Essays on Institutional Investors

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2024

A thesis submitted for the award of Doctor of Philosophy

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

Signed: *Partha Proteem Roy*
Date: March 7, 2024

Acknowledgment

It has been a long-cherished dream of mine to pursue a PhD in Finance, the area for which I have grown a strong passion since my undergraduate days. I am forever grateful and indebted to my doctoral supervisors, Professor Chandra Thapa and Professor Andrew Marshall, for their continuous support, guidance, motivation, and encouragement throughout my PhD journey at Strathclyde. It has been a wonderful journey working under their supervision and obtaining the necessary skills, expertise, and knowledge to complete this doctoral thesis.

I would like to extend my gratitude to my senior PhD colleagues and friends, Dr Sandeep Rao, and Dr Santosh Koirala for all the intellectual discussions, critical reviews, and constructive suggestions which have greatly enriched the quality of my PhD work. They have been a great inspiration for me from the very beginning of my PhD journey.

I am truly grateful to my dearest parents, Kamalendu Roy and Nandita Roy for their lifelong unconditional love and unparalleled support for me to excel in my chosen path of life and to become the best version of myself. I would also like to express my gratitude to my late grandfather, Karnadhar Roy, who had put all his trust and faith in me and encouraged me to pursue my dream. Finally, I am sincerely grateful to my dear partner, Min Zhu, for her immense love, care, and support during the past seven years in the UK within which I completed my MSc and PhD studies.

I sincerely acknowledge the helpful comments from numerous discussants, chairs, reviewers, and participants from numerous conferences including 50th Financial Management Association (FMA) Annual Meeting 2020, 60th Southern Finance

Association (SFA) Annual Meeting 2020, 1st BOCA Corporate Finance and Governance Annual Conference 2020, Edinburgh-Shanghai Management Conference on Environment and Climate Change 2021, 63rd SFA Annual Meeting 2023, and Sustainable Financial Innovation Centre (SFiC) Annual Conference 2023.

I am grateful to the University of Strathclyde for awarding me the prestigious Student Excellence Award (SEA) studentship and fully funding my doctoral studies.

I sincerely appreciate all the support and guidance extended to me by Professor Dick Davies, Professor Graeme Acheson, Professor Jonathan Fletcher, Dr Patrick McColgan, and all other academic staff members at the Department of Accounting and Finance who have influenced me in shaping my academic expertise and prospects. I extend my gratitude to all the non-academic staff (Lorna, Barbara, Ryan, Katie, Donald, Martin, and Donna) at the Department of Accounting and Finance for all their research and teaching-related support. Finally, I am thankful to my fellow PhD colleagues Sulaiman, Frima, Mehrin, Shivani, Rose, and others for their company and friendship.

Sincerely,

Partha Proteem Roy

Dedicated to all my teachers.

Statement on Published and Conference Work

This thesis consists of three major empirical chapters. A version of the empirical chapter titled 'Corporate Social Responsibility and Foreign Institutional Investor Heterogeneity' has been published in the *Journal of Corporate Finance (JCF), (2022) Volume 76.* This paper was presented at the 50th FMA Annual Meeting 2020, 60th SFA Annual Meeting 2020, and 1st BOCA Corporate Finance and Governance Annual Conference 2020 among others. The paper was the semi-finalist of the Best Paper award at the 2020 FMA Annual Meeting. Further, the second empirical chapter titled 'Extreme Rainfall and Institutional Investor Behavior' was presented at the Edinburgh-Shanghai Management Conference on Environment and Climate Change 2021. Finally, the third empirical chapter titled 'Immigration Fear, Populism, and Institutional Investors' was presented at the 63rd SFA Annual Meeting 2023 and SFiC Annual Conference 2023.

All the published and conference papers have been developed from the original research ideas I developed throughout my doctoral studies. Additionally, I conducted a comprehensive literature review, formulated all the research hypotheses, collected data, and performed all empirical analyses. Following the completion of the initial drafts of the chapters, my co-authors offered recommendations for doing supplementary robustness checks and provided valuable critiques and direction. I incorporated their suggestions to refine the papers in accordance with the requisite style and standards for academic journal submissions.

