively with CSR performance. In Column (2), we replace the independent variable of interest of the fraction of long-horizon insiders for a firm (*Frac\_LH*) and find that the higher ratio of long-horizon insiders is related to better CSR performance because of the positive and significant coefficient on *Frac\_LH*.

Next, we construct more measures of insider investment horizon based on insiders' trading patterns. According to Narayanan (1985), insiders tend to focus on short-term performance when they possess private information, i.e., taking advantage of private information may indicate that insiders are less likely to pursue long-term value. In this spirit, we focus on insiders with opportunistic trading behavior following Ali and Hirshleifer (2017). We define *opportunistic insiders* as the type of insiders who trade profitably before quarterly earnings announcements (QEAs), which may suggest that insiders frequently use private information. We find a negative relation between the fraction of opportunistic insiders (*Frac\_opportunistic*) and CSR performance, as evidenced in Column (3) of Table IA2.3 of the Internet Appendix, suggesting that firms with opportunistic insiders, who may be less willing to pursue long-term value, tend to exhibit a lower level of CSR performance. Finally, we analyze the timing of insider trading and defined insiders with persistent trading timing (i.e., those who always trade in the same calendar year across years) as *routine insiders*, building on Cohen, Malloy, and Pomorski (2012), who show that routine insiders' trades include less information content than insiders who do not trade with persistent timing. We then calculate the fraction of routine

insiders in each firm and posit that routine insiders are less likely to take advantage of private information and, thus, are more likely to pursue long-term value. Consistent with our hypothesis, we find the coefficient of *Frac\_routine* is positive and significant as presented in Column (4), indicating that the higher ratio of routine insiders within a firm may lead to better CSR performance.

**Subsample period analyses**. In addition to using alternative measures for CSR performance and insider horizon, we also conduct a subsample analysis by splitting our sample into two parts: 1996 to 2005 and 2006 to 2015. As CSR has become increasingly important to firms' decision-making processes in recent years, we expect our baseline results are more likely to materialize in the latter period. Table IA2.4 of the Internet Appendix tabulates the results of this subsample analysis. Columns (1) shows the results from the period 1996 to 2005 have no significance. In contrast, we find our baseline results remain similar in the latter period based on Columns (2). These results are consistent with our expectation and indicate that CSR has begun to materialize in recent years.

## 2.4 Identification Strategy

In this section, we conduct the analyses to support a causal interpretation for the baseline results and discuss the corresponding empirical results. Although we implement a variety of precautions to ensure the positive association between insider investment horizon and CSR performance is robust, our findings may still be subject to potential endogeneity. First, omitted variables may drive the results despite a variety of firm-level and insider-level control variables. For example, compensation contracts that encourage insiders to pursue long-term goals could simultaneously lead to longer insider investment horizon and better firm-level CSR performance. Second, the positive relation may be spurious due to reverse causality, because better CSR performers are more likely to attract talents who wish to pursue long-term value compared to firms with worse CSR performance. To address the endogeneity problem and facilitate a causal interpretation, we adopt two types of potential shocks – the reductions of managerial career horizon and Inevitable Disclosure Doctrine (IDD) – that may affect the willingness of insiders to pursue long-term value.

## 2.4.1 The effects of CEO career concerns

Managerial career horizon can play an important role in shaping a manager's short-term policies (e.g., Holmstrom, 1999). Managers with a shorter career horizon are more likely to engage in myopic activities, such as reducing long-term investments and R&D inputs. In the context of our setting, insiders may become less willing to pursue long-term value when they suffer a reduction in career horizon, thereby reducing CSR investments and deteriorating CSR performance.

To explore the effects of managerial career horizon reduction, we focus on the exogenous changes to managerial career horizon driven by the serious illness (e.g., cancer) of CEOs or their close relatives, or by the death of the CEOs' close relatives, following Aktas, Boone, Croci, and Signori (2021). Although these unforeseeable events are relatively exogenous, they have significant impacts on corporate policies. Aktas et al. (2021) document that affected CEOs have a shorter time in office and higher turnover. Most importantly, firms with affected CEOs exhibit a lower level of capital expenditures and R&D expenses but a higher level of repurchase and profitability, suggesting that these affected CEOs may yield short-term performance at the expense of long-term firm value. In the context of our study, these exogenous events that raise managerial career concerns may impede insiders from pursuing long-term value, leading to a reduced insider investment horizon.<sup>25</sup> Consequently, these events would weaken the positive relation between insider investment horizon and CSR performance, even though these unforeseeable events may not directly influence CSR activities.

To explore, we adopt a difference-in-difference-in-difference approach to examine whether and how reductions in managerial career horizon influence firms' CSR policies. The differencein-difference-in-difference model is as follows:

$$CSR_{j,t+1} = \beta_0 + \beta_1 HOR_{i,j,t} \times CEO\_Careershock_{j,t} + \beta_2 HOR_{i,j,t} + \beta_3 CEO\_Careershock_{j,t} + \beta_4 Treated\_Firm_j + \gamma_1 X_{j,t} + \gamma_2 Y_{i,j,t} + \delta Industry_k + \theta Year_t + \varepsilon_{i,j,t},$$
(2)

in which *CEO\_Careershock* indicates the post-event period after a reduction in managerial career horizon, taking the value of one if a firm was hit by an event that reduces CEO career

 $<sup>^{25}</sup>$  Put more clearly, CEOs affected by such unexpected career disruptions tend to face increased turnover and have shorter tenures. This situation might prompt them to prioritize short-term gains. As a result, they could adjust their insider trading behaviors to secure short-term profits before exiting the company, which would manifest as a decreased value of *HOR*.

horizon, or zero otherwise. As such, the indicator *CEO\_Careershock* is equivalent to a *Post×Treatment* indicator in a conventional difference-in-difference setting. As the CEO or firm fixed effect is not controlled in the model, we add the indicator *Treated Firm* in the model, which is equal to one if a firm suffers a reduction in CEO career horizon, regardless of time. To build the sample, we first manually match these events with our sample and benchmark those treated firms against up to 10 peers with similar total assets in the same industry. We then require all the observations in the sample to be centered from -3 to +3 years around the occurrence of the events. Finally, we identify 15 events that change managerial career horizon in our sample.<sup>26</sup>

The results are presented in Table 2.6. The key variable of interest is the interaction term of CEO Careershock and HOR. The coefficient of the interaction term (HOR  $\times$ CEO Careershock) measures how insider investment horizon affects CSR performance in response to events that reduce managerial career horizon. As insiders may have shorter investment horizons due to these unforeseeable events, we expect the coefficient of the interaction term to be negative. Indeed, we find the interaction term's coefficient to be negative and significant, as presented in Column (1), when only considering CEOs of treated firms and their matched control firms. This finding suggests that an exogenous shock-reducing CEO career horizon may attenuate the positive relation between insider investment horizon and CSR performance, which is consistent with our conjecture. We also consider all insiders in this matched sample. The idea is that reductions in CEOs' career horizons also may shorten other insiders' horizons temporarily. Based on Aktas et al. (2021), firms that CEO career horizon reduction affects tend to have a higher level of tournament for the future CEO position among other top managers, as affected CEOs may delegate more tasks to these managers. In this case, these managers may attempt to boost short-term performance to demonstrate their ability and compete to be the next CEO, indicating that they temporarily may have shorter horizons. As presented in Column (2), we include all insiders from treated firms and find a negative and significant coefficient for the interaction term's loading, suggesting that firms hit by reductions in CEO career horizon exhibit a deteriorated positive relation between insider investment

<sup>&</sup>lt;sup>26</sup> The detailed event data including 49 events are provided in the Appendix B of Aktas et al. (2021).

horizon and CSR performance.<sup>27</sup> Comparing the coefficients of the interaction term in Columns (1) and (2), we find that each coefficient becomes stronger in terms of statistical significance when considering all insiders, which may corroborate the argument that career horizon reductions may influence not only CEOs' horizons, but also those of other insiders.<sup>28</sup>

## [Insert Table 2.6 here]

Recent studies have raised concerns about the staggered difference-in-difference method, pointing to possible biases estimates stemming from heterogeneous treatment effects (e.g., Baker, Larcker, and Wang, 2022; Roth et al., 2023). The issue arises because the estimations include both "good comparisons" (between treated and not-yet-treated units) and "bad" comparisons (where both units having already received treatment). To mitigate this concern, we apply the stacked regression approach (Baker, Larcker and Wang, 2022). This method ensures that the control groups are "clean", only comprising units that have never been treated. The evidence presented in Column (3) and (4) reinforces the robustness of our findings using the stacked regression approach, whether considering only CEOs or all insiders in our sample. In addition, we test the validity of the parallel trend assumption by examining whether and how the CEO career concern shock influences the relation between insider investment horizon and CSR around its effective timing. Following Aktas et al. (2021), we conduct the dynamic analysis and present the results in Table IA2.5 of the Internet Appendix. We do not find evidence of pre-existing trends when only considering CEOs and all insiders, as shown in Column (1) and (2) of Table IA2.5, respectively.

Overall, the difference-in-difference-in-difference regression results based on managerial career horizon illustrate that CSR performance may deteriorate in response to unforeseen negative shocks to insider investment horizon, thereby supporting a causal interpretation of the relation between insider investment horizon and CSR performance.

<sup>&</sup>lt;sup>27</sup> These results are not qualitatively changed when adding individual-level effects, particularly for the analysis including all insiders.

<sup>&</sup>lt;sup>28</sup> Though the coefficient of *Treated Firm* is positive and significant as shown in Column (2), this does not suggest a failure of parallel trend as we include all insiders in Column (2) so the coefficient could be biased. Rather, we should refer to the coefficient of *Treated Firm* in Column (1) – it is not significant – suggesting that treated and control firms do not exhibit a difference in firm-level CSR.

## 2.4.2 The effects of Inevitable Disclosure Doctrine

Next, we employ the staggered rejection of the inevitable disclosure doctrine (IDD) by multiple states as additional exogenous shocks to insider investment horizon. The IDD aims to enhance the protection of trade secrets by preventing employees with access to trade secrets from working for rival firms, leading to lower labor market mobility. In our sample, over 85% of insiders are top managers and directors who very likely work with trade secrets and, therefore, are affected by IDD. As such, insiders may have fewer outside opportunities under IDD, resulting in higher job loss costs and managerial career concerns. Based on this argument, Li, Shevlin, and Zhang (2022) document that insiders engage in tax avoidance activities to entrench themselves in response to adoption of IDD, indicating that insiders may focus on short-term outcomes due to increased career concerns driven by IDD. However, insiders would have more outside opportunities and decreased career concerns after rejection of IDD and, therefore, would become more willing to pursue long-term value. Furthermore, Na (2020) finds that rejection of IDD leads to less relative performance evaluation (RPE) used in managerial compensation, which may reduce pressure for insiders to achieve short-term goals and encourage them to pursue long-term value because their compensations are linked heavily to systematic performance that is beyond their control. Collectively, the rejection of IDD may strengthen the positive relation between insider investment horizon and CSR performance, as it prompts insiders to focus on long-term value.

To explore, we build the regression model based on a difference-in-difference-indifference approach as follows:

$$CSR_{j,t+1} = \beta_0 + \beta_1 HOR_{i,j,t} \times IDD_{s,t} + \beta_2 HOR_{i,j,t} + \beta_3 IDD_{s,t} + \beta_4 Treated \_States_s,$$
  

$$\gamma_1 X_{j,t} + \gamma_2 Y_{i,j,t} + \delta Industry_k + \theta Year_t + \varepsilon_{i,j,t},$$
(3)

Compared with the baseline regression model, we add the indicators to identify whether state *s* has rejected the IDD (*IDD Rejection*) and their interaction terms with *HOR. IDD Rejection* takes the value of one if the state in which the firm is headquartered has rejected the IDD before the current year, or zero otherwise. In this case, this *IDD* indicator plays the role of a *Post×Treatment* indicator in a conventional difference-in-difference setting. We also add the indicator *Treated States*, which is equal to one if one state rejects IDD, regardless of time frame,

as we do not include state or firm fixed effect in the model.

The key variable of interest is the interaction terms *HOR* and IDD *Rejection*: the difference-in-difference-in-difference estimator. Intuitively, the positive effects of insider investment horizon on CSR are likely to be enhanced by the rejection of IDD, as it may lengthen insider investment horizon. This implies that the coefficient of the interaction term, which captures the change in CSR performance to insider investment horizon in response to the rejection of the IDD, should be positive.

# [Insert Table 2.7 here]

In line with our expectations, Column (1) of Table 2.7 indicates that the loading on the interaction term between *HOR* and *IDD Rejection* is 0.055, with a *t*-statistic of 2.36, suggesting that a stronger positive relation exists between insider investment horizon and CSR performance in response to positive shocks to insiders' willingness to pursue long-term value.<sup>29</sup> To mitigate the concern of potential estimation bias due to staggered treatment timing in our setting, we repeat the results in Column (1) using a stacked regression approach, as advised by Baker, Larcker and Wang (2022). As shown in Column (2), our findings remain consistent and robust when using the stacked regression approach.

We also conduct dynamic analysis to test the validity of the parallel trend assumption. In a similar spirit of Na (2020), we examine the timing of changes in the relation between CSR and insider investment horizon relative to the timing of rejections of the IDD. The year that one state rejects IDD is regarded as the reference year. We tabulate the results in Table IA2.6 of the Internet Appendix and find no evidence of a pre-existing trend.

To further validate the IDD treatment effects, we conduct the analysis based on the adoption of IDD. Intuitively, the positive relation between insider investment horizon and CSR performance should be weaker under the adoption of IDD. This is because insiders may encounter fewer external opportunities and increased career concerns, potentially diminishing their willingness to pursue long-term value. Indeed, we find this is the case as the interaction term between *HOR* and *IDD Adoption* contrasts sharply with results based on the rejection of

<sup>&</sup>lt;sup>29</sup> This result does not change when adding individual-level fixed effects.

IDD, as evidenced in Table IA2.7 of the Internet Appendix.<sup>30</sup>

#### 2.5 Cross-sectional Analyses

Having established a causal link between insider investment horizon and firm-level CSR performance, we next explore the mechanisms through which insider investment horizon affects CSR performance. To this end, we design multiple tests to examine the cross-sectional heterogeneity of our main results with respect to firm-level and insider-level characteristics, respectively. If the insider investment horizon indeed reflects insiders' desire to pursue long-term value, we would expect that our main results are stronger (weaker) with factors that encourage (discourage) insiders' willingness to pursue long-term value.

## 2.5.1 Institutional investors

We first consider institutional investors, as they play vital roles in shaping insiders' horizon. Long-horizon institutional investors are usually more patient and focus more on long-run performance compared to short-horizon investors; therefore, long-horizon institutional investors are more likely to encourage insiders to engage in activities that may create long-run value (e.g., Bushee, 2001; Cadman and Sunder, 2014). As such, we expect a stronger (weaker) positive relation between insider investment horizon and CSR performance when a firm's institutional investors have longer (shorter) investment horizon.

Two measures are employed for institutional investor investment horizon. The first is institutional investor turnover (Gasper, Massa, and Matos, 2005), which is calculated using data from the Thomson Reuters Institutional Holdings (13F) database. We first analyze the turnover rate of each institutional investor and construct firm-level investor turnover by calculating the weighted average of total portfolio turnover rates of the firm's all investors over the previous four quarters (*Turnover*). The second measure is churn rate (Yan and Zhang, 2009). Similar to turnover, we first calculate investor-level churn rate and construct a firm-level churn

<sup>&</sup>lt;sup>30</sup> Although the analysis based on the IDD supports a causal interpretation, we caution that the rejection and adoption of the IDD may not be an ideal example of an exogenous shock. Flammer and Kacperczyk (2019) demonstrate that firms improve their CSR after the rejection of the IDD to retain talent and avoid trade secret spillover. Nevertheless, our results complement Flammer and Kacperczyk (2019) by revealing that insiders are more willing to pursue long-term value as captured by a longer insider investment horizon, after the rejection of IDD. This indicates another potential channel through which the rejection of the IDD can promote a firm's CSR strategies.

rate using a value-weighted method (*Churn*). For these measures, higher value indicates shorter institutional investors' investment horizon.

As shown in Table 2.8, Column (1) reports the results of Gasper et al. (2005) turnover measure. Compared to the baseline model, we add the interaction term of *HOR* and *Turnover* together with *Turnover*. The interaction term is the variable of interest. The coefficient of the interaction term ( $HOR \times Turnover$ ) is negative and significant, with a *t*-statistic of -1.88, confirming that the positive relation between insider investment horizon and CSR performance is weakened by short-term institutional ownership. In the same vein, we estimate the baseline model again by adding the interaction term of *Churn* and *HOR* together with *Churn*. As shown in Column (2), we find that the positive effects of insider investment horizon on CSR performance are weaker when short-term institutional ownership is higher, because the loading on the interaction term ( $HOR \times Churn$ ) is negative and significant at the 1% level. Consistent with our conjecture, we demonstrate that the baseline results are weaker when more short-term institutional investors hold stakes as these short-term investors may impede insiders from pursuing long-term value such as CSR.

# [Insert Table 2.8 here]

Furthermore, SRI investors, who are proponents of CSR investments, are usually patient and willing to consider the combined effects of financial returns and social objectives (e.g., Bialkowski and Starks, 2016), suggesting that they tend to have longer investment horizon than their non-SRI peers. Thus, we expect the positive relation between insider investment horizon and CSR performance is stronger when SRI investor ownership is higher.

We define SRI institutional investors as signatories of the United Nations Principles for Responsible Investment (UNPRI), as they have committed to incorporating ESG issues into investment decisions actively and engaging in prosocial activities. Launched in 2006, only 32 organizations initiated the program, but the number of signatories has increased exponentially to 3,038, with about \$103.4 trillion of assets under management in 2020. UNPRI aims to become the world's leading proponent of responsible investment and establish a sustainable global financial system. To achieve these goals, it has outlined six principles for responsible investment.<sup>31</sup> Consistent with UNPRI goals, Dyck et al. (2019) find that institutional investors who are UNPRI signatories have stronger positive effects on CSR performance of their portfolio firms compared to non-signatories.

We manually match UNPRI signatories with institutional investors from the Thomson Reuters Institutional Holdings (13F) database and calculate ownership of UNPRI signatories for each firm. We then estimate the baseline model by including the interaction term of UNPRI signatories' ownership (*UNPRI*) and insider investment horizon (*HOR*) together with *UNPRI*. The results are reported in Column (3). The loading on the interaction term (*HOR×UNPRI*) is positive and significant at the 1% level, showing that UNPRI signatories' ownership enhances the positive relation between insider investment horizon and CSR performance.

## 2.5.2 Compensation contracts

We investigate whether and how insiders' compensation contracts alter our main results, as compensation contracts may affect insiders' desire to pursue long-term value (e.g., Gopalan et al., 2014; Edmans, Fang, and Lewellen, 2017). Long-term compensation contracts can align the interests of insiders with long-term value, thereby encouraging insiders to pursue long-term value.

Two characteristics of insiders' compensation contracts are considered, the first of which is the sensitivity of insiders' wealth to stock volatility (Vega). Coles, Daniel, and Naveen (2006) find that insiders with higher Vega invest more in R&D, indicating that Vega can encourage insiders to take long-run risks and pursue long-term value. Accordingly, we expect that vega can enhance the positive effects of insider investment horizon on CSR. Vega is defined as the change in the dollar value of the executive's wealth for a 0.01 change in the annualized standard deviation of stock returns. Using insiders' compensation data from ExecuComp, we calculate Vega following Coles et al. (2006). Another characteristic related to the willingness of insiders to pursue long-term value is pay duration (Gopalan et al., 2014). Longer pay duration is associated with higher R&D intensity and lower earnings management, suggesting that it can encourage insiders to pursue long-term value. As such, we expect that our main results are

<sup>&</sup>lt;sup>31</sup> For more information, see https://www.unpri.org/pri/what-are-the-principles-for-responsible-investment.

stronger when an insider's pay duration is longer. Following Gopalan et al. (2014), we calculate the duration of insider as the weighted average duration of four primary components (salary, bonus, restricted stock, and options) of an insider's pay using data from the Institutional Shareholder Services (ISS) Incentive Lab.<sup>32</sup>

# [Insert Table 2.9 here]

We first estimate the baseline model by including the interaction term of the sensitivity of insiders' wealth to stock volatility (*Vega*) and insider investment horizon (*HOR*) together with *Vega*. Column (1) of Table 2.9 tabulates the results. The variable of interest is the interaction term. Consistent with our prediction, we find the coefficient of the interaction term (*HOR* × *Vega*) is positive and significant at the 1% level, suggesting that the positive effects of insider investment horizon on CSR performance are stronger when an insider's Vega is higher.<sup>33</sup> We then repeat the baseline model, adding the interaction term of pay duration (*Pay duration*) and insider investment horizon (*HOR*) together with *Pay duration*. The results are presented in Column (2). The loading on the interaction term (*HOR* × *Pay duration*) is positive and significant at the 1% level, indicating that pay duration can enhance the positive effects of insider investment horizon on CSR performance.<sup>34</sup>

# 2.6 Real Effects

To further explore how long-term insiders can promote CSR performance, we examine the real

<sup>&</sup>lt;sup>32</sup> The ISS Incentive Lab compensation database provides data beginning in 1998. Our pay duration measure is constructed from 2006 due to the availability of detailed vesting information regarding insiders' restricted stocks and options.

<sup>&</sup>lt;sup>33</sup> Gopalan, Milbourn, Song, and Thakor (2014) argue that Vega may not fully capture the duration component of pay. In other words, it is unclear whether a high Vega incentivizes managers to take more risk in the long term or the short term. Therefore, it is essential to consider managers' alignment with short-term performance, such as through vesting schedules. To explore this issue, we conduct a cross-sectional analysis focusing on Vega while incorporating controls for managerial pay-performance sensitivity (Delta), which directly measures managerial incentives in the short run. We find qualitatively similar results after accounting for both Delta and its interaction with insider investment horizon.

<sup>&</sup>lt;sup>34</sup> Apart from the characteristics of institutional investors and compensation contracts, we also examine the heterogeneity of our baseline results with respect to different levels of antitakeover pressure, as it is one of the major sources of managerial short-termism (Stein, 1998). As evidenced in Table IA8 of the Internet Appendix, we find that the relation between insider investment horizon and CSR is stronger under less takeover pressure, as proxied by the enactment of business combination law (BC law). One caveat for the analysis is that antitakeover laws, including BC law, may have weak real effects on takeovers, since companies can defend against hostile takeovers by adopting a poison pill even in the absence of standard antitakeover laws (Catan and Kahan, 2016).

effects of insider investment horizon on various raw CSR metrics. These analyses not only add evidence regarding the channels through which insider investment horizon affects CSR performance, but also improve the robustness of our main results by using alternative CSR measures in addition to CSR rating scores.

## 2.6.1 Toxic releases

First, we test whether firms with long-horizon insiders are associated with a lower level of toxic releases. The level of toxic releases is a crucial metric used by prior studies that assess the real impact on CSR.<sup>35</sup> If long-horizon insiders indeed have positive real effects on CSR, we expect a negative relation between insider investment horizon and toxic releases.

We retrieve toxic release data from the Toxics Release Inventory (TRI) database administered by the United States Environmental Protection Agency (EPA). In response to public concern surrounding human health and the ambient environment, Section 313 of the Emergency Planning and Community Right-to-Know Act (EPCRA) created the TRI in 1986, which requires facilities with 10 or more employees using one of approximately 800 chemicals to report their annual quantities of both on-site and off-site toxic releases.<sup>36</sup> Nevertheless, the TRI database only covers the economic sectors comprising the roughly 400 industries distinguished by a six-digit NAICS code. Although TRI data are self-reported by facilities, the database is reliable, as EPA provides report training for facilities and conducts audits to mitigate misreporting concerns.

We first examine the relation between insider investment horizon and total toxic releases in future three years, calculated as the natural logarithm of one plus one firm's total quantity of toxic chemical releases in pounds (*total releases*). The results are presented in Panel A of Table 2.10. We document firms with long-horizon insiders exhibit a lower level of toxic releases in the future three years. Next, we divide the total releases into on-site and off-site releases and examine insider investment horizon's impacts separately. We present corresponding results in Panels B and C of Table 2.10, respectively. We find long-horizon insiders tend to reduce the

<sup>&</sup>lt;sup>35</sup> For example, Kim, Wan, Wang, and Yang (2019) document negative effects of local institutional ownership on toxic releases. Xu and Kim (2022) find that toxic releases decrease under relaxed financial constraints.

<sup>&</sup>lt;sup>36</sup> In general, the TRI database includes three main types of chemicals that may cause 1) cancer or other chronic human health effects, 2) significant adverse acute human health effects, or 3) significant adverse environmental effects. Currently, 770 chemicals within 33 chemical categories (e.g., air pollution, ground pollution) are covered.

future on-site releases but not the off-site releases. This finding is consistent with Kim, Wan, Wang, and Yang (2019), who document that firms care more about on-site releases because of their social ties with the local community.

# [Insert Table 2.10 here]

One caveat of our analysis is that, without considering the toxicity of the releases, we cannot accurately evaluate the efforts made by long-horizon insiders to reduce toxic releases. Some chemical releases are highly toxic and may pose significant risks to public health, while others are relatively inert and less harmful. In this case, long-horizon insiders are expected to focus on reducing the releases of highly toxic chemicals. To explore, we construct two toxic release measures which incorporate the toxicity of releases. First, we construct the RSEI hazard (i.e., toxicity-weighted release) using the EPA Risk-Screening Environmental Indicators (RSEI) Model<sup>37</sup>. Specifically, the RSEI hazard is calculated as the chemical release in pounds, multiplied by a chemical- and exposure route-specific toxicity weight. Second, we calculate the release of harmful chemicals listed in EPA Integrated Risk Information System (IRIS) in a similar spirit of Akey and Appel (2020). We estimate the baseline model by replacing the dependent variable with these two toxic releases measures. The results are presented in Table IA2.9 of the Internet Appendix. As shown in Panel A, we find evidence that firms with longterm insiders are likely to have a lower level of RSEI hazard in the future one year. Similarly, our analyses in Panel B reveal that long-horizon insiders tend to reduce the level of harmful release in the future three years. Collectively, our analysis using toxicity-weighted release measures confirms that long-horizon insiders make efforts to reduce highly toxic release.

# 2.6.2 Compliance violations

We then investigate whether firms with long-term insiders are less likely to commit compliance violations and receive fewer penalties from violations. Firms with better CSR performance as reflected by CSR rating score may suffer less from CSR compliance violations. As such, our expectation is that firms with long-horizon insiders are less likely to commit CSR violations

<sup>&</sup>lt;sup>37</sup> For details about Risk-Screening Environmental Indicators (RSEI) Model, see https://www.epa.gov/rsei/learn-about-rsei.

and have fewer CSR violation penalties.

CSR violation data are obtained from the Violation Tracker database, established by the non-profit organization Good Jobs First. Starting in 2000, the database collects a wide range of violations resolved by more than 300 federal and local agencies<sup>38</sup> with total penalties of around \$720 billion. These violations are classified into nine types: competition, consumer protection, employment, environment, finance, government contracting, healthcare, workforce safety, and miscellaneous. Following Raghunandan and Rajgopal (2021), we restrict the sample to ES-related violations by including three types of violations: environment, employment, and workforce safety. These ES violations comprise the vast majority (over 90%) of violations in the database.

## [Insert Table 2.11 here]

The dependent variable in the baseline model is replaced with the violation indicator (*CSR violation indicator*) or the dollar amount of violation penalties (*CSR violation penalties*) in the next three years. If a firm has committed at least one CSR compliance violation in a year, the violation indicator takes the value of one, or zero otherwise. The dollar amount of violation penalties denotes the total amount of CSR violation penalties (in millions) for each firm in a year's time. We tabulate the results in Table 2.11. As presented in Column (1) of Panel A, firms with long-horizon insiders are less likely to have CSR violations recorded in the Violation Tracker database during the next year because the loading on *HOR* is negative and significant when estimating a probit specification. Nevertheless, we do not find that firms with long-horizon insiders are less likely to commit CSR violations in two or three years given the insignificant coefficient of *HOR*, as evidenced in Columns (2) and (3). In Panel B, we narrow the sample to firms with CSR violations and the corresponding penalties as the dependent variable. We find that the insider investment horizon is related negatively to CSR violation penalties as the dependent variable. We find that the insider investment horizon is related negatively to CSR violation penalties during the next year as the loading on *HOR* is negative and significant, as presented

<sup>&</sup>lt;sup>38</sup> For example, workforce safety violations are reported by the Occupational Safety and Health Administration (OSHA) and the Labor Department Wage and Hour Division (WHD); meanwhile, environment-related violations are reported by the Environmental Protection Agency (EPA). For the full list of agencies, see https://www.goodjobsfirst.org/violation-tracker-data-sources.

in Column (1). Similar to the violation indicator, we do not find a significant relation between insider investment horizon and future two- and three-year CSR violation penalties despite negative coefficients in Columns (2) and (3). One possible explanation for the insignificant relation between insider investment horizon and future violation measures (i.e., violation indicator and penalties) may be the time-variant regulation and investigation intensity, which make it difficult for long-horizon insiders to anticipate whether the regulation and investigation of CSR violations will be more or less stringent in the future. In this case, they only can take efficient measures to reduce the probability of committing violations and violation penalties during the most recent period, but not future periods.

## 2.6.3 Employee satisfaction

Employee satisfaction can be incorporated into overall CSR performance. Our expectation is that firms with long-horizon insiders tend to have a higher level of employee satisfaction. To explore this idea, we refer to the list of the "Best 100 Companies to Work for in America" ("Best 100"), initially produced by the Great Place to Work Institute. The list was first published in a book in 1984, updated in 1993, and has been published in *Fortune* magazine every January since 1998. For example, Google has been ranked the number one on the list in the consecutive years from 2012 to 2017. Following Edmans (2011), we define firms listed on the "Best 100" as those with high employee satisfaction.<sup>39</sup> The dummy variable (*Best 100 indicator*) takes the value of one if the firm is on the list in a given year, and zero otherwise.

# [Insert Table 2.12 here]

The results are presented in Table 2.12. In Column (1), we estimate a probit specification based on the baseline model, replacing the dependent variable with *Best 100 Indicator* during the next period. We find the coefficient of *HOR* to be positive and significant at the 1% level, indicating that firms with long-term insiders are more likely to be included in the *Best 100*. Similarly, we demonstrate that firms with long-horizon insiders are more likely to be listed in the *Best 100* for the next two and three years given the positive and significant coefficient, as

<sup>&</sup>lt;sup>39</sup> We appreciate Alex Edmans for sharing the "100 Best Companies to Work for in America" list on https://alexedmans.com/data/.

evidenced in Columns (2) and (3).

## 2.6.4 RepRisk incidents and index

Finally, we explore whether insider investment horizon affects ESG incidents and exposure to ESG risks. Intuitively, firms with long-horizon insiders are likely to better manage ESG risks and incidents. Thus, we expect that insider investment horizon is negatively related to ESG incidents and ESG risk exposure.

We obtain firm-level data on ESG incidents and risk exposure from RepRisk, a comprehensive database focusing on ESG and business risks. Using advanced machine learning algorithms, RepRisk screens more than 100,000 media, regulatory, and commercial documents in 23 different languages to search for ESG incidents since 2007. We adopt two measures from RepRisk. The first measure is the number of ESG incidents, which is considered objective as it is less likely to be manipulated by corporate insiders or data providers. The second measure is the RepRisk index (RRI), which is calculated by a proprietary algorithm based on different dimensions of ESG incidents. The index quantifies a firm's risk exposure to ESG issues. Both measures are reported on a monthly basis. We count the total annual number of ESG incidents and calculate the annual average RRI, in order to align with our yearly insider investment horizon measure.

# [Insert Table 2.13 here]

We regress the number of ESG incidents and RRI in the next three periods on insider investment horizon with the various control variables used in our baseline regression. We present the results in Table 2.13. In Panel A, we find that the *HOR* coefficient is negative and significant, suggesting that firms with long-horizon insiders tend to have fewer ESG incidents, as presented in RepRisk. As evidenced in all columns of Panel B, the *HOR* coefficients are negative and significant for all three future periods, indicating a negative relation between insider investment horizon and the RepRisk index.

## 2.7 Conclusion

The effects of CSR may not be realized in the short run. Thus, a commitment to CSR may

require a long-term perspective. In this paper, we investigate whether and how insider investment horizon, the reflection of insiders' desire to pursue long-term value, affects firm-level CSR performance. Consistent with CSR's long-term perspective, we find a positive relation between insider investment horizon and CSR performance. Furthermore, we find that good internal corporate governance, rather than selfish agency motives, is likely to drive the documented positive relation between insider investment horizon and CSR performance.

To support a causal interpretation for the positive relation between insider investment horizon and CSR performance, we use both the managerial career horizon reductions and the staggered rejection and adoption of inevitable disclosure doctrine (IDD) as exogenous shocks. Having employed a difference-in-difference-in-difference approach, we can support a causal interpretation for the positive relation between insider investment horizon and CSR performance.

Next, we corroborate the argument that insider investment horizon captures the desire of insiders to pursue long-term value by using cross-sectional analyses. Specifically, we show that the positive effects of insider investment horizon on CSR performance are stronger when long-term institutional ownership and SRI institutional ownership are higher, when insiders' Vega and pay duration are higher, and when firms face less takeover pressure.

Finally, we test the real effects of insider investment horizon using raw CSR metrics. We document that firms with long-horizon insiders have a lower level of toxic releases (especially on-site toxic releases), a lower probability of committing CSR compliance violations, fewer penalties for CSR violations, a higher probability of becoming firms with high employee satisfaction and a lower level of ESG-related incidents and risk exposure.

Overall, our paper provides new evidence on the determinants of CSR and supports the view that CSR requires long-term commitment. Given the increasing importance of CSR in financial markets, our findings are practically relevant and provide important insights for firms and their key stakeholders. The results show that firms should implement long-run policies to shape their key stakeholders' long-term perspectives. These long-term perspectives can help firms improve their CSR practices and achieve their CSR goals.