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Abstract

This thesis comprises of three major empirical chapters examining the investment choices and preferences of institutional investors under various exogenous factors. The first empirical chapter examines whether the heterogeneity of foreign institutional investors (FIIs) matters when investing in socially responsible investee firms. Exploiting a mandated corporate social responsibility (CSR) regulation in India and using manually collected CSR expenditure data, the results of a quasi-natural experiment confirm that firms that comply with the CSR mandate attract more investments from FIIs. However, the heterogeneity of FIIs plays a significant moderating role, as FIIs from civil law origin countries, and those considered to be independent and long-term investors, invest more in mandated CSR firms. Finally, the empirical evidence also indicates that firms that comply with the CSR mandate experience higher long-term market-based valuations in the post-CSR reform period.

In the second empirical chapter, I investigate institutional investor behavior and firm valuation surrounding extreme rainfall conditions in rain-sensitive firms. Using Indian monsoon data and exploiting extreme rainfall conditions as ongoing natural experiments, I show that institutional investors significantly increase (decrease) their ownership in rain-sensitive firms during the excess (deficit) rainfall years. Despite the extreme rainfall conditions, I show that institutional investors gain from investing in rain-sensitive firms during excess periods, as those firms have superior financial performance in the following period. Further analysis shows that although both domestic and foreign institutional investors increase their ownership in rain-sensitive firms following excess rainfall periods, only domestic institutional

investors significantly divest from rain-sensitive firms in deficit periods. The results support the view that extreme climate conditions can impact firm value and change investor behavior.

In the third and final empirical chapter, I investigate whether immigration induced fear sentiments affect the investment decisions of institutional investors. Using a text-based measure of immigration fear and data from four developed economies, I show that higher immigration fear sentiments trigger institutional investors to divest from their investee firms. This effect is most pronounced among domestic, independent, and short-term institutional investors. Further, right-wing populism intensifies the negative impact of immigration fear sentiments on institutional investors' investments. I use an instrumental variable approach and exploit an exogenous event that caused a surge in immigration fear sentiments in my empirical analyses to establish causality and strengthen the findings. Finally, I demonstrate that it is the institutional investors' fear-based risk-aversion and not information on future firm performance that induces them to make their divestment choices during periods of heightened immigration fear.

Overall, from the findings of my thesis, it can be concluded that institutional investors demonstrate differing investment behavior under varying exogenous factors. More importantly, heterogenous institutional investors, characterized by different attributes, investment approaches, and objectives, exhibit differential reactions under different exogenous circumstances.

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List of Abbreviations

BM	Book to Market ratio
BSE	Bombay Stock Exchange Ltd
CAPEX	Capital Expenditure
CSR	Corporate Social Responsibility
CMIE	Centre for Monitoring the Indian Economy
DiD	difference-in-differences
DiDiD	difference-in-difference-in-differences
DIIs	Domestic Institutional Investors
EBIT	Earnings before interest and taxes
EBITDA	Earnings before interest, taxes, depreciation, and amortization
ERC	European Refugee Crisis
FIIs	Foreign Institutional Investors
GDP	Gross Domestic Product
IMD	Indian Meteorological Department
IO	Institutional Ownership
INR	Indian Rupees
MB	Market to Book ratio
IV	Instrumental Variable
MRDD	Multivariate Regression Discontinuity Design
NSE	National Stock Exchange of India Ltd
PAT	Profit after tax
PP&E	Property, Plant, And Equipment
PRI	Principles of Responsible Investment
PSM	Propensity score matching
PSM-DiD	Propensity-score matched difference-in-differences
R&D	Research and Development
RDD	Regression Discontinuity designs
ROA	Return on Assets
ROE	Return on Equity
RWP	Right Wing Populism
S-135	Section 135 of India's Companies Act 2013
UK	United Kingdom
USA	United States of America
USD	United States Dollar

1. Chapter 1: Introduction

1.1 Background and motivation

Over the past few decades, institutional investors have become the most dominant players in international capital markets, owning significant stakes of market capitalizations (Stambaugh, 2014; Stein, 2009). The growing presence of institutional investors in capital markets has made them price-setting traders as they bring in greater informational efficiency related to pricing (Boehmer and Kelley, 2009; Nofsinger and Sias, 1999). Further, on the corporate side, institutional investors are playing crucial roles such as improving corporate governance mechanisms, driving up corporate sustainability practices, and promoting corporate innovation and investments of their investee firms (Aghion et al., 2013; Dyck et al., 2019; McCahery et al., 2016). Given the prominence of institutional investors in financial markets and their strong influence on corporations, it is of utmost importance to understand how institutional investors make their investment choices under the influence of different exogenous factors that they have no control over. More importantly, it is crucial to understand what factors drive institutional investors to make their investments in their investee firms under various exogenous factors, and whether different types/groups of institutional investors have differential investment preferences under the same circumstances.

Extant literature suggests that institutional investors are sophisticated in that they possess superior trading information and stock-picking skills (Baker et al., 2010; Gompers and Metrick, 2001; Huang et al., 2020). Contrary to this view, some studies suggest that institutional investors may not have superior trading skills (Carhart, 1997; Jensen, 1968). Moreover, many recent studies suggest that institutional investors are prone to psychological biases, exhibiting herding, salient, and even irrational trading behavior (Alok et al., 2020; DeVault et al., 2019; Sias, 2004). Such divergence in investment skills and choices among institutional investors could stem from the heterogenous characteristics of different institutional investors, such as geographic proximity, investment styles and objectives, investment horizons, legal origins and cultures, and access to information and expertise (Coval and Moskowitz, 2001; Ferreira and Matos, 2008; Kacperczyk and Seru, 2007; Yan and Zhang, 2009). In other words, the heterogeneous nature of different institutional investors could be crucial for understanding their investment preferences and choices. To better understand whether the heterogenous nature of different institutional investors matters for their investment decisions, in this thesis, I study the investment behavior and preferences of different types of institutional investors under various exogenous conditions. Specifically, I study how heterogeneous institutional investors make their investment choices in investee firms with regard to mandatory corporate social responsibility (CSR) regulations, under extreme rainfall conditions and during periods of heightened immigration fear sentiments.

1.2 Research questions, related hypotheses and findings

1.2.1 Mandatory corporate social responsibility

In Chapter 2, I investigate how foreign institutional investors (FIIs) react when their potential investee firms are mandated to expend in specific corporate social responsibility (CSR) activities and whether heterogenous FIIs invest differentially in mandated CSR firms. Motivated by the concurrent growing demand for environmental, social, and governance (ESG) associated metrics by professional asset managers and analysts (Amel-Zadeh and Serafeim, 2018; Ioannou and Serafeim, 2015), I exploit Section 135 of India's Companies Act 2013 (S-135) mandatory CSR regulation in a natural experiment setup to examine whether mandated CSR firms that actually expend on prescribed CSR activities are able to attract higher levels of investments from FIIs. To better measure firms' ESG performance, I utilize a novel hand-collected CSR expenditure dataset.

Drawing on the literature that higher levels of CSR activities at the firm level may help investors by minimizing information asymmetry and lowering agency concerns (Cui et al., 2018; Dhaliwal et al., 2011), I first explore the relationship between mandatory CSR engagement and FIIs' investments. Studies suggest that, compared to domestic institutional investors (DIIs), FIIs significantly suffer from information asymmetry when investing in local firms, which could lead them to misestimate the true value of local stocks and underweight their investments due to higher monitoring costs (Baik et al., 2013; Leuz et al., 2009). In this regard, mandatory CSR obligations of investee firms could alleviate such information disadvantage for FIIs by promoting improved transparency and governance. Moreover, a growing body of recent literature advocates that such CSR activities could build social capital and trust, consequently acting as insurance against various risks as well as promoting financial performance and growth (Albuquerque et al., 2019; Guiso et al., 2004; Roy et al., 2022). Mandatory CSR engagement should encourage FIIs to invest more in mandated CSR firms.

Next, I dig deeper and try to uncover whether the heterogeneity in FIIs matters when investing in mandated CSR firms. According to Liang and Renneboog (2017), legal origin could be a major factor in determining different preferences for CSR. Since countries belonging to civil law jurisdictions promote a high stakeholder-oriented corporate social culture and maintain stronger CSR philosophies compared to common law origin countries, I expect FIIs domiciled in civil law countries to be more inclined towards investing in mandatory CSR firms compared to their common law origin counterparts (La Porta et al., 2008; Liang and Renneboog, 2017). Further, FIIs with different investment styles/objectives and investment horizons may also invest differentially in mandated CSR firms. I conjecture that independent FIIs being active monitors and pension fund FIIs and long-term investors are more likely to invest in mandated CSR firms as CSR tends to lower monitoring costs and payoff in the long run (Dyck et al., 2019; Ferreira and Matos, 2008).