# Chapter 2 - Appendix A: Variable Construction

| Variable                   | Definition  |
|----------------------------|---|
| CSR variables              |   |
| CSR                        | Strengths minus Concerns (Source: KLD).   |
| Strengths                  | The sum of environment, community, employee relation, diversity and product strengths scaled by maximum number of strength indicators in each category in a given year (Source: KLD).   |
| Concerns                   | The sum of environment, community, employee relation, diversity and product concerns scaled by maximum number of concern indicators of each category in a given year (Source: KLD).   |
| Material                   | The CSR score that are financially material as defined by the hand-mapped industry-specific guidelines following SASB and Khan, Serafeim, and Yoon (2016) (Source: KLD).  |
| Immaterial                 | The CSR score that are financially immaterial as defined by the hand-mapped industry-specific guidelines following SASB and Khan, Serafeim, and Yoon (2016) (Source: KLD).  |
| Refinitiv CSR score        | Following Dyck et al. (2019), the Refinitiv CSR score is calculated as the natural logarithm of raw CSR score. The raw CSR score is defined as the average of raw Refinitiv environment score and social score (Source: Refinitiv)                |
| Sustainalytics CSR score   | The average of raw Sustainalytics environment score and social score (Source: Sustainalytics).  |
| Raw                        | The sum of environment, community, diversity,<br>employee relations, and product strengths deducts<br>after deducting the sum of environment, community,<br>diversity, employee relations, and product concerns<br>in a given year (Source: KLD). |
| Non-zero                   | A dummy takes the value of one if the CSR measure<br>is not equal to zero and zero otherwise (Source:<br>KLD).  |
| Rank                       | Firms are sorted into deciles based on CSR performance measure each year (Source: KLD).   |
| Other firm-level variables |   |

| Size              | Natural logarithm of total assets (AT) (Source: Compustat).   |
|-------------------|---|
| Cash ratio        | Cash holdings plus short-term investments (CHE) scaled by total assets (AT) (Source: Compustat).  |
| Capex ratio       | The ratio of capital expenditures (CAPX) over total assets (AT) (Source: Compustat).  |
| Tangibility       | The net property, plant and equipment (PPENT) divided by total assets (AT) (Source: Compustat).   |
| Tobin's Q         | The ratio of total assets (AT) plus market value<br>(CSHO*PRCC_F) minus book equity<br>(CEQ+TXDB) over total assets (AT) (Source:<br>Compustat).  |
| Leverage          | The sum of long-term debt (DLTT) and current debt (DLC) deflated by total assets (AT) (Source: Compustat).  |
| ROA               | The ratio of operating income before depreciation<br>(OIBDP) over total assets (AT) (Source:<br>Compustat).   |
| R&D intensity     | The ratio of research and development expenses (XRD) over total assets (AT). We Assign zeros to missing R&D values. (Source: Compustat).  |
| A&D intensity     | The ratio of advertising expenditures (XAD) over<br>total assets (AT). Missing values of advertising<br>expenses are assigned zeros. (Source: Compustat).   |
| Blue              | A dummy is equal to one if the firm is headquartered<br>in a state supporting the Democratic Party in the US<br>president election (Source: Compustat).   |
| Prior-year return | Annual stock return over the past twelve months (Source: CRSP)  |
| Ю                 | The annual institutional ownership is defined as the<br>average of percentage of common shares held by<br>institutional investors across four quarters within a<br>year (Source: Thomson Reuters 13F and CRSP). |
| IDD rejection     | A dummy is equal to one if the state that one firm is<br>headquartered rejected the IDD before year $t$<br>(Source: Na, 2020).  |
| Rejection state   | An indicator is equal to one for states rejecting IDD, regardless of time (Source: Na, 2020)  |

| IDD adoption            | A dummy is equal to one during the period that IDD takes effect in the state that one firm is headquartered (Source: Na, 2020).   |
|-------------------------|---|
| Adoption state          | An indicator is equal to one for states adopting IDD, regardless of time (Source: Na, 2020)   |
| Turnover                | Following Gasper, Massa and Matos (2005), we first<br>calculate the investor-level turnover rate in each<br>quarter and then define the firm-level churn ratio as<br>the weighted average of the total portfolio churn<br>turnover of one firm's investors over previous four<br>quarters. (Source: Thomson Reuters 13F and<br>CRSP). |
| Churn                   | Following Yan and Zhang (2009), we first calculate<br>the investor-level churn rate in each quarter and then<br>define the firm-level churn ratio as the weighted<br>average of the total portfolio churn rate of one firm's<br>investors over previous four quarters. (Source:<br>Thomson Reuters 13F and CRSP).                     |
| UNPRI                   | The percentage of shares held by institutional<br>investors who have signed the Principles for<br>Responsible Investment (UNPRI) over the total<br>shares outstanding (Source: UNPRI website,<br>Thomson Reuters 13F and CRSP).   |
| RSEI hazard             | The natural logarithm of one plus toxicity weighted<br>pollution amount, calculated as the releases for each<br>chemical in pounds, multiplied by a chemical- and<br>exposure route-specific toxicity weight (Source:<br>EPA Risk-Screening Environmental Indicators<br>(RSEI) Model)   |
| Harmful release         | The natural logarithm of one plus harmful release in<br>pounds, in which harmful release is defined as the<br>total release of harmful chemicals, listed by EPA's<br>Integrated Risk Information System (IRIS), that are<br>known to cause harm to humans (Source: EPA TRI<br>Toxic Release database and IRIS system)                 |
| CSR violation indicator | A dummy takes the value of one if one firm commits<br>CSR violations recorded in Violation Tracker<br>database in a given year and otherwise zero (Source:<br>Violation Tracker database).  |

| CSR violation penalties | The amount of total CSR violation penalties in millions for a firm-year (Source: Violation Tracker database).  |
|-------------------------|--|
| Best 100 indicator      | A dummy equals one if one firm is listed on Fortune<br>magazine's "Best 100 Companies to work for in<br>America" in each year and otherwise zero (Source:<br>Alex Edman's website)   |
| ESG incidents           | The number of ESG incidents in a given year (Source: RepRisk)  |
| RRI index               | The index developed by RepRisk to capture current<br>level of a company's exposure to ESG risks (Source:<br>RepRisk)   |
| Insider-level variables |  |
| STR                     | For each insider $I$ of firm $j$ at year $t$ , the trading   |
|                         | strength is calculated as: $STR_{i,j,t} = \frac{P_{i,j,t} - S_{i,j,t}}{VOL_{j,t}}$ . P (S)   |
|                         | is the number of shares of firm <i>j</i> purchased (sold) by<br>insider <i>I</i> during year <i>t</i> and $VOL_{j,t}$ refers to the<br>number trading volume of firm <i>j</i> during year <i>t</i> . The<br>aim of this measure is to capture the trading direction<br>of each insider. (Source: Thomson Reuters Insider<br>and CRSP). |
| STR_RK                  | The insiders are grouped into quintiles based on their trading strength in each year with assigned values from 0 to 4. To make the measure range between 0 and 1, we scale the values by 4. (Source: Thomson Reuters Insider and CRSP).  |
| HOR                     | Following Akbas, Jiang and Koch (2020), we construct this insider investment horizon measure based on one insider's trading pattern of own-company shares over the previous 10 years. For insider $i$ of firm $j$ in year $t$ , the measure is calculated as follows:  |
|                         | $HOR_{i,j,t} = \left  \frac{\sum_{T=9}^{T} IOF_{i,j,y}}{N} \right $  |
|                         | Where the net annual insider order flow of insider $I$ in firm $j$ at year $y$ , $IOF_{i,j,y}$ , is calculated as  |
|                         | $\frac{P_{i,j,y} - S_{i,j,y}}{P_{i,j,y} + S_{i,j,y}}$ . P (S) is the number of stock-split adjusted  |
|                         | shares purchased (sold) of the insider during year y   |

|            | and N refers to the number of calendar years that the<br>insider traded over the period from year T-9 to year<br>T. Overall, the range of HOR lies between zero and<br>one and. Higher value of HOR indicates a longer<br>insider investment horizon for the insider. (Source:<br>Thomson Reuters Insider and CRSP). |
|------------|--|
| Age        | The age of one insider in each year (Source: BoardEx).   |
| Tenure     | The number of years that an insider works for a given firm (Source: BoardEx).  |
| Gender     | A dummy is equal to one if the insider is male and 0 if female (Source: BoardEx).  |
| Netbuyer   | A dummy is equal to one if one insider's net<br>purchase in current year is positive, and zero<br>otherwise (Source: Thomson Reuters Insider).   |
| Netbuyer10 | A dummy is equal to one if one insider's net<br>purchase over past 10 years is positive, and zero<br>otherwise (Source: Thomson Reuters Insider).  |
| Officer    | A dummy is equal to one if one insider takes the<br>position of officer as classified by Thomson Reuters<br>Insider database and 0 otherwise (Source: Thomson<br>Reuters Insider).   |
| Director   | A dummy is equal to one if one insider takes the<br>position of director as classified by Thomson<br>Reuters Insider database and 0 otherwise (Source:<br>Thomson Reuters Insider).  |
| CEO        | A dummy is equal to one if one insider takes the<br>position of CEO as classified by Thomson Reuters<br>Insider database and 0 otherwise (Source: Thomson<br>Reuters Insider).   |
| СВ         | A dummy is equal to one if one insider takes the<br>position of board chairman as classified by Thomson<br>Reuters Insider database and 0 otherwise (Source:<br>Thomson Reuters Insider).  |
| CFO        | A dummy is equal to one if one insider takes the<br>position of CFO as classified by Thomson Reuters<br>Insider database and 0 otherwise (Source: Thomson<br>Reuters Insider).   |
| 7-year HOR | The HOR measure is constructed based on one insider's trading pattern of own-company shares  |

|                 | over the previous 7 years (Source: Thomson Reuters Insider).   |
|-----------------|--|
| 5-year HOR      | The HOR measure is constructed based on one insider's trading pattern of own-company shares over the previous 5 years (Source: Thomson Reuters Insider).   |
| LH              | LH refers to long-horizon insiders. Following<br>Akbas, Jiang and Koch (2020), we define this<br>dummy variable as one when the HOR measure is<br>equal to one. If HOR measure is between 0 and 1<br>(excluded), we set this dummy as zero (Source:<br>Thomson Reuters Insider). |
| CEO Careershock | An indicator is equal to one after a CEO (firm) has<br>suffered events reducing career horizon as<br>documented by Aktas et al. (2021)   |
| Treated Firm    | An indicator is equal to one for firms hit by a CEO career shock, regardless of time (Source: Aktas et al., 2021)  |
| Vega            | Following Coles, Daniel and Naveen (2006), vega is<br>defined as the dollar change in one insider's wealth<br>to 0.01 change in the annualized standard deviation<br>of the firm's stock return (in millions) (Source:<br>ExecuComp).  |
| Pay duration    | Following Gopalan et al. (2014), the pay duration is<br>calculated as the weighted average duration of four<br>components of one insider's pay: salary, bonus,<br>restricted stock and options (Source: Institutional<br>Shareholder Services (ISS) Incentive Lab)               |

# Table 2.1 Summary Statistics

This table reports the descriptive statistics for the firm-level measures and insider-level measures used in our main regressions. Panel A presents descriptive statistics of primary measure of firm-level CSR performance, decomposed CSR performance, and other firm-level control variables. Panel B reports statistics of insider-level measures, including insider investment horizon, trading strength, and other insider-level control variables. All variables are described in Appendix A. The sample consists of 12,120 firm-year observations and 30,545 insider-year observations from 1996 to 2015.

|                            | Ν      | Mean          | SD          | Median | P25   | P75   |  |
|----------------------------|--------|---------------|-------------|--------|-------|-------|--|
| Panel A Firm-level measure |        |               |             |        |       |       |  |
| CSR                        | 12,120 | -0.06         | 0.48        | 0.00   | -0.33 | 0.13  |  |
| Strengths                  | 12,120 | 0.24          | 0.41        | 0.08   | 0.00  | 0.29  |  |
| Concerns                   | 12,120 | 0.30          | 0.35        | 0.25   | 0.00  | 0.50  |  |
| Material                   | 12,120 | -0.03         | 0.25        | 0.00   | -0.14 | 0.00  |  |
| Immaterial                 | 12,120 | -0.04         | 0.34        | 0.00   | -0.33 | 0.11  |  |
| Size                       | 12,120 | 7.56          | 1.68        | 7.44   | 6.36  | 8.54  |  |
| Cash ratio                 | 12,120 | 0.18          | 0.19        | 0.11   | 0.04  | 0.27  |  |
| Capex ratio                | 12,120 | 0.04          | 0.05        | 0.03   | 0.01  | 0.06  |  |
| Tangibility                | 12,120 | 0.21          | 0.22        | 0.13   | 0.04  | 0.29  |  |
| Tobin's Q                  | 12,120 | 2.12          | 1.65        | 1.64   | 1.15  | 2.48  |  |
| Leverage                   | 12,120 | 0.19          | 0.20        | 0.16   | 0.03  | 0.30  |  |
| ROA                        | 12,120 | 0.12          | 0.14        | 0.12   | 0.07  | 0.18  |  |
| R&D intensity              | 12,120 | 0.04          | 0.08        | 0.00   | 0.00  | 0.05  |  |
| A&D intensity              | 12,120 | 0.01          | 0.04        | 0.00   | 0.00  | 0.01  |  |
| Blue                       | 12,120 | 0.69          | 0.46        | 1.00   | 0.00  | 1.00  |  |
| Prior-year return          | 12,120 | 0.21          | 0.72        | 0.13   | -0.08 | 0.38  |  |
| ΙΟ                         | 12,120 | 0.75          | 0.21        | 0.80   | 0.64  | 0.91  |  |
|                            | Ра     | anel B Inside | er-level me | asure  |       |       |  |
| HOR                        | 30,545 | 0.82          | 0.29        | 1.00   | 0.63  | 1.00  |  |
| STR*10^3                   | 30,545 | -0.72         | 4.26        | -0.14  | -0.51 | -0.03 |  |
| Age                        | 30,545 | 57.91         | 9.17        | 57.00  | 51.00 | 64.00 |  |
| Tenure                     | 30,545 | 15.13         | 7.18        | 14.00  | 10.00 | 19.00 |  |
| Gender                     | 30,545 | 0.93          | 0.26        | 1.00   | 1.00  | 1.00  |  |
| Officer                    | 30,545 | 0.65          | 0.48        | 1.00   | 0.00  | 1.00  |  |
| Director                   | 30,545 | 0.54          | 0.50        | 1.00   | 0.00  | 1.00  |  |
| CEO                        | 30,545 | 0.16          | 0.37        | 0.00   | 0.00  | 0.00  |  |
| CB                         | 30,545 | 0.09          | 0.29        | 0.00   | 0.00  | 0.00  |  |
| CFO                        | 30,545 | 0.08          | 0.28        | 0.00   | 0.00  | 0.00  |  |

## Table 2.2 Insider Investment Horizon and CSR

This table presents the regression results from a baseline model testing the association between insider investment horizon and overall CSR performance. The dependent variable is the measure of firm-level CSR performance, gauged by MSCI KLD ratings. The independent variables are insider investment horizon—calculated following Akbas, Jiang, and Koch (2020)—and a set of firm-level and insider-level control variables defined in Appendix A. The sample period is 1996–2015. Standard errors are clustered at the insider level, and the t-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                   | Dependent Variable: CSR |           |           |           |  |
|-------------------|-------------------------|-----------|-----------|-----------|--|
|                   | (1)                     | (2)       | (3)       | (4)       |  |
| HOR               | 0.071***                | 0.038***  | 0.055***  | 0.026**   |  |
|                   | (5.59)                  | (3.16)    | (4.30)    | (2.19)    |  |
| Size              | 0.114***                | 0.126***  | 0.112***  | 0.124***  |  |
|                   | (28.11)                 | (29.55)   | (27.80)   | (29.25)   |  |
| Cash ratio        | 0.129***                | 0.130***  | 0.128***  | 0.128***  |  |
|                   | (4.90)                  | (4.83)    | (4.84)    | (4.75)    |  |
| CAPEX ratio       | 0.098                   | 0.125     | 0.134     | 0.135     |  |
|                   | (0.98)                  | (1.23)    | (1.35)    | (1.34)    |  |
| Tangibility       | -0.133***               | -0.027    | -0.146*** | -0.035    |  |
|                   | (-4.39)                 | (-0.73)   | (-4.81)   | (-0.97)   |  |
| Tobin's Q         | 0.013***                | 0.009***  | 0.013***  | 0.009***  |  |
|                   | (4.57)                  | (3.66)    | (4.81)    | (3.81)    |  |
| Leverage          | -0.088***               | -0.087*** | -0.075*** | -0.077*** |  |
|                   | (-3.75)                 | (-3.89)   | (-3.29)   | (-3.50)   |  |
| ROA               | 0.399***                | 0.270***  | 0.379***  | 0.265***  |  |
|                   | (8.18)                  | (6.47)    | (7.99)    | (6.43)    |  |
| R&D intensity     | 0.821***                | 0.549***  | 0.837***  | 0.565***  |  |
|                   | (8.79)                  | (6.09)    | (9.01)    | (6.31)    |  |
| A&D intensity     | 1.206***                | 1.171***  | 1.177***  | 1.167***  |  |
|                   | (7.89)                  | (8.09)    | (7.87)    | (8.16)    |  |
| Prior-year return | -0.039***               | -0.017*** | -0.038*** | -0.017*** |  |
|                   | (-6.34)                 | (-4.66)   | (-6.56)   | (-4.88)   |  |
| Blue              | 0.078***                | 0.064***  | 0.078***  | 0.063***  |  |
|                   | (7.55)                  | (6.08)    | (7.56)    | (6.11)    |  |
| IO                | 0.031                   | -0.095*** | 0.034     | -0.086*** |  |
|                   | (1.49)                  | (-3.78)   | (1.63)    | (-3.43)   |  |
| Age               |                         |           | -0.000    | -0.001    |  |
|                   |                         |           | (-0.48)   | (-1.50)   |  |
| Tenure            |                         |           | 0.004***  | 0.003***  |  |
|                   |                         |           | (6.01)    | (4.06)    |  |
| Gender            |                         |           | -0.131*** | -0.115*** |  |
|                   |                         |           | (-6.95)   | (-6.72)   |  |
| Year FE           | NO                      | YES       | NO        | YES       |  |
| Industry FE       | NO                      | YES       | NO        | YES       |  |
| Adj R2            | 0.162                   | 0.261     | 0.169     | 0.265     |  |
| Ν                 | 30,545                  | 30,543    | 30,545    | 30,543    |  |

#### Table 2.3 Long-horizon buyers and sellers

This table presents the results from using three different measures to distinguish long-term buyers from long-term sellers. Column (1) presents results using the interaction term of insider investment horizon and trading strength rank in a given year (*STR\_RK*), calculated as the rank of the ratio of net purchases to total trading volume for the firm to which an insider belongs. Column (2) presents the results from using the interaction term of insider investment horizon and *Netbuyer*, which is equal to one if the net purchase of one insider is positive in a given year, or zero otherwise. Column (3) introduces the interaction term of insider investment horizon and *Netbuyer10*, which takes the value of one if the insider made a net purchase during the past 10 years, or zero otherwise. All firm- and insider-level control variables used in the baseline model are considered and are defined in Appendix A. The sample period is 1996–2015. Standard errors are clustered at the insider level, and the t-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                | Ι      | Dependent Variable: | CSR     |
|----------------|--------|---------------------|---------|
|                | (1)    | (2)                 | (3)     |
| HOR            | 0.011  | 0.021               | 0.028** |
|                | (0.65) | (1.56)              | (2.07)  |
| HOR×STR_RK     | 0.042  |                     |         |
|                | (1.32) |                     |         |
| STR_RK         | 0.018  |                     |         |
|                | (0.71) |                     |         |
| HOR×Netbuyer   |        | 0.041               |         |
|                |        | (1.63)              |         |
| Netbuyer       |        | -0.029              |         |
|                |        | (-1.50)             |         |
| HOR×Netbuyer10 |        |                     | -0.006  |
|                |        |                     | (-0.23) |
| Netbuyer10     |        |                     | 0.028   |
|                |        |                     | (1.30)  |
| Controls       | YES    | YES                 | YES     |
| Year FE        | YES    | YES                 | YES     |
| Industry FE    | YES    | YES                 | YES     |
| Adj R2         | 0.266  | 0.265               | 0.265   |
| Ν              | 30,543 | 30,543              | 30,543  |

## Table 2.4 Good internal corporate governance or agency problems

Panel A shows the results of the regression to test the relation between two subcategories (CSR strengths and concerns) of overall CSR performance and insider investment horizon. Column (1) tabulates the results regarding CSR strength while column (2) presents the results of CSR concerns. Panel B shows the results of the regression to test the relation between two subcategories (material and immaterial CSR) of overall CSR performance and insider investment horizon. Column (1) tabulates the results regarding material CSR while column (2) presents immaterial CSR. The classification for material and immaterial CSR is conducted based on Sustainability Accounting Standards Board (SASB) Materiality Map for different industries. The sample period runs from 1996 to 2015. All firm- and insider-level control variables used in baseline model are included. Variables are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

| Panel A: Strengths and Concerns |                            |            |  |  |  |  |
|---------------------------------|----------------------------|------------|--|--|--|--|
| Dependent variable              | Strength                   | Concern    |  |  |  |  |
|                                 | (1)                        | (2)        |  |  |  |  |
| HOR                             | 0.001                      | -0.025***  |  |  |  |  |
|                                 | (0.16)                     | (-2.92)    |  |  |  |  |
| Controls                        | YES                        | YES        |  |  |  |  |
| Year FE                         | YES                        | YES        |  |  |  |  |
| Industry FE                     | YES                        | YES        |  |  |  |  |
| Adj R2                          | 0.464                      | 0.311      |  |  |  |  |
| Ν                               | 30,543                     | 30,543     |  |  |  |  |
| Panel                           | B: Material and Immaterial |            |  |  |  |  |
| Dependent variable              | Material                   | Immaterial |  |  |  |  |
|                                 | (1)                        | (2)        |  |  |  |  |
| HOR                             | 0.015**                    | 0.012      |  |  |  |  |
|                                 | (2.31)                     | (1.37)     |  |  |  |  |
| Controls                        | YES                        | YES        |  |  |  |  |
| Year FE                         | YES                        | YES        |  |  |  |  |
| Industry FE                     | YES                        | YES        |  |  |  |  |
| Adj R2                          | 0.172                      | 0.246      |  |  |  |  |
| N                               | 30,543 30,543              |            |  |  |  |  |

## Table 2.5 Different Insiders

This table reports the regression results of our baseline model to test the association between insider investment horizon and overall CSR performance with respect to different insiders from 1996 to 2015. Dependent variable is firm-level CSR performance. All firm- and insider-level control variables used in the baseline model are considered. Variables are defined in Appendix A. Column (1) reports the results of directors and Column (2) shows the results of officers. Column (3), (4) and (5) tabulate the results of CEO, chairman of board (CB) and CFO, respectively. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

|             | Director | Manager | CEO      | CB     | CFO    |
|-------------|----------|---------|----------|--------|--------|
|             | (1)      | (2)     | (3)      | (4)    | (5)    |
| HOR         | 0.043*** | 0.030*  | 0.086*** | 0.064* | 0.04   |
|             | (2.97)   | (1.85)  | (3.31)   | (1.78) | (0.93) |
| Controls    | YES      | YES     | YES      | YES    | YES    |
| Year FE     | YES      | YES     | YES      | YES    | YES    |
| Industry FE | YES      | YES     | YES      | YES    | YES    |
| Adj R2      | 0.264    | 0.266   | 0.273    | 0.278  | 0.251  |
| N           | 16,560   | 19,860  | 4,854    | 2,745  | 2,511  |

## Table 2.6 CEO Career Concern Effects

This table presents the difference-in-difference-in-difference regression results using the CEO career concerns as exogenous shocks to insider investment horizon. The dependent variable is firm-level CSR performance. We build the sample by matching firms with CEO career concerns (treated firms) against up to 10 firms without such concerns (control firms) that belong to the same industry (Fama-French 48 industry) and have similar total assets. Observations are kept if they are within -3 to +3 years of the occurrence of career shocks. Column (1) and (2) present the results using the standard regression approach including only CEOs and all insiders of treated and control firms, respectively. Column (3) and (4) repeat the analyses of Column (1) and (2) with a stacked regression approach. CEO Carrershock is a dummy taking the value of one after a CEO (firm) has suffered a CEO career shock, or zero otherwise. Treated Firm is an indicator equal to one for firms in which the CEO is hit by a career shock, regardless of time. All firm- and insider-level control variables used in the baseline model are considered and are defined in Appendix A. Standard errors are clustered at the insider level, and the *t*-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                     | Standard Regression |              | Stacked I | Regression   |
|---------------------|---------------------|--------------|-----------|--------------|
|                     | CEO only            | All insiders | CEO only  | All insiders |
|                     | (1)                 | (2)          | (3)       | (4)          |
| HOR×CEO Careershock | -0.537*             | -0.264***    | -0.537*   | -0.201**     |
|                     | (-1.66)             | (-3.11)      | (-1.67)   | (-2.06)      |
| HOR                 | 0.263*              | 0.05         | 0.285**   | 0.049        |
|                     | (1.83)              | (0.95)       | (2.11)    | (0.87)       |
| CEO Careershock     | 0.346               | 0.051        | 0.409     | 0.067        |
|                     | (1.19)              | (0.57)       | (1.35)    | (0.63)       |
| Treated Firm        | 0.139               | 0.346***     | 0.101     | 0.287***     |
|                     | (0.74)              | (4.64)       | (0.45)    | (3.50)       |
| Controls            | YES                 | YES          | YES       | YES          |
| Year FE             | YES                 | YES          | NO        | NO           |
| Industry FE         | YES                 | YES          | NO        | NO           |
| Year × Stack FE     | NO                  | NO           | YES       | YES          |
| Industry × Stack FE | NO                  | NO           | YES       | YES          |
| Adj R2              | 0.282               | 0.337        | 0.337     | 0.332        |
| Ν                   | 365                 | 2,397        | 2,883     | 18,696       |

# Table 2.7 Inevitable Disclosure Doctrine Effects

This table shows the difference-in-difference-in-difference regression results using the rejection of IDD as exogenous shocks to insider investment horizon. The sample period spans from 1996 to 2015. The dependent variable is firm-level CSR performance. Column (1) and (2) present the results using the standard regression approach and the stacked regression approach, respectively. *IDD rejection* is equal to one after one state rejects IDD and *Rejection state* is an indicator equal to one for states rejecting IDD, irrespective of time. All firm- and insider-level control variables used in baseline model are considered and variables in the table are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

|                    | Standard Regression | Stacked Regression |
|--------------------|---------------------|--------------------|
| HOR×IDD rejection  | 0.055**             | 0.048*             |
|                    | (2.36)              | (1.72)             |
| HOR                | 0.002               | 0.119***           |
|                    | (0.10)              | (6.16)             |
| IDD rejection      | -0.008              | -0.029             |
|                    | (-0.38)             | (-1.14)            |
| Rejection state    | -0.004              | 0.030**            |
|                    | (-0.30)             | (2.31)             |
| Controls           | YES                 | YES                |
| Year FE            | YES                 | NO                 |
| Industry FE        | YES                 | NO                 |
| Year × Stack FE    | NO                  | YES                |
| Industry× Stack FE | NO                  | YES                |
| Adj R2             | 0.266               | 0.189              |
| Ν                  | 30,543              | 132,363            |
#### Table 2.8 Cross-Sectional Analyses -- Institutional Investors

This table shows the cross-sectional regression results based on two characteristics of institutional investors. Dependent variable is firm-level CSR performance. Column (1) tabulates the results of institutional investor turnover, which is calculated following Gasper, Massa and Matos (2005). Column (2) reports the results using institutional investor churn ratio as dependent variable, which is defined based on Yan and Zhang (2009). Column (3) shows results of socially responsible institutional (SRI) ownership proxied by UNPRI signatories' ownership. All firm- and insider-level control variables used in baseline model are considered. Variables are defined in Appendix A. Sample period is 1996–2015. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

|              | Dependent Variable: CSR |           |          |
|--------------|-------------------------|-----------|----------|
|              | (1)                     | (2)       | (3)      |
| HOR          | 0.110**                 | 0.155***  | 0.002    |
|              | (2.29)                  | (3.19)    | (0.12)   |
| HOR×Turnover | -0.443*                 |           |          |
|              | (-1.88)                 |           |          |
| Turnover     | -0.264                  |           |          |
|              | (-1.29)                 |           |          |
| HOR×Churn    |                         | -1.903*** |          |
|              |                         | (-2.87)   |          |
| Churn        |                         | -0.555    |          |
|              |                         | (-0.98)   |          |
| HOR×UNPRI    |                         |           | 0.287*** |
|              |                         |           | (3.05)   |
| UNPRI        |                         |           | -0.127   |
|              |                         |           | (-1.28)  |
| Controls     | YES                     | YES       | YES      |
| Year FE      | YES                     | YES       | YES      |
| Industry FE  | YES                     | YES       | YES      |
| Adj R2       | 0.267                   | 0.268     | 0.266    |
| Ν            | 30,543                  | 30,543    | 30,543   |

#### Table 2.9 Cross-Sectional Analyses -- Compensation Contracts

This table shows the cross-sectional regression results with respect to two characteristics of compensation contracts. Dependent variable is firm-level CSR performance. Column (1) tabulates the results regarding Vega, which is calculated following Coles, Daniel and Naveen (2006). Column (2) shows the results of pay duration, which is defined based on Gopalan et al, (2014). The sample period for Vega results is 1996 to 2015 while for pay duration results is 2006 to 2015. All firm- and insider-level control variables used in baseline model are considered. Variables are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

|                  | Dependent Variable: CSR |          |
|------------------|-------------------------|----------|
| -                | (1)                     | (2)      |
| HOR              | 0.032                   | -0.087*  |
|                  | (1.47)                  | (-1.71)  |
| HOR×Vega         | 0.313***                |          |
|                  | (2.83)                  |          |
| Vega             | -0.172                  |          |
|                  | (-1.65)                 |          |
| HOR×Pay duration |                         | 0.010*** |
|                  |                         | (3.40)   |
| Pay duration     |                         | -0.006** |
|                  |                         | (-2.44)  |
| Controls         | YES                     | YES      |
| Year FE          | YES                     | YES      |
| Industry FE      | YES                     | YES      |
| Adj R2           | 0.251                   | 0.312    |
| Ν                | 12,439                  | 6,510    |

### Table 2.10 Real Effects — TRI Toxic Releases

This table shows the regression results regarding the real effects of insider investment horizon on future TRI toxic releases. The sample spans from 1996 to 2015. Panel A reports the results of total toxic release. *Total release* is calculated as natural logarithm of one plus the total amount of toxic release under TRI program. The results based on onsite toxic release are presented in Panel B. *Onsite release* is defined as natural logarithm of one plus the amount of onsite toxic release under TRI program. Panel C tabulates the results of offsite toxic release and *Offsite release* is calculated as natural logarithm of one plus the amount of offsite toxic release under TRI program. All firm-and insider-level control variables used in baseline model are considered. Variables are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

| Panel A: Total Toxic Release   |                      |                      |                      |
|--------------------------------|----------------------|----------------------|----------------------|
| Dependent Variable             | Total release(t+1)   | Total release(t+2)   | Total release(t+3)   |
|                                | (1)                  | (2)                  | (3)                  |
| HOR                            | -0.610**             | -0.553**             | -0.521**             |
|                                | (-2.49)              | (-2.27)              | (-2.11)              |
| Controls                       | YES                  | YES                  | YES                  |
| Year FE                        | YES                  | YES                  | YES                  |
| Industry FE                    | YES                  | YES                  | YES                  |
| Adj R2                         | 0.420                | 0.423                | 0.433                |
| N                              | 6,182                | 6,058                | 5,932                |
|                                | Panel B: Onsite      | Toxic Release        |                      |
| Dependent Variable             | Onsite release(t+1)  | Onsite release(t+2)  | Onsite release(t+3)  |
|                                | (1)                  | (2)                  | (3)                  |
| HOR                            | -0.792***            | -0.687**             | -0.624**             |
|                                | (-2.89)              | (-2.48)              | (-2.25)              |
| Controls                       | YES                  | YES                  | YES                  |
| Year FE                        | YES                  | YES                  | YES                  |
| Industry FE                    | YES                  | YES                  | YES                  |
| Adj R2                         | 0.406                | 0.409                | 0.419                |
| N                              | 6,182                | 6,058                | 5,932                |
| Panel C: Offsite Toxic Release |                      |                      |                      |
| Dependent Variable             | Offsite release(t+1) | Offsite release(t+2) | Offsite release(t+3) |
|                                | (1)                  | (2)                  | (3)                  |
| HOR                            | 0.098                | 0.106                | -0.01                |
|                                | (0.30)               | (0.32)               | (-0.03)              |
| Controls                       | YES                  | YES                  | YES                  |
| Year FE                        | YES                  | YES                  | YES                  |
| Industry FE                    | YES                  | YES                  | YES                  |
| Adj R2                         | 0.367                | 0.355                | 0.344                |
| Ν                              | 6,182                | 6,058                | 5,932                |

#### Table 2.11 Real Effects — CSR Compliance Violations

This table shows the regression results regarding the real effects of insider investment horizon on future CSR violations from 2000 to 2015. In Panel A, the dependent variable is the *Violation* indicator, which is equal to one if one firm has at least one CSR violation recorded in Violation Tracker database, and zero otherwise. A probit specification is adopted to test the relation between insider investment horizon and *Violation* indicator. In Panel B, the dependent variable is total amount of related CSR violation penalties collected by Violation Tracker. We estimate a linear specification using the sample including firms with non-missing amount of CSR penalties. All firm- and insider-level control variables used in baseline model are considered. Variables are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

| Panel A: CSR Violation Indicator |                    |                |                |
|----------------------------------|--------------------|----------------|----------------|
| Dependent Variable               | Violation(t+1)     | Violation(t+2) | Violation(t+3) |
|                                  | (1)                | (2)            | (3)            |
| HOR                              | -0.104**           | -0.073         | -0.061         |
|                                  | (-1.99)            | (-1.42)        | (-1.21)        |
| Controls                         | YES                | YES            | YES            |
| Year FE                          | YES                | YES            | YES            |
| Industry FE                      | YES                | YES            | YES            |
| Pseudo R2                        | 0.321              | 0.315          | 0.321          |
| N                                | 30,371             | 30,384         | 30,318         |
|                                  | Panel B: CSR Viola | tion Penalties |                |
| Dependent Variable               | Penalties(t+1)     | Penalties(t+2) | Penalties(t+3) |
|                                  | (1)                | (2)            | (3)            |
| HOR                              | -3.179*            | -1.066         | -1.650         |
|                                  | (-1.87)            | (-0.79)        | (-0.77)        |
| Controls                         | YES                | YES            | YES            |
| Year FE                          | YES                | YES            | YES            |
| Industry FE                      | YES                | YES            | YES            |
| Adj R2                           | 0.406              | 0.409          | 0.419          |
| N                                | 6,374              | 6,462          | 6,608          |

### Table 2.12 Real Effects — Employee Satisfaction

This table shows the regression results regarding the real effects of insider investment horizon on future employee satisfaction. Dependent variable is *Best 100*, an indicator that takes the value one if one firm is listed on "Best 100 Companies to Work for in America" in a given year, and zero otherwise. We estimate a probit specification to examine the relation between insider investment horizon and the *Best 100* indicator. All firm- and insider-level control variables used in baseline model are considered. Variables are defined in Appendix A. Sample period is 1996–2015. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

| Dependent Variable | Best100(t+1) | Best100(t+2) | Best100(t+3) |
|--------------------|--------------|--------------|--------------|
|                    | (1)          | (2)          | (3)          |
| HOR                | 0.429***     | 0.392***     | 0.199*       |
|                    | (3.69)       | (3.32)       | (1.73)       |
| Controls           | YES          | YES          | YES          |
| Year FE            | YES          | YES          | YES          |
| Industry FE        | YES          | YES          | YES          |
| Pseudo R2          | 0.413        | 0.404        | 0.397        |
| N                  | 25,614       | 25,407       | 25,019       |

### Table 2.13 Real Effects - RepRisk index and ESG incidents

This table shows the regression results regarding the real effects of insider investment horizon on future RepRisk index (RRI) and ESG incidents from 2007 to 2015. In Panel A, the dependent variable is *ESG incidents*, defined as the annual number of ESG incidents detected by RepRisk. In panel B, the dependent variable is *RRI*, calculated as the average RepRisk index within a year for each firm. All firm- and insider-level control variables used in the baseline model are considered. Variables are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

| Panel A: ESG Incidents |                       |                    |                    |  |
|------------------------|-----------------------|--------------------|--------------------|--|
| Dependent Variable     | ESG<br>incidents(t+1) | ESG incidents(t+2) | ESG incidents(t+3) |  |
|                        | (1)                   | (2)                | (3)                |  |
| HOR                    | -1.419**              | -1.784***          | -1.845***          |  |
|                        | (-2.51)               | (-3.03)            | (-3.25)            |  |
| Controls               | YES                   | YES                | YES                |  |
| Year FE                | YES                   | YES                | YES                |  |
| Industry FE            | YES                   | YES                | YES                |  |
| Pseudo R2              | 0.296                 | 0.313              | 0.314              |  |
| N                      | 15,880                | 17,365             | 18,707             |  |
|                        | Panel B: R            | RepRisk Index      |                    |  |
| Dependent Variable     | RRI(t+1)              | RRI(t+2)           | RRI(t+3)           |  |
|                        | (1)                   | (2)                | (3)                |  |
| HOR                    | -0.804**              | -0.986***          | -0.864***          |  |
|                        | (-2.38)               | (-3.09)            | (-2.83)            |  |
| Controls               | YES                   | YES                | YES                |  |
| Year FE                | YES                   | YES                | YES                |  |
| Industry FE            | YES                   | YES                | YES                |  |
| Adj R2                 | 0.544                 | 0.552              | 0.559              |  |
| N                      | 15,880                | 17,365             | 18,707             |  |