In line with the above expectations, I find that in the post-CSR regulatory mandate period, FIIs substantially raised their investment stakes in mandated CSR firms compared to non-CSR firms. In economic terms, based on various parameters, I find that the average rise in FIIs' ownership in CSR firms ranges from 7.5% to 8.5%. Additional tests reveal that in the years following the CSR legislation, CSR firms attracted investments from both new and existing FIIs. From the FIIs' heterogeneity tests, I observe that, compared to common law FIIs, civil law FIIs are more likely to increase their investments in CSR firms. Additionally, and in line with the conjecture that mandatory CSR regulations enhance transparency and lower monitoring costs, I find that independent FIIs, who tend to be active monitors, and pension funds FIIs, who have long investment horizons, are more inclined to invest in mandated CSR firms.

Finally, despite empirical research suggesting that mandatory CSR regulations may have a short-term negative impact on market value (Grewal et al., 2019; Manchiraju and Rajgopal, 2017), I examine the long-term value relevance for companies that adhere to the CSR regulation. It is observed that mandated CSR firms have greater market-based valuations than non-CSR firms in the long run (Ferrell et al., 2016; Lins et al., 2017; Roy et al., 2022). Overall, the findings from Chapter 2 indicate that FIIs indeed care about firms' CSR/ESG profiles, as mandated CSR engagement tends to attract greater levels of investments from FIIs. Nevertheless, FIIs' heterogeneity based on legal origins and investment objectives significantly matters when they consider firms' mandatory CSR activities.

1.2.2 Extreme rainfall conditions

In Chapter 3, I study institutional investor investment behavior and firm valuation surrounding extreme rainfall conditions in rain-sensitive firms. Motivated by the recent studies showing that climate-related risks are not efficiently priced in financial markets and that institutional investors are increasingly considering such extreme weather-related risks for their investment portfolios (Alok et al., 2020; Hong et al., 2019; Krueger et al., 2020), I focus on extreme rainfall conditions as a source of exogenous risk for rain sensitive firms and their investors. Using Indian monsoon data, I exploit extreme rainfall conditions as ongoing natural experiments to uncover how institutional investors invest in rain-sensitive firms following heterogenous extreme rainfall episodes (i.e., excess and deficit rainfall conditions).

As the literature suggests that the two extreme ends of extreme rainfall conditions, excess and deficit, could lead to differential uncertainty conditions for rain-sensitive firms (Rao et al., 2022), I first explore whether institutional investors react differentially to such heterogeneous extreme rainfall episodes. On the one hand, excess rain-induced flooding and landslides could cause direct physical damage to the infrastructure and tangible assets of rain-sensitive firms, leading them to undertake additional corporate investments to recuperate the lost value (Huang et al., 2018; Rao et al., 2022). Further, due to the sudden and severe nature, excess rainfall events could lead financial markets to quickly discount rain-sensitive stocks, resulting in mispricing, higher liquidity and volatility, and greater investor attention (Alok et al., 2020; Ben-Rephael et al., 2017; Kruttli et al., 2020). Such excess rainfall conditions may create a favorable investment window in rain-sensitive firms for institutional investors.

On the contrary, in deficit rainfall conditions, rain-sensitive firms suffer from underutilizing existing assets, leading them to shrink their corporate investments due to higher operational costs (de Sherbinin et al., 2011; Rao et al., 2022). Moreover, markets tend to be slow in incorporating deficit rainfall-induced information due to longer periods of uncertainty and information asymmetry, resulting in reduced liquidity of rain-sensitive stocks (Diamond and Verrecchia, 1991; Rehse et al., 2019). Thus, deficit rainfall conditions could make it unfavorable for institutional investors to invest in rain-sensitive firms.

In line with my economic intuitions, from the empirical analysis, I find that institutional investors significantly increase (decrease) their ownership in rain-sensitive firms in the range of 2.47% to 2.59% (-2.13% to -2.83%) compared to non-rain-sensitive firms following excess (deficit) rainfall conditions. Further analysis reveals that institutional investors' geographic proximity affects their investment allocations in rain-sensitive firms following extreme rainfall episodes, as I find that both DIIs and FIIs increase their ownership in rain-sensitive firms during excess rainfall conditions, whereas only DIIs seem to decrease their ownership in rain sensitive firms following deficit rainfall periods.

Finally, in spite of these extreme rainfall conditions, the results show that institutional investors benefit from investments in rain-sensitive firms after excess rainfall because these firms tend to have greater market-based valuations and profitability relative to non-rain-sensitive firms. This increase in performance could be attributed to the rapid mispricing of rain-sensitive stocks as well as the increased risk-taking and strategic investment decisions of rain-sensitive firms during excess rainfall periods (Rao et al., 2022). Overall, the findings from Chapter 3 suggest that institutional investors, particularly DIIs, do consider extreme weather-induced risks in their portfolios and may exploit extreme rainfall conditions to gain from their investments in rain-sensitive firms.

1.2.3 Immigration fear sentiments

In Chapter 4, I examine whether fear sentiments stemming from immigration inflow cause changes in the investment behavior of institutional investors. Motivated by the recent literature showing that fear and anxiety substantially influence investors' financial decisions by increasing their risk aversion (Guiso et al., 2018; Kuhnen and Knutson, 2011), I utilize immigration-induced fear sentiments as an exogenous source of fear and anxiety among the local populace to causally identify how fear as a negative emotion affects institutional investors' investment choices in their investee firms. To proxy for immigration fear, I use the text-based measure of immigration fear sentiments of Baker et al. (2015) and conduct my study on four developed economies (United States, United Kingdom, France, and Germany). To establish causality, I use the instrumental variable (IV) approach as well as exploit an exogenous shock (the 2015 European refugee crisis or ERC) in a natural experiment setup.

First, I try better to understand the various mechanisms of immigration-induced fear sentiments, and then I explore how such fear sentiments could affect institutional investors in their investment decisions. The literature suggests that some members of the local populace view increased immigration influx as a threat to personal and national security that could lead to higher levels of risk aversion (Helbling and Meierrieks, 2020; Lerner and Keltner, 2001). Further, the economic and cultural threat elements of immigration concerns could erode social capital and trust, leading to higher information asymmetry, lower stock liquidity, and slower macroeconomic and financial growth (Guiso et al., 2004, 2008; Ziller et al., 2019). As such, increased immigration fears could cause institutional investors to withdraw their investments from their investee firms.

As the heterogeneity in institutional investors matters for investment choices and preferences (Ferreira and Matos, 2008), I explore whether heterogeneous institutional investors react differentially to immigration fear sentiments. First, since DIIs tend to own more local stocks than FIIs, DIIs tend to have higher exposures to local market risks (Baik et al., 2013; Choe et al., 2005). As immigration fear attitudes tend to accrue locally where DIIs are based, it is expected that immigration fear would cause greater risk aversion in DIIs than in FIIs. Further, independent institutional investors are active monitors, which makes them more likely to invest in riskier portfolios than grey institutional investors (Bennett et al., 2003; Chen et al., 2007). As such, I conjecture that independent institutional investors would be more exposed to increasing immigration fear, leading them to divest from their investee firms more than grey institutional investors. Moreover, I predict that, compared to long-term institutional investors, short-term institutional investors would be more likely to reduce their investment stakes during increased immigration fear as they have greater risk profiles and behavioral biases (DeVault et al., 2019; Yan and Zhang, 2009).

Finally, I investigate whether right-wing populism (RWP) moderates the relationship between immigration fear sentiments and investment decisions of institutional investors. RWP parties tend to encourage xenophobia by inflaming locals' anti-immigrant sentiments and enacting protectionist economic policies hindering economic growth (De Vreese and Boomgaarden, 2005; Rodrik, 2018). Thus, I propose that the inverse relationship between immigration fear sentiments and institutional investors' investments would be more pronounced in RWP regimes.