# **Chapter 2 - Internet Appendix**

### Table IA2.1 Alternative CSR measures from Refinitiv and Sustainalytics

This table presents the results of robustness test using alternative CSR score measures based on different data providers. Column (1) shows the results of the relation between HOR and Refinitiv CSR score. The Refinitiv CSR score is calculated as the logarithm of raw CSR score, defined as the average of Refinitiv environment and social score. The sample spans from 2002 to 2015. Column (2) presents the effects of insider investment horizon on Sustainalytics CSR score, calculated as the average of Sustainalytics' environment and social score. The sample period is from 2009 to 2015. All firm- and insider-level control variables used in the baseline model are considered and are defined in Appendix A. The sample period is from 1996 to 2015. Standard errors are clustered at the insider level, and the *t*-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| Dependent variable | Refinitiv CSR score | Sustainalytics CSR score |
|--------------------|---------------------|--------------------------|
|                    | (1)                 | (2)                      |
| HOR                | 0.063**             | 1.045*                   |
|                    | (2.08)              | (1.77)                   |
| Controls           | YES                 | YES                      |
| Year FE            | YES                 | YES                      |
| Industry FE        | YES                 | YES                      |
| Adj R2             | 0.462               | 0.331                    |
| Ν                  | 15,222              | 9,580                    |

Table IA2.2 Alternative measures of insider investment horizon and KLD scores

This table presents the results from robustness tests according to the baseline model by adopting a battery of alternative measures of insider investment horizon and CSR performance. Panel A presents the results with respect to three alternative measures of insider investment horizon. Column (1) indicates whether seven-year HOR affects CSR performance, while the results based on five-year HOR are presented in Column (2). Column (3) presents the effects of long-horizon insiders (LH) on CSR performance. Panel B presents the results regarding three alternative CSR performance measures. Column (1) presents the results of raw CSR without considering the maximum number of positive and negative indicators under each ESG subcategory. Column (2) indicates how CSR performance, excluding zero CSR rating scores, is affected by insider investment horizon, while the results using the rank of firm-level CSR performance are presented in Column (3). All firm- and insider-level control variables used in the baseline model are considered and are defined in Appendix A. The sample period is 1996–2015. Standard errors are clustered at the insider level, and the t-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|             | Panel A Alternative inst | ider investment horiz | ion      |
|-------------|--------------------------|-----------------------|----------|
|             | 7-year                   | 5-year                | LH       |
|             | (1)                      | (2)                   | (3)      |
| HOR         | 0.022*                   | 0.014                 | 0.021*** |
|             | (1.89)                   | (1.19)                | (2.67)   |
| Controls    | YES                      | YES                   | YES      |
| Year FE     | YES                      | YES                   | YES      |
| Industry FE | YES                      | YES                   | YES      |
| Adj R2      | 0.265                    | 0.264                 | 0.265    |
| N           | 29,564                   | 29,535                | 30,543   |
|             | Panel B Alterna          | tive KLD CSR          |          |
|             | Raw                      | Non-zero              | Rank     |
|             | (1)                      | (2)                   | (3)      |
| HOR         | 0.095                    | 0.031**               | 0.350*** |
|             | (1.60)                   | (2.09)                | (4.20)   |
| Controls    | YES                      | YES                   | YES      |
| Year FE     | YES                      | YES                   | YES      |
| Industry FE | YES                      | YES                   | YES      |
| Adj R2      | 0.352                    | 0.301                 | 0.210    |
| Ν           | 30,543                   | 25,004                | 30,543   |

## Table IA2.3 Firm-level analysis

This table presents the replicated baseline results using alternative firm-level insider horizon measures. The results using the average investment horizon (average horizon), defined as the average investment horizon of all insiders within a firm in a given year, are presented in Column (1). Column (2) presents results using the fraction of long horizon insiders (Frac LH), calculated as the ratio of the number of insiders with HOR equaling one who made at least one trade in a recent year compared with all insiders who made at least one trade in a recent year for a given firm. Column (3) presents a measure of a fraction of opportunistic insiders (Frac opportunistic) for each firm as the ratio of the number of opportunistic insiders who made at least one trade in a recent year compared with all insiders who make at least one trade in a recent year (Ali and Hirshleifer, 2017). To define opportunistic insiders, we first calculate profits from insider trades before quarterly earnings announcements (QEAs) and the average profits of all pre-QEA trades in the past for each insider. Next, we rank insiders at the beginning of each year into quintiles based on their average pre-QEA trading profits, and the five insiders with the highest pre-QEA profitability in each quintile are viewed as opportunistic insiders. Column (4) presents results using fractions of routine insiders, calculated as the ratio of the number of routine insiders who made at least one trade in a recent year compared with all insiders who made at least one trade in a recent year for a given firm. Building on Cohen, Malloy, and Pomorski (2012), we define routine insiders as those who place a trade in the same calendar month for at least three consecutive years. All firm-level control variables used in the baseline model are considered and are defined in Appendix A. The sample period is 1996-2015. Standard errors are clustered at the insider level, and the t-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. Dependent veriable: CSP

|                    | Dependent variable: CSK |          |          |          |
|--------------------|-------------------------|----------|----------|----------|
|                    | (1)                     | (2)      | (3)      | (4)      |
| Average horizon    | 0.036*                  |          |          |          |
|                    | (1.82)                  |          |          |          |
| Frac_LH            |                         | 0.055*** |          |          |
|                    |                         | (2.88)   |          |          |
| Frac_opportunistic |                         |          | -0.052** |          |
|                    |                         |          | (-2.20)  |          |
| Frac_routine       |                         |          |          | 0.046*** |
|                    |                         |          |          | (3.83)   |
| Controls           | Yes                     | Yes      | Yes      | Yes      |
| Industry FE        | Yes                     | Yes      | Yes      | Yes      |
| Year FE            | Yes                     | Yes      | Yes      | Yes      |
| Adj R2             | 0.212                   | 0.197    | 0.203    | 0.199    |
| N                  | 14,302                  | 23,304   | 22,170   | 24,605   |

### Table IA2.4 Subsample analysis

This table presents the results from a subsample analysis. We first split the sample into two parts (i.e., 1996–2005 and 2006–2015), then replicate our baseline results within these two samples, respectively. Column (1) presents the results for the sample spanning 1996–2005, while Column (2) presents the results from 2006–2015. All firmand insider-level control variables used in the baseline model are considered and are defined in Appendix A. Standard errors are clustered at the insider level, and the t-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|             | 1996-2005 | 2006-2015 |
|-------------|-----------|-----------|
|             | (1)       | (2)       |
| HOR         | 0.016     | 0.031**   |
|             | (0.91)    | (2.27)    |
| Controls    | YES       | YES       |
| Year FE     | YES       | YES       |
| Industry FE | YES       | YES       |
| Adj R2      | 0.260     | 0.288     |
| N           | 6,214     | 24,329    |

### Table IA2.5 CEO Career Concern Effects – Dynamic analysis

This table presents the dynamic effects of CEO career concerns as exogenous shocks to insider investment horizon around the timing of CEO career shocks using a difference-in-difference setting. The dependent variable is firm-level CSR performance. We build the sample by matching firms with CEO career concerns (treated firms) against up to 10 firms without such concerns (control firms) that belong to the same industry (Fama-French 48 industry) and have similar total assets. Observations are kept if they are within -3 to +3 years of the occurrence of career shocks. CEO *Carrershock(-3), CEO Carrershock(-2), CEO Carrershock(-1),* CEO Carrershock(+1), CEO Carrershock (+2), and CEO Carrershock(+3) are indicator variables equal to one if a CEO (firm) will suffer a CEO career shock in three years, will suffer a CEO career shock in two years, will suffer a CEO career shock in one year, suffered a CEO career shock one year ago, suffered a CEO career shock two years ago, suffered a CEO career shock three years ago, respectively. Treated Firm is an indicator equal to one for firms in which the CEO is hit by a career shock, regardless of time. Columns (1) and (2) present the results by including only CEOs and all insiders of treated and control firms, respectively. All firm- and insider-level control variables used in the baseline model are considered and are defined in Appendix A. Standard errors are clustered at the insider level, and the *t*-statistics are in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                                  | Dependent variable: CSR |              |
|----------------------------------|-------------------------|--------------|
|                                  | CEO Only                | All insiders |
|                                  | (1)                     | (2)          |
| HOR $\times$ CEO Careershock(-3) | 0.15                    | -0.222       |
|                                  | (0.40)                  | (-1.45)      |
| HOR × CEO Careershock(-2)        | -0.205                  | -0.149       |
|                                  | (-0.34)                 | (-0.64)      |
| HOR × CEO Careershock(-1)        | -0.591                  | -0.174       |
|                                  | (-0.56)                 | (-0.99)      |
| HOR $\times$ CEO Careershock(+1) | -0.675                  | -0.451*      |
|                                  | (-1.39)                 | (-1.84)      |
| HOR $\times$ CEO Careershock(+2) | -0.29                   | -0.305**     |
|                                  | (-0.62)                 | (-2.11)      |
| HOR $\times$ CEO Careershock(+3) | -0.056                  | -0.083       |
|                                  | (-0.05)                 | (-0.78)      |
| CEO Careershock(-3)              | 0.223                   | 0.314**      |
|                                  | (0.76)                  | (2.39)       |
| CEO Careershock(-2)              | 0.136                   | 0.163        |
|                                  | (0.40)                  | (0.97)       |
| CEO Careershock(-1)              | 0.414                   | 0.282*       |
|                                  | (0.71)                  | (1.88)       |
| CEO Careershock(+1)              | 0.533                   | 0.323**      |
|                                  | (1.24)                  | (2.08)       |
| CEO Careershock(+2)              | 0.448                   | 0.233*       |
|                                  | (1.43)                  | (1.82)       |
| CEO Careershock(+3)              | -0.132                  | -0.180*      |
|                                  | (-0.14)                 | (-1.65)      |
| HOR                              | 0.279*                  | 0.065        |
|                                  | (1.84)                  | (1.20)       |
| Treated Firm                     | 0.029                   | 0.240***     |
|                                  | (0.21)                  | (4.29)       |
| Controls                         | YES                     | YES          |
| Year FE                          | YES                     | YES          |
| Industry FE                      | YES                     | YES          |
| Adj R2                           | 0.263                   | 0.334        |
| Ν                                | 365                     | 2,397        |

### Table IA2.6 Inevitable Disclosure Doctrine Effects – Dynamic analysis

This table examines the timing of changes in CSR around rejections of the IDD using a difference-in-difference-in-difference setting. The sample period spans from 1996 to 2015. The dependent variable is firm-level CSR performance. *IDD rejection* (-3), *IDD rejection* (-2), *IDD rejection* (-1), *IDD rejection* (+1), *IDD rejection* (+2) and *IDD rejection* (+3) denote dummy variables equal to one if the firm is headquartered in a state that will reject the IDD in three years, two years, one year, or rejected the IDD one year ago, two years ago, three years ago, respectively. *Rejection state* is an indicator equal to one for states rejecting the IDD, irrespective of time. All firm- and insider-level control variables used in baseline model are considered, and the variables in the table are defined in Appendix A. Standard errors are clustered at the insider level, and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

|                       | CSR       |
|-----------------------|-----------|
| HOR×IDD rejection(-3) | 0.057     |
|                       | (1.25)    |
| HOR×IDD rejection(-2) | 0.043     |
|                       | (0.72)    |
| HOR×IDD rejection(-1) | -0.037    |
|                       | (-0.86)   |
| HOR×IDD rejection(+1) | 0.004     |
|                       | (0.09)    |
| HOR×IDD rejection(+2) | -0.02     |
|                       | (-0.50)   |
| HOR×IDD rejection(+3) | 0.071***  |
|                       | (2.68)    |
| IDD rejection(-3)     | 0.001     |
|                       | (0.06)    |
| IDD rejection(-2)     | 0.021     |
|                       | (0.57)    |
| IDD rejection(-1)     | 0.024     |
|                       | (0.48)    |
| IDD rejection(+1)     | 0.078**   |
|                       | (2.09)    |
| IDD rejection(+2)     | 0.022     |
|                       | (0.60)    |
| IDD rejection(+3)     | 0.043     |
|                       | (1.20)    |
| HOR                   | 0.023     |
|                       | (0.94)    |
| Rejection state       | -0.036*** |
|                       | (-2.69)   |
| Controls              | YES       |
| Year FE               | YES       |
| Individual FE         | YES       |
| Adj R2                | 0.268     |
| Ν                     | 30,543    |

# Table IA2.7 The effects of IDD adoption

This table shows the difference-in-difference-in-difference regression results using the adoption of IDD as an exogenous shock. The dependent variable is firm-level CSR performance. *IDD adoption* is equal to one after one state adopts IDD and *Adoption state* is an indicator equal to one for states adopting IDD, irrespective of time. All firm-and insider-level control variables used in baseline model are considered and variables in the table are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

|                  | CSR       |  |
|------------------|-----------|--|
| HOR×IDD adoption | -0.074*** |  |
|                  | (-3.24)   |  |
| HOR              | 0.055***  |  |
|                  | (3.58)    |  |
| IDD adoption     | 0.011     |  |
|                  | (0.57)    |  |
| Adoption state   | 0.002     |  |
|                  | (0.19)    |  |
| Controls         | YES       |  |
| Year FE          | YES       |  |
| Industry FE      | YES       |  |
| Adj R2           | 0.267     |  |
| N                | 30,543    |  |

### Table IA2.8 Cross-sectional analysis -- Antitakeover law

This table shows the difference-in-difference regression results using the adoption of business combination (BC) laws as exogenous shocks. The sample period spans from 1996 to 2015. Dependent variable is firm-level CSR performance. Column (1) shows the regression results without controlling for other major antitakeover laws. The results after controlling other antitakeover laws are displayed in Column (2). *BC law* is an indicator equal to one if a firm headquartered in the state which has adopted the BC law. All firm- and insider-level control variables used in baseline model are considered and variables in the table are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively.

|             | Dependent Variable: CSR |           |  |
|-------------|-------------------------|-----------|--|
|             | (1)                     | (2)       |  |
| HOR×BC law  | 0.083**                 | 0.090**   |  |
|             | (2.06)                  | (2.22)    |  |
| HOR         | -0.050                  | -0.056    |  |
|             | (-1.29)                 | (-1.45)   |  |
| BC law      | -0.045                  | -0.050    |  |
|             | (-1.28)                 | (-1.43)   |  |
| CS law      |                         | -0.039*** |  |
|             |                         | (-2.73)   |  |
| FP law      |                         | 0.008     |  |
|             |                         | (0.55)    |  |
| DD law      |                         | -0.024    |  |
|             |                         | (-1.10)   |  |
| PP law      |                         | 0.094***  |  |
|             |                         | (4.49)    |  |
| Controls    | YES                     | YES       |  |
| Year FE     | YES                     | YES       |  |
| Industry FE | YES                     | YES       |  |
| Adj R2      | 0.265                   | 0.268     |  |
| N           | 30,543                  | 30,543    |  |

### Table IA2.9 Toxicity-weighted and harmful release

This table shows the regression results regarding the real effects of insider investment horizon on future TRI toxic releases after considering the toxicity. The sample spans from 1996 to 2015. Panel A reports the results of toxicity-weighted release, which is calculated as the product of TRI releases in pounds for each chemical and the chemicaland exposure route-specific toxicity weight. The *RSEI hazard* is defined as natural logarithm of one plus the total toxicity-weighted release in pounds. The results of harmful release are presented in Panel B. We define the harmful release by mapping the TRI toxic release data to Integrated Risk Information System (IRIS) listed harmful chemicals and calculate harmful release only for those chemicals that can influence public health. The *Harmful release* is defined as natural logarithm of one plus the total insider-level control variables used in baseline model are considered. Variables are defined in Appendix A. Standard errors are clustered at the insider-level and t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at 1%, 5%, and 10% level, respectively.

| Panel A RSEI hazard (Toxicity-weighted release) |                      |                      |                      |  |  |
|---|----------------------|----------------------|----------------------|--|--|
| Dependent Variable                              | RSEI hazard(t+1)     | RSEI hazard(t+2)     | RSEI hazard(t+3)     |  |  |
|   | (1)                  | (2)                  | (3)                  |  |  |
| HOR   | -0.826*              | -0.597               | -0.509               |  |  |
|   | (-1.88)              | (-1.37)              | (-1.16)              |  |  |
| Controls  | YES                  | YES                  | YES                  |  |  |
| Year FE   | YES                  | YES                  | YES                  |  |  |
| Industry FE                                     | YES                  | YES                  | YES                  |  |  |
| Adj R2  | 0.365                | 0.360                | 0.370                |  |  |
| N   | 6,182                | 6,058                | 5,932                |  |  |
| Panel B Harmful release                         |                      |                      |                      |  |  |
| Dependent Variable                              | Harmful release(t+1) | Harmful release(t+2) | Harmful release(t+3) |  |  |
|   | (1)                  | (2)                  | (3)                  |  |  |
| HOR   | -0.570*              | -0.536*              | -0.541*              |  |  |
|   | (-1.95)              | (-1.82)              | (-1.83)              |  |  |
| Controls  | YES                  | YES                  | YES                  |  |  |
| Year FE   | YES                  | YES                  | YES                  |  |  |
| Industry FE                                     | YES                  | YES                  | YES                  |  |  |
| Adj R2  | 0.412                | 0.403                | 0.407                |  |  |
| Ν   | 6,182                | 6,058                | 5,932                |  |  |

## **Chapter 3: How do Active Mutual Funds Respond to Firm's Climate**

# **Change Exposure?**

**Abstract**: This paper examines whether and how mutual fund managers adjust their portfolio holdings in response to firms' climate change exposure. Using the 2015 Paris Agreement as a pivotal event changing awareness and perception of climate change risk, we employ a difference-in-differences approach and find that fund managers reduce holdings in firms with higher climate change exposure post the Paris Agreement. Further analysis reveals that the stringency of climate policies and climate change exposure of funds play important roles in the divestment decision. Heterogeneity tests reveal that divestment effects are more pronounced for firms in pollutive industries and during the period of the Trump administration. Finally, we explore the real effects of fund managers' divestments on portfolio firms' green outcomes and find that highly exposed firms improve environmental scores and reduce carbon emissions following the Paris Agreement. Overall, our findings shed light on the positive impacts of institutional investors on the transition to a green economy.

### 3.1 Introduction

In recent years, the increasing frequency of extreme weather events has intensified public concerns about climate change, increasing the demand to combat climate change and transit to a green economy. The green transition relies not only on governments' efforts to establish stringent climate regulations, but also participation of investors and institutions in the financial markets. Recent climate finance surveys show that institutional investors play a pivotal role as catalyst for a green economy as they incorporate climate concerns into investment decisions (e.g., Krueger, Sautner and Starks, 2020; Ilhan et al. 2023). Specifically, institutional investors facilitate the transition to the green economy primarily through two channels. They can pose pressure to portfolio firms through the threat of exit, allocating more funds to green companies while tilting away from brown firms (e.g., Gibson et al., 2022; Atta-Darkua et al., 2023, Huynh, Li and Xia, 2025). Alternatively, they can affect portfolio firms' green profiles through voting and engagement (e.g., Azar et al., 2021; Dimson, Karakas and Li, 2015; Naaraayanan, Sachdeva, and Sharma, 2021).

In this paper, we explore whether and how mutual fund managers adjust their portfolio holdings depending on portfolio firms' climate change exposure in response to the Paris Agreement. As the first comprehensive agreement signed by the majority of countries, the Paris Agreement boosts the commitment of governments in different countries to combat climate change by taking some enforcement actions. Thus, the prospect of tighter climate policies may alter fund managers' awareness and perception of climate change risk, thereby affecting their portfolio construction pertaining to portfolio firms' climate change exposure.

There are three potential responses from funds depending on climate change exposure of their holding firms. First, fund managers may *divest* firms with high exposure to climate change after the Paris Agreement to cater to investors' tastes. To pursue higher fund flows and larger sizes, fund managers are more likely to sell brown firms (i.e., with higher exposure to climate change) as investors tend to abstain from investing in these firms (e.g., Heinkel, Kraus, Zechner, 2001; Riedl and Smeets, 2017; Hartzmark and Sussman, 2019). Second, fund managers may *increase* their holdings of highly exposed firms after the Paris Agreement for the sake of potential financial rewards, because brown firms tend to have higher risk premiums (e.g., Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2021; Pastor, Stambaugh and Taylor, 2021). Third, fund managers' investment behavior may remain *unchanged* if the Paris Agreement does not alter their perception of climate change risks, following scientists who challenge the scientific consensus on climate change and different tightness of climate policies across countries and regions<sup>40</sup>.

To measure firm-level exposure to climate change, we employ measures developed by Sautner et al. (2023), who use a machine-learning keyword-discovery algorithm to identify a firm's climate change exposure from earnings conference calls. We first calculate average firm-level exposure prior to the Paris Agreement and split firms into two groups based on their pre-shock average exposures. Firms with above-median preshock average exposure are classified as those with high climate change exposure, while the rest are categorized as those with low exposure. After combining mutual fund holding data and firm-level climate change exposure, we investigate whether and how mutual fund managers adjust their portfolios following the Paris Agreement relying on a difference-in-difference (DiD) approach.

We find that fund managers indeed adjust their portfolio holdings depending on portfolio firms' climate change exposure following the Agreement. Specifically, they reduce portfolio holdings of highly exposed firms, which is consistent with the notion that their adjustments are based on the preferences of investors. Notably, fund managers sell, on average, 2.42% of holdings for a single firm with high climate change exposure, which values at 0.415 million US dollars. When aggregating to a fund-level divestment magnitude, the total divestment value is 25.69 million US dollars since one fund has, on average, 61.9 portfolio firms with high climate change exposure. These findings corroborate the argument that mutual fund managers can direct funds into a green

<sup>&</sup>lt;sup>40</sup> For example, the stringency of climate policies varies dramatically across states and highly correlates with political affiliation (e.g., Giuli and Kostovetsky, 2014) in the US. In addition, US President Donald Trump is a climate change denier who announced the withdrawal of the United States from the Paris Agreement in 2017.

economy, therefore contributing to tackling climate change.

We then disentangle whether these divestment actions reflect the proactive actions of mutual fund managers to satisfy the demands of investors. To this end, we compare the divestment effects between active and passive mutual fund managers. Since the primary goal of passive mutual fund managers is to minimize the tracking error relative to the underlying index, they may have little flexibility to adjust their portfolio holding depending on firm-level climate change exposure. Accordingly, active mutual fund managers may divest more highly exposed firms compared to passive ones. We find this is indeed the case.

Next, we explore whether state-level climate regulations influence the baseline results. Given the variation of climate regulations across states, the fund managers' awareness and perception of climate change shaped by the Paris Agreement may differ. In this case, fund managers may underweight more for highly exposed firms headquartered in states with more stringent climate regulations. Consistent with the notion, we find that the divestment actions of fund managers on firms with high climate change exposure are concentrated in headquarter states of portfolio firms enacting the greenhouse gas (GHG) emission targets to reduce statewide emissions. Furthermore, we examine how a fund's existing exposure to climate change influences investment decisions pertaining to high-exposure firms. When a fund is highly exposed to climate change (i.e., holding firms with high exposure), they may not be willing to divest highly exposed firms since this may threaten the price of its exiting holdings. To mitigate potentially adverse effects, a fund with existing high climate change exposure may overweight highly exposed firms. To explore this, we calculate fund-level valueweighted average climate change risk exposure before the Paris Agreement and define those funds with above-median exposure as highly exposed funds. The empirical results show that funds with high exposure tend to increase their weights in highly exposed firms, while the divestment effects are concentrated in funds with low exposure.

We investigate the heterogeneity of the main findings from several perspectives. First, we examine whether the divestment actions vary with respect to portfolio firms belonging to different industries. Specifically, we divide our sample into salient (i.e., energy, utility, and transportation) and non-salient industries based on the industry classification of portfolio firms. On the one hand, firms in salient industries may be more susceptible to climate change since carbon emissions are concentrated on these industries (e.g., Bolton and Kacperczyk, 2021). On the other hand, firms in these industries exhibit more technological opportunities since they can produce more green patents (e.g., Cohen, Gurun, Nguyen, 2021). Based on this rationale, we reveal that the divestment effects of fund managers, especially in terms of magnitude, are stronger in salient industries except for climate change exposure related to technological opportunities, which increase the holdings of fund managers in firms within the salient industries. Second, we consider the heterogeneous effects of fund managers' beliefs on climate change, which may influence trading behavior of fund managers regarding portfolio firms' climate change exposure. We define fund managers with high climate change beliefs when they are located in states with high public views on climate change and find little evidence that the divestment effects are stronger among high-belief fund managers. Third, we explore the heterogeneity of fund managers' investment decisions under Obama and Trump administration since these two presidents have divergent view about climate change. Our findings indicate that fund managers divest firms with high climate change exposure under the administration of both presidents. However, the divestment magnitude is larger under the Trump administration.

Finally, we focus on the potential responses of firms with high climate change exposure since the divestments of fund managers may lead to lower valuation and higher cost of capital (e.g., Hong and Kacperczyk, 2009; Chava, 2014; Choi et al. 2021). As such, highly exposed firms may react to divestment campaigns by improving their environmental performance in the subsequent periods. To explore, we adopt the environmental score and carbon emissions for firm-level environmental performance. Our empirical results present that firms with high climate change exposure improve their environmental scores and reduce carbon emissions following the Paris Agreement, suggesting the real discipline effects of fund managers' divestment on firms'

environmental performance.

This study adds to the burgeoning literature investigating the institutional investors' responses to climate change risks. In addition to the evidence from survey results (e.g., Krueger, Sautner and Starks, 2020; Ilhan et al. 2023), empirical studies document that institutional investors tend to divest portfolio firms with higher climate change risks (e.g., Alok, Kumar, Wermers, 2020; Gibson et al., 2022; Atta-Darkua et al., 2023, Huynh, Li and Xia, 2025). Our work differs from prior studies from three perspectives. First, prior studies examine the how institutional investors respond to climate change risks based on various "hard" measures<sup>41</sup>, while we examine the responses from different perspectives of climate change risk (e.g., technological opportunities, regulatory stringency and physical risk) relying on the novel measures constructed using "soft" information extracted from firms' earnings conference calls. In other words, we provide new evidence on how institutional investors respond to different types of climate change concerns. Second, our study emphasizes the importance of regulatory enforcement on institutional investors' responses to climate change risk by showing that the divestment actions of institutional investors on firms with high climate change exposure are concentrated on the places with more stringent climate regulations. Third, we not only focus on portfolio firms' climate change risks but also examine the role of fund-level risks. Our findings reveal that the divestment decisions hinge on the fundlevel climate change exposure.

This study is also related to literature regarding the real effects of institutional investors on the corporate green outcomes. Institutional investors can incorporate climate change concerns and change target firms' green policies primarily through divestments and engagement. A large literature documents the real effects of divestments (e.g., Gantchev, Giannetti and Li, 2022; Heath et al., 2023), while another strand of literature focuses on engagement (e.g., Azar et al., 2021, Dimson, Karakas

<sup>&</sup>lt;sup>41</sup> More specifically, Alok, Kumar, Wermers (2020) explore how fund managers rebalance their portfolios depending on the climate disasters such as floods and Gibson et al. (2022) focus on firms' environmental performance as measured by rating scores. Additionally, Atta-Darkua et al (2023) and Huynh, Li and Xia (2025) investigate fund managers' investment decisions based on carbon emissions of portfolio firms.

and Li, 2015; Naaraayanan, Sachdeva, and Sharma, 2021). A debate on the most effective strategy between divestment and engagement is growing rapidly, for example, Heinkel et al. (2001) find that divestment can effectively reduce the stock price of polluting firms by limiting risk sharing while the theoretical model of Berk and van Binsbergen (2025) suggests little impact of divestment on the target firms' cost of capital. Instead, the more effective strategy for socially conscious investors is to invest and change corporate green policies through engagement. Our work adds to this strand of literature and contributes to the debate by showing that firms with high climate change exposure improve their environmental scores and reduce carbon emissions following the Paris Agreement in response to the divestments of mutual fund managers, supporting the effectiveness of divestments on corporate green outcomes.

Furthermore, this paper contributes to the studies exploring the impact of the Paris Agreement. By adopting the Paris Agreement as a shock reshaping investors' awareness and perception of climate change, Bolton and Kacperczyk (2023) find that large carbon risk premiums only exist in the period following the Agreement. Using a similar empirical setting, Seltzer, Starks and Zhu (2025) reveal that firms with higher climate change risk experience a decline in credit rating after the Paris Agreement. Our work extends these studies and provides new evidence on how the Paris Agreement affects the awareness of climate change, thus influencing the portfolio adjustments of fund managers depending on portfolio firms' climate change exposure.

# 3.2 Data, Sample and Summary Statistics

In this section, we describe the data source of variables used in the main analyses and explain how we construct these variables. We then present the summary statistics. The details of key variable definitions are provided in Appendix A.

# 3.2.1 Firm-level Climate Change Exposure

To measure firm-level climate change exposure, we obtain the data developed by

Sautner et al. (2021).<sup>42</sup> They adopt a machine-learning keyword-discovery algorithm to construct time-varying measures of climate change at the firm level by analyzing transcripts of earnings conference calls. Their measures include an overall climate change exposure measure as well as three sub climate change exposure measures associated with opportunity, regulatory, and physical shocks. To distinguish between firms with high climate change exposure and those with low exposure, we first calculate the average firm-level climate change exposure prior to the Paris Agreement (i.e., before the last quarter of 2015). We then split our sample into two parts: firms with above-median climate change exposure before Paris Agreement are defined as high-exposure firms while the rest of firms are defined as low-exposure firms.

### 3.2.2 Fund Portfolio Weights and Other Controls

We obtain mutual fund data, including net fund returns, total net assets, and expense ratios, from the CRSP Survivorship-Bias-Free U.S. Mutual Fund Database. We use Lipper, Strategic Insight, Weisenberger, and CRSP investment objective codes to identify actively managed domestic equity mutual funds.<sup>43</sup> When fund objective codes conflict or are missing, we check the character strings of fund names for keywords suggesting whether the fund is an index fund, an exchange-traded fund, an international fund, a bond fund, or a balanced fund.<sup>44</sup> We exclude funds with less than 80% or more

<sup>&</sup>lt;sup>42</sup> Climate change measures developed by Sautner et al. (2023) are available through the link <u>https://osf.io/fd6jq/</u>.<sup>43</sup> In line with Kacperczyk et al. (2008), our sample includes funds with the Lipper class codes AU, CA, CG, CS, EI, FS, G, GI, H, ID, MC, MR, S, SG, SP, TK, TL, and UT or the Lipper objective codes EIEI, G, LCCE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE. If none of the above objectives is available, we include all funds with the Strategic Insights objective AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SEC, TEC, SCG, UTI, and GLD. If no Lipper or Strategic Insights objectives are available, we use the Wiesenberger objective codes ENR, FIN, HLT, IEQ, G, GCI, GPM, LTG, MCG, SCG, TCH, and UTL. If none of these objectives is available but the fund's policy is common stocks (CS), then the fund is also included in the sample. Finally, a fund is also included if its CRSP objective code has *E* as its first character, *D* as its second character, and *C*, *Y*, or *S* as the third character, without the third and fourth characters being *CL*, *YH*, *YS*, or *SR*.

 $<sup>^{43}</sup>$  In line with Kacperczyk et al. (2008), our sample includes funds with the Lipper class codes AU, CA, CG, CS, EI, FS, G, GI, H, ID, MC, MR, S, SG, SP, TK, TL, and UT or the Lipper objective codes EIEI, G, LCCE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE. If none of the above objectives is available, we include all funds with the Strategic Insights objective AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SEC, TEC, SCG, UTI, and GLD. If no Lipper or Strategic Insights objectives are available, we use the Wiesenberger objective codes ENR, FIN, HLT, IEQ, G, GCI, GPM, LTG, MCG, SCG, TCH, and UTL. If none of these objectives is available but the fund's policy is common stocks (CS), then the fund is also included in the sample. Finally, a fund is also included if its CRSP objective code has *E* as its first character, *D* as its second character, and *C*, *Y*, or *S* as the third character, without the third and fourth characters being *CL*, *YH*, *YS*, or *SR*.

<sup>&</sup>lt;sup>44</sup> We identify index funds by the CRSP index fund flag, by their names, or by their stated objective.

than 105% of their portfolios invested in equities. For funds with multiple share classes, we compute fund-level variables by aggregating across the different share classes.

Mutual fund holdings data are extracted from the Thomson Reuters Mutual Fund Holdings (s12) database. This database provides information on mutual funds reporting to the U.S. Securities and Exchange Commission (SEC) regarding their NYSE, AMEX, and NASDAQ stock. For each quarter, we calculate the weight of one stock in the portfolio of a given mutual fund as the dollar value of the stock held by the mutual fund over the total dollar value of the fund's portfolio holdings. In addition, we construct various fund-level control variables. We calculate fund size as the natural logarithm of total net assets (TNA) across all share classes. Expense ratio and turnover ratio are defined as fund-weighted average expense ratio and turnover ratio based on the weight of different share classes. Similarly, we calculate fund return as the weighted average quarterly return over share classes. Lastly, we calculate quarterly fund flows as the quarterly growth of TNA net of reinvested returns.

# 3.2.3 Firm-level Controls

We obtain firm-level market and financial data from CRSP and Compustat and construct a variety of control variables that may influence fund holdings. Firm size is defined as the natural logarithm of market capitalization, which is calculated by multiplying stock price and total shares outstanding. Book-to-market ratio is calculated as the book value scaled by market value, in which the book value is equal to the book value of shareholders' equity plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of the preferred stock. Prior return is defined as the cumulative monthly stock return over the past 12 months.

## 3.2.4 Sample and Summary Statistics

Our final sample spans the last quarter of 2011 to the third quarter of 2019, which begins four years before and ends four years after the Paris Agreement takes into effect. The choice of an eight-year sample around Paris Agreement in the last quarter of 2015 enables us to assess the sharpness of our treatment effects and avoid the risk of incorporating confounding effects stemming from other influential events (e.g., global financial crisis and Covid-19 outbreak). The sample consists of over 4 million observations of 44,428 unique funds and 55,117 unique portfolio firms.

#### [Insert Table 3.1 here]

Table 3.1 includes the summary statistics for all key variables used for the primary results. In Panel A, we report the summary statistics for fund-firm level key variables. On average, the portfolio weight of a stock accounts for 1.03% relative to the dollar value of total portfolio holdings, with a standard deviation of 1.63%. These numbers are comparable to the summary statistics of Huynh, Li and Xia (2025) which use similar fund-stock-quarter observations spanning from 2005 to 2018. One fund holds 0.32 million shares with the value of 17.13 million USD for a given portfolio firm. The firmlevel variables are reported in Panel B. The variable of particular interest is the average firm-level climate change exposure before the Paris Agreement. The average overall climate change risk exposure is 0.95 with a standard deviation of 2.28. Specifically, the three components of overall climate change exposure-opportunity, regulatory, and physical—have an average value of 0.35, 0.04, and 0.01, respectively. These numbers are all comparable to the descriptive statistics of Sautner et al. (2023). Meanwhile, the average natural logarithm of market capitalization (firm size) is 7.42, the average bookto-market ratio is 0.60, and the average past 12-month stock return is 13%. We also present the summary statistics of fund-level variables in Panel C. The fund-level overall climate change risk exposure has a mean of 0.80 with a standard deviation of 0.70. The fund-level opportunity, regulatory, and physical exposures have an average value of 0.29, 0.04, and 0.01, respectively. The average value of the natural logarithm of total net assets (Fund size) is 6.00 and exhibits an average turnover ratio of 0.62, an average expense ratio of 0.01, an average quarterly cumulative fund returns of 3%, and an average fund flow of -0.01.

#### 3.3 Identification strategy

In this section, we outline our identification strategy and evaluate the validity of identifying assumptions using parallel analyses.

#### 3.3.1 Model Specification

We employ a difference-in-difference (DiD) design to examine whether and how active equity fund managers adjust portfolio holdings after the Paris Agreement, depending on the pre-shock average climate change exposure of portfolio firms. Specifically, we estimate the following regression:

$$Weight_{j,i,q+1} = \beta_1 High_i \times Post_q + \alpha_1 X_{i,q} + \alpha_2 S_{j,q} + \zeta_{j,i} + \zeta_q + \varepsilon_{j,i,q}, \tag{1}$$

where  $Weight_{j,i,q+1}$  is defined as the weight of firm *i* in fund *j*'s portfolio at the end of quarter q+1.  $High_i$  is a dummy variable that takes the value of 1 if firm *i* has an average value of climate change risk exposure prior to the Paris Agreement above the median, and 0 otherwise.  $Post_q$  is a dummy variable that takes the value of 1 if the sample period is after the last quarter of 2015 since the Paris Agreement was formally signed on December 2015.  $X_{i,q}$  is a set of firm-level control variables in quarter q, including the log of market capitalization, book-to-market ratio, and past 12-month cumulative stock return.  $S_{j,q}$  is a set of fund-level control variables in quarter q, including fund size, expense ratio, turnover ratio, quarterly fund return, and fund flow.  $\zeta_{j,i}$  is fund-firm fixed effect controlled for time-invariant fund and firm characteristics that may influence each fund-firm pair.  $\zeta_q$  is year-quarter fixed effect controlled for time-variant characteristics in each year-quarter. After adding these two fixed effects, the single term  $High_i$  is absorbed by fund-firm fixed effects while  $Post_q$  is absorbed by year-quarter fixed effects.

### 3.3.2 Validity of Identifying Assumptions

To ensure the validity of our difference-in-difference setting, we examine the crucial assumption that treatment and control groups follow the same trend irrespective of treatment. Specifically, we compare the average of various key variables for firms with

above-median climate change risk exposure (i.e., the treatment group) and that with below-median exposure (i.e., the control group) prior to the Paris Agreement. Following Imbens and Wooldridge (2009), we calculate the normalized differences between the averages of the treatment and control groups. Normalized differences smaller than 0.25 indicate no significant difference between groups and validity of model specification.<sup>45</sup>

# [Insert Table 3.2 here]

Table 3.2 presents the average values of key variables, as well as the normalized differences between these averages across the two groups. Panel A reports parallel trends at the fund and firm levels. The normalized difference in average fund weights across the two groups is -0.02, indicating firms with high exposure to climate change risk exhibit a similar fund weight as those with low exposure before the Paris Agreement. The normalized differences for number of shares and dollar value of shares are both below 0.25, which suggests that funds hold similar number and dollar value of shares irrespective of a firm's climate change exposure. Panel B shows parallel trends for firm-level covariates. The normalized differences for firm size, book-to-market ratio, and prior-year return are all below 0.25, indicating that firms with different exposure to climate change have a similar trend prior to the Paris Agreement. Panel C assesses the parallel trends at fund level. The normalized differences for all fund-level covariates across the two groups are below 0.25, which confirms that funds exhibit parallel trends before the Paris Agreement.

Collectively, we find little evidence that fund managers exhibit different preferences toward firms with high climate change exposure and those with low exposure before the Paris Agreement. Similarly, there are negligible differences for firm- and fund-level covariates across the two groups. These findings suggest the parallel trend assumption

 $<sup>^{45}</sup>$  We do not test the parallel trend assumption using *t*-statistics of the differences between averages across groups because the *t*-statistic increases dramatically with sample size, while normalized differences are not influenced by the sample size (Imbens and Wooldridge, 2009). Given the large sample size of our analysis at the fund-firm level (i.e., millions of observations), we adopt normalized differences to compare averages across groups.

holds prior to the Paris Agreement.

#### 3.4 Results

### 3.4.1 Baseline results

To explore how funds respond to climate change exposure of portfolio firms, we estimate baseline model (1) and present the results in Table 3.3. The variable of interest is the interaction term of *High* and *Post*. Column (1) displays the results regarding climate change exposure. Firms with above-median average climate change exposure are defined as highly exposed firms. The estimated coefficient of *High* x *Post*, -0.025 with a *t*-statistic of -4.66, is negative and significant at the 1% level, indicating fund managers decrease portfolio weights for firms with high exposure to climate change post Paris Agreement.

#### [Insert Table 3.3 here]

Climate change may have multifaceted effects, ranging from physical threats to regulatory interventions and technological opportunities. We repeat the analysis using three pillars of climate change exposure: opportunity, regulatory, and physical exposure related to climate change. The results are presented in Columns (2), (3), and (4), respectively. The fund portfolio weights in firms with high opportunity- and physical exposure decrease after the Paris Agreement, since the coefficients of the interaction terms of *High* and *Post* are -0.034 with a *t*-statistic of -5.57 in Column (2), and -0.025 with a *t*-statistic of -3.51 in Column (4). We find little evidence that managers adjust weights for firms with high regulatory exposure related to climate change after the Agreement, as the *t*-statistic is -1.54 in Column (3).<sup>46</sup> In terms of the economic magnitude, we find that fund managers, on average, reduce 0.025% portfolio weight for a firm with high climate change exposure in response to Paris Agreement. A back-of-envelop calculation suggests that the portfolio weight declines by 2.42% (calculated

<sup>&</sup>lt;sup>46</sup> For robustness, we repeat the baseline analyses by using the term frequency–inverse document frequency (tfidf) measure for climate change exposure constructed by Sautner et al. (2021). We find qualitatively similar results.

as 0.025 / 1.031) relative to the unconditional sample mean of fund weight. The corresponding dollar value of the divestment for a single highly exposed portfolio firm is thus 0.415 million USD (calculated as  $2.42\% \times 17.136$ ). As one fund has an average number of 61.9 portfolio firms with high climate change exposure in each year-quarter, the total divestment magnitude can be estimated as 25.69 million USD (61.9 × 0.415) stemming from the concerns regarding climate change exposure of portfolio firms.

These findings so far indicate that fund managers divest portfolio firms with high climate change exposure, aiming to satisfy investors' demands and therefore attract more fund flows (e.g., Hartzmark and Sussman, 2019). To reinforce the argument that these divestments driven by portfolio firms' climate change exposure reflect the proactive measures taken by fund managers to attract investors, we then compare the portfolio adjustments between active and passive mutual fund managers. Since the majority of passive mutual fund managers aim to reduce the tracking error relative to the underlying index, they may not have discretion to adjust portfolio holdings based on climate change exposure of portfolio firms. As such, we expect that the divestment effects fund managers are stronger among active mutual fund managers.

To explore, we combine the sample in baseline analysis including only active mutual funds with a new sample of passive mutual funds and estimate the following regression model with a triple-interaction term by incorporating an indicator for whether a fund is active:

$$\begin{split} Weight_{j,i,q+1} &= \beta_1 High_i \times Post_q \times Active_j + \beta_2 High_i \times Post_q + \beta_3 Active_j \times Post_q + \alpha_1 X_{i,q} + \alpha_2 S_{j,q} + \zeta_{j,i} + \zeta_q + \varepsilon_{j,i,q}, \end{split}$$

(2)

in which the coefficient of interest is  $\beta_1$  and  $\beta_2$  suggesting how the active and passive mutual fund managers adjust portfolio holdings based on firms' climate change exposure, respectively. A more negative parameter of  $\beta_1$  (compared with  $\beta_2$ ) reveals that the active mutual fund managers divest more firms with high climate change exposure in response to Paris Agreement. We find this is indeed the case as evidenced in Table 3.4. Specifically, Column (1) shows that active mutual funds reduce 0.020 % portfolio weight for a firm with high climate change exposure after Paris Agreement, while the reduction in portfolio weight is 0.006% among passive mutual funds. The findings regarding the three pillars of overall climate change exposure are also consistent as shown in Column (2) to (4). These results support the view that these climate-driven divestments reflect the proactive actions that mutual fund managers take to cater to investors' demands.

# [Insert Table 3.4 here]

Taken together, our baseline results indicate that fund managers do respond to climate change exposure of their holding firms after the Paris Agreement. More explicitly, these managers proactively reduce their portfolio weights for firms with high exposure to climate change, and these adjustments align with the Paris Agreement commitment to make "finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" (Article 2).

# 3.4.2 The role of climate regulations

The divestments on firms with high climate change exposure are primarily driven by climate change exposure related to technological opportunities (e.g., renewable energy) and physical threats (e.g., sea level rise) as documented in baseline results. In comparison, little evidence shows that regulatory climate change exposure influences the investment decisions of fund managers. This result may be counterintuitive since Paris Agreement should have raised the awareness of regulatory risks related to climate change. For instance, prior studies show the expectations of tighter climate regulations driven by Paris Agreement have significant impacts on banks' credit reallocation (e.g., Mueller and Sfrappini, 2022), carbon premiums (e.g., Bolton and Kacperczyk, 2023) and corporate bonds (e.g., Seltzer, Starks and Zhu, 2025)<sup>47</sup>. To interpret the

<sup>&</sup>lt;sup>47</sup> More specifically, Mueller and Sfrappini (2022) document that banks reallocate more credits to US firms with high climate change exposure while lending more to firms with low exposure in Europe after Paris Agreement. The results of Bolton and Kacperczyk (2023) indicate significant and large carbon premium after Paris Agreement. Additionally, Seltzer, Starks and Zhu (2025) reveal that corporate bonds issued by firms performing poorly in environmental issues prior to Paris Agreement experience a decrease in credit ratings and an increase in yield spreads.

insignificance regarding the regulatory climate change exposure and reconcile with existing literature, we focus on the stringency of climate regulations in the state where one portfolio firm is located in. In the US, there is rarely federal climate regulation, and these regulations vary across states. Since the Paris Agreement is a programmatic document establishing the overall targets to combat climate change, the real effects of the Agreement may rely on the tightness of local climate policies. For example, Choi, Park and Xu (2022) find that mutual funds respond to the changes in local climate regulations by rebalancing their portfolios. As such, we hypothesize that the divestments of mutual fund managers regarding portfolio firms' regulatory climate change exposure exist when portfolio firms reside in states with more stringent climate regulations. To measure the state-level stringency of climate policies, we adopt the enactment of GHG emission targets to limit state-wide carbon emissions. To achieve these emission targets, local governments may design more stringent climate policies to manage firms' carbon emissions, therefore posing a higher level of pressure on firms' climate actions.

# [Insert Table 3.5 here]

To examine whether the state-level GHG emission targets affect portfolio adjustments of fund managers depending on firms' climate change exposure, we collect the information on GHG emission targets from Center for Climate and Energy Solutions  $(C2ES)^{48}$  and repeat model (2) by replacing the variable *Active* with *GHGtarget*, which is a dummy variable taking the value of one if one state that the portfolio firm resides has enacted a GHG emission target prior to Paris Agreement. The parameter of interest is the coefficient of the triple-interaction term of *High* (*Firm*), *Post* and *GHGTarget*, reflecting whether and how fund managers adjust their portfolio holdings depending on firm-level climate change exposure following Paris Agreement if the portfolio firms are located in states with GHG emission targets. The regression results are presented in Table 3.5. As shown in Column (1), the loading on the triple-interaction term is -0.061,

<sup>&</sup>lt;sup>48</sup> See <u>https://www.c2es.org/document/greenhouse-gas-emissions-targets/</u> for more information.

with a *t*-statistic of -4.61, suggesting that fund managers divest more firms with high climate change exposure in states with GHG emission targets. Notably, consistent with our hypothesis, Column (3) reports that the coefficient of the triple-interaction term regarding regulatory climate change exposure is negative and significant, which indicates that fund managers divest firms highly exposed to regulatory climate change and located in states with GHG emission targets.

### 3.4.3 The role of funds pre-exposure

Next, we consider whether the fund-level exposure to climate change before Paris Agreement plays a role in adjusting fund weights in firms with high climate change exposure following Paris Agreement. The more exposed a fund is, the more its portfolio could be adversely affected if firms with high climate change exposure are divested, as this may threaten the price of its existing holdings. Consequently, a fund with high climate change exposure prior to the Agreement may overweight highly exposed firms to mitigate potential adverse effects. To investigate the effects of fund-level exposure to climate change, we first construct the variable of fund-level exposure by calculating the quarterly average value-weighted climate change exposure of all the portfolio firms prior to Paris Agreement. We then define those funds with above-median climate change exposure before the Agreement as high-exposure funds while funds with belowmedian measures are categorized as low-exposure ones.

### [Insert Table 3.6 here]

We follow the regression model (2) and incorporate a triple-interaction term of *High* (*Firm*), *Post*, and *High* (*Fund*). We tabulate the results in Table 3.6. In Column (1), the coefficient of the triple-interaction term is positive and significant at the 1% level, indicating funds with high portfolio exposure to climate change increase their holdings for highly exposed firms, revealing the negative effects of a firm's exposure on fund weight are primarily driven by funds with low exposure prior to the Paris Agreement. It may not be optimal for highly exposed funds to divest firms with high exposure, as

this may threaten the value of their existing holdings. In contrast, fund managers whose existing portfolios contain firms with low exposure can screen highly exposed firms to avoid the potential adverse implications of climate change after the Paris Agreement. When considering fund exposure to opportunity, regulatory, and physical exposure related to climate change, we find similar results, as shown in Columns (2), (3), and (4).

### 3.4.4 Heterogenous effects of salient industries

Bolton and Kacperczyk (2021) show that carbon emissions are highly concentrated in several specific industries (i.e., energy, utility, and transportation). As carbon emission tends to be an important metric for a firm's climate change exposure, the divestment effects of fund managers on firms with high climate change exposure that we document could be concentrated on specific industries with high climate change exposure. To explore this potential heterogeneity, we define salient industries as oil and gas, utility and transportation industries as per Bolton and Kacperczyk (2021), and repeat our baseline analysis except for dividing the sample into firms in salient and non-salient industries, respectively.

## [Insert Table 3.7 here]

The results are reported in Table 3.7. Panel A reports the results for firms from all industries but salient industries, while Panel B reports the results for firms from salient industries. As shown in Column (1), fund managers reduce their holdings for firms with high overall climate change exposure in both salient and non-salient industries. Notably, the coefficient of the interaction term is -0.021 and -0.032 for non-salient and salient industries, respectively. This indicates that the divestment effects of fund managers on highly exposed firms are stronger in salient industries, which is consistent with the investment strategies of institutional investors in recent years. Interestingly, fund managers increase their holdings for firms with high opportunity exposure in salient industries based on Column (2) of Panel B. One possible explanation is if firms in salient industries have potential opportunities regarding climate change, they are likely
to produce more green patents with the pressure from divestments of institutional investors (Cohen, Gurun and Nguyen, 2021). As green patent is a positive signal for firms to combat climate change, fund managers may respond to these positive actions by increasing their holdings for these firms. In addition, the divestment effects with respect to regulatory climate change exposure are only captured for firms in salient industries as shown in Column (3). Fund managers reduce the holdings for firms with high physical climate change exposure in both non-salient and salient industries based on Column (4).

Overall, our analysis based on non-salient and salient industries indicates that the divestment effects are, in general, stronger in salient industries. Moreover, fund managers tend to increase holdings for firms with potential opportunities for climate change in salient industries as prior studies show that these firms can produce more green patents.

# 3.4.5 Heterogenous effects of beliefs on climate change

Fund managers' trading behavior may depend on their beliefs about climate change<sup>49</sup>. During 2008 and 2013, Yale Project on Climate Change Communication and George Mason Center for Climate Change Communication conducted a comprehensive survey across US states to capture the public beliefs about climate change and created the Yale Climate Opinion Maps. In this survey, 63% of Americans believe that global warming is happening, but the state- and county-level estimates diverge, suggesting that people in different areas may have different beliefs about climate change<sup>50</sup>. These survey data are widely used in studies exploring the effects of climate change on real estate prices (e.g., Bernstein, Gustafson, Lewis, 2019; Baldauf, Garlappi, Yannelis, 2020). As fund managers can be influenced by local public views about climate change, the divestment effects may hinge on local attitudes towards climate change.

To proxy for the state-level public views about climate change, we adopt the state-

<sup>&</sup>lt;sup>49</sup> For example, Choi, Gao and Jiang (2020) document that people revise and increase their beliefs about climate change during abnormal warm weather and thus investors sell carbon-intensive firms.

<sup>&</sup>lt;sup>50</sup> For more details including survey questions and estimation methodology, see Howe, Mildenberger, Marlon and Leiserowitz (2015).

level measure showing the percentage of residents who agree that global warming is happening. We then calculate the median of this state-level measure and split our samples into two groups based on the median value. States with above-median proportion of local people who agree global warming is happening are defined as the high-belief group, indicating people in these states may have higher attention and beliefs on climate change, while the rest of the states are defined as the low-belief group. We postulate that the fund managers located in states with high beliefs on climate change are more likely to reduce fund weights for firms with high climate change exposure.

# [Insert Table 3.8 here]

To explore, we repeat the baseline regression in the subsamples containing different states and report the results in Table 3.8. Panel A tabulates the results for states with high beliefs and Panel B reports the results for low-belief states. We find little evidence that the divestment effects are stronger for the mutual funds headquartered in states with high climate change beliefs since both coefficients of the interaction terms regarding the overall climate change exposure are negative and significant, as evidenced in Column (1). However, Column (2) shows that the coefficient of the interaction term with respect to opportunity exposure is -0.037 and significant at the 1% level for the high group while the corresponding coefficient is not significant for the low group, which suggests that the divestment effects of fund managers based on opportunity climate change exposure are concentrated on states with high beliefs on climate change. Regarding the results of using the climate change exposure related to physical activities in Column (4), the loading on the interaction term is negative and significant at the 1% level for the high group, while the loading for the low group is not significant, indicating that only fund managers located in high-belief states underweight firms with high physical climate change exposure.

Taken together, the subsample analysis based on the beliefs on climate change across states shows that fund managers do not exhibit a significant difference in divesting high-exposure firms with respect to beliefs on climate change<sup>51</sup>.

# 3.4.6 Heterogenous effects of Obama and Trump Administration

Next, we explore the potential heterogeneity of fund managers' decisions during the Obama administration and after the election of former President Trump. On the one hand, the two former presidents likely have different beliefs, as Democrats are often considered to be more committed to curbing the effects of climate change. Consequently, divestment effects may be stronger during the Obama period. On the other hand, despite their heterogenous beliefs about climate change, climate regulation was lenient under Obama relative to Trump, as the Paris Agreement did not have any in-built enforcement mechanisms. Accordingly, the divestment effects may be stronger during the Trump administration.

We repeat the baseline analysis but exclude all observations after the fourth quarter of 2016, when Trump was elected. This enables us to isolate and compare the pre-and post-Paris Agreement periods under the Obama administration. The results are reported in Panel A of Table 3.9. Fund managers reduce portfolio weights in firms with higher exposure to climate change during the Obama administration, though the divestment effects are slightly weaker: the coefficient of the interaction term of *High* (*Firm*) × *Post* is -0.015 with a *t*-statistic of -3.14, compared to the corresponding estimate of -0.025 with a t-statistic of -4.66 in Column (1) of Table 3.3. The divestment effects are not statistically significant for regulatory or physical exposure: the *t*-statistics are -0.90 and -1.53, shown in Columns (3) and (4), respectively.

#### [Insert Table 3.9 here]

We consider the period after Trump's election by excluding the observations from the last quarter of 2015 to the third quarter of 2016. The results are reported in Panel B of Table 3.6. We find that fund managers prompt stronger divestment effects during the

<sup>&</sup>lt;sup>51</sup> One potential explanation for the insignificant difference of divestment actions regarding the fund managers' beliefs on climate change could be that the first-order focus of these fund managers is the stringency of climate regulations (as shown in section 3.4.2) rather than their subjective beliefs.

Trump administration. In Column (1), the coefficient of the interaction term of *High* and *Post* is -0.033 with a *t*-statistic of -5.11, while the corresponding coefficient during the Obama administration is -0.015 with a *t*-statistic of -3.14, suggesting that fund managers' divestments on firms highly exposed to climate change are stronger, in terms of magnitude, under the Trump administration. In Columns (2), (3), and (4), the estimated coefficients of the interaction term of *High* and *Post* are -0.045 with a *t*-statistic of -5.79, -0.013 with a *t*-statistic of -1.80, and -0.038 with a *t*-statistic of -4.15, respectively. This indicates that fund managers divest firms with high exposure to climate change issues related to opportunities, regulatory environment, and physical impact.<sup>52</sup> The above evidence is also consistent with the findings of Ramelli et al. (2021) concluding that investors expect the laxer climate policies under Trump administration are transitory and the regulations would be more stringent after Trump's presidency. In this case, they are willing to hold firms with low climate change exposure during this period.

# 3.4.7 How do firms respond to the reallocation of fund managers?

The direct consequences of fund managers' divestments on firms with high exposure to climate change are limited access to capital, and therefore lower valuation and higher cost of capital (e.g., Hong and Kacperczyk, 2009; Chava, 2014; Choi et al. 2021). Given the pressure stemming from fund managers' capital reallocation, a natural question is whether and how highly exposed firms respond to environmentally motivated fund managers' divestment actions. If firms care about their valuation and cost of capital, they should react to divestment actions by improving their environmental profile and reducing their exposure to climate change, thereby reducing the propensity and magnitude of fund managers' divestments<sup>53</sup>. As such, we expect that firms with high exposure to climate change to fund managers' divestments by improving their

<sup>&</sup>lt;sup>52</sup> We also find the baseline results hold before the United States' withdrawal announcement in the second quarter of 2017.

<sup>&</sup>lt;sup>53</sup> A strand of literature documents that firms respond to divestments of mutual funds due to environmental concerns by improving their environmental scores, reducing carbon emissions and toxic releases (e.g., Gantchev, Giannetti and Li, 2022; Rohleder, Wilkens and Zink, 2022; Heath et al., 2023).

environmental performance. To investigate, we conduct firm-level analysis and estimate the following model:

$$EnvP_{i,q+1} = \beta_1 High_i \times Post_q + \alpha_1 X_{i,q} + \zeta_i + \zeta_q + \varepsilon_{i,q}$$
(3)

The dependent variable is the measures of environmental performance in the subsequent quarter and the independent variable of interest is the interaction term between  $High_i$  and  $Post_q$ . Since this regression is conducted at firm level, we include a battery of firm-level controls, as well as the firm and year-quarter fixed effects.

#### [Insert Table 3.10 and 3.11 here]

Two measures are employed to proxy for environmental performance. The first one is firm-level environmental score collected from MSCI KLD databases. Given the concerns about ESG rating disagreement across different data providers (e.g., Berg, Kolbel and Rigobon, 2022), we adopt carbon emissions as an alternative measure for environmental performance. The results are reported in Table 3.10 and 3.11. As reported in Table 3.10, we find that firms with high climate change exposure improve their environmental scores in the following Paris Agreement as the coefficients of the interaction term are positive and significant except for the physical climate change exposure. Consistent with the notion that divested firms improve environmental performance, we find firms with high climate change exposure exhibit a lower level of carbon emissions post Paris Agreement<sup>54</sup>. Collectively, these findings corroborate the argument that the divestment of fund managers has discipline effects on firms' environmental performance as firms with high exposure to climate change take measures to address the climate change concerns in response to the divestments of fund managers in the context of Paris Agreement<sup>55</sup>.

<sup>&</sup>lt;sup>54</sup> It is worth noting that firms do not respond to physical climate change exposure as shown in both results of environmental scores and carbon emissions. One possible explanation may be that firms do not take physically climate risk into consideration as it may materialize over the long run (e.g., Stroebel and Wurgler, 2021) while Paris Agreement reflects the short-term climate concerns related to regulatory issues.

<sup>&</sup>lt;sup>55</sup> These findings also indicate that these mutual fund managers are less likely to engage in greenwashing activities since their divestment actions indeed help pollutive portfolio firms improve their green performance.

#### 3.5 Conclusion

The aim of this study is to investigate whether and how mutual fund managers adjust their portfolio holdings depending on portfolio firms' climate change exposure in response to Paris Agreement. We start with three competing hypotheses predicting three divergent responses of mutual fund managers. Relying on the firm-level climate change exposure measures constructed by Sautner et al. (2023) and a difference-in-difference approach, we find that fund managers underweight firms with high climate change exposure following the Paris Agreement. Further analysis comparing active and passive mutual funds supports the view that these divestment effects reflect the proactive actions of fund managers to incorporate climate change concerns into investment decisions. Next, we examine whether the variation regarding state-level climate policies affects our baseline results. Notably, we find that fund managers tend to divest more highly exposed firms located in states with GHG emission targets. More importantly, fund managers respond to the Paris Agreement by reducing the portfolio weights for firms with high climate change exposure related to regulatory issues only when these firms reside in states with more stringent climate regulations, which help us reconcile with prior studies. Moreover, the triple-interaction analysis regarding fund-level climate change exposure indicates that fund managers underweight firms with different climate change exposure, reflecting the importance of financial returns when fund managers rebalance their portfolio holdings.

We conduct various tests to examine the heterogenous effects of climate change exposure on fund managers' portfolio adjustments. First, we examine the different responses of fund managers when portfolio firms belong to salient industries (e.g., oil and gas), which are susceptible to climate change. Second, we explore whether fund managers' divestments vary with respect to their beliefs on climate change. Third, we investigate the different divestment effects under the Obama and Trump administration following the Paris Agreement. Finally, our firm-level analysis shows that the divestments of fund managers have some real effects on disciplining climate actions of firms. Specifically, we find that firms with high exposure to climate change improve their environmental scores and reduce carbon emissions following Paris Agreement.

To summarize, this study presents evidence that mutual fund managers take climate change concerns into account when making investment decisions. Their divestments on firms with high climate change exposure contribute to the transition to a low-carbon economy. Furthermore, their divestments have some real effects on firms' future climate practices, reflecting the discipline effects of mutual fund managers. Collectively, we find strong evidence that mutual fund managers contribute to the transition to a green economy.

It is worth noting that the awareness and attitudes of institutional investors toward climate change have changed in recent years. Azar et al. (2021) conclude that the "Big Three" (i.e., BlackRock, Vanguard, and State Street) play important roles in facilitating the transition to a low-carbon economy by disciplining pollutive firms in their portfolios to reduce carbon emissions. However, their attitudes toward climate change have become more negative in recent years. For example, BlackRock quit the climate change group in 2024, as reported by the Financial Times (2025). Building on this study, one potential future research question is to investigate the portfolio decisions of mutual fund managers in relation to firms' climate change exposure, particularly in response to these anti-climate actions which may influence their financial rewards<sup>56</sup>. That is, will fund managers become less responsive to portfolio firms' climate change exposure if they cease to pursue green goals?

<sup>&</sup>lt;sup>56</sup> Rajgopal, Srivastava and Zhao (2024) focus on the Texas anti-ESG sanctions in 2021 requiring statemanaged agencies to divest from green companies and funds. They find that those banned funds earn lower returns after the ban.

# Chapter 3 - Appendix A: Variable Definitions

| Variable                    | Definition   |  |  |  |  |
|-----------------------------|--|--|--|--|--|
| Climate change exposure van | riables (Sautner, van Lent, Vilkov and Zhang, 2023)  |  |  |  |  |
| Firm average CC exposure    | Average firm-level overall climate change exposure during 2011Q4–2015Q4 (i.e., the adoption of Paris Agreement)  |  |  |  |  |
| Firm average OP exposure    | Average firm-level climate change exposure related to opportunities during 2011Q4–2015Q4   |  |  |  |  |
| Firm average RG exposure    | Average firm-level climate change exposure related to regulatory shocks during 2011Q4–2015Q4   |  |  |  |  |
| Firm average PH exposure    | The average firm-level climate change exposure related to physical shocks during 2011Q4–2015Q4   |  |  |  |  |
| Fund average CC exposure    | Value-weighted average fund-level overall climate change<br>exposure based on portfolio weights for stocks during 2011Q4–<br>2015Q4  |  |  |  |  |
| Fund average OP exposure    | Value-weighted average fund-level climate change exposure<br>related to opportunities based on portfolio weights for stocks<br>during 2011Q4–2015Q4                                      |  |  |  |  |
| Fund average RG exposure    | Value-weighted average fund-level climate change exposure<br>related to regulatory shocks based on portfolio weights for<br>stocks during 2011O4–2015O4                                  |  |  |  |  |
| Fund average PH exposure    | Value-weighted average fund-level climate change exposure<br>related to physical shocks based on portfolio weights for stocks<br>during 2011Q4–2015Q4                                    |  |  |  |  |
| High (Firm)                 | Dummy variable that takes the value of one if firm <i>i</i> has an average value of climate change exposure above the median breakpoint prior to the Paris Agreement, and zero otherwise |  |  |  |  |
| High (Fund)                 | Dummy variable that takes the value of one if fund $f$ has an average value of climate change exposure above the median breakpoint prior to the Paris Agreement, and zero otherwise      |  |  |  |  |
| Fund-level variables (CRSP) | Mutual Fund and Thomson Reuter s12)  |  |  |  |  |
| Fund weight                 | Dollar value of firm <i>i</i> held by fund <i>j</i> scaled by total dollar value of fund <i>f</i> portfolio holdings   |  |  |  |  |
| Fund size                   | Natural logarithm of total net assets (TNA) of fund <i>j</i>   |  |  |  |  |
| Expense ratio               | Weighted-average expense ratio over all share classes of fund $j$  |  |  |  |  |
| Fund turnover               | Weighted-average turnover ratio over all share classes of fund $j$   |  |  |  |  |
| Fund return                 | Weighted-average quarter return over all share classes of fund $j$   |  |  |  |  |

| Fund flow                         | Quarterly growth of total net assets (TNA) net of reinvested                |
|-----------------------------------|---|
|                                   | returns. Specifically, it is calculated as $[TNA_{j, q} - (1 + Fund$        |
|                                   | $Returns) \times TNA_{j, q-1}] / TNA_{j, q-1}$                              |
| Active                            | A dummy variable which equals to one if the fund <i>j</i> is an actively    |
|                                   | managed fund, and zero otherwise  |
| <i>Firm-level variables</i> (CRSI | P, Compustat, C2ES, MSCI KLD and Refinitiv)                                 |
| Firm size                         | Natural logarithm of total market capitalization of firm <i>i</i> , where   |
|                                   | market capitalization is calculated as stock price multiply by              |
|                                   | shares out standing   |
| Book-to-market                    | Book value over market value of firm <i>i</i> , where book value is         |
|                                   | calculated as the book value of shareholders' equity plus balance           |
|                                   | sheet deferred taxes and investment tax credit (if available),              |
|                                   | minus the book value of the preferred stock (Fama and French,               |
|                                   | 1993).  |
| Prior-year return                 | Cumulative monthly return over the past 12 months of firm <i>i</i>          |
| GHGTarget                         | An indicator taking the value of one if the firm <i>i</i> is located in the |
|                                   | state with GHG emission targets   |
| KLD Env Score                     | The environmental pillar score of firm <i>i</i> , as recorded in MSCI       |
|                                   | KLD database  |
| Refinitiv CO2 emission            | The natural logarithm of scope1 and scope2 carbon emissions                 |
|                                   | of firm <i>i</i> , as recorded in Refinitiv Asset4 database                 |

# Table 3.1 Summary statistics

This table reports the descriptive statistics for fund-firm level measures, as well as fundand firm-level variables in our main analyses. The sample is 2011Q4–2019Q3. Panel A shows the summary statistics of fund-firm level variables, including portfolio weight of a stock in a fund, number of shares (in millions) of one firm held by one fund, and dollar value (in millions) of one firm held by one fund. Panel B reports statistics of firm-level measures, including a firm's average overall and three sub climate change exposures pre-Paris Agreement. Fund-level variables are reported in Panel C. Detailed definitions of all variables are provided in the appendix.

|                              | Mean         | SD            | Median     | P25    | P75   |
|------------------------------|--------------|---------------|------------|--------|-------|
| Pa                           | nel A Fund-f | ĩrm level (N= | 4,221,254) |        |       |
| Fund weight (%)              | 1.031        | 1.629         | 0.516      | 0.092  | 1.422 |
| Number of shares (Mil)       | 0.318        | 1.460         | 0.036      | 0.007  | 0.180 |
| Dollar value of shares (Mil) | 17.136       | 90.869        | 1.608      | 0.274  | 8.690 |
|                              | Panel B Fir  | rm level (N = | 55,117)    |        |       |
| Firm average CC exposure     | 0.855        | 1.991         | 0.292      | 0.157  | 0.695 |
| Firm average OP exposure     | 0.309        | 0.958         | 0.079      | 0.024  | 0.205 |
| Firm average RG exposure     | 0.039        | 0.201         | 0.000      | 0.000  | 0.016 |
| Firm average PH exposure     | 0.013        | 0.072         | 0.000      | 0.000  | 0.000 |
| Firm size                    | 7.319        | 1.826         | 7.212      | 6.099  | 8.409 |
| Book-to-market               | 0.597        | 0.590         | 0.470      | 0.265  | 0.770 |
| Prior-year return            | 0.140        | 0.485         | 0.099      | -0.119 | 0.324 |
|                              | Panel C Fu   | nd level (N = | 44,428)    |        |       |
| Fund average CC exposure     | 0.802        | 0.698         | 0.685      | 0.509  | 0.899 |
| Fund average OP exposure     | 0.287        | 0.312         | 0.234      | 0.169  | 0.319 |
| Fund average RG exposure     | 0.036        | 0.042         | 0.028      | 0.017  | 0.043 |
| Fund average PH exposure     | 0.011        | 0.008         | 0.009      | 0.006  | 0.013 |
| Fund size                    | 6.001        | 1.998         | 6.120      | 4.625  | 7.405 |
| Fund turnover                | 0.622        | 0.717         | 0.470      | 0.260  | 0.780 |
| Expense ratio                | 0.011        | 0.004         | 0.010      | 0.009  | 0.013 |
| Fund return                  | 0.033        | 0.069         | 0.036      | 0.003  | 0.070 |
| Fund flow                    | -0.010       | 0.110         | -0.018     | -0.045 | 0.011 |

Table 3.2 High- and low-exposure sample: Parallel trends pre-Paris Agreement This table reports the mean and standard deviation of different variables related to high and low pre-shock climate change exposure. Panel A reports statistics of fund-firm level variables. The statistics of firm- and fund-level variables are presented in Panels B and C, respectively. All means and standard deviations are calculated over the pre-Paris Agreement period (2011Q4–2015Q3). The normalized difference, calculated as the gap between the average values of different characteristics for low-exposure and highexposure firms, is shown in the last column.