In line with my empirical predictions, I observe that under increased immigration fear sentiments, institutional investors considerably decrease their ownership in their investee firms. In more precise terms, I find that a one standard deviation increase in immigration fear sentiments is associated with an average decrease in institutional ownership of roughly 0.95 percent across all firms. Further analyses reveal that heightened immigration fear sentiments significantly influence domestic, independent, and short-term institutional investors to withdraw their investments from their respective investee firms more than foreign, grey, and long-term institutional investors.

Finally, the results indicate that during times of elevated immigration fear, countries with RWP parties in power (RWP countries) tend to deter institutional investors' investments more than non-RWP countries. My exogenous shock-based analysis further supports this finding by showing that institutional investors decreased their ownership by 1.57% to 1.88% more on average in firms domiciled in RWP countries than those based in non-RWP countries in the three years following the ERC. Overall, the findings from Chapter 4 imply that immigration fear sentiments could significantly deter investments from specific groups of institutional investors. Moreover, RWP could considerably intensify the negative effect of immigration fear on institutional investors' investments.

1.3 Thesis contributions

The primary contributions of this thesis can be summarized as follows. Chapter 2 demonstrates that firms' increasing CSR efforts, as evidenced by adherence to legal requirements and, more importantly, by real spending on mandated CSR projects, attract greater levels of investment from FIIs. Furthermore, I show that heterogenous FIIs based on different legal origins or having different investment styles and objectives react differentially to the same mandated CSR regulations when making their investments. On the relationship between CSR and institutional investors, the majority of the existing literature focuses on how institutional investors affect firms' voluntary CSR practices (Chen et al., 2020; Dyck et al., 2019; Nguyen et al., 2020). To this end and to the best of my knowledge, my study is the first to utilize mandatory CSR regulation and make use of a novel CSR expenditure dataset in a natural experiment setup to explore the causal association between heterogeneous FIIs and firms' mandatory CSR engagement.

Moreover, I add to the literature on the effect of CSR on firm performance. Contrary to the studies showing that mandatory CSR regulations could decrease shareholder wealth (Grewal et al., 2019; Manchiraju and Rajgopal, 2017), I provide compelling evidence that mandatory CSR engagement increases the long-term market value of CSR firms. Finally, from a policy perspective, my study sheds light on whether mandatory CSR regulations can attract foreign institutional investments and recommends that regulators should consider investor preferences. This is particularly important for capital constraint emerging markets where foreign investments could significantly promote economic development and growth (Bekaert and Harvey, 2003; Henry, 2000).

Next, Chapter 3 contributes to the literature in several ways. First, I add to the nascent yet growing body of literature on climate risk and institutional investors (Alok et al., 2020; Krueger et al., 2020) by showing how institutional investors respond differentially to heterogenous extreme rainfall conditions in terms of making their investment choices in rain sensitive firms. To the best of my knowledge, this is the first study to empirically investigate the impact of extreme rainfall as an exogenous weather anomaly on the investment behavior of institutional investors. Moreover, my study also adds to the literature on stock selection criteria of institutional investors by considering the information surrounding extreme rainfall conditions. Prior studies show that institutional investors are sophisticated as they demonstrate superior trading and stock-picking ability (Baker et al., 2010; Huang et al., 2020). My study complements these studies by suggesting that institutional investors exhibit superior investment skills not only because of better information about their investee firms but also because they possess superior information and knowledge regarding exogenous climatic conditions, enabling them to earn better returns from rain-sensitive stocks.

Finally, my study contributes to the literature on the effect of geographic location on institutional investors' information and investment decisions (Baik et al., 2010; Coval and Moskowitz, 2001). I find that geographically proximate DIIs tend to have an informational advantage in terms of superior information, experience, and knowledge over FIIs regarding local climatic and rainfall conditions.

Lastly, Chapter 4 also makes several contributions to the literature. First, I add to the body of knowledge regarding the detrimental effects of fear and anxiety on investors' risk aversion and investment behavior (Guiso et al., 2018; Kuhnen and Knutson, 2011; Lee and Andrade, 2011). Although the majority of the research in this field focuses on individual investors in various experimental settings, my study demonstrates how institutional investors react to fears related to immigration. I demonstrate that institutional investors' risk aversion increases in response to immigration fear, leading them to reduce their investments in their investee firms. To my knowledge, this is the first study to investigate and demonstrate this negative nexus between institutional investors and immigration fear.