|                              | Low exposure |             | High exposure |        | Norm Diff |  |
|------------------------------|--------------|-------------|---------------|--------|-----------|--|
|                              | Mean         | SD          | Mean          | SD     | Low- High |  |
|                              | Par          | nel A Fund- | firm level    |        |           |  |
| Fund weight (%)              | 1.016        | 1.384       | 1.063         | 1.760  | -0.030    |  |
| Number of shares (Mil)       | 0.326        | 1.531       | 0.314         | 1.379  | 0.008     |  |
| Dollar value of shares (Mil) | 14.962       | 73.434      | 14.532        | 69.011 | 0.006     |  |
| Panel B Firm level           |              |             |               |        |           |  |
| Firm size                    | 8.542        | 1.819       | 8.633         | 1.791  | -0.051    |  |
| Book-to-market               | 0.548        | 0.479       | 0.551         | 0.390  | -0.009    |  |
| Prior-year return            | 0.228        | 0.407       | 0.184         | 0.380  | 0.111     |  |
|                              | F            | Panel C Fur | nd level      |        |           |  |
| Fund size                    | 6.238        | 1.918       | 6.230         | 1.921  | 0.004     |  |
| Fund turnover                | 0.606        | 0.665       | 0.584         | 0.668  | 0.032     |  |
| Expense ratio                | 0.009        | 0.004       | 0.009         | 0.004  | 0.010     |  |
| Fund return                  | 0.038        | 0.066       | 0.039         | 0.066  | -0.006    |  |
| Fund flow                    | 0.001        | 0.109       | -0.001        | 0.107  | 0.017     |  |

Table 3.3 Baseline results: Fund portfolio weights and firm climate change exposure

This table presents the regression results of baseline model (1), exploring whether and how fund managers adjust their holdings based on portfolio firms' climate change exposure post Paris Agreement. The sample period is 2011Q4-2019Q3. The dependent variable is *fund weight*. The primary independent variable is the interaction term of *High (Firm)* and *Post*. Other firm- and fund-level control variables are included. In Column (1), high- and low-exposure firms are defined based on overall climate change (CC) exposure. Firms are classified based on three components of overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) – (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for fund-firm and year-quarter fixed effects. Standard errors are clustered at fund level. *t*-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                    | Dependent variable: Fund weight (q+1) |             |             |             |
|--------------------|---------------------------------------|-------------|-------------|-------------|
|                    | CC exposure                           | OP exposure | RG exposure | PH exposure |
|                    | (1)                                   | (2)         | (3)         | (4)         |
| High (Firm) x Post | -0.025***                             | -0.034***   | -0.009      | -0.025***   |
|                    | (-4.66)                               | (-5.57)     | (-1.54)     | (-3.51)     |
| Firm size          | 0.300***                              | 0.300***    | 0.301***    | 0.301***    |
|                    | (13.59)                               | (13.59)     | (13.59)     | (13.59)     |
| Book-to-market     | 0.024***                              | 0.025***    | 0.024***    | 0.024***    |
|                    | (4.59)                                | (4.63)      | (4.51)      | (4.57)      |
| Prior-year return  | 0.045***                              | 0.045***    | 0.044***    | 0.044***    |
|                    | (10.84)                               | (10.93)     | (10.73)     | (10.60)     |
| Fund size          | -0.047***                             | -0.047***   | -0.047***   | -0.047***   |
|                    | (-6.00)                               | (-6.00)     | (-6.01)     | (-5.99)     |
| Expense ratio      | 1.951                                 | 1.964       | 1.915       | 1.937       |
|                    | (0.74)                                | (0.74)      | (0.72)      | (0.73)      |
| Fund turnover      | 0.014                                 | 0.014       | 0.014       | 0.014       |
|                    | (1.06)                                | (1.05)      | (1.05)      | (1.06)      |
| Fund return        | -0.155***                             | -0.155***   | -0.156***   | -0.156***   |
|                    | (-4.20)                               | (-4.19)     | (-4.22)     | (-4.22)     |
| Fund flow          | -0.013                                | -0.013      | -0.013      | -0.014      |
|                    | (-1.22)                               | (-1.21)     | (-1.23)     | (-1.24)     |
| Fund-firm FEs      | YES                                   | YES         | YES         | YES         |
| Year-quarter FEs   | YES                                   | YES         | YES         | YES         |
| Adj R2             | 0.870                                 | 0.870       | 0.870       | 0.870       |
| Ν                  | 3,355,208                             | 3,355,208   | 3,355,208   | 3,355,208   |

#### Table 3.4 Baseline Results: Active versus Passive Funds

This table presents the regression results of model (2), which examines whether and how fund managers of active and passive equity mutual funds perform differently in adjusting their holdings based on portfolio firms' climate change exposure post Paris Agreement. The sample aggregates active and passive domestic mutual funds, spanning from 2011Q4 to 2019Q3. The dependent variable is *fund weight*. The primary independent variable is the triple-interaction term of *High (Firm)*, *Post*, and *Active*, which is a binary variable taking the value of one if the fund is defined as active fund, and zero otherwise. Other firm- and fund-level control variables are included. In Column (1), high- and low-exposure firms are defined based on overall climate change (CC) exposure. Firms are classified based on three components of overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) - (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for fund-firm and year-quarter fixed effects. Standard errors are clustered at fund level. t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                             | Dependent variable: Fund weight (q+1) |           |           |           |  |  |
|-----------------------------|---------------------------------------|-----------|-----------|-----------|--|--|
|                             | CC                                    | OP        | RG        | PH        |  |  |
|                             | exposure                              | exposure  | exposure  | exposure  |  |  |
|                             | (1)                                   | (2)       | (3)       | (4)       |  |  |
| High (Firm) x Post x Active | -0.020***                             | -0.023*** | -0.008    | -0.023*** |  |  |
|                             | (-3.39)                               | (-3.06)   | (-1.29)   | (-2.99)   |  |  |
| High (Firm) x Post          | -0.006***                             | -0.015*** | -0.002    | -0.004*   |  |  |
|                             | (-3.28)                               | (-5.01)   | (-1.19)   | (-1.89)   |  |  |
| Active x Post               | 0.012*                                | 0.013**   | 0.004     | 0.006     |  |  |
|                             | (1.92)                                | (2.04)    | (0.63)    | (0.96)    |  |  |
| Controls                    | YES                                   | YES       | YES       | YES       |  |  |
| Fund-firm FEs               | YES                                   | YES       | YES       | YES       |  |  |
| Year-quarter FEs            | YES                                   | YES       | YES       | YES       |  |  |
| Adj R2                      | 0.880                                 | 0.880     | 0.880     | 0.880     |  |  |
| Ν                           | 4,458,059                             | 4,458,059 | 4,458,059 | 4,458,059 |  |  |

Table 3.5 The effects of environmental regulation stringency of portfolio firms

This table presents the regression results examining whether and how the environmentally regulatory stringency of portfolio firms influences portfolio adjustments of fund managers based on these firms' climate change exposure post-Paris Agreement. The sample spans from 2011Q4 to 2019Q3. The dependent variable is *fund weight*. The primary independent variable is the triple-interaction term of *High (Firm)*, *Post*, and *GHGTarget*, which is a binary variable taking the value of one if the portfolio firm is located in a state adopting a statutory or executive GHG emission target to limit carbon emission before Paris Agreement, and zero otherwise. In Column (1), high- and low-exposure firms are defined based on overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) - (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for fund-firm and year-quarter fixed effects. Standard errors are clustered at fund level. *t*-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                                | Dependent variable: Fund weight (q+1) |             |             |             |  |
|--------------------------------|---------------------------------------|-------------|-------------|-------------|--|
|                                | CC exposure                           | OP exposure | RG exposure | PH exposure |  |
|                                | (1)                                   | (2)         | (3)         | (4)         |  |
| High (Firm) x Post x GHGTarget | -0.061***                             | -0.109***   | -0.039***   | -0.025**    |  |
|                                | (-4.61)                               | (-7.70)     | (-2.78)     | (-2.37)     |  |
| High (Firm) x Post             | 0.030**                               | 0.062***    | 0.026**     | -0.003      |  |
|                                | (2.50)                                | (4.93)      | (2.02)      | (-0.18)     |  |
| GHGTarget x Post               | 0.055***                              | 0.077***    | 0.036***    | 0.028***    |  |
|                                | (5.62)                                | (7.67)      | (4.63)      | (3.60)      |  |
| Fund-firm FEs                  | YES                                   | YES         | YES         | YES         |  |
| Year-quarter FEs               | YES                                   | YES         | YES         | YES         |  |
| Adj R2                         | 0.870                                 | 0.870       | 0.870       | 0.870       |  |
| Ν                              | 3,355,208                             | 3,355,208   | 3,355,208   | 3,355,208   |  |

#### Table 3.6 The effects of fund-level climate risk exposure

This table presents the regression results investigating whether and how fund managers with different fund-level exposures perform differently after adjusting their holdings post-Paris Agreement. The sample is 2011Q4–2019Q3. The dependent variable is *fund weight*. The primary independent variable is the interaction term of *High (Firm)*, *Post*, and *High (Fund)*. Other firm- and fund-level control variables are included. In Column (1), high- and low-exposure firms are defined based on overall climate change exposure. Firms are classified based on three components of overall climate change exposure in Columns (2) – (4). The detailed variable definitions are presented in Appendix A. All regressions control for fund-firm and year-quarter fixed effects. Standard errors are clustered at fund level. *t*-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                                  | Dependent variable: Fund weight (q+1) |             |             |             |  |
|----------------------------------|---------------------------------------|-------------|-------------|-------------|--|
|                                  | CC exposure                           | OP exposure | RG exposure | PH exposure |  |
|                                  | (1)                                   | (2)         | (3)         | (4)         |  |
| High (Firm) x Post x High (Fund) | 0.051***                              | 0.103***    | 0.048***    | 0.002       |  |
|                                  | (3.88)                                | (6.12)      | (3.53)      | (0.16)      |  |
| High (Firm) x Post               | -0.061***                             | -0.107***   | -0.043***   | -0.028**    |  |
|                                  | (-5.16)                               | (-6.61)     | (-3.71)     | (-2.29)     |  |
| High (Fund) x Post               | 0.010                                 | -0.003      | 0.012       | 0.022*      |  |
|                                  | (0.76)                                | (-0.21)     | (0.99)      | (1.93)      |  |
| Controls                         | YES                                   | YES         | YES         | YES         |  |
| Fund-firm FEs                    | YES                                   | YES         | YES         | YES         |  |
| Year-quarter FEs                 | YES                                   | YES         | YES         | YES         |  |
| Adj R2                           | 0.871                                 | 0.871       | 0.871       | 0.871       |  |
| Ν                                | 3,355,208                             | 3,355,208   | 3,355,208   | 3,355,208   |  |

#### Table 3.7 All-but-salient and salient industries

This table presents the regression results of baseline model (1) in two subsamples depending on whether portfolio firms belong to salient industries that are sensitive to climate change. The sample period is 2011Q4-2019Q3. The dependent variable is *fund weight*. The primary independent variable is the interaction term of *High (Firm)* and *Post*. Other firm- and fund-level control variables are included. We define salient industries as oil and gas, utilities, and transportation industries. Panel A reports the results after excluding firms from these salient industries, while Panel B reports the results for salient industries. In Column (1), high- and low-exposure firms are defined based on overall climate change (CC) exposure. Firms are classified based on three components of overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) – (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for fund-firm and year-quarter fixed effects. Standard errors are clustered at fund level. *t*-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                    | Dependent variable: Fund weight (q+1) |                    |             |             |  |
|--------------------|---------------------------------------|--------------------|-------------|-------------|--|
|                    | CC exposure                           | OP exposure        | RG exposure | PH exposure |  |
|                    | (1)                                   | (2)                | (3)         | (4)         |  |
|                    | Panel A Al                            | l-but-salient indu | istries     |             |  |
| High (Firm) x Post | -0.021***                             | -0.041***          | 0.000       | -0.017**    |  |
|                    | (-3.77)                               | (-6.09)            | (0.07)      | (-2.06)     |  |
| Controls           | YES                                   | YES                | YES         | YES         |  |
| Fund-firm FEs      | YES                                   | YES                | YES         | YES         |  |
| Year-quarter FEs   | YES                                   | YES                | YES         | YES         |  |
| Adj R2             | 0.872                                 | 0.872              | 0.872       | 0.872       |  |
| Ν                  | 2,954,076                             | 2,954,076          | 2,954,076   | 2,954,076   |  |
|                    | Panel E                               | 3 Salient industri | es          |             |  |
| High (Firm) x Post | -0.032**                              | 0.047***           | -0.030*     | -0.047***   |  |
|                    | (-2.07)                               | (3.05)             | (-1.82)     | (-3.39)     |  |
| Controls           | YES                                   | YES                | YES         | YES         |  |
| Fund-firm FEs      | YES                                   | YES                | YES         | YES         |  |
| Year-quarter FEs   | YES                                   | YES                | YES         | YES         |  |
| Adj R2             | 0.857                                 | 0.857              | 0.857       | 0.857       |  |
| Ν                  | 400,419                               | 400,419            | 400,419     | 400,419     |  |

#### Table 3.8 High and low climate change beliefs

This table presents the regression results of baseline model (1) in two subsamples depending on whether the headquarter of the mutual fund is located in a state with high climate change beliefs. The sample period is 2011Q4-2019Q3. The dependent variable is *fund weight*. The primary independent variable is the interaction term of *High (Firm)* and Post. Other firm- and fund-level control variables are included. We define the states with high climate change belief as those states having above-median measure on the percentage of residents who are conscious of climate change. Panel A reports the results for mutual funds in high-belief states, while Panel B reports the results in low-belief states. In Column (1), high- and low-exposure firms are defined based on overall climate change (CC) exposure. Firms are classified based on three components of overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) - (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for fund-firm and yearquarter fixed effects. Standard errors are clustered at fund level. t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                    | Dependent variable: Fund weight (q+1) |                     |             |             |  |  |  |
|--------------------|---------------------------------------|---------------------|-------------|-------------|--|--|--|
|                    | CC exposure                           | OP exposure         | RG exposure | PH exposure |  |  |  |
|                    | (1)                                   | (2)                 | (3)         | (4)         |  |  |  |
|                    | Pane                                  | Panel A High belief |             |             |  |  |  |
| High (Firm) x Post | -0.024***                             | -0.037***           | -0.008      | -0.028***   |  |  |  |
|                    | (-4.13)                               | (-5.30)             | (-1.21)     | (-3.42)     |  |  |  |
| Controls           | YES                                   | YES                 | YES         | YES         |  |  |  |
| Fund-firm FEs      | YES                                   | YES                 | YES         | YES         |  |  |  |
| Year-quarter FEs   | YES                                   | YES                 | YES         | YES         |  |  |  |
| Adj R2             | 0.871                                 | 0.871               | 0.871       | 0.871       |  |  |  |
| Ν                  | 2,728,205                             | 2,728,205           | 2,728,205   | 2,728,205   |  |  |  |
|                    | Pane                                  | el B Low belief     |             |             |  |  |  |
| High (Firm) x Post | -0.024**                              | -0.020              | -0.012      | -0.012      |  |  |  |
|                    | (-2.22)                               | (-1.60)             | (-1.29)     | (-0.86)     |  |  |  |
| Controls           | YES                                   | YES                 | YES         | YES         |  |  |  |
| Fund-firm FEs      | YES                                   | YES                 | YES         | YES         |  |  |  |
| Year-quarter FEs   | YES                                   | YES                 | YES         | YES         |  |  |  |
| Adj R2             | 0.870                                 | 0.870               | 0.870       | 0.870       |  |  |  |
| Ν                  | 623,149                               | 623,149             | 623,149     | 623,149     |  |  |  |

#### Table 3.9 Obama Administration and Trump Administration

This table presents the regression results of baseline model (1) in two subsamples during the periods under administration of Obama and Trump post Paris Agreement. The post-Paris Agreement sample period is divided into the Obama administration period (i.e., 2015Q4-2016Q3) and Trump administration period (i.e., 2016Q4-2019Q3). Panel A reports the results during Obama administration period, while the results regarding Trump administration period is presented in Panel B. The dependent variable is *fund weight*. The primary independent variable is the interaction term of High (Firm) and Post. Other firm- and fund-level control variables are included. In Column (1), high- and low-exposure firms are defined based on overall climate change (CC) exposure. Firms are classified based on three components of overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) - (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for fund-firm and year-quarter fixed effects. Standard errors are clustered at fund level. t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                    | Dependent variable: Fund weight (q+1) |                 |             |             |  |
|--------------------|---------------------------------------|-----------------|-------------|-------------|--|
|                    | CC exposure                           | OP exposure     | RG exposure | PH exposure |  |
|                    | (1)                                   | (2)             | (3)         | (4)         |  |
|                    | Panel A Ol                            | oama Administra | ation       |             |  |
| High (Firm) x Post | -0.015***                             | -0.019***       | -0.005      | -0.009      |  |
|                    | (-3.14)                               | (-3.95)         | (-0.90)     | (-1.53)     |  |
| Controls           | YES                                   | YES             | YES         | YES         |  |
| Fund-firm FEs      | YES                                   | YES             | YES         | YES         |  |
| Year-quarter FEs   | YES                                   | YES             | YES         | YES         |  |
| Adj R2             | 0.884                                 | 0.884           | 0.884       | 0.884       |  |
| Ν                  | 2,307,606                             | 2,307,606       | 2,307,606   | 2,307,606   |  |
|                    | Panel B Tr                            | rump Administra | tion        |             |  |
| High (Firm) x Post | -0.033***                             | -0.045***       | -0.013*     | -0.038***   |  |
|                    | (-5.11)                               | (-5.79)         | (-1.80)     | (-4.15)     |  |
| Controls           | YES                                   | YES             | YES         | YES         |  |
| Fund-firm FEs      | YES                                   | YES             | YES         | YES         |  |
| Year-quarter FEs   | YES                                   | YES             | YES         | YES         |  |
| Adj R2             | 0.868                                 | 0.868           | 0.868       | 0.868       |  |
| Ν                  | 2,887,033                             | 2,887,033       | 2,887,033   | 2,887,033   |  |

#### Table 3.10 Firm Response – Environmental Score

This table presents the results of firm-level analysis investigating whether and how climate change exposure influences the firms' environmental performance post Paris Agreement. The sample period is 2011Q4–2019Q3. The dependent variable is MSCI KLD environmental score, and the key independent variable of interest is the interaction term of *High (Firm)* and *Post*. Other firm- level control variables are included. In Column (1), high- and low-exposure firms are defined based on overall climate change (CC) exposure. Firms are classified based on three components of overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) – (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for firm and year-quarter fixed effects. Standard errors are clustered at fund level. *t*-statistics are reported in parentheses. \*\*\*, \*\*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                     | Dependent variable: KLD Env Score (q+1) |          |             |             |  |
|---------------------|---|----------|-------------|-------------|--|
|                     | CC exposure OP exposure RG exposure     |          | RG exposure | PH exposure |  |
|                     | (1)                                     | (2)      | (3)         | (4)         |  |
| High (Firm) x Post  | 0.015***                                | 0.010*** | 0.020***    | 0.003       |  |
|                     | (5.51)                                  | (3.68)   | (5.38)      | (0.68)      |  |
| Firm-level controls | YES                                     | YES      | YES         | YES         |  |
| Firm FE             | YES                                     | YES      | YES         | YES         |  |
| Year-quarter FEs    | YES                                     | YES      | YES         | YES         |  |
| Adj R2              | 0.679                                   | 0.678    | 0.680       | 0.676       |  |
| Ν                   | 40,749                                  | 40,749   | 40,749      | 40,749      |  |

#### Table 3.11 Firm Response - Carbon Emissions

This table presents the results of firm-level analysis investigating whether and how climate change exposure influences the firms' carbon emissions post Paris Agreement. The sample period is 2011Q4–2019Q3. The dependent variable is natural logarithm of Refinitiv carbon emissions, and the key independent variable of interest is the interaction term of *High (Firm)* and *Post*. Other firm- level control variables are included. In Column (1), high- and low-exposure firms are defined based on overall climate change (CC) exposure. Firms are classified based on three components of overall climate change exposures, related to opportunities (OP), regulatory shocks (RG) and physical shocks (PH), in Columns (2) – (4), respectively. The detailed variable definitions are presented in Appendix A. All regressions control for firm and year-quarter fixed effects. Standard errors are clustered at fund level. *t*-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                     | Dependent variable: Refinitiv CO2 emission (q+1) |             |             |             |
|---------------------|--|-------------|-------------|-------------|
|                     | CC exposure                                      | OP exposure | RG exposure | PH exposure |
|                     | (1)  | (2)         | (3)         | (4)         |
| High (Firm) x Post  | -0.649***  | -0.568***   | -1.030***   | -0.680      |
|                     | (-2.51)  | (-2.28)     | (-3.04)     | (-1.40)     |
| Firm-level controls | YES  | YES         | YES         | YES         |
| Firm FE             | YES  | YES         | YES         | YES         |
| Year-quarter FEs    | YES  | YES         | YES         | YES         |
| Adj R2              | 0.980  | 0.980       | 0.980       | 0.980       |
| Ν                   | 11,370   | 11,370      | 11,370      | 11,370      |

# Chapter 4: The (Unintended) Consequences of Strategic Disclosure on Green Transition: Evidence from Supply Chain

**Abstract**: Customer firms strategically disclose relationships with environmentally responsible suppliers while concealing associations with less sustainable suppliers. We demonstrate that this green-induced nondisclosure for unsustainable suppliers hinders the green transition of supply chains by deterring the positive influence that customer firms can exert on their suppliers' environmental performance. Notably, customer firms achieve improved environmental performance at the expense of their suppliers' environmental profiles. To establish causality, we adopt the enactment of greenhouse gas (GHG) emission targets across US states and the implementation of GHG emission trading systems across regions and countries as regulatory shocks. Our cross-sectional analyses show that our baseline results vary regarding three types of common stakeholders, suppliers' environmental pressure, and financial constraints of customer firms. Moreover, we explore the real effects of such strategic disclosure, showing that customers outsource carbon emissions to hidden suppliers. Overall, these findings provide critical insights into the consequences of strategic disclosure and its implications for supply chain sustainability management.

#### 4.1 Introduction

Global transition to a green economy is imperative to address climate change and achieve sustainable goals as laid out by the Paris Agreement. The green transition does not rely solely on government's efforts to make green policy frameworks, create market mechanisms, and incentivize low-carbon practices <sup>57</sup>. It also requires inclusive stakeholder engagement, especially the participation of corporations to reduce carbon emissions and output green innovations.

Supply chain management plays a crucial role in the green transition of corporations. First, the majority of a company's environmental footprint arises from the supply chain. Notably, McKinsey has estimated that the carbon emissions stemming from the supply chain (Scope 3 emission) accounts for approximately 90% of a company's total emissions<sup>58</sup>. Second, firms tend to experience non-compliance scrutiny and penalties since increasingly stringent regulations may threaten the unsustainable supply chain<sup>59</sup>. Third, firms may experience a deterioration in operating and stock performance due to the poor management of sustainability in supply chain (e.g., Jabos and Singhal, 2020; Pankratz and Schiller, 2023; Lin et al. 2024). Anecdotal evidence highlights a variety of strategies that firms adopt to establish a green supply chain. For example, BMW group has committed to conducting multistage due diligence process and launching preventive and remediation measures for unsustainable suppliers<sup>60</sup>. Besides, a growing body of research shows the influence that firms exert on their suppliers for better CSR practices (e.g., Schiller, 2018; Dai, Liang and Ng, 2021; Darendeli et al. 2022).

<sup>&</sup>lt;sup>57</sup> Examples of government's efforts for green transition may include imposing carbon tax (e.g., Martinsson et al., 2024), establishing carbon emission trading system (e.g., Bai and Ru, 2024), and taking environmental performance into consideration when allocating governments' procurement contracts (e.g., Flammer, 2018; Kim et al. 2024).

<sup>&</sup>lt;sup>58</sup> For more details, see <u>https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-are-scope-1-2-and-3-emissions</u>.

<sup>&</sup>lt;sup>59</sup> SEC enhanced the climate-related disclosures for investors, requiring firms to disclose material climate-related information of their suppliers' activities. See <u>https://www.sec.gov/rules-regulations/2024/03/s7-10-22</u> for more details.

<sup>&</sup>lt;sup>60</sup> See https://www.bmwgroup.com/en/sustainability/supply-chain.html.

Nevertheless, many firms choose to shirk their obligations for green transition and transfer environmental risks to supplier firms. Prior studies document that firms may outsource their pollution to suppliers in other states or countries, particularly when facing tightened environmental policies (e.g., Dai et al., 2024; Bartram, Hou and Kim, 2022; Duchin, Gao and Xu, 2024). One alternative strategy to avoid responsibility is selectively establishing relationships with suppliers from weaker environmental regulation enforcement (Lu et al., 2023). These green obligation evasion behaviors of firms can have negative impacts on the sustainability of supply chain and, consequently, impede the transition to green economy. In this paper, we focus on strategic disclosure of firms caused by their suppliers' environmental profiles and investigate whether and how this green-induced strategic disclosure behavior influences green transition in supply chain.

Current reporting regulations for supply chain disclosure may exacerbate the actions that firms evade and transfer green responsibility. More explicitly, existing supply chain disclosure regulations emphasize relationships with downstream customers, and it is not mandatory for firms to disclose the information of their suppliers, as required by accounting standards<sup>61</sup>. Given the voluntary disclosure requirements, Shi et al. (2023) find that customer firms tend to intentionally reveal the connections with environmentally good suppliers while hiding the relationships with environmentally bad suppliers, aiming to create a deceptive green image for investors and customers.

This strategic disclosure impairs the transparency of firms' environmental profiles and therefore intensifies the green information asymmetry, preventing stakeholders from checking unsustainable practices through supply chain. Thus, the stakeholders' perceptions of sustainability progress are distorted and they cannot direct the funds

<sup>&</sup>lt;sup>61</sup> In the US, previous accounting standards, such as SFAS 14 and SFAS 131, usually require that public firms disclose the information of major customers (i.e., contributing 10% or above to revenues) and the extent of dependence on these customers in their annual reports. However, SEC amended the regulatory framework (S-K regulation) in 2020 and eliminated the 10% reporting line. Instead, firms should disclose customer information which is material to an understanding of company's business. As there is no specific or quantitative definition of "material", firms still have discretion in disclosure approach.

flows to green businesses<sup>62</sup>. Most importantly, the lack of mandatory disclosure of supplier information enables firms to avoid investigations by stakeholders and regulators and keep them innocent from collaborating with less sustainable suppliers, leading to weaker incentives to helping environmentally bad suppliers improve their performance. Instead, they may even transfer environmental risk to hidden suppliers without being punished by stakeholders and regulators. As a result, we postulate that the green-induced strategic disclosure of customer firms impedes the green transition of supply chain.

We adopt two primary global databases to conduct baseline empirical analysis. First, we use FactSet Revere database providing firm-level supply chain data, which enables us to identify whether a customer firm voluntarily discloses or selectively conceals the relationship with a specific supplier. Second, we collect firm-level environmental performance indicators from Refinitiv Asset 4 ESG database. After combining these two databases and adding a variety of firm and country-level control variables from WorldScope and WorldBank, our final sample includes 132,942 supplier-customer pairs, comprising over 390,000 yearly supplier-customer observations from 2003 to 2023.

We construct an indicator for green-induced strategic disclosure by considering whether a supplier firm is concealed by the customer and whether the supplier firm exhibits bad environmental performance. More specifically, supplier firms are sorted each year based on their environmental score and those firms below the thirtieth percentile are defined as unsustainable suppliers. We then construct a dummy, *greeninduced nondisclosure*, which equals one if a supplier is hidden by customers and unsustainable. Intuitively, this measure can rule out the possibility of undisclosed customer-supplier relationships due to other factors such as geopolitical and operational concerns, which are irrelevant to the environmental performance of supplier firms.

Our main analysis focuses on whether the green-induced nondisclosure terminates

<sup>&</sup>lt;sup>62</sup> Institutional investors, financial intermediaries and customers play pivotal roles in steering capital flows to green economy. For example, see Krueger, Sautner, Starks, 2020; Houston and Shan, 2021; Meier et al., 2023.

and even reverses the positive unilateral impacts of customers on suppliers' environmental performance documented by Dai, Liang and Ng (2021). If so, do customers transfer the environmental risk to unsustainable suppliers and enjoy improvements in environmental profile at the expense of suppliers' sustainability? Relying on the large sample of customer-supplier relationships, we find that the positive relation between the environmental performance of customers and suppliers disappears when customers withhold supplier information due to its poor environmental performance. Intriguingly, we find a negative relation between the environmental performance of customers and suppliers under the green-induced nondisclosure, suggesting that customers may evade obligations and transfer their environmental risk to suppliers. To reinforce the argument that the green-induced nondisclosure serves as a tool for customers' green obligation evasion, we examine whether the behavior that customers voluntarily disclose unsustainable suppliers enhances the positive effects of customers' green practices on suppliers' environmental performance. The rationale is that customer firms are more likely to commit to supporting the green practices for unsustainable supplier firms when they choose to unveil these relationships. As a result, we hypothesize an unchanged or even stronger relation between customers' and suppliers' environmental scores. Indeed, empirical findings confirm this expectation.

Next, we disentangle whether the negative relation between the environmental score of customers and suppliers caused by green-induced nondisclosure can be interpreted as that customers experience improved environmental performance at the expense of suppliers' sustainability. The negative relation may be also consistent with the notion that customers sacrifice their own environmental profiles to support the promotion of unsustainable suppliers' environmental performance, which can be beneficial to the green transition in the supply chain. To explore, we calculate the change of suppliers' and customers' environmental score and test the effects of green-induced nondisclosure on the changes in environmental score. Unsurprisingly, we demonstrate a negative relation between green-induced nondisclosure and change in suppliers' environmental scores, whereas the relation is positive when considering the

customers' environmental score change. Obviously, this evidence supports the view of green obligation evasion for customer firms. In addition, we aggregate the changes of suppliers' and customers' environmental score, aiming to investigate whether the green-induced nondisclosure leads to an aggregated deterioration in environmental scores of suppliers and customers<sup>63</sup>. We show that the overall changes in environmental scores of the supply chain are negatively related to green-induced nondisclosure, suggesting an obstacle for green transition of the supply chain.

Given the reluctance of customer firms to support the green development of hidden unsustainable suppliers, we explore whether the customer-supplier links are more likely to be terminated when customer firms opt for concealing the information for unsustainable suppliers. Firms may terminate existing supply-chain links when perceiving heightened environmental risks of suppliers (e.g., Pankratz and Schiller, 2023; Lu et al., 2023). On the one hand, customer firms tend to get rid of those unsustainable suppliers as quickly as possible since they are reluctant to help them. On the other hand, customer firms can transfer environmental risks to unsustainable suppliers without undertaking penalties from regulators or other stakeholders as they withhold the information of these suppliers. In this case, they may not be eager to sever the supply-chain relationships and continue to exploit them for increased environmental performance. Accordingly, the empirical results regarding the relation between greeninduced nondisclosure and the termination probability of supply-chain link are intriguing. Our results show that there is a positive relation between green-induced nondisclosure and supply-chain termination probability, supporting the former view. In contrast, we find that the customer-supplier relationships are less likely to be terminated when customer firms unveil the information of less responsible suppliers, indicating that customers may seek long-lasting relationships when they engage in improving the environmental profiles of unsustainable suppliers.

While we have shown that green-induced nondisclosure reverses the positive

<sup>&</sup>lt;sup>63</sup> Alex Edmans (2023) sheds light on the conflicts between partial and general equilibrium regarding the environmental externalities. A firm can improve its environmental metrics at the expense of other firms, causing a negative effect on aggregate externalities.

relation between suppliers' and customers' environmental scores, the causal inference of this link may be subject to endogeneity problems. To alleviate these concerns and support a causal interpretation for our baseline results, we exploit two regulatory shocks that may affect the incentives of firms to evade green obligations and transfer environmental risks. Intuitively, customer firms affected by the increasing stringency of environmental regulations have stronger incentives to transfer environmental risks to suppliers rather than support their green practices since they need to promptly comply with regulatory requirements and cater to stakeholders' demands. Based on this rationale, we first focus on the enactment of greenhouse gas (GHG) emissions targets across the different US states. Relying on a triple-interaction analysis with a sample only including US customer firms, we find stronger reversing effects of green-induced nondisclosure on the relationship between suppliers' and customers' environmental scores following the establishment of state-level GHG emission targets in the states where customer firms reside. In a similar spirit, we adopt the enforcement of GHG emission trading systems (ETS) across regions and countries, which enables us to conduct the analysis in an international setting. As the implementation of GHG ETSs imposes greater pressure on firms to reduce carbon emissions, they may shift this burden to their suppliers. Thus, the reversing effects of green-induced nondisclosure may be stronger when customer firms are affected by GHG ETSs. Consistent with this hypothesis, our triple-interaction analysis reveals stronger reversing effects of greeninduced nondisclosure on the positive association between customers' and suppliers' environmental scores after the GHG ETSs are implemented in customers' countries.

We examine the heterogeneity of the main findings from various perspectives to provide a better understanding of the mechanisms through which the green-induced nondisclosure behavior can reverse the positive relation between customers' and suppliers' environmental scores. First, we test the channel related to information transparency. More explicitly, if customer firms can evade obligations and transfer environmental risks at a low cost by withholding relationships with unsustainable suppliers, they are less motivated to help these suppliers. Nevertheless, when these hidden relationships may be disclosed by a third party, customers are under greater pressure to support unsustainable suppliers. Consistent with this conjecture, we find attenuated negative effects of green-induced nondisclosure on the link between customers' and suppliers' environmental scores when the customers and suppliers are held by common institutional investors, served by common auditors and followed by common analysts<sup>64</sup>.

Our second set of heterogeneity analysis focuses on the environmental pressure of suppliers. The rationale is that the resistance of customer firms to evade green obligations and shift environmental risks may be higher when supplier firms are under tighter environmental regulations. In this case, the reversing effects of green-induced nondisclosure should be attenuated with tighter environmental regulations in suppliers' countries. We find this is indeed the case by employing the enactment of mandatory ESG disclosure in suppliers' countries and the country-level environmental regulations. Third, we consider the capabilities of customer firms to support the green practices of suppliers. The intuition is that customer firms may become more reluctant to help unsustainable suppliers when they have limited resources. We adopt financial constraints to measure the inability of customer firms to support green practices of suppliers (e.g., Xu and Kim ,2022) and find that financial constraints exacerbate the effects of green-induced nondisclosure to reverse the positive relation between suppliers' and customers' environmental scores.

Finally, we investigate the real consequences of green-induced nondisclosure on supplier firms, paying attention to the carbon leakage that firms outsource their carbon emissions to supplier firms. Our results indicate that green-induced nondisclosure is positively related to carbon outsource behavior, that is, customers outsource part of their carbon emissions to concealed unsustainable suppliers.

<sup>&</sup>lt;sup>64</sup> Existing literature documents that the information environment and supply chain transparency can be improved by common institutional investors (e.g., Freeman 2023), common auditors (e.g., Ren, Xu and Kim, 2024) and common analysts (e.g., Luo and Nagarajan, 2015).

Our study makes significant contributions to literature in several ways. First, it contributes to the burgeoning research exploring the determinants of green transition in business sectors, particularly the factors related to regulatory requirements. Conventional wisdom suggests that government mandates, such as environment-related disclosure policy and carbon trading system, are effective in reducing firm-level pollution and thus facilitate the green transition (e.g., Downar et al., 2021; Bai and Ru, 2024; Martinsson et al., 2024). Nevertheless, some studies challenge the positive effects of government mandates on green transition, documenting that firms export their pollution activities to places with weaker green policies when facing tightened regulatory requirements (e.g., Ben-David et al., 2021; Bartram, Hou and Kim, 2022). While prior studies mostly focus on the government's green policies that exert direct influence on firms' green transition, relatively little is known about whether policies unrelated to green practices have unintended effects on green transition in business sectors. Our study concentrates on supply-chain disclosure policy and finds that the prerogative of customer firms to voluntarily disclose their suppliers can impede the green transition since it reverses the positively unilateral effect from customers to suppliers regarding the green practices and leads to deterioration in overall environmental performance of the supply chain.

Second, our study adds to the literature examining the real effects of voluntary disclosure. A large theoretical literature on voluntary disclosure suggests that firms may conceal information to keep competitive advantage (e.g., Verrecchia 1983; Darrough and Stoughton, 1990). Empirical studies demonstrate the real effects of voluntary disclosure on a variety of corporate strategies and outcomes<sup>65</sup>. Most relatedly, Shi et al. (2023) find that firms strategically disclose suppliers with good environmental performance but conceal the relationships with unsustainable suppliers. Through engaging in this green-induced strategic disclosure, firms can experience better stock market and operating performance. We extend the study of Shi et al. (2023) by

<sup>&</sup>lt;sup>65</sup> For example, voluntary disclosure can lead to higher stock liquidity (e.g., Balakrishnan et al. 2014), diverse stock market reactions to information (e.g., Kothari, Shu and Wysocki, 2009), reduced litigation risk (e.g., Field, Lowry and Shu, 2005).

examining the effects of green-induced strategic disclosure on the green transition in supply chain and find robust evidence that this strategic disclosure can hinder the transition to green economy since customer firms are no longer eager to support the green practices of their hidden unsustainable suppliers. Meanwhile, our study also offers new insights on the real effects of voluntary disclosure by showing that voluntary disclosure can be regarded as a tool for firms to evade obligations and transfer risks. To the best of our knowledge, we are among the first to investigate whether and how firms can evade obligations and transfer risks by strategically disclosing information.

Third, our paper contributes to understanding the propagation of green practices through economically linked stakeholders, especially along the supply chain<sup>66</sup>. More explicitly, Dai, Liang and Ng (2021) and Schiller (2018) document a unilaterally positive effect on environmental performance from customers to suppliers. One recent study of Homroy and Rauf (2024) concludes that the adoption of emission reduction targets of customer firms can encourage suppliers to launch similar emission reduction projects, though suppliers do not ultimately walk the talk<sup>67</sup>. Our study extends this strand of literature by providing new evidence regarding the factors that deter the propagation of green practices along supply chain, which is detrimental to green transition in business sectors.

#### 4.2 Data and Summary Statistics

The aim of this study is to examine whether firms' strategic disclosure behavior driven by suppliers' environmental performance mitigate or even reverse the positive link between suppliers' and customers' environmental scores. To this end, we combine three primary databases to construct our final sample from 2003 to 2023: supply-chain relationship data from FactSet Reverse, environmental performance data from Refinitiv

<sup>&</sup>lt;sup>66</sup> It is worth noting that another strand of literature finds that green practices propagate among competitors (e.g., Cao, Liang and Zhan, 2019; Asgharian et al., 2024).

<sup>&</sup>lt;sup>67</sup> Suppliers rarely have discipline effects on customers' environmental practices primarily for two reasons. First, it is relatively difficult for suppliers to push customers to commit to environmental standards since they have lower bargaining power in the customer-supplier relationship. Second, suppliers have lower incentives to manage environmental practices in the supply chain because they are distant from end customers who are sensitive to the green practices of firms (Dai, Liang and Ng, 2021).

Asset4, and accounting data from Refinitiv Worldscope. In this section, we introduce the data sources and discuss the construction for key and control variables used in the main analysis. Meanwhile, we present and discuss the summary statistics of our sample.

#### 4.2.1 Data and Variables

We begin by retrieving the information for international supply-chain relationships from FactSet Revere, which is a specialized database providing relationship information with economically linked stakeholders such as suppliers, customers and competitors of large and mostly listed firms. This dataset covers over 450,000 unique business relationships from 2003 and has been widely used in a battery of finance and accounting studies such as Dai, Liang and Ng (2021), Darendeli et al. (2022) and Asgharian et al. (2024).

FactSet Reverse reports sixteen types of business relationships<sup>68</sup>, we restrict our focus on customer-supplier relationships. FactSet Revere collects business relationship information from several public sources such as SEC 10-K filings, investor presentations and press releases, relying on a proprietary research method. Compared with Compustat Segment data, the coverage of FactSet Revere is noticeably broader since Compustat Segment only collects customer-supplier relationship information from 10-K filings, and thus is subject to the accounting standards requiring firms to disclose the information of customers that account for more than 10% of a firm's annual revenues in 10-K filings. Accordingly, FactSet Revere is more appealing than Compustat Segment in our study. First, our focus is the green-induced voluntary or strategic disclosure behavior of customers while Compustat Segment data only includes supplier-disclosed information. Second, FactSet Revere allows us to study the effects of green-induced strategic disclosure on green transition in supply chain globally while Compustat Segment data only covers US firms. FactSet Revere also reports detailed information regarding the start year and end year for each documented customer-

<sup>&</sup>lt;sup>68</sup> In addition to customers, suppliers and competitors, there are other business types including partnerships: in-licensing, manufacturing, marketing, joint venture, out-licensing, technology, equity investment, distribution, integrated product, investor, research, product licensing and unknown.

supplier relationship, enabling us to calculate the accurate relationship duration and track the termination of each relationship.

We then extract firm-level environmental performance data from Refinitiv Asset4 (formerly Thomson Reuter Asset4), which is one of the most widely used databases in ESG studies (e.g., Dyck et al., 2019; Dai et al., 2024). Starting from 2002, Asset4 has established a comprehensive ESG database, collecting numerous publicly available ESG-related information from various sources including firm-level annual reports, company websites, CSR reports, NGO websites, stock exchange filing s and public news. The professional research analysts in Refinitiv then process and evaluate this raw information and ultimately generate the performance scores for four major categories: environmental, social, governance and ESG controversy, based on more than 500 different ESG metrics. Thanks to the rigorous data collection and evaluation, the Refinitiv ESG database has a broad coverage of over 11,000 companies and over 80% global market cap. Our focus is firm-level environmental performance, which is evaluated within three primary subcategories: resource use, emission reduction and environmental innovation. Based on these subcategories, Asset4 constructs an environmental pillar score for each firm, ranging from 0 to 1. Firms with higher environmental scores are regarded as leaders while firms with lower scores are laggards in environmental practices.

After merging supply-chain data from FactSet Revere with firm-level environmental score from Refinitiv Asset4 using ISIN (International Security Identification Number) code, we can construct the main independent variable of interest in this study, *green-induced nondisclosure*, representing the behavior that firms withhold the information of suppliers due to their bad environmental performance. More specifically, we first define one supplier-customer relationship as nondisclosure if this is not voluntarily disclosed by customer firms. Next, we divide supplier firms into three groups based on their environmental scores in each year – those suppliers with environmental score exceeding seventieth percentile are labelled as sustainable firms while suppliers with environmental scores falling below thirtieth percentile are labelled as unsustainable suppliers. Accordingly, we define the dummy variable greeninduced nondisclosure that equals one if the supplier-customer relationship is not voluntarily disclosed by customer firm and the supplier firm is unsustainable, and zero otherwise.

In addition, we also collect annual accounting data from Refinitiv Worldscope and construct a series of firm-level control variables for the main analyses. We define the firm size (Size) as the natural logarithm of total assets in US dollars plus one. Leverage is calculated as the percentage of total debt on total assets. Return on assets (ROA) is defined as the ratio of net income over total assets. We calculate *TobinQ* as the sum of market capitalization and total liabilities, divided by the book value of assets. Sales growth is defined as the one-year annual growth rate of net sales. Moreover, the country-level control variable, GDPperCap, is obtained from World Bank Indicator database and calculated as the natural logarithm of GDP per capita in current US dollars. The detailed variable construction process and data sources of all variables used in this study are presented in Appendix A.

### 4.2.2 Summary Statistics

The final sample comprises 395,189 observations, covering 132,942 unique suppliercustomer pairs from 2003 to 2023.

#### [Insert Table 4.1 here]

Table 4.1 summarizes the variables used in main empirical analyses. The first series of variables are the supply chain-level variables. Since the first order focus of this study is to explore whether the green-induced nondisclosure behavior of customer firms deters the propagation of environmental practices from customers to suppliers, the independent variable of particular interest is green-induced nondisclosure. It has a mean value of 0.23, indicating that 23% of supplier-customer relationships in our sample are concealed by customer firms due to the bad environmental performance of suppliers<sup>69</sup>.

<sup>&</sup>lt;sup>69</sup> Unreported descriptive statistics show that about 70% of supplier-customer relationships are hidden 140

In a similar vein, we also construct the variable, *green-induced disclosure*, a dummy indicating whether a supplier-customer relationship is voluntarily reported by customer firms even though the supplier firms perform poorly in environmental issues. The mean value of *green-induced disclosure* is 0.03, suggesting that very few customer firms are willing to voluntarily disclose unsustainable suppliers. The average relationship length for a supplier-customer pair is approximately 3.6 years and 21% of supplier-customer relationships are terminated during our sample period.

The second and third series of variables supplier- and customer-level environmental variables, as well as other firm and country-level characteristics. The average environmental score for supplier firms is 0.46, while this value is 0.58 for customer firms, implying that customer firms have slightly better environmental performance than supplier firms on average.

#### [Insert Table 4.2 here]

In addition to summary statistics, Table 4.2 presents the distribution of supplier and customer firms across countries or regions. The average environmental score of all supplier firms and customer firms in each country is also calculated. Though our sample consists of supplier (customer) firms from 75 (80) unique countries, we only report the distribution in 32 countries with more than 1,500 supplier firms in our sample<sup>70</sup>. Some stylized facts can be summarized from Table 4.2. For example, the environmental performance of customer firms is generally better than that of suppliers since the greater bargaining power allows customer firms to outsource pollution to upstream suppliers. Second, firms located in developed countries (e.g., UK and France) have, on average, better environmental performance than those in developing countries (e.g., China and India) since green practices correlate strongly with economic development.

by customer firms, regardless of suppliers' environmental performance.

<sup>&</sup>lt;sup>70</sup> Similar to the US, few countries explicitly mandate the disclosure of detailed customer identity information for public firms. Instead, their disclosure requirements usually focus on the material contracts or relationships for customers and suppliers (e.g., Companies Act 2006 in the UK).

4.3 Green-induced Nondisclosure and Green Transition in Supply Chain

In this section, we examine whether green-induced nondisclosure hinders the green transition of supply chain. More explicitly, we explore whether the green-induced nondisclosure terminates or even reverses the positive impacts that customers exert on suppliers' environmental performance. To corroborate the argument that customer firms exploit strategic disclosure to evade green obligations for unsustainable suppliers, we explore the relation between suppliers' and customers' environmental scores under the circumstances that customer firms voluntarily disclosure unsustainable suppliers. Furthermore, we disentangle whether customers experience improved environmental performance at the expense of unsustainable suppliers, and whether green-induced nondisclosure has an aggregate negative impact on the environmental practices of the supply chain.

#### 4.3.1 Baseline Results

To investigate whether and how green-induced nondisclosure influences the association between suppliers' and customers' environmental scores, we estimate the following regression model:

$$EnvScore_{i,t}^{S} = \alpha + \beta_{1}EnvScore_{j,t-1}^{C} \times Green - induced \ Nondisclosure_{i,j,t} + \beta_{2}EnvScore_{j,t-1}^{C} + \beta_{3}Green - induced \ Nondisclosure_{i,j,t} + \gamma_{1}Z_{i,t} + \gamma_{2}Z_{j,t} + FE + \varepsilon_{i,j,t} ,$$

$$(1)$$

where the  $EnvScore_{i,t}^{S}$  denotes the environmental score of the supplier firm *i* in year *t* and  $EnvScore_{j,t-1}^{C}$  measures the environmental score of the customer firm *j* in year *t*-1. The primary independent variable of interest,  $Green - induced Nondisclosure_{i,j,t}$ , is a dummy that equals one if the supplier firm *i* is not voluntarily disclosed by the customer firm *j* in year *t*, and the environmental score of supplier *i* falls below the thirtieth percentile among other supplier firms in year *t*. A set of supplier and customer control variables described in Section 4.3.1 are represented by  $Z_{i,t}$  and  $Z_{j,t}$ , respectively. Additionally, we incorporate different combinations of fixed effects as reflected by *FE*,

such as customer-supplier industry fixed effect<sup>71</sup>, customer-supplier country fixed effect, supplier firm fixed effect and year fixed effect, to mitigate the concerns of supply-chain-level, supplier-firm-level and time variant omitted variables driving the results. Standard errors are clustered at supplier-customer level in all regressions. In the baseline regression model (1), the parameter of particular interest is  $\beta_1$ , which dictates the role of green-induced nondisclosure playing in the relationship between suppliers' and customers' environmental scores.

#### [Insert Table 4.3 here]

Table 4.3 reports the regression results of model (1) using various control variables and fixed effects<sup>72</sup>. We first estimate the baseline model by incorporating only supplierlevel control variables and customer-supplier industry, country and year fixed effects. As presented in Column (1), the coefficient of the interaction term between customers' environmental scores and green-induced nondisclosure (*EnvScore<sup>C</sup>×Green-induced Nondisclosure*) is -0.030, and significant at 1% level, indicating a negative relation between environmental performance of suppliers and customers when customer firms conceal suppliers due to their bad environmental performance. In contrast, the positive coefficient of *EnvScore<sup>C</sup>* is consistent with Dai, Liang and Ng (2021), suggesting that customer firms still play an important role in supporting suppliers' green practices when they do not withhold the information of suppliers due to their poor environmental performance<sup>73</sup>. Collectively, our results show that the green-induced nondisclosure reverses the positive relation between suppliers' and customers' environmental scores, and consequently, hinders the propagation of positive environmental practices along the supply chain.

<sup>&</sup>lt;sup>71</sup> We adopt four-digit Standard Industrial Classification code (SIC4) to define industries.

<sup>&</sup>lt;sup>72</sup> Since we incorporate a battery of fixed effects at baseline regression model, the sample size is slightly smaller than the total number of supply-chain pair-years summarized in Table 1 due to dropped singleton observations.

<sup>&</sup>lt;sup>73</sup> A supplier-customer relationship is defined as a relationship that customers do not conceal the information of suppliers when it satisfies the either condition of the following: 1) customers voluntarily disclose suppliers irrespective of suppliers' environmental performance, or 2) customers withhold the information of suppliers without bad environmental performance.
To rule out the possibility that supplier firm-level omitted variables drive the results, we control for the fixed effect at supplier firm-level. The results are reported in Column (2). We find the baseline results remain qualitatively similar despite a smaller magnitude of the coefficient in interaction term. In Column (3) and (4), we replicate the results in Column (1) and (2) but add customer-level control variables. The loadings on the interaction term are negative and significant at 1% level, while the coefficients of *EnvScore<sup>C</sup>* are positive and significant, supporting the argument that green-induced nondisclosure deters the positive influence of customer firms exert on suppliers.

We then calculate the economic magnitude based on the regression results with all sets of control variables and fixed effects, as shown in Column (4). Specifically, the supplier environmental score (*EnvScore*<sup>S</sup>) declines by 0.974% (calculated as  $-0.016 \times$ 0.28 / 0.46) on average, relative to the unconditional sample mean, with a one-standarddeviation increase in one-year lagged customer environmental score (*EnvScore<sup>C</sup>*), when green-induced nondisclosure exists in the customer-supplier relationship. In comparison, if customer firms do not conceal the information of suppliers with bad environmental performance, a one-standard-deviation increase in one-year lagged customer environmental score leads to, on average, a 0.426% (calculated as  $0.07 \times 0.28$ / 0.46) improvement in supplier environmental score relative to sample mean<sup>74</sup>. As a result, green-induced nondisclosure can generate a 1.4% (calculated as 0.426% - (-0.974)) decline in supplier environmental score relative to sample mean, given a onestandard-deviation increase in customer environmental score. Despite the seemingly small numbers of changes in supplier environmental score, it is worth emphasizing that these figures only reflect the impact on a single supplier firm. Since customer firms in our sample have 7.78 supplier firms in each year on average, the multiplier effect of green-induced nondisclosure on supplier environmental score should be 10.89%

<sup>&</sup>lt;sup>74</sup> Dai, Liang and Ng (2021) show that supplier environmental score rises by 1.67% for a one-standarddeviation increase in customer environmental score based on the regression model only incorporating customer-supplier industry, customer-supplier country and year fixed effects. Our results are comparable to theirs if we calculate the economic magnitude using the regression results with identical model specification (as shown in Column (1) of Table 3). That is, a one-standard-deviation increase in one-year lagged customer environmental score generates, on average, a 1.339% improvement in supplier environmental score.

(calculated as  $1.4\% \times 7.78$ ) in the supply chain.

One potential interpretation for the negative effects of green-induced nondisclosure on the positive links of supplier-customer environmental scores is that customer firms aim to evade green obligations that help unsustainable suppliers improve their environmental performance by withholding the information of these suppliers. However, this interpretation is subject to the concern that customer firms conceal suppliers' information and cease supporting or disciplining activities on suppliers due to other unexplored factors, which are related to suppliers' environmental performance<sup>75</sup>. To address this concern, we explore whether and how the relation between suppliers' and customers' environmental performance evolves when customer firms voluntarily disclose the information of suppliers with bad environmental performance. Intuitively, if customer firms choose to voluntarily disclose unsustainable suppliers rather than withholding them, they are more likely to help unsustainable suppliers improve their environmental performance rather than evading these green obligations. In this case, we may find a stronger or, at the very least, unchanged positive relation between suppliers' and customers' environmental score when customer firms voluntarily disclose their unsustainable suppliers.

# [Insert Table 4.4 here]

We repeat the baseline regression model by replacing the variable *Green-induced Nondisclosure* with *Green-induced disclosure*, which takes the value of one if a customer firm voluntarily discloses the information of a supplier firm even though the supplier has an environmental score below the bottom thirtieth percentile. The results are reported in Table 4.4. As evidenced in Column (1) of Table 4.4, the coefficient of the interaction term of customer environmental score and green-induced disclosure (*EnvScore<sup>C</sup>* × *Green-induced Disclosure*) is 0.026 and significant at 1% level, indicating a stronger positive environmental practice propagating from customers to

<sup>&</sup>lt;sup>75</sup> For example, corporate governance (e.g., Li and Ye, 2023) and operating risks (e.g., Ersahin, Giannetti and Huang, 2024) of supplier firms play important roles in the stability of supply-chain relationship.

suppliers when customer firms opt for disclosing unsustainable suppliers. According to Column (2), we find the coefficient of the interaction term remains positive and statistically significant after adding supplier firm fixed effects. These findings corroborate the argument that evading green obligations is the primary purpose behind green-induced nondisclosure, which ultimately reverses the positive relation between environmental scores of suppliers and customers.

To summarize, our baseline results demonstrate that corporate customers no longer play important roles in supporting or disciplining green practices of suppliers when they strategically conceal the information of unsustainable suppliers<sup>76</sup>. Our further analysis focusing on the voluntary disclosure of unsustainable suppliers supports the interpretation regarding green obligation evasion for the reversed positive relation between suppliers' and customers' environmental scores triggered by green-induced nondisclosure. Most importantly, the propagation of positive environmental effects from customers to suppliers is disrupted for suppliers with the lowest environmental performance — those who may be in greatest need of external support to improve their green practices. However, the strategic disclosure behavior of customer firms that conceal information about unsustainable suppliers enables them to evade their obligation to support these suppliers in adopting greener practices and overcoming their challenges. Consequently, green-induced nondisclosure hinders the green transition of the supply chain.

# 4.3.2 Changes in Environmental Performance

The negative relation between the environmental scores of suppliers and customers caused by green-induced nondisclosure suggests that customer firms may improve their environmental performance at the expense of unsustainable suppliers by transferring environmental risks to these hidden suppliers. Nevertheless, an alternative explanation

<sup>&</sup>lt;sup>76</sup> We acknowledge that many firms play the roles of suppliers and customers simultaneously and they receive of transferred environmental obligations from downstream customers while they evade and transfer green obligations to upstream suppliers. Since the focus of this study is not to identify the aggregate environmental obligations that one firm receive or transfer, we do not have further discussion on this issue.

for the negative relation is that customer firms help the unsustainable suppliers promote environmental performance by sacrificing their own green performance, which may benefit the green transition in supply chain. To discriminate between these two potential explanations, we examine how green-induced nondisclosure affects the changes in environmental scores of suppliers and customers. If hiding the information of unsustainable supplier reduces the costs of customer firms to evade green obligations and transfer environmental risks, we may observe a decrease in supplier environmental scores and an increase in customer environmental score.

## [Insert Table 4.5 here]

Table 4.5 tabulates the regression results. In Column (1), we test the relation between green-induced nondisclosure and one-year change in supplier environmental score. The coefficient of green-induced nondisclosure is -0.079 and significant at 1% level, suggesting deteriorated environmental performance of suppliers. Conversely, we find an improved customer environmental score when customer firms withhold information of unsustainable suppliers since the loading on green-induced nondisclosure is positive and significant, as evidenced in Column (2). These evidence support the view that concealing information of unsustainable suppliers enables customer firms to transfer environmental risks to these suppliers, therefore leading to a negative relation between environmental scores of suppliers and customers. We then aggregate the changes in supplier and customer environmental score and construct the variable  $\Delta EnvScore^{C+S}$ . By examining the impact of green-induced nondisclosure on the overall changes in these environmental scores, we can determine whether greeninduced nondisclosure has a negative effect on the environmental performance of the supply chain. In other words, we aim to answer the key question of this study: does green-induced nondisclosure hinder the green transition of the supply chain? According to Column (3) of Table 4.5, the coefficient of green-induced nondisclosure is negative and significant at the 1% level, indicating that green-induced nondisclosure, in aggregate, leads to a decline in the environmental performance of the supply chain. This finding further reinforces the evidence of its detrimental impact on supply chain green transition.

## 4.3.3 Termination Probability and Relationship Length

As customer firms are reluctant to support the green development of hidden unsustainable suppliers, it is crucial to examine whether these customer-supplier relationships are more likely to be terminated. On the one hand, since customer firms are unwilling to undertake responsibility for supporting unsustainable suppliers, they may be more inclined to sever these relationships. On the other hand, green-induced nondisclosure enables firms to transfer environmental risks to suppliers while enhancing their own environmental performance at a low cost, which may reduce their likelihood of terminating the relationships.

# [Insert Table 4.6 here]

To test whether and how green-induced nondisclosure affects the termination probability of customer-supplier relationship, we construct a dummy variable, *Termination Year*, which equals to one if a given supplier-customer relationship ends after the current year and estimate a liner probability regression model. Column (1) of Table 4.6 reports the results. We find that the green-induced nondisclosure is related to a higher probability of customer-supplier relationship severance as the coefficient of green-induced nondisclosure is positive and significant at the 5% level. In comparison, a customer-supplier relationship is less likely to be terminated when customer firms voluntarily disclose unsustainable suppliers, as evidenced in Column (2) of Table 4.6. This indicates that customer firms tend to establish long-standing relationships with unsustainable supplier firms when they are willing to support them to improve environmental performance. Collectively, the opposite impacts of green-induced nondisclosure on termination probability of supply chain are consistent with the argument that customer firms are more inclined to get rid of these unsustainable supplier firms. Moreover, we test the relation between green-induced nondisclosure

(disclosure) and relationship length of a given customer-supplier pair, which is calculated as the gap between current year and the starting year of this relationship plus one. Column (3) and (4) of Table 4.6 tabulate and results. In line with the results regarding termination probability, green-induced nondisclosure reduces the customer-supplier relationship length as the loading on green-induced nondisclosure is negative and significant as shown in Column (3). By contrast, Column (4) indicates a positive relationship between green-induced disclosure and relationship length, albeit statistically insignificant.

## 4.4 Identification Strategies

While the baseline results so far are consistent with our hypothesis and robust to various precautions, the reversing effects of green-induced nondisclosure on the positive relation between may be subject to endogeneity concerns. First, our baseline results may stem from omitted variables despite a variety of control variables and fixed effects. For example, short-term managers and institutional investors of customer firms could simultaneously affect the customer firms' incentives to support suppliers' green practices and the propensity to conceal the information of suppliers performing poorly in environmental issues<sup>77</sup>. Second, it is also plausible that the customer firms engaging in green obligation evasion and environmental risk transfer through the supply chain are less likely to voluntarily disclose their suppliers. Hence, our baseline results could be driven by reverse causality. To alleviate these concerns and facilitate a causal inference of our baseline results, we employ two regulatory shocks to the incentives of customer firms to evade green obligations and transfer environmental risks. Specifically, we examine whether and how the enactment of US state-level GHG emission target and the implementation of global GHG emission trading system influence the reversing effects of green-induced nondisclosure on the relation between suppliers' and customers'

<sup>&</sup>lt;sup>77</sup> Pursuing short-term profits is the goal of short-term managers and institutional investors. In this case, they are less likely to allocate resources to support the green practices of suppliers since green activities may not pay off over the short run (e.g., Martin and Moser, 2016; Edmans, 2020). Meanwhile, they are more likely to withhold the information of unsustainable suppliers because this strategic disclosure can create near-term benefits (Shi et al., 2023).

environmental performance.

# 4.4.1 The Enactment of US State-level GHG Emission Target

The stringency of environmental regulations varies across US states. In response to heightened regional regulations, affected firms adjust their corporate policies such as capital structure (e.g., Dang, Gao and Yu, 2023) and the design of executive compensation contracts (e.g., Choi et al., 2024). Most importantly, Bartram, Hou and Kim (2022) and Dai et al. (2024) show that the increasing stringency of environmental regulations can incentive firms to shift emissions to suppliers with lax regulations. In a similar vein to these studies, we focus on the enactment of US state-level GHG emission targets and examine whether these targets influence our baseline results. As of 2023, 23 US states have established economy-wide GHG emission targets while 3 states have published recommended targets. To meet their targets, these states may implement enforceable statutory measures and executive actions and thus pose a higher level of environmental pressure on firms in these states. Consequently, customer firms in these states may engage more in shifting their emissions to suppliers to avoid contingent scrutiny and penalties. In the context of our study, the reversing effects of green-induced nondisclosure on the relation between suppliers' and customers' environmental performance are expected to be stronger.

To explore, we estimate the following regression model with a triple-interaction term using the information on US state-level GHG emission targets from Center for Climate and Energy Solutions (C2ES)<sup>78</sup>:

$$\begin{split} & EnvScore_{i,t}^{S} = \alpha + \beta_{1}EnvScore_{j,t-1}^{C} \times Green - induced \ Nondisclosure_{i,j,t} \times \\ & GHGTarget_{j,t-1} + \beta_{2}EnvScore_{j,t-1}^{C} \times Green - induced \ Nondisclosure_{i,j,t} + \\ & \beta_{3}Greeninduced \ Nondisclosure_{i,j,t} \times GHGTarget_{j,t-1} + \beta_{4}EnvScore_{j,t-1}^{C} \times \\ & GHGTarget_{j,t-1} + \beta_{5}EnvScore_{j,t-1}^{C} + \beta_{6}Greeninduced \ Nondisclosure_{i,j,t} + \\ & \beta_{7}GHGTarget_{j,t-1} + \gamma_{1}Z_{i,t} + \gamma_{2}Z_{j,t} + FE + \varepsilon_{i,j,t} \ , \end{split}$$

<sup>78</sup> For more details, see https://www.c2es.org/document/greenhouse-gas-emissions-targets/.

(2)

where *GHGTarget*<sub>*j*,*t*-1</sub> is a binary indicator that takes the value of one for if a state that the customer firm *j* resides enacted the statutory or executive targets for GHG emissions within the past five years, or zero otherwise. We incorporate all control variables and fixed effects as used in Model (1). We limit the sample to US customer firms since our focus is domestic state-level regulatory shocks in the US. The coefficient of the tripleinteraction term,  $\beta_1$ , captures the impacts of GHG emission targets on the intensity that green-induced nondisclosure reverses the positive relation between environmental performance of suppliers and customers. Accordingly, a negative coefficient of this triple-interaction term suggests greater reversing effects of green-induced nondisclosure, and therefore a stronger effect of environmental risk shifting from customers to suppliers.

### [Insert Table 4.7 here]

Table 4.7 presents the regression results of Model (2). Consistent with our hypothesis, we find a negative coefficient of the triple-interaction term as the *t-statistic* is -2.24 as evidenced in Column (1). This finding indicates that customer firms affected by the establishment of GHG emission targets become more reluctant to support the green practices of suppliers with poor environmental performance when they withhold the information of these suppliers. Instead, these customer firms even transfer more environmental risks to these suppliers when facing increasing regulatory stringency and consequently have greater negative impacts on the propagation of positive environmental practices along the supply chain. To mitigate the concern that the above results are driven spuriously, we conduct a placebo test with falsified timing for the enactment of state-level GHG emission target. More explicitly, we construct a falsified dummy of *GHGTarget* by assuming that one state enacts GHG emission target two years before the actual enactment year. As reported in Column (2), there is no evidence for the placebo test since the coefficient of the triple-interaction term is statistically insignificant<sup>79</sup>.

<sup>&</sup>lt;sup>79</sup> Another shock potentially influencing the incentives of US customer firms to evade green obligations

## 4.4.2 The Implementation of Global GHG Emission Trading System

Another regulatory shock to the incentives of customer firms to evade green obligations and transfer environmental risks is the implementation of GHG Emission Trading Systems (ETS) globally. Similar to US state-level GHG emission targets, GHG ETSs exert pressure on firms to reduce carbon emissions (e.g., Bai and Ru, 2024) and, in turn, firms are more likely to shift their emissions to suppliers, which may be reflected as a stronger reversing effect of green-induced nondisclosure on the positive relation between the environmental performance of customers and suppliers. Additionally, the implementation of GHG ETSs across countries and regions enables us to examine the impacts of heightened environmental regulations in an international setting, while the scope for the enactment of state-level GHG emission targets is restricted to the US.

# [Insert Table 4.8 here]

To investigate whether the establishment of GHG ETSs affects our baseline results, we collect data of GHG ETSs at regional, national and subnational levels dating back to 1991 from World Bank Carbon Pricing Dashboard<sup>80</sup> and following the preceding test based on Model (2). We replace the variable  $GHGTarget_{j,t-1}$  in Model (2) with  $ETS_{j,t-1}$ , which is a dummy variable equaling one if a country or US state<sup>81</sup> that customer firms reside adopt GHG ETSs after year *t*-1. As shown in Column (1) of Table 4.8, we find a negative and significant coefficient of the triple-interaction term of oneyear lagged customer environmental score, green-induced nondisclosure and the indicator for GHG ETSs, suggesting that the reversing effects of green-induced nondisclosure become stronger after the implementation of GHG ETSs in customer

and transfer environmental risks may be the disclosure policy change in 2020 which abolish the requirements for US public firms to disclose major customers contributing 10% or more to their revenues. In this case, customer firms may face lower pressure to engage in the activities of environmental risk transfer along the supply chain. Consistent with this rationale, we find stronger reversing effects of green-induced nondisclosure for US customer firms after 2020 in unreported analysis.

<sup>&</sup>lt;sup>80</sup> See <u>https://carbonpricingdashboard.worldbank.org/compliance/instrument-detail</u> for more details.

<sup>&</sup>lt;sup>81</sup> Since US customer firms account for more than 40% in our sample and there is no federal-level ETS scheme in the US, we consider the state-level implementation of GHG ETSs to ensure the validity of our results.

firms' countries or states. This finding further corroborates the argument that tightened environmental regulations induce firms to transfer more environmental risks to unsustainable suppliers when they can hide the relationship with these suppliers, which is consistent with the evidence in the previous section<sup>82</sup>. We also conduct a falsification test by assuming the implementation of GHG ETSs in one country or state happens two years before the actual implementation year. The result in Column (2) of Table 4.8 shows no evidence with respect to the falsified GHG ETS indicator because of the statistically insignificant triple-interaction coefficient.

Taken together, these two shocks capture the increasing stringency of environmental regulations for customer firms. Under the pressure of these regulations, customer firms may opt for shifting environmental risks to suppliers rather than supporting the green practices of unsustainable suppliers. Thus, we find that stronger reversing effects of green-induced nondisclosure on the positive relation between customers' and suppliers' environmental performance. These findings also support the interpretation for our baseline results that the main purposes for customer firms to withhold the relationship with unsustainable suppliers are evading green obligations and transferring environmental risks.

#### 4.5 Cross-Sectional Heterogeneity

To better understand the mechanisms by which customer firms engage in green obligation evasion and environmental risk shift for unsustainable suppliers with hidden relationships, we conduct several tests to examine the cross-sectional heterogeneity of our main results from various perspectives. If the green-induced nondisclosure indeed reflects the intention of customer firms to evade green obligations and transfer environmental risks, we would expect that our main results become stronger (weaker)

 $<sup>^{82}</sup>$  It is noteworthy that one of the largest GHG ETSs – ETS in European Union (EU ETS) – is shown to be unrelated to carbon outsourcing activities (Colmer et al., 2024). To check the robustness of our results, we exclude customer firms located in European Union and find qualitatively similar results in unreported analysis.

with factors encouraging (discouraging) customer firms to avoid green responsibility and transfer environmental risks to suppliers.

#### 4.5.1 Common Stakeholders

The first possible channel through which green-induced nondisclosure can reverse the positive relation between customers' and suppliers' environmental performance is related to information transparency. Intuitively, customer firms are less likely to evade green obligations and shift environmental risks to hidden unsustainable suppliers if these supply-chain relationships are possibly unveiled by a third party. When a third party potentially discloses the relationship, customer firms are under pressure to support green practices of unsustainable suppliers and facilitate the green transition along the supply chain since their actions on these suppliers may be monitored by regulators, because their unethical actions on suppliers may incur regulators' penalties and stakeholders' boycott. As such, we expect that the reversing effects of green-induced nondisclosure are weaker with a higher level of information environment transparency improved by common stakeholders in the supply chain. More specifically, we consider three types of common stakeholders: common institutional investors who simultaneously hold stakes of both suppliers and customers, common auditors who serve suppliers and customers at the same time, and common analysts who follow both sides in the supply chain.

Existing literature documents that these three types of common stakeholders play important roles in improving information transparency. For instance, Freeman (2023) concludes that overlapping institutional ownership in customers and suppliers can enhance the stability of supply-chain relationships and alleviate information asymmetry. Another study of Tian, Wang and Wu (2024) shows that common institutional ownership in the supply chain can enhance information sharing and coordination between suppliers and customers, thereby reducing creditor risk premiums. Similar to common institutional investors, common auditors also contribute to a more transparent information environment in the supply chain. In particular, Kim, Ren and Xu (2024) find that common auditors can enhance supply chain relationships by reducing information-processing costs and Dhaliwal, Shenoy and Williams (2017) conclude that the reduced information asymmetry driven by common auditors can mitigate the holdup problem in the supply chain. In terms of common analysts, a strand of literature documents that analysts who simultaneously follow customers and suppliers provide more accurate earnings forecasts for supplier firms by benefiting from informational complementarities along the supply chain (Guan, Wong and Zhang, 2015; Luo and Nagarajan, 2015). Collectively, these evidence suggests that these three types of common stakeholders in the supply chain can increase information transparency, thereby deterring customer firms from evading green obligations and shifting environmental risks to hidden unsustainable suppliers. Accordingly, we hypothesize that the reversing effects of green-induced nondisclosure are weaker when the three types of common stakeholders exist in the supply chain.