Moreover, the literature on institutional investors largely focuses on their superior stock selection, information gathering, and trading skills (Baker et al., 2010; Gompers and Metrick, 2001). Recent studies, however, contradict this notion and show that institutional investors are prone to psychological and behavioral biases (Alok et al., 2020; DeVault et al., 2019). I contribute to this later body of literature by demonstrating how institutional investors also display risk aversion as a result of increased immigration fears. I also contribute to the literature on institutional investor heterogeneity by illuminating how different institutional investor groups react differently to immigration fears (Ferreira and Matos, 2008; Marshall et al., 2022).

Finally, my research contributes to the body of literature examining the relationship between political ideologies and financial markets by demonstrating how RWP amplifies the adverse effects of immigration fear on institutional investors' investments (Addoum and Kumar, 2016; Bonaparte et al., 2017).

1.4 Overall conclusions

In this thesis, I study the investment choices and preferences of institutional investors under various exogenous factors. From the overall findings, first, it could be inferred that institutional investors could exhibit very different investment behavior under different circumstances. For instance, with regard to extreme rainfall conditions, institutional investors tend to invest in rain sensitive firms by assessing relevant investment information and exhibiting rational trading behavior. However, institutional investors could also demonstrate psychological biases such as fear induced risk aversion as they tend to divest from their investee firms during times of heightened immigration fear. More importantly, I find that different groups of institutional investors possessing differential characteristics, investment styles and objectives respond very differently under these exogenous factors. For instance, DIIs seem to not differentiate between mandated CSR and non-CSR firms for making their investments, unlike their foreign counterparts. Furthermore, even though FIIs seem to prefer CSR firms for making their investments, it is primarily the FIIs from civil law countries and independent and long-term FIIs that are more likely to invest in such mandated CSR firms.

Finally, studies suggest that geographically proximate and short-term institutional investors tend to possess better investment information (Baik et al., 2010;

Yan and Zhang, 2009). I find some support in this regard, as the geographically more proximate DIIs seem to have better information regarding local climatic conditions and rain sensitive firms than FIIs. Nevertheless, I also find that DIIs and short-term institutional investors tend to exhibit the highest levels of psychological biases as evidenced by their immigration fear induced substantial divestment choices. These contrasting findings in different settings suggest that not only do heterogeneous institutional investors have differential investment preferences, but also they could demonstrate very differential investment responses under different exogenous factors.

1.5 Thesis structure

The remainder of this thesis is structured as follows. Chapter 2 investigates the effect of mandatory CSR engagement on foreign institutional investors. Chapter 3 examines how institutional investors make their investment choices in rain-sensitive firms following extreme rainfall episodes. Chapter 4 studies the effect of immigration fear and populism on institutional investors. Finally, Chapter 5 discusses the overall findings, identifies the limitations of the thesis, and offers suggestions for future research.

2. Chapter 2: Corporate Social Responsibility and Foreign Institutional Investor Heterogeneity

"Society is demanding that companies, both public and private, serve a social purpose. To prosper over time, every company must not only deliver financial performance, but also show how it makes a positive contribution to society. Contribute to society, or risk losing our support."

BlackRock CEO Laurence D. Fink (New York Times, January 15, 2018)

2.1 Introduction

In the aftermath of the 2008 financial crisis, engagement in environmental, social, and governance (ESG) associated metrics have become an important dimension in the assessment of firms' financial and sustainability performance for analysts and investors.[1] As such, professional asset managers are increasingly integrating firms' corporate social responsibility (CSR) pursuits in their investment allocation decisions (Amel-Zadeh and Serafeim, 2018). Analysts are also progressively demanding that firms disclose more information associated with their CSR activities (Ioannou and Serafeim, 2015).

To meet the increasing demands of external investors, regulatory bodies around the world are mandating the disclosure and reporting of firms' CSR activities (Ioannou and Serafeim, 2017). In this study, I examine how heterogeneous foreign institutional investors (FIIs) react when investee firms are mandated to not only disclose their CSR activities but are also legally obliged to engage with and spend a minimum threshold

[1] Asset managers around the world are continuously shifting their investment philosophy toward a sustainability-based approach, with responsible investment becoming a mainstream criterion for asset allocation during the last decade. Recent studies provide evidence that institutional investors are indeed actively engaging with firms to encourage better CSR practices and discourage any irresponsibility through activism (Dimson et al., 2015; McCahery et al., 2016). Further, Ailman et al. (2017), Eccles et al. (2017), and Hanson et al. (2017) discuss how analysts and investors are utilizing ESG metrics in their investment decisions.

of their income on CSR projects. Motivated by recent literature, I particularly examine whether FIIs from different legal origins and with different investment objectives invest differentially in mandated CSR firms (Dyck et al., 2019; Liang and Renneboog, 2017).

The literature on FIIs suggests that high levels of information asymmetry is one of the key factors in explaining the varying investment levels of FIIs in domestic (investee) firms.[2] Extensive evidence supports the argument that, compared to domestic institutional investors (DIIs), FIIs suffer from informational disadvantages, with the severity of this friction being greater in informationally more inefficient and more opaque emerging markets (Ferreira and Matos, 2008; Tsang et al., 2019). Such information asymmetry can hinder FIIs from adequately assessing the risk-adjusted economic value, particularly with respect to agency concerns (Baik et al., 2013; Leuz et al., 2009). This increases their deadweight monitoring costs and can induce FIIs to underweight overseas stocks. Nonetheless, a number of studies suggest that a greater level of CSR activities could play a positive role in reducing information asymmetry for investors, thus mitigating the severity of agency concerns (Cui et al., 2018; Dhaliwal et al., 2011). A better information environment should reduce the agency concerns for FIIs and lessen the information gap between them and their domestic counterparts (Tsang et al., 2019).

[2] It is generally accepted that higher levels of foreign portfolio investors (FPIs) are associated with a lower cost of capital which in turn boosts the growth of real investments (Henry, 2000). Specific to emerging markets, Errunza (2001) documents a number of benefits of attracting higher levels of FPI. For example, FPIs generally demand prompt and quality disclosure of information on the firms they invest in, which accords a higher degree of minority shareholder protection, and initiates regulations governing the capital market and its trading activities.

If higher levels of CSR engagement mitigate agency concerns for FIIs by improving transparency and instigating better governance, then mandatory CSR requirements for investee firms should attract greater levels of investment from FIIs. In this study, for the first time to the best of my knowledge, by using actual CSR expenditure data and exploiting a mandated CSR regulation, I examine the following two questions. First, and on an aggregate basis, I consider whether investee firms complying with the mandatory CSR regulation attract more FIIs' (existing and new) investment, relative to firms that do not comply. I refer to this as the *CSR engagement attraction* hypothesis.

Second, since the literature emphasizes that legal origin can play a key role in explaining variations in CSR activities (Liang and Renneboog, 2017), I examine whether heterogeneous FIIs, based on different legal origins, react differentially to the CSR regulatory mandate. Also, I investigate whether heterogeneous investment styles and objectives of FIIs differentially influence the investment decisions following mandated CSR regulation. I refer to this as *FIIs' heterogeneity* hypotheses.

I answer these questions by exploiting the introduction of a mandated Indian CSR regulation.[3] India enacted Section 135 of the Companies Act 2013 (referred to as S-135 hereafter), which mandates firms that meet a certain size threshold to comply with certain CSR-related provisions, including the expenditure of at least 2% of their net profit on CSR projects (Manchiraju and Rajgopal, 2017). The mandate also enforces severe criminal and financial penalties for any violation of the CSR provisions. As S-135 imposes strict CSR provisions and exogenously determines

[3] FIIs are one of the key categories of outside investors in India where they own approximately 40% of the free float Indian market capitalization. Source: *Financial Times*, April 13, 2015.

treated (firms that need to comply) and control groups (firms that do not need to comply), I exploit the S-135 regulatory shock and actual CSR expenditure in my empirical analysis using a sample of listed Indian non-financial firms for the period 2012-2017. As an empirical identification strategy, I use two quasi-natural experimental approaches, namely the propensity score matched difference-in-differences (PSM-DiD) and multivariate regression discontinuity design (MRDD). My robust quasi-natural experiments report the following findings.

First, on an aggregate level, the results support the *CSR engagement attraction* hypothesis as FIIs significantly increase their investment stakes in treated firms compared to control firms in the post-CSR regulatory mandate period. In economic terms and drawing on different specifications, I