To explore, we estimate the following regression model with triple-interaction term of one-year lagged customer environmental score, green-induced nondisclosure and the variables for common stakeholders:

$$\begin{split} & EnvScore_{i,t}^{S} = \alpha + \beta_{1}EnvScore_{j,t-1}^{C} \times Green - induced \ Nondisclosure_{i,j,t} \times \\ & Common_{i,j,t} + \beta_{2}EnvScore_{j,t-1}^{C} \times Green - induced \ Nondisclosure_{i,j,t} + \\ & \beta_{3}Greeninduced \ Nondisclosure_{i,j,t} \times Common_{i,j,t} + \beta_{4}EnvScore_{j,t-1}^{C} \times \\ & Common_{i,j,t} + \beta_{5}EnvScore_{j,t-1}^{C} + \beta_{6}Greeninduced \ Nondisclosure_{i,j,t} + \\ & \beta_{7}Common_{i,j,t} + \gamma_{1}Z_{i,t} + \gamma_{2}Z_{j,t} + FE + \varepsilon_{i,j,t} \ , \end{split}$$

(3)

where  $Common_{i,j,t}$  denotes the variables regarding different types of common stakeholders. More specifically, we define common institutional ownership (*Common IO*) as the number of institutional investors who own the shares of both suppliers and customers simultaneously using the data collected from FactSet Ownership. Common auditor (*Common Auditor*) is a binary variable taking the value of one if the supplier and customer in the supply chain is served by the same auditor based on the auditor information obtained from Audit Analytics. We also construct a dummy variable (*Common Analyst*) that equals one if at least one analyst issues earnings forecasts for both supplier and customer in the supply chain.

## [Insert Table 4.9 here]

Table 4.9 reports the regression results of Model (3). The coefficients of interests are those of the triple-interaction terms, which capture the variation of baseline results with respect to different types of common stakeholders. As evidenced in Column (1), the loading on the triple-interaction term is 0.030, with a *t-statistic* of 2.60, indicating that common institutional investors in the supply chain can play a role in disciplining customer firms for evading green obligations and shifting environmental risks to concealed unsustainable suppliers. Consistent with common institutional investors, we find the coefficients of the triple-interaction terms regarding common auditor and analyst are positive and significant based on Column (2) and Column (3), respectively. These findings support the view that reduced information asymmetry and improved transparency stemming from common stakeholders can deter customer firms engaging in unethical actions on hidden suppliers with poor environmental performance.

# 4.5.2 Supplier Environmental Pressure

We then investigate whether the environmental pressure on suppliers alters our baseline results. The rationale is that suppliers are more likely to resist the environmental risks shifting from customers when they are located in places with tighter environmental regulations. As such, the environmental pressure on suppliers may attenuate the reversing effects of green-induced nondisclosure on the positive relation between environmental performance of customers and suppliers.

Two measures for country-level tightness of environmental regulations are adopted, the first of which is the enactment of mandatory ESG disclosure in suppliers' countries. When suppliers' ESG information is unveiled to the public, they have stronger incentives to pursue better performance on environmental issues to attract investors and customers. In this case, they are not reluctant to be the receiver of environmental risks shifting from suppliers. The second measure is the country-level environmental performance index (EPI) scores, which proxy for the enforcement strength of ESG-related standards. Lu et al. (2023) find that customer firms are less likely to transfer environmental risks to suppliers located in countries with higher EPI even when they face tighter environmental regulations.

# [Insert Table 4.10 here]

To explore, we first collect the information of ESG mandatory disclosure worldwide from Krueger et al. (2024) and country-level EPI scores from Yale Center for Environmental Law and Policy (YCELP). Next, we repeat the regression Model (3) but replace the variables of common stakeholders with the variables representing suppliers' environmental pressure. The variables of interests are the triple-interaction terms. If tight environmental regulations in suppliers' countries could retard the unethical actions of customer firms to transfer environmental risks to hidden unsustainable suppliers, we would expect positive and significant coefficients of these triple-interaction terms. Table 4.10 summarizes the regression results. Column (1) shows that the enactment of mandatory ESG disclosure in suppliers' countries attenuates the reversing effects of green-induced nondisclosure as the loading on the interaction term is positive and significant. As presented in Column (2), we find similar evidence with respect to suppliers' country-level EPI because of the positive and significant coefficient of the triple-interaction term. Overall, the above evidence corroborates the argument that suppliers' environmental pressure plays an important role in suppressing the green obligation evasion and environmental risk transfer of customer firms.

## 4.5.3 Customer Inability

The third possible mechanism by which green-induced nondisclosure negatively influences the relation between customers' and suppliers' environmental performance is the inability of customer firms to support green practices of unsustainable suppliers. First, we focus on the financial constraints of customer firms. More explicitly, a large literature shows that financial constraints hinder firms from engaging in green practices (e.g., Bartram, Hou and Kim, 2022; Xu and Kim, 2022). In other words, when customer firms suffer financial constraints, they tend not to support the green practices of suppliers due to limited resources. As such, the reversing effects of green-induced nondisclosure are expected to be stronger when customer firms are financially constrained. We measure firm-level financial constraint using Kaplan-Zingales (KZ) index (see Kaplan and Zingales, 1997; Lamont, Polk and Saa-Requejo, 2001). A customer firm is categorized as financially constrained if it has an above-median KZ index compared with other customer firms. Second, customer firms may not have adequate resources to support the green practices of suppliers when they have multiple suppliers. Based on this rationale, we postulate that the reversing effects of green-induced nondisclosure become stronger with the increasing number of suppliers.

## [Insert Table 4.11 here]

We repeat the regression Model (3) but construct the triple-interaction term with two measures of customer inability. As presented in Column (1) of Table 4.11, we find that the coefficient of the triple-interaction term regarding financial constraints of customer firms is negative and significant, indicating that customer firms are more likely to evade green obligations and transfer environmental risks to hidden unsustainable suppliers when facing financial constraints. Column (2) indicates that the reversing effects of green-induced nondisclosure become stronger when customer firms have more suppliers since the coefficient of the triple-interaction term is significant and negative. These findings are consistent with the notion that the customer firms engage more in shifting environmental risks to suppliers when they have no capability to support the green development of suppliers.

#### 4.6 Carbon Outsource

To further examine whether the green-induced nondisclosure of customer firms leads to green obligation evasion and environmental risk shift, we focus on the carbon outsourcing activities along the supply chain. One drawback of environmental rating is that it may not reflect the real effects of green-induced nondisclosure since environmental rating is processed by data providers with ambiguous methods. To explore the real effects, we investigate whether green-induced nondisclosure is related to carbon outsourcing activities in the supply chain. Carbon outsourcing activities have been widely documented in prior studies (e.g., Li and Zhou, 2017; Dai et al., 2024) that firms outsource their carbon emissions to upstream suppliers with lax environmental regulations. In the context of our setting, customer firms tend to outsource carbon emissions to unsustainable suppliers when they can withhold the information of these suppliers. Thus, we hypothesize that green-induced nondisclosure is positively related to carbon outsource activities in the supply chain.

## [Insert Table 4.12 here]

We estimate the baseline regression Model (1) by replacing the environmental scores of customers and suppliers with the carbon emission measures (i.e., the natural logarithm of carbon emissions) calculated using the data from S&P Trucost. More explicitly, we separately examine the effects of green-induced nondisclosure on carbon outsources regarding scope 1 and scope 2 carbon emissions and tabulate the results in Table 4.12. Column (1) shows a positive relation between scope 1 carbon emissions of customers and suppliers, which is consistent with the finding of Dai et al. (2024)<sup>83</sup>. More importantly, we find a negative and significant coefficient of the interaction term of green-induced nondisclosure and customers' scope 1 carbon emissions, suggesting the propensity of customer firms to impose heavier carbon burden on hidden suppliers

<sup>&</sup>lt;sup>83</sup> The empirical setting of Dai et al. (2024) slightly differ from ours. Since they conduct baseline analysis at firm level instead of chain level, they find that scope 1 emission correlates strongly with scope3 upstream for customer firms.

with poor environmental performance. Put differently, these hidden unsustainable suppliers may undertake the reduced carbon emissions shifting from customers. In a similar vein, we conduct the analysis regarding scope 2 emissions and find a consistent result as evidenced in Column (2). Overall, these results indicate that green-induced nondisclosure is positively related to carbon outsourcing activities in the supply chain, thus reinforcing the argument that green-induced nondisclosure is detrimental to the green transition in supply chain.

#### 4.7 Conclusion

Since there is no mandatory disclosure requirement for customer firms to unveil the information of their suppliers, customer firms strategically disclose suppliers with good environmental performance while withholding the information of suppliers with poor environmental performance, aiming to create a green image (Shi et al., 2023). In this study, we focus on the unintended consequences of this disclosure policy on the green transition in the supply chain by exploring whether the green-induced nondisclosure behavior of customer firms instigate them to evade green obligations and even transfer environmental risks to those hidden unsustainable suppliers. Specifically, we find robust evidence that the positive relation between environmental scores of customers and suppliers is dampen by the green-induced nondisclosure, suggesting that the propagation of positive green practices from customers to suppliers terminates. More seriously, further analysis shows that customer firms achieve improved environmental performance by sacrificing the environmental performance of those hidden unsustainable suppliers, reflecting severely detrimental effects of green-induced nondisclosure on green transition in the supply chain. To support a causal interpretation for baseline results, we adopt two shocks to the incentives of customer firms to transfer environmental risks.

We investigate the three possible mechanisms to interpret the reversing effects of green-induced nondisclosure on the positive relation between customers' and suppliers'

environmental scores. Our empirical results show that information transparency, suppliers' environmental pressure and capabilities of customer firms to support the green practices of suppliers can be regarded as possible mechanisms for our baseline results. Finally, we find that green-induced nondisclosure has some real effects by establishing a positive relation between green-induced nondisclosure and carbon outsourcing activities in the supply chain.

In summary, our study provides new evidence on the consequences of strategic disclosure behavior on the green transition of supply chain. In particular to stakeholders and policymakers, our study offers several important insights for them. First, for stakeholders such as shareholders and customers, they may need to manually collect the information of target firms' supply chain and cautiously evaluate the environmental performance of these firms in the context of supply chain when making investment or purchasing decisions. Second, policymakers and regulators should re-evaluate the efficiency of the disclosure policy not mandating customer firms to disclose suppliers, since it may pose negative impacts on the green transition of the whole supply chain, thereby hindering the transition to green economy.

#### Table 4.1 Summary Statistics

This table reports the summary statistics for a variety of supply chain-level variables and customer/supplier firm-level variables used in the baseline analyses. Chain-level variables include indicators representing nondisclosure behavior of firms due to suppliers' bad environmental performance (*green-induced nondisclosure*) and voluntary disclosure of unsustainable suppliers (*green-induced disclosure*), as well as the length of customer-supplier relationship (*relationship length*), a dummy indicating whether the year is the last year of this relationship (*termination year*) and the sum of changes in environmental scores of customers and suppliers ( $\Delta Envscore^{C+S}$ ). Firm-level variables are reported for both suppliers and customers, including firm-level environmental score (*Envscore*), the annual change of environmental score ( $\Delta Envscore$ ), and a series of firm and country characteristics. The sample period is from 2003 to 2023. All the variables are defined in Appendix A.

|                                      | Ν       | Mean  | SD    | p25   | p50   | p75   |
|--------------------------------------|---------|-------|-------|-------|-------|-------|
| <u>Supply Chain-Level Variables</u>  |         |       |       |       |       |       |
| Green-induced Nondisclosure          | 395,189 | 0.23  | 0.42  | 0.00  | 0.00  | 0.00  |
| Green-induced Disclosure             | 395,189 | 0.03  | 0.17  | 0.00  | 0.00  | 0.00  |
| Relationship Length                  | 395,189 | 3.65  | 3.17  | 2.00  | 3.00  | 5.00  |
| Termination Year                     | 395,189 | 0.21  | 0.41  | 0.00  | 0.00  | 0.00  |
| $\Delta EnvScore^{C+S}$              | 362,328 | 0.04  | 0.12  | -0.02 | 0.02  | 0.08  |
| <u>Supplier Firm-Level Variables</u> |         |       |       |       |       |       |
| EnvScore <sup>S</sup>                | 395,189 | 0.46  | 0.30  | 0.19  | 0.49  | 0.73  |
| ΔEnvScore <sup>S</sup>               | 362,328 | 0.02  | 0.08  | -0.01 | 0.00  | 0.04  |
| Size <sup>S</sup>                    | 395,189 | 22.44 | 2.05  | 21.02 | 22.35 | 23.87 |
| Leverage <sup>S</sup>                | 395,189 | 0.26  | 0.21  | 0.12  | 0.24  | 0.37  |
| ROA <sup>s</sup>                     | 395,189 | 0.03  | 0.14  | 0.01  | 0.04  | 0.08  |
| TobinQ <sup>S</sup>                  | 395,189 | 2.20  | 3.93  | 1.12  | 1.54  | 2.44  |
| Sales Growth <sup>S</sup>            | 395,189 | 0.19  | 20.76 | -0.01 | 0.07  | 0.18  |
| GDPperCap <sup>S</sup>               | 395,189 | 10.67 | 0.77  | 10.61 | 10.89 | 11.09 |
| Customer Firm-Level Variables        |         |       |       |       |       |       |
| EnvScore <sup>C</sup>                | 395,189 | 0.58  | 0.28  | 0.38  | 0.65  | 0.81  |
| ΔEnvScore <sup>C</sup>               | 395,189 | 0.02  | 0.08  | -0.01 | 0.00  | 0.03  |
| Size <sup>C</sup>                    | 395,189 | 23.66 | 1.95  | 22.35 | 23.76 | 25.06 |
| Leverage <sup>C</sup>                | 395,189 | 0.29  | 0.22  | 0.15  | 0.26  | 0.39  |
| ROA <sup>C</sup>                     | 395,189 | 0.04  | 0.20  | 0.01  | 0.04  | 0.08  |
| TobinQ <sup>C</sup>                  | 395,189 | 1.84  | 1.70  | 1.05  | 1.34  | 2.02  |
| Sales Growth <sup>C</sup>            | 395,189 | 0.25  | 24.79 | -0.01 | 0.05  | 0.14  |
| GDPperCap <sup>C</sup>               | 395,189 | 10.64 | 0.78  | 10.59 | 10.85 | 11.07 |

Table 4.2 Supplier and Customer Firm Distribution by Country and Region

This table shows the distribution of supplier- and customer-year observations in each country or region. Only countries with more than 1,500 suppliers in our sample are presented in this table. The *supplier score* and *customer score* refer to the average environmental scores of all the suppliers and customers in the corresponding country.

| Country/Region | Supplier Firms | Customer Firms | EnvScore <sup>S</sup> | EnvScore <sup>C</sup> |
|----------------|----------------|----------------|-----------------------|-----------------------|
| US             | 180,775        | 167,784        | 0.38                  | 0.52                  |
| UK             | 25,234         | 23,894         | 0.48                  | 0.64                  |
| Japan          | 22,662         | 33,973         | 0.66                  | 0.70                  |
| France         | 17,617         | 18,885         | 0.68                  | 0.80                  |
| Germany        | 15,655         | 18,542         | 0.63                  | 0.74                  |
| China          | 11,268         | 8,312          | 0.37                  | 0.46                  |
| India          | 10,795         | 9,870          | 0.44                  | 0.58                  |
| Canada         | 10,736         | 10,035         | 0.40                  | 0.52                  |
| South Korea    | 10,369         | 12,769         | 0.62                  | 0.67                  |
| Australia      | 9,832          | 9,256          | 0.34                  | 0.47                  |
| Switzerland    | 7,714          | 7,495          | 0.55                  | 0.73                  |
| Sweden         | 7,041          | 5,708          | 0.50                  | 0.62                  |
| Netherlands    | 4,358          | 4,042          | 0.61                  | 0.70                  |
| Italy          | 3,641          | 3,387          | 0.56                  | 0.69                  |
| Finland        | 3,490          | 1,959          | 0.69                  | 0.74                  |
| Spain          | 3,428          | 3,666          | 0.70                  | 0.80                  |
| Hong Kong      | 3,302          | 4,701          | 0.62                  | 0.57                  |
| Mexico         | 3,276          | 2,280          | 0.46                  | 0.53                  |
| Ireland        | 3,237          | 3,141          | 0.57                  | 0.57                  |
| South Africa   | 3,204          | 5,153          | 0.44                  | 0.47                  |
| Malaysia       | 2,947          | 2,645          | 0.40                  | 0.41                  |
| Brazil         | 2,934          | 4,172          | 0.50                  | 0.59                  |
| Singapore      | 2,833          | 2,257          | 0.48                  | 0.56                  |
| Thailand       | 2,712          | 2,366          | 0.47                  | 0.57                  |
| Israel         | 2,615          | 1,460          | 0.23                  | 0.30                  |
| Chile          | 2,108          | 2,855          | 0.49                  | 0.47                  |
| Norway         | 1,956          | 2,219          | 0.49                  | 0.64                  |
| Denmark        | 1,746          | 1,673          | 0.54                  | 0.61                  |
| Belgium        | 1,614          | 1,356          | 0.57                  | 0.61                  |
| Bermuda        | 1,606          | 943            | 0.33                  | 0.31                  |
| Indonesia      | 1,597          | 2,166          | 0.41                  | 0.36                  |
| Luxembourg     | 1,562          | 1,164          | 0.49                  | 0.59                  |

Table 4.3 Baseline Results - The Effects of Green-induced Nondisclosure

This table presents the regression results from the baseline model, which examines whether and how the green-induced nondisclosure of customer firms influences the positive relation between suppliers' and customers' environmental scores. The dependent variable is the environmental score of supplier firms (*EnvScore<sup>S</sup>*). The main independent variables include the one-year lagged environmental score of customer firms (*EnvScore<sup>C</sup>*), a dummy representing green-induced nondisclosure (*Green-induced Nondisclosure*) and their interaction terms, which is the variable of particular interest. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|   | Dependent Variable: EnvScore <sup>S</sup> |           |           |           |
|---|---|-----------|-----------|-----------|
|   | (1)                                       | (2)       | (3)       | (4)       |
| EnvScore <sup>C</sup> × Green-induced Nondisclosure | -0.030***                                 | -0.017*** | -0.030*** | -0.016*** |
|   | (-10.27)                                  | (-8.57)   | (-10.15)  | (-8.30)   |
| EnvScore <sup>C</sup>                               | 0.022***                                  | 0.014***  | 0.018***  | 0.007***  |
|   | (10.10)                                   | (12.47)   | (7.01)    | (5.28)    |
| Green-induced Nondisclosure                         | -0.271***                                 | -0.179*** | -0.272*** | -0.179*** |
|   | (-122.92)                                 | (-96.82)  | (-123.16) | (-97.27)  |
| Size <sup>s</sup>                                   | 0.072***                                  | 0.032***  | 0.072***  | 0.032***  |
|   | (205.05)                                  | (28.21)   | (204.27)  | (28.20)   |
| Leverage <sup>S</sup>                               | -0.035***                                 | 0.001     | -0.035*** | 0.001     |
|   | (-9.84)                                   | (0.39)    | (-9.82)   | (0.43)    |
| ROA <sup>S</sup>                                    | 0.007**                                   | -0.001    | 0.007**   | -0.001    |
|   | (2.33)                                    | (-0.78)   | (2.34)    | (-0.78)   |
| TobinQ <sup>S</sup>                                 | 0.000***                                  | -0.000*** | 0.000***  | -0.000*** |
|   | (6.60)                                    | (-2.69)   | (6.64)    | (-2.67)   |
| Sales Growth <sup>S</sup>                           | 0.000                                     | 0.000     | 0.000     | 0.000     |
|   | (-0.81)                                   | (1.41)    | (-0.79)   | (1.41)    |
| GDPperCap <sup>S</sup>                              | 0.021***                                  | 0.091***  | 0.023***  | 0.092***  |
|   | (4.29)                                    | (20.84)   | (4.56)    | (20.72)   |
| Size <sup>C</sup>                                   |   |           | 0.001***  | 0.002***  |
|   |   |           | (2.89)    | (10.07)   |
| Leverage <sup>C</sup>                               |   |           | 0.001     | 0.001     |
|   |   |           | (0.28)    | (0.81)    |
| ROA <sup>C</sup>                                    |   |           | -0.001    | -0.001    |
|   |   |           | (-0.39)   | (-0.51)   |
| TobinQ <sup>C</sup>                                 |   |           | 0.000     | 0.000     |
|   |   |           | (-0.43)   | (0.40)    |
| Sales Growth <sup>C</sup>                           |   |           | -0.000*   | 0.000     |
|   |   |           | (-1.73)   | (-0.75)   |
| GDPperCap <sup>C</sup>                              |   |           | -0.008*   | -0.004    |
|   |   |           | (-1.74)   | (-1.16)   |
| CS-Industry FE                                      | Yes                                       | Yes       | Yes       | Yes       |
| CS-Country FE                                       | Yes                                       | Yes       | Yes       | Yes       |
| Supplier Firm FE                                    | No  | Yes       | No        | Yes       |
| Year FE   | Yes                                       | Yes       | Yes       | Yes       |
| Adj R2  | 0.805                                     | 0.923     | 0.805     | 0.923     |
| Ν   | 391,174                                   | 390,700   | 391,174   | 390,700   |

## Table 4.4 The Effects of Green-induced Disclosure

This table reports the regression results regarding whether and how the green-induced disclosure of customer firms influences the positive relation between suppliers' and customers' environmental scores. The *Green-induced Disclosure* takes the value of one if customer firms voluntarily disclose the information of suppliers with bad environmental performance (below bottom thirtieth percentile). The dependent variable is the environmental score of supplier firms (*EnvScore<sup>S</sup>*). The main independent variables include the one-year lagged environmental score of customer firms (*EnvScore<sup>C</sup>*), a dummy representing green-induced disclosure (*Green-induced disclosure*) and their interaction terms, which is the key variable of interest. A battery of firm-level and country-level control variables are included. All the variables are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|  | Dependent Variable: EnvScore <sup>S</sup> |           |
|--|---|-----------|
|  | (1)                                       | (2)       |
| $EnvScore^{C} \times Green-induced Disclosure$ | 0.026***                                  | 0.019***  |
|  | (3.37)                                    | (3.27)    |
| EnvScore <sup>C</sup>                          | 0.006**                                   | 0.000     |
|  | (2.02)                                    | (-0.25)   |
| Green-induced Disclosure                       | -0.246***                                 | -0.120*** |
|  | (-63.80)                                  | (-38.50)  |
| Supplier Controls                              | Yes                                       | Yes       |
| Customer Controls                              | Yes                                       | Yes       |
| CS-Industry FE                                 | Yes                                       | Yes       |
| CS-Country FE                                  | Yes                                       | Yes       |
| Supplier Firm FE                               | No  | Yes       |
| Year FE  | Yes                                       | Yes       |
| Adj R2   | 0.731                                     | 0.907     |
| Ν  | 391,174                                   | 390,700   |

## Table 4.5 Changes in Environmental Scores

This table reports the regression results examining the relation between green-induced nondisclosure and changes in environmental scores of suppliers and customers. The main dependent variables are one-year changes in suppliers' and customers' environmental scores in Column (1) and (2), respectively. Column (3) presents the results regarding the aggregate changes in environmental scores of both suppliers and customers. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                             | Dependent Variable:   |                       |                         |
|-----------------------------|-----------------------|-----------------------|-------------------------|
|                             | $\Delta EnvScore^{S}$ | $\Delta EnvScore^{C}$ | $\Delta EnvScore^{C+S}$ |
|                             | (1)                   | (2)                   | (3)                     |
| Green-induced Nondisclosure | -0.079***             | 0.002***              | -0.077***               |
|                             | (-96.29)              | (3.33)                | (-72.27)                |
| Supplier Controls           | Yes                   | No                    | Yes                     |
| Customer Controls           | No                    | Yes                   | Yes                     |
| CS-Industry FE              | Yes                   | Yes                   | Yes                     |
| CS-Country FE               | Yes                   | Yes                   | Yes                     |
| Supplier Firm FE            | Yes                   | Yes                   | Yes                     |
| Year FE                     | Yes                   | Yes                   | Yes                     |
| Adj R2                      | 0.201                 | 0.056                 | 0.150                   |
| Ν                           | 357,522               | 390,700               | 357,522                 |

# Table 4.6 Relationship Length and Termination Probability

This table shows the regression results regarding whether and how the green-induced nondisclosure and disclosure influences the supplier-customer termination probability and relationship length. Column (1) and (2) present the regression results based on a linear probability model specification. The dependent variable is termination year, a dummy equaling one if the current year is the last year of supplier-customer relationship. Column (3) and (4) report the regression results using relationship length as dependent variable, which is calculated using the current year minus starting year of relationship plus one. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                             | Dependent Variable: |           |            |           |  |
|-----------------------------|---------------------|-----------|------------|-----------|--|
|                             | Termination Year    |           | Relationsh | ip Length |  |
|                             | (1)                 | (2)       | (3)        | (4)       |  |
| Green-induced Nondisclosure | 0.008**             |           | -0.135***  |           |  |
|                             | (2.51)              |           | (-4.85)    |           |  |
| Green-induced Disclosure    |                     | -0.045*** |            | 0.070     |  |
|                             |                     | (-9.87)   |            | (1.32)    |  |
| Supplier Controls           | Yes                 | Yes       | Yes        | Yes       |  |
| Customer Controls           | Yes                 | Yes       | Yes        | Yes       |  |
| CS-Industry FE              | Yes                 | Yes       | Yes        | Yes       |  |
| CS-Country FE               | Yes                 | Yes       | Yes        | Yes       |  |
| Supplier Firm FE            | Yes                 | Yes       | Yes        | Yes       |  |
| Year FE                     | Yes                 | Yes       | Yes        | Yes       |  |
| Adj R2                      | 0.415               | 0.415     | 0.086      | 0.086     |  |
| Ν                           | 390,700             | 390,700   | 390,700    | 390,700   |  |

## Table 4.7 US State-level GHG Emission Target

This table presents the results of triple-interaction effects using the establishment of US state-level GHG emission targets. The dependent variable is the environmental score of supplier firms. Column (1) reports the main results, where the key explanatory variable is the triple-interaction term of the one-year lagged customer environmental score, the green-induced nondisclosure dummy, and the GHG target indicator (*GHGtarget*). This indicator takes the value of one if a state enacted an executive or statutory GHG emission reduction target within the past five years. Column (2) shows the results of a placebo test, replacing the *GHGtarget* with *FalseGHGTarget*, which assumes the enactment year of GHG target is two years earlier than the actual year. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|  | GHGTarget | FalseGHGTarget |
|--|-----------|----------------|
|  | (1)       | (2)            |
| $EnvScore^{C} \times Green-induced Nondisclosure \times GHGtarget$ | -0.011**  | -0.003         |
|  | (-2.24)   | (-0.57)        |
| EnvScore <sup>C</sup> × Green-induced Nondisclosure                | -0.019*** | -0.021***      |
|  | (-5.81)   | (-6.08)        |
| Green-induced Nondisclosure × GHGtarget                            | 0.005     | 0.001          |
|  | (1.57)    | (0.32)         |
| EnvScore <sup>C</sup> × GHGtarget                                  | 0.012***  | 0.005          |
|  | (3.54)    | (1.55)         |
| EnvScore <sup>C</sup>  | 0.005**   | 0.007**        |
|  | (2.05)    | (2.47)         |
| Green-induced Nondisclosure  | -0.180*** | -0.179***      |
|  | (-63.79)  | (-62.44)       |
| GHGtarget  | -0.005**  | -0.002         |
|  | (-2.30)   | (-1.27)        |
| Supplier Controls  | Yes       | Yes            |
| Customer Controls  | Yes       | Yes            |
| CS-Industry FE   | Yes       | Yes            |
| CS-Country FE  | Yes       | Yes            |
| Supplier Firm FE   | Yes       | Yes            |
| Year FE  | Yes       | Yes            |
| Adj R2   | 0.921     | 0.921          |
| Ν  | 165,379   | 165,379        |

#### Table 4.8 Global Implementation of GHG Emission Trading System

This table presents the results of triple-interaction effects using the implementation of GHG emission trading system (ETS) worldwide. The dependent variable is the environmental score of supplier firms. Column (1) reports the main results, where the key explanatory variable is the triple-interaction term of the one-year lagged customer environmental score, the green-induced nondisclosure dummy, and ETS indicator (*ETS*). This indicator takes the value of one if a country or a US state has launched ETS. Column (2) shows the results of a placebo test, replacing the *ETS* with *FalseETS*, which assumes the implementation year of ETS is two years earlier than the actual year. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|  | ETS       | FalseETS  |
|--|-----------|-----------|
|  | (1)       | (2)       |
| $EnvScore^{C} \times Green-induced Nondisclosure \times ETS$ | -0.006*   | -0.004    |
|  | (-1.66)   | (-1.29)   |
| EnvScore <sup>C</sup> × Green-induced Nondisclosure          | -0.015*** | -0.015*** |
|  | (-6.03)   | (-5.88)   |
| Green-induced Nondisclosure × ETS                            | 0.007***  | 0.007***  |
|  | (2.91)    | (2.95)    |
| EnvScore <sup>C</sup> × ETS                                  | 0.003*    | 0.003     |
|  | (1.65)    | (1.50)    |
| EnvScore <sup>C</sup>  | 0.006***  | 0.006***  |
|  | (3.88)    | (3.81)    |
| Green-induced Nondisclosure                                  | -0.181*** | -0.181*** |
|  | (-88.01)  | (-85.38)  |
| ETS  | 0.000     | -0.001    |
|  | (0.29)    | (-0.96)   |
| Supplier Controls  | Yes       | Yes       |
| Customer Controls  | Yes       | Yes       |
| CS-Industry FE   | Yes       | Yes       |
| CS-Country FE  | Yes       | Yes       |
| Supplier Firm FE   | Yes       | Yes       |
| Year FE  | Yes       | Yes       |
| Adj R2   | 0.923     | 0.923     |
| Ν  | 390,700   | 390,700   |

## Table 4.9 Cross-sectional heterogeneity – Common Stakeholders

This table reports the heterogenous effects of green-induced nondisclosure on the relationship between suppliers' and customers' environmental scores depending on the existence of various common stakeholders in the supply chain. The dependent variable is the environmental score of supplier firms. The main explanatory variable of interest is the triple-interaction term of *EnvScore<sup>C</sup>*, *Green-induced Nondisclosure* and *Common*, which alternately represents common institutional investors (*Common IO*), common auditor (*Common Auditor*) and common analyst (*Common Analyst*). Column (1) shows whether and how our baseline results vary with common institutional investors, which is defined as the number of common institutional investors for customer and supplier firms. In Column (2), we tabulate the heterogeneity of baseline results with respect to the common auditor, which is a dummy taking the value of one if the customer and supplier firms are served by the same auditor. Column (3) presents the heterogeneous effects of common analyst on baseline results, in which common analyst is an indicator that equals one if at least one analyst issues earnings forecasts for both the supplier and customer firms. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|   | Common IO | Common Auditor | Common Analyst |
|---|-----------|----------------|----------------|
|   | (1)       | (2)            | (3)            |
| $EnvScore^{C} \times Green-induced Nondisclosure \times Common$ | 0.030***  | 0.015**        | 0.014***       |
|   | (2.60)    | (2.18)         | (3.56)         |
| EnvScore <sup>C</sup> × Green-induced Nondisclosure             | -0.022*** | -0.017***      | -0.027***      |
|   | (-8.81)   | (-8.79)        | (-7.68)        |
| Green-induced Nondisclosure × Common                            | -0.074*** | -0.019***      | -0.018***      |
|   | (-8.40)   | (-4.03)        | (-6.61)        |
| EnvScore <sup>C</sup> × Common                                  | -0.015*** | -0.005         | -0.002         |
|   | (-3.71)   | (-1.31)        | (-0.92)        |
| EnvScore <sup>C</sup>   | 0.011***  | 0.008***       | 0.009***       |
|   | (7.03)    | (5.48)         | (4.52)         |
| Green-induced Nondisclosure                                     | -0.164*** | -0.177***      | -0.166***      |
|   | (-72.87)  | (-95.62)       | (-60.89)       |
| Common  | 0.011***  | 0.005*         | 0.004***       |
|   | (3.60)    | (1.95)         | (3.17)         |
| Supplier Controls   | Yes       | Yes            | Yes            |
| Customer Controls   | Yes       | Yes            | Yes            |
| CS-Industry FE  | Yes       | Yes            | Yes            |
| CS-Country FE   | Yes       | Yes            | Yes            |
| Supplier Firm FE  | Yes       | Yes            | Yes            |
| Year FE   | Yes       | Yes            | Yes            |
| Adj R2  | 0.923     | 0.923          | 0.923          |
| Ν   | 390,700   | 390,700        | 390,700        |

## Table 4.10 Cross-sectional heterogeneity - Supplier Environmental Pressure

This table reports the heterogenous effects of green-induced nondisclosure on the relationship between suppliers' and customers' environmental scores depending on the environmental pressure of suppliers. The dependent variable is the environmental score of supplier firms. The main explanatory variable of interest is the triple-interaction term of  $EnvScore^{C}$ , *Green-induced Nondisclosure* and *Pressure<sup>S</sup>*, which alternately represents the requirement of mandatory ESG disclosure in suppliers' country (*Mandatory ESG disclosure*) and supplier country-level Environmental Performance Index (*EPI*). Column (1) shows whether and how our baseline results vary with the enactment of mandatory ESG disclosure in suppliers' countries and Column (2) presents the heterogeneous effects of supplier country-level EPI on baseline results. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|   | Mandatory      | EDI       |
|---|----------------|-----------|
|   | ESG disclosure | LFI       |
|   | (1)            | (2)       |
| $EnvScore^{C} \times Green-induced Nondisclosure \times Pressure^{S}$ | 0.010**        | 0.001***  |
|   | (2.36)         | (8.33)    |
| EnvScore <sup>C</sup> × Green-induced Nondisclosure                   | -0.019***      | -0.075*** |
|   | (-8.09)        | (-10.46)  |
| Green-induced Nondisclosure × Pressure <sup>S</sup>                   | -0.006***      | -0.001*** |
|   | (-2.77)        | (-10.58)  |
| EnvScore <sup>C</sup> × Pressure <sup>S</sup>                         | -0.009**       | -0.001*** |
|   | (-2.49)        | (-7.44)   |
| EnvScore <sup>C</sup>   | 0.009***       | 0.053***  |
|   | (5.51)         | (11.58)   |
| Green-induced Nondisclosure   | -0.176***      | -0.139*** |
|   | (-82.03)       | (-25.10)  |
| Pressure <sup>S</sup>   | -0.018***      | -0.000*** |
|   | (-7.38)        | (-4.69)   |
| Supplier Controls   | Yes            | Yes       |
| Customer Controls   | Yes            | Yes       |
| CS-Industry FE  | Yes            | Yes       |
| CS-Country FE   | Yes            | Yes       |
| Supplier Firm FE  | Yes            | Yes       |
| Year FE   | Yes            | Yes       |
| Adj R2  | 0.923          | 0.923     |
| Ν   | 390,700        | 390,700   |

## Table 4.11 Cross-sectional heterogeneity – Customer Inability

This table reports the heterogenous effects of green-induced nondisclosure on the relationship between suppliers' and customers' environmental scores depending on the inability of customer firms to support the green practices of suppliers. The main explanatory variable of interest is the triple-interaction term of *EnvScore<sup>C</sup>*, *Green-induced Nondisclosure* and *Inability*, which alternately represents the financial constraints of customer firms (i.e., measured by KZ index of Kaplan and Zingales (1997)) and number of suppliers. Column (1) shows whether and how our baseline results vary with the financial constraints of customer firms and Column (2) presents heterogenous effects with respect to the number of suppliers. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|  | Financial   | Number of |
|--|-------------|-----------|
|  | Constraints | Suppliers |
|  | (1)         | (2)       |
| $EnvScore^{C} \times Green-induced Nondisclosure \times Inability^{C}$ | -0.006**    | -0.015*** |
|  | (-1.96)     | (-2.64)   |
| $EnvScore^{C} \times Green-induced Nondisclosure$                      | -0.013***   | -0.016*** |
|  | (-4.59)     | (-6.72)   |
| Green-induced Nondisclosure × Inability <sup>C</sup>                   | 0.001       | 0.015***  |
|  | (0.32)      | (3.21)    |
| EnvScore <sup>C</sup> × Inability <sup>C</sup>                         | 0.003       | 0.013***  |
|  | (1.36)      | (3.39)    |
| EnvScore <sup>C</sup>  | -0.181***   | -0.181*** |
|  | (-79.01)    | (-91.46)  |
| Green-induced Nondisclosure  | 0.007***    | 0.006***  |
|  | (4.12)      | (3.46)    |
| Inability <sup>C</sup>   | 0.000       | -0.011*** |
|  | (-0.00)     | (-3.49)   |
| Supplier Controls  | Yes         | Yes       |
| Customer Controls  | Yes         | Yes       |
| CS-Industry FE   | Yes         | Yes       |
| CS-Country FE  | Yes         | Yes       |
| Supplier Firm FE   | Yes         | Yes       |
| Year FE  | Yes         | Yes       |
| Adj R2   | 0.923       | 0.923     |
| Ν  | 390,700     | 390,700   |

## Table 4.12 Carbon Outsource

This table reports the effects of green-induced nondisclosure on the relationship between carbon emissions of customers and suppliers. The dependent variables are the natural logarithm of suppliers' Scope1 and Scope2 carbon emissions in Column (1) and (2), respectively. The key independent variables of interest are the interaction terms of natural logarithm of customers' carbon emissions and green-induced nondisclosure. A battery of firm-level and country-level control variables are included. All the variables are defined in Appendix A. The sample spans from 2003 to 2023. Standard errors are clustered at customer-supplier pair level and the t-statistics are reported in parentheses. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|   | Dependent Variable:       |                           |  |
|---|---------------------------|---------------------------|--|
| _   | Log(Scope1 <sup>S</sup> ) | Log(Scope2 <sup>S</sup> ) |  |
|   | (1)                       | (2)                       |  |
| Log(Scope1 <sup>C</sup> ) * Green-induced Nondisclosure | -0.017***                 |                           |  |
|   | (-10.60)                  |                           |  |
| Log(Scope1 <sup>C</sup> )                               | 0.007***                  |                           |  |
|   | (5.56)                    |                           |  |
| Log(Scope2 <sup>C</sup> ) * Green-induced Nondisclosure |                           | -0.008***                 |  |
|   |                           | (-5.42)                   |  |
| Log(Scope2 <sup>C</sup> )                               |                           | 0.009***                  |  |
|   |                           | (6.36)                    |  |
| Green-induced Nondisclosure                             | 0.281***                  | -0.003                    |  |
|   | (12.93)                   | (-0.17)                   |  |
| Supplier Controls                                       | Yes                       | Yes                       |  |
| Customer Controls                                       | Yes                       | Yes                       |  |
| CS-Industry FE  | Yes                       | Yes                       |  |
| CS-Country FE   | Yes                       | Yes                       |  |
| Supplier Firm FE  | Yes                       | Yes                       |  |
| Year FE   | Yes                       | Yes                       |  |
| Adj R2  | 0.959                     | 0.961                     |  |
| N   | 335,066                   | 335,759                   |  |

# Chapter 4 - Appendix A: Variable Definition

| Variable                    | Definition and Data Source   |
|-----------------------------|--|
| Supply Chain Variables      |  |
| Green-induced Nondisclosure | A dummy is equal to one if the supplier-<br>customer relationship is not voluntarily<br>disclosed by customer firms and the supplier<br>firms' environmental performance falls into<br>the bottom thirtieth percentile in a given year<br>(Source: FactSet Revere and Refinitiv<br>Asset4) |
| Green-induced Disclosure    | A dummy is equal to one if the supplier-<br>customer relationship is voluntarily disclosed<br>by customer firms and the supplier firms'<br>environmental performance falls into the<br>bottom thirtieth percentile in a given year<br>(Source: FactSet Revere and Refinitiv<br>Asset4)     |
| Termination Year            | A dummy takes the value of one if the current<br>year is the last year of the supplier-customer<br>relationship (Source: FactSet Revere)   |
| Relationship Length         | The length of a supplier-customer<br>relationship in year, using current year minus<br>starting year of this relationship plus one<br>(Source: FactSet Revere)   |
| Environmental Variables     |  |
| EnvScore <sup>S</sup>       | The Asset4 environmental pillar score of supplier firms (Source: Refinitiv Asset4)   |
| ΔEnvScore <sup>S</sup>      | The one-year change in a supplier's<br>environmental score, calculated as the gap<br>between environmental score in current and<br>prior year (Source: Refinitiv Asset4)   |

This table reports the details about the data source and methodology to construct all variables used in this study.

| EnvScore <sup>C</sup>     | The Asset4 environmental pillar score of customer firms (Source: Refinitiv Asset4)  |
|---------------------------|---|
| ΔEnvScore <sup>C</sup>    | The one-year change in a customer's<br>environmental score, calculated as the gap<br>between environmental score in current and<br>prior year (Source: Refinitiv Asset4)                                    |
| Log(Scope1 <sup>S</sup> ) | The natural logarithm of scope 1 GHG<br>emissions of supplier firms (Source: S&P<br>Trucost)  |
| Log(Scope1 <sup>C</sup> ) | The natural logarithm of scope 1 GHG<br>emissions of customer firms (Source: S&P<br>Trucost)  |
| Log(Scope2 <sup>S</sup> ) | The natural logarithm of scope 2 GHG<br>emissions of supplier firms (Source: S&P<br>Trucost)  |
| Log(Scope2 <sup>C</sup> ) | The natural logarithm of scope 2 GHG<br>emissions of customer firms (Source: S&P<br>Trucost)  |
| Identification Variables  |   |
| ΔEnvScore <sup>C+S</sup>  | The sum of one-year changes in<br>environmental scores of suppliers and<br>customers (Source: Refinitiv Asset4)   |
| GHGTarget                 | A binary indicator takes the value of one for<br>five years starting from one year after one<br>state that the customer firm resides enacts<br>executive or statutory GHG emission target<br>(Source: C2ES) |
| FalseGHGTarget            | A similar binary indicator to GHGTarget by<br>assuming that the enactment year of state-<br>level GHG emission target is two years before<br>the actual enactment year (Source: C2ES)                       |
| ETS                       | A binary indicator takes the value of one if<br>one country or US state has implemented<br>GHG emission trading systems before year t<br>(Source: World Bank Carbon Pricing<br>Dashboard)                   |

| FalseETS                              | A similar binary indicator to ETS by<br>assuming that the implementation year of<br>country- or state-level ETS is two years<br>before the actual enactment year (Source:<br>World Bank Carbon Pricing Dashboard) |
|---------------------------------------|---|
| Mechanism Variables                   |   |
| Common IO                             | The number of common institutional<br>investors who own the shares of both<br>suppliers and customers in a given year<br>(Source: FactSet Ownership)  |
| Common Auditor                        | A dummy variable equals one if supplier and<br>customer is served by the same auditor in a<br>given year (Source: Audit Analytics)  |
| Common Analyst                        | A dummy variable equals one if at least one<br>analyst issues earnings forecasts for both<br>supplier and customer in a given year<br>(Source: Thomson Reuters IBES)  |
| Mandatory ESG Disclosure <sup>S</sup> | An indicator takes the value of one if the country of one supplier has adopted mandatory ESG disclosure in the past (Source: Krueger et al., 2024)  |
| EPI <sup>S</sup>                      | The country-level environmental<br>performance index of suppliers' countries<br>(Source: YCELP)   |
| Constraints <sup>C</sup>              | A dummy variable takes the value of one if a customer's KZ index calculated based on Kaplan and Zingales (1997) is above the median of KZ index among other customer firms in a given year (Source: WorldScope)   |
| Number of Suppliers <sup>C</sup>      | The number of suppliers for each customer<br>firm, divided by 100 (Source: FactSet<br>Revere)   |

# **Control Variables**

| Size         | The natural logarithm of total assets in US dollars plus one (Source: Worldscope)  |
|--------------|--|
| Leverage     | The percentage of total debt over total assets (Source: Worldscope)  |
| ROA          | The net income before preferred dividends<br>dividend divided by the total assets (Source:<br>Worldscope)  |
| TobinQ       | The sum of market capitalization and total<br>liabilities divided by the aggregated value of<br>common equity, total liabilities and common<br>or preferred redeemed funds (Source:<br>Worldscope) |
| Sales Growth | The one-year net sales growth (Source: Worldscope)   |
| GDPperCap    | The natural logarithm of gross domestic<br>product in current US dollars divided by<br>domestic population (Source: World Bank<br>Indicator)   |
## **Chapter 5: Thesis Conclusion**

This thesis offers a comprehensive exploration of the antecedents and consequences of ESG and CSR engagement by focusing on three central stakeholder groups—corporate insiders, institutional investors, and supply chain participants—and their roles in shaping sustainable corporate practices. Through rigorous empirical analyses, this study focuses on the complex interplay between long-term commitment, regulatory environments, strategic behavior, and stakeholder incentives in influencing the green transition, contributing important insights for both academics and policymakers.

Chapter 2 highlights the critical influence of corporate insiders' investment horizons on firm-level CSR outcomes. The findings demonstrate a strong positive association between insiders' long-term investment commitments and enhanced CSR performance, driven primarily by robust internal governance rather than opportunistic managerial conduct. By employing exogenous shocks related to managerial career horizons and disclosure policies, the chapter provides evidence supporting a causal effect of insider long-termism on CSR engagement. This underscores the necessity of fostering long-term perspectives among key corporate decision-makers as a fundamental driver of sustainable business practices. From a policy perspective, these results suggest that regulatory frameworks encouraging or rewarding long-term ownership and governance alignment may effectively promote better CSR commitments and improved ESG outcomes.

Chapter 3 investigates the responses of mutual fund managers to climate change risks post-Paris Agreement. The study documents that institutional investors actively reduce portfolio exposure to firms with high climate risk, particularly in states with stringent environmental regulations and among actively managed funds. This divestment behavior not only reflects investors' growing climate awareness but also exerts a disciplining effect on firms, motivating reductions in carbon emissions and improvements in environmental scores. The findings validate the role of institutional investors as influential agents in facilitating the low-carbon transition. Policy implications include the potential benefits of encouraging greater transparency and accountability among institutional investors and reinforcing climate-related financial disclosures to sustain investor engagement in climate risk mitigation.

Chapter 4 reveals unintended but consequential effects of voluntary supplier disclosure policies on supply chain sustainability. The absence of mandatory disclosure enables customer firms to strategically reveal suppliers with strong environmental performance while concealing those with poorer records, undermining the propagation of green practices along the supply chain. This selective nondisclosure results in environmental risk shifting, where customer firms improve their apparent environmental standing at the expense of hidden suppliers. The study identifies key mechanisms—including supply-chain information transparency, supplier regulatory pressures, and customer support capacity—that drive these dynamics, and links nondisclosure behavior to increased carbon outsourcing. For policymakers, these results signal the need to reevaluate the effectiveness of voluntary disclosure regimes and advocate for mandatory, standardized supply chain transparency requirements. Strengthening enforcement mechanisms and encouraging coordinated regulation across regions can further mitigate risk-shifting and promote genuine sustainability throughout supply chains.

Taken together, these chapters emphasize that advancing ESG and CSR requires multifaceted strategies that address stakeholder incentives, governance structures, and information asymmetries. Policymakers should focus on creating enabling environments that foster long-term orientations among corporate insiders, incentivize institutional investors to integrate climate risks in their investment decisions, and mandate transparent supply chain disclosures.

181

## References

Akbas, F., Jiang, C., Koch, P.D. 2020. Insider investment horizon. *Journal of Finance* 75 (3), 1579-1627.

Akey, P., Appel, I. 2020. Environmental externalities of activism. *Working Paper*, University of Toronto.

Aktas, N., Boone, A., Croci, E., Signori, A. 2021. Reductions in CEO career horizons and corporate policies. *Journal of Corporate Finance* 66, 101862.

Albuquerque, R., Yrjo, K., Zhang, C. 2019. Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science* 65 (10), 4451-4469.

Ali, U., Hirshleifer, D. 2017. Opportunism as a firm and managerial trait: Predicting insider trading profits and misconduct. *Journal of Financial Economics* 126 (3), 490-515.

Almeida, H., Ersahin, N., Fos, V., Irani, R.M., Kronlund, M. 2019. Do short-term incentives affect long-term productivity? *Working Paper*, University of Illinois at Urbana-Champaign.

Alok, S., Kumar, N., Wermers, R. 2020. Do fund managers misestimate climatic disaster risk. *Review of Financial Studies* 33 (3), 1146-1183.

Asgharian, H., Dzieliński, M., Hashemzadeh, Z., Liu, L. 2024. Green links: corporate networks and environmental performance, *Review of Finance* 28(3), 1027–1058.

Atta-Darkua, V., Glossner, S., Krueger, P., Matos, P. 2023. Decarbonizing institutional investor portfolios: Helping to green the planet or just greening your portfolio? *Working Paper*, University of Virginia.

Azar, J., Duro, M., Kadach, I., Ormazebal, G. 2021. The Big Three and corporate carbon emissions around the world. *Journal of Financial Economics* 142 (2), 674-696.

Bai, J., Ru, H. 2024. Carbon emissions trading and environmental protection: International evidence. *Management Science* 70(7), 4593-4603.

Baker, A., David, L. Wang, C. 2022. How much should we trust staggered difference-indifferences estimates? *Journal of Financial Economics* 144 (2), 370-395.

Balakrishnan, K., Billings, M.B., Kelly, B., Ljungqvist, A. 2014. Shaping liquidity: On the causal effects of voluntary disclosure. *Journal of Finance* 69(5), 2237-2278.

Baldauf, M., Garlappi, L. Yannelis, C. 2020. Does climate change affect real estate prices? Only if you believe in it. *Review of Financial Studies* 33 (3), 1256-1295.

Baron, D.P. 2008. Managerial contracting and corporate social responsibility. *Journal of Public Economics* 92, 268-288.

Bartram, S.M., Hou, K., Kim S. 2022. Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics* 143(2), 668-696.

Ben-David, I., Jang, Y., Kleimeier, S., Viehs., M. 2021. Exporting pollution: where do multinational firms emit CO2? *Economic Policy* 36(107), 377–437.

Benabou, R., Tirole, J. 2010. Individual and corporate social responsibility. *Economica* 77, 1-19.

Bennedsen, M., Perez-Gonzales, F., Wolfenzon, D. 2020. Do CEOs matter? Evidence from hospitalization events. *Journal of Finance* 75 (4), 1877-1911.

Berg, F., Kolbel, J.F., Rigobon, R. 2022. Aggregate confusion: The divergence of ESG ratings. *Review of Finance* 26 (6), 1315-1344.

Berk, B.J., van Binsbergen, H. J. 2025. The impact of impact investing. *Journal of Financial Economics* 164, 103972.

Bernstein, A., Gustafson, T.M., Lewis, R. 2019. Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics* 134 (2), 253-272.

Bialkowski, J., Starks, L.T. 2016. SRI funds: Investor demand, exogenous shocks and ESG profiles. *Working Paper*, University of Canterbury.

Bolton, P., Kacperczyk, M. 2023. Global pricing of carbon-transition risk. *Journal of Finance* 78 (6), 3677-3754.

Bolton, P., Kacperczyk, M. 2021. Do investors care about carbon risk? *Journal of Financial Economics* 142 (2), 517-549.

Borghesi, R., Houston, J.F., Naranjo, A. 2014. Corporate socially responsible investments: CEO altruism, reputation, and shareholder interests. *Journal of Corporate Finance* 26, 164-181.

Brochet, F., Loumioti, M., Serafeim, G. 2015. Speaking of the short-term: Disclosure horizon and managerial myopia. *Review of Accounting Studies* 20, 1122-1163.

Bushee, B.J. 2001. Do institutional investors prefer near-term earnings over long-run value? 183

Contemporary Accounting Research 18 (2), 207-246.

Cadman, B., Sunder, J. 2014. Investor horizon and CEO horizon incentives. *The Accounting Review* 89 (4), 1299-1328.

Cao, J., Liang, H., Zhan, X. 2019. Peer effects of corporate social responsibility. *Management Science* 65(12), 5487–5503.

Chava, S. 2014. Environmental externalities and cost of capital. *Management Science* 60 (9), 2223-2247.

Chen, T., Dong, H., Lin, C. 2020. Institutional shareholders and corporate social responsibility. *Journal of Financial Economics* 135 (2), 483-504.

Cheng, I., Hong, H., Shue, K. 2023. Do managers do good with other people's money? *Review* of Corporate Finance Studies 12 (3), 443-487.

Choi, D., Gao, Z. Jiang, W. 2020. Attention to global warming. *Review of Financial Studies* 33 (3), 1122-1145.

Choi, D., Gao, Z., Jiang, W., Zhang, H. 2021. Global carbon divestment and firms' actions. *Working Paper*, The Chinese University of Hong Kong.

Choi, S., Levine, R., Park, R., Xu, S. 2024. CEO Compensation and Adverse Shocks: Evidence from Changes in Environmental Regulations. *NBER Working Paper* 32663.

Choi, S., Park, J. R., Xu, S. 2022. Environmental regulatory risks, firm pollution and mutual funds' portfolio choices. *Working Paper*, Hanyang University.

Cohen, L., Gurun, U.G., Nguyen, Q. 2021. The ESG-innovation disconnect: Evidence form green patenting. *European Corporate Governance Institute - Finance Working Paper No.744*.

Cohen, L. Malloy, C., Pomorski, L. 2012. Decoding insider information. *Journal of Finance* 67 (3), 1009-1043.

Cohen, S., Kadach, I., Ormazabal, G., Reichelstein, S. 2023. Executive compensation tied to ESG performance: International Evidence. *Journal of Accounting Research* 61 (3), 805-853.

Coles, J.L., Daniel, N.D., Naveen, L. 2006. Managerial incentives and risk-taking. *Journal of Financial Economics* 79, 431-468.

Colmer, J., Martin, R., Muuls, M., Wagner, U.J. 2024. Does Pricing Carbon Mitigate Climate Change? Firm-level Evidence from the European Union Emissions Trading System. *Review of Economic Studies*, 1-36.

Dai, R., Duan, R., Liang, H., Ng, L. 2024. Outsourcing Climate Change. *European Corporate Governance Institute – Finance Working Paper No.* 723/2021.

Dai, R., Liang, H., Ng. L. 2021. Socially responsible corporate customers. *Journal of Financial Economics* 142(2), 598-626.

Dang, V.A., Gao, N., Yu, T. 2023. Climate Policy Risk and Corporate Financial Decisions: Evidence from the NO<sub>x</sub> Budget Trading Program. *Management Science* 69 (12), 7517-7539.

Darendeli, A., Fiechter, P., Hitz, J.M., Lehmann, N. 2022. The role of corporate social responsibility (CSR) information in supply-chain contracting: Evidence from the expansion of CSR rating coverage. *Journal of Accounting and Economics* 74(2–3), 101525.

Darrough, M.N., Stoughton, N.M. 1990. Financial disclosure policy in an entry game, *Journal* of Accounting and Economics 12(1-3), 219-243.

Deng, X., Kang, J.K., Low, B.S. 2013. Corporate social responsibility and stakeholder value maximization: Evidence from mergers. *Journal of Financial Economics* 110 (1), 87-109.

Derrien, F., Krueger, P., Landier, A., Yao, T. 2024. ESG news, future cash flows, and firm value. *Swiss Finance Institute Research Paper No. 21-84 / HEC Paris Research Paper No FIN-2021-1441*.

Dhaliwal, D.S., Shenoy, J., Williams, R. 2017. Common auditors and relationship-specific investment in supplier-customer Relationships. *Working Paper*.

Dimson, E., Karakas, O., Li, X. 2015. Active ownership. *Review of Financial Studies* 28 (12), 3225–3268.

Downar, B., Ernstberger, J., Reichelstein, S., Schwenen, S., Zaklan, A. 2021. The impact of carbon disclosure mandates on emissions and financial operating performance. *Review of Accounting Studies* 26, 1137-1175.

Duan, T., Li, W., Wen, Q. 2023. Is carbon risk priced in the cross-section of corporate bond returns? *Journal of Financial and Quantitative Analysis* forthcoming.

Duchin, R., Gao, J., Xu, O. 2024. Sustainability or greenwashing: Evidence from the asset market for industrial pollution. *Journal of Finance* forthcoming.

Dyck, A., Lins, K.V., Roth, L., Wagner, H.F. 2019. Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics* 131 (3), 693-714.

Edmans, A. 2023. Applying economics-Not gut feel-to ESG. Financial Analyst Journal

79(4), 16-29.

Edmans, A. 2023. The end of ESG. Financial Management 52 (3), 3-17.

Edmans, A. 2020. *Grow the Pie: How Great Companies Deliver Both Purpose and Profit-Updated and Revised*. Cambridge University Press.

Edmans, A. 2011. Does the stock market fully value intangibles? Employee satisfaction and equity sales. *Journal of Financial Economics* 101 (3), 621-640.

Edmans, A., Fang, V.W., Huang, A. 2022. The long-term consequences of short-term incentives. *Journal of Accounting Research 60(3)*, 1007-1046.

Edmans, A., Fang, V.W., Lewellen, K.A. 2017. Equity vesting and investment. *Review of Financial studies* 30 (7), 2229-2271.

Edmans, A., Goncalves-Pinto, L., Groen-Xu, M., Wang, Y. 2018. Strategic news releases in equity vesting months. *Review of Financial Studies* 31 (11), 4099-4141.

Edmans, A., Gosling, T., Jenter, D. 2023. CEO compensation: Evidence from the field. *Journal* of *Financial Economics* 150, 103718.

Edmans, A., Gosling, T., Jenter, D. 2025. Sustainable investing in practices: Objectives, constraints and limits to impact. *ECGI Working Paper Series in Finance* N° 1028/2024.

Ernstberger, J., Link, B., Stich, M., Vogler, O. 2017. The real effects of mandatory quarterly reporting. *The Accounting Review* 92 (5), 33-60.

Ersahin, N., Giannetti, M., Huang, R. 2024. Trade credit and the stability of supply chains. *Journal of Financial Economics* 155, 103830.

Farzamfar, A., Foroughi, P., Ng, L. 2022. The hidden cost of going green: Evidence from firmlevel violations. *Working Paper*, York University.

Field, L., Lowry, M., Shu, S. 2005. Does disclosure deter or trigger litigation? *Journal of Accounting and Economics* 39(3), 487-507.

Financial Times. 2025. BlackRock quits climate change group in latest green climbdown. Retrieved from <u>https://www.ft.com/content/f0fb9841-db1d-442e-a757-1a1327497fb1</u>.

Flammer, C. 2018. Competing for government procurement contracts: The role of corporate social responsibility. *Strategic Management Journal* 39(5), 1299-1324.

Flammer, C. 2015. Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science* 61, 2549-2568.

Flammer, C., Bansal, P. 2017. Does a long-term orientation create value? Evidence from a regression discontinuity. *Strategic Management Journal* 38 (9), 1827-1847.

Flammer, C., Kacperczyk, A. 2019. Corporate social responsibility as a defense against knowledge spillovers: Evidence from the Inevitable disclosure doctrine. *Strategic Management Journal* 40 (8), 1243-1267.

Freeman, K.M. 2023. Overlapping ownership along the supply chain. *Journal of Financial and Quantitative Analysis*, 1-30.

Fu, X., Shen, R., Tang, T., Yan, X. 2021. Horizon to sustainability: Uncover the instrumental nature of corporate social responsibility. *Unpublished Working Paper*, University of Louisville.Gantchev, N., Giannetti, M., Li, R. 2021. Does money talk? Market discipline through selloffs

and boycotts. European Corporate Governance Institute - Finance Working Paper No.634.

Gao, F., Lisic, L., Zhang, I.X. 2014. Commitment to social good and insider trading. *Journal of Accounting Economics* 57, 149-175.

Gasper. J., Massa, M., Matos, P. 2005. Shareholder investment horizons and the market for corporate control. *Journal of Financial Economics* 76, 135-165.

Gibson, R., Glossner, S., Krueger, P., Matos, P., Steffen, T. 2022. Do responsible investors invest responsibly? *Review of Finance* 26 (6), 1389-1432.

Giuli, A.D., Kostovetsky, L. 2014. Are red or blue companies more likely to go green? Politics and corporate social responsibility. *Journal of Financial Economics* 111, 158-180.

Glossner, S. 2019. Investor horizons, long-term blockholders, and corporate responsibility. *Journal of Banking and Finance* 103, 78-97.

Gopalan, R., Milbourn, T., Song, F., Thakor, A.V. 2014. Duration of executive compensation. *Journal of Finance* 69 (6), 2777-2817.

Guan, Y., Wong, F., Zhang, Y. 2015. Analyst Following along the Supply Chain. *Review of Accounting Studies* 20, 210-241.

Hartzmark, S.M., Sussman, A.B. 2019. Do investors value sustainability? A natural experiment examining ranking and fund flows. *Journal of Finance* 74 (6), 2789-2837.

Heinkel, R., Kraus, A., Zechner, J. 2001. The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis* 36 (4), 431-449.

Hiller, D., Korczak, A., Korczak, P. 2015. The impact of personal attributes on corporate insider 187

trading. Journal of Corporate Finance 30, 150-167.

Hong, H., Kacperczyk, M. 2009. The price of sin: The effects of social norms on markets. Journal of Financial Economics 93 (1), 15–36.

Hong, H., Kubik, J.D., Scheinkman, J.A. 2012. Financial constraints on corporate goodness. NBER Working Paper No. 18476.

Holmstrom, B. 1999. Managerial incentive problems: A dynamic perspective. Review of Economic Studies 66, 169-182.

Homroy, S., Rauf, A. 2024. Green washing in supply chains? Working Paper, University of Groningen.

Houston, J.F., Shan, H. 2022. Corporate ESG profiles and banking relationships. *Review of* Financial Studies 35(7), 3373-3417.

Howe, P.D., Mildenberger, M., Marlon, J.R., Leiserowtiz, A. 2015. Geographic variation in opinions on climate change at state and local scales in the USA. Nature Climate Change 5, 593-603.

Huynh, D. T., Li, W., Xia, Y. 2025. Something in the air: does air pollution affect fund managers' carbon divestments? Review of Accounting Studies forthcoming.

Imbens, G.W., Wooldridge, J.M. 2009. Recent developments in the econometrics of program evaluation. Journal of Economic Literature 47 (1), 5-86.

Jacobs, B.W., Singhal, V.R. 2020. Shareholder value effects of the Volkswagen emissions scandal on the automotive ecosystem. Production and Operations Management 29(10), 2230-2251.

Kacpercyzk, M., Sialm, C. Zheng, L. 2008. Unobserved actions of mutual funds. Review of Financial Studies 21(6), 2379-2416.

Kaplan, S.N., Zingales, L. 1997. Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints. The Quarterly Journal of Economics 112 (1), 169-215.

Khan, M., Serafeim, G., Yoon, A. 2016. Corporate sustainability: First evidence on materiality. The Accounting Review 91, 697-1724.

Kim, H., Kim, T., Kim, Y., Park, K. 2019. Do long-term institutional investors promote corporate social responsibility activities? Journal of Banking and Finance 101, 256-269.

Kim, Y. H., Ren, B., Xu, N. 2024. Common auditors and within-relationship information-

processing costs: Evidence from supply chain relationships. Donald G. Costello College of Business at George Mason University Research Paper.

Kim, Y., Sun, C., Xiang, Y., Zeng, C. 2024. Cross-border impact of ESG disclosure mandate: Evidence from foreign government procurement contracts. Working Paper, Santa Clara University.

Kim, I., Wan, H., Wang, B., Yang, T. 2019. Institutional investors and corporate environmental, social, and governance policies: Evidence from toxic release data. Management Science 65, 4901-4926.

Kothari, S. P., Shu, S., Wysocki, P.D. 2009. Do managers withhold bad news. Journal of Accounting Research 47(1), 1-276.

Kraft, A.G., Vashishtha, R., Venkatachalam, M. 2018. Frequent financial reporting and managerial myopia. The Accounting Review 93 (2), 249-275.

Krueger, P. 2015. Corporate goodness and shareholder wealth. Journal of Financial Economics 115, 304-329.

Krueger, P., Metzger, D., Wu, J. 2024. The sustainability wage gap. Swiss Finance Institute Research Paper No. 21-17.

Krueger, P., Sautner, Z., Tang, Y., Zhong, R. 2024. The Effects of Mandatory ESG Disclosure around the World. Journal of Accounting Research 62 (5), 1795-1847.

Krueger, P., Sautner, Z., Starks, L.T. 2020. The importance of climate risks for institutional investors. Review of Financial Studies 33 (3), 1067-1111.

Ladika, T., Sautner, Z. 2020. Managerial short-termism and investment: Evidence from accelerated option vesting. Review of Finance 24 (2), 305-344.

Lamont, O., Polk, C., Saa-Requejo, J. 2001. Financial Constraints and Stock Returns. Review of Financial Studies 14 (2), 529-544.

Li, X., She, G., Yoon, A., Zhu, H. 2024. Shareholder value implications of supply chain ESG: Evidence from negative incidents. Working Paper, University of Hong Kong.

Li, N., Shevlin, T., Zhang, W. 2022. Managerial career concerns and corporate tax avoidance: Evidence from the Inevitable Disclosure Doctrine. Contemporary Accounting Research 39 (1), 7-49.

Li, J., Ye, X. 2023. Do customers play a disciplinary role on suppliers' short-term incentives.

Working Paper, NHH Norwegian School of Economics.

Li, X., Zhou, Y.M. 2017. Offshoring Pollution while Offshoring Production? *Strategic Management Journal* 38 (11), 2310-2329.

Lu, H., Peng, Q., Shin, J., Yu, L. 2023. Migration of global supply chains: A real effect of mandatory ESG disclosure. *Working Paper*, University of Toronto.

Luo, S., Nagarajan, N.J. 2015. Information complementarities and supply chain analysts. *The Accounting Review* 90(5), 1995-2029.

Malmendier, U., Tate, G. 2005. CEO overconfidence and corporate investment. *Journal of Finance* 60 (6), 2661-2700.

Mark, S., Yan, J., Yao, Y. 2022. What drives a firm's ES performance? Evidence from stock returns. *Journal of Banking and Finance* 136, 106304.

Martin, P.R., Moser, D.V. 2016. Managers' green investment disclosures and investors' reaction. *Journal of Accounting and Economics* 61 (1), 239-254.

Martinsson, G., Sajtos, L., Strömberg, P., Thomann, C. 2024. The effect of carbon pricing on firm emissions: Evidence from the Swedish CO2 tax. *Review of Financial Studies* 37(6), 1848-1886.

Masulis, R.W., Reza, S.W. 2015. Agency problems of corporate philanthropy. *Review of Financial Studies* 28 (2), 592-636.

McCarthy, S., Oliver, B., Song, S. 2017. Corporate social responsibility and CEO confidence. *Journal of Banking and Finance* 75, 280-291.

Meier, J., Servaes, H., Wei, J., Xiao, C. 2023. Do consumers care about ESG? Evidence from barcode-level sales data. *European Corporate Governance Institute – Finance Working Paper* No. 926/2023, *Kilts Center at Chicago Booth Marketing Data Center Paper*.

Mueller, I., Sfrappni, E. 2022. Climate change-related regulatory risks and bank lending. *ECB Working Paper No.2022 / 2670*.

Na, K. 2020. CEOs' outside opportunities and relative performance evaluation: Evidence from a natural experiment. *Journal of Financial Economics* 137, 679-700.

Narayanan, M.P. 1985. Managerial incentives for short-term results. *Journal of Finance* 40 (5), 1469-1484.

Naaraayanan, L.S., Sachdeva, K., Sharma, V. 2021. The real effects of environmental activist 190

investing. European Corporate Governance Institute – Finance Working Paper No. 743/2021. Pankratz, N.M.C., Schiller, C.M. 2024. Climate Change and Adaptation in Global Supply-Chain Networks, Review of Financial Studies 37(6), 1729–1777.

Pastor, L., Stambaugh, R.F., Taylor, L.A. 2021. Sustainable investing in equilibrium. Journal of Financial Economics 142 (2), 550-571.

Raghunandan, A., Rajgopal, S. 2021. Do socially responsible firms walk the talk? Working Paper, London School of Economics.

Rajgopal, S. Srivastava, A., Zhao, R. 2024. Economic substance behind Texas political anti-ESG sanctions. Working Paper, Columbia University.

Ramelli, S., Wagner, F.A., Zeckhauser, R., Ziegler, A. 2021. Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 US elections. Review of Corporate Finance Studies 10 (4), 748-787.

Riedl, A., Smeets, P. 2017. Why do investors hold socially responsible mutual funds? Journal of Finance 72 (6), 2505-2550.

Roth, J., Sant'Anna, P.H.C., Bilinski, A., Poe, J. 2023. What's trending in difference-indifferences? A synthesis of the recent econometrics literature. Journal of Econometrics 235 (2), 2218-2244.

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R. 2023. Firm-level climate change exposure. Journal of Finance 78 (3), 1449-1498.

Schiller, C.M. 2018. Global supply-chain networks and corporate social responsibility. Working Paper, Ohio State University.

Seltzer, L., Starks, L. Zhu, Q. 2025. Climate regulatory risks and corporate bonds. FRB of New York Staff Report No. 1014, Rev. March 2025.

Servaes, H., Tamayo, A. 2013. The impact of corporate social responsibility on firm value: The role of customer awareness. Management Science 59 (5), 1045-1061.

Smith, C.W., Watts, R.L. 1992. The investment opportunity set and corporate financing, dividend and compensation policies. Journal of Financial Economics 32, 263-292.

Shi, Y., Wu, J., Zhang, Y., Zhou, Y. 2023. Green image management in supply chains: Strategic Disclosure of corporate suppliers. Working Paper, The Chinese University of Hong Kong.

Starks, L., Venkat, P., Zhu, Q. 2023. Corporate ESG profiles and investor horizons. Working 191

Paper, University of Texas at Austin.

Stein, J. 1988. Takeover threats and managerial myopia. *Journal of Political Economy* 96 (1), 61-80.

Stroebel, J., Wurgler, J. 2021. What do you think about climate finance? *Journal of Financial Economics* 142 (2), 487-498.

Tian, H., Wang, J., Wu, S. 2024. Supply Chain Vertical Common Ownership and Cost of Loans. *Journal of Corporate Finance* 102677.

Verrecchia, R.E. 1983. Discretionary disclosure. *Journal of Accounting and Economics* 5, 179-194.

Xu, Q., Kim, T. 2022. Financial constraints and corporate environmental policies. *Review of Financial Studies* 35 (2), 576-635.

Yan, X., Zhang, Z. 2009. Institutional investors and equity returns: Are short-term institutions better informed? *Review of Financial Studies*, 22(2), 893-924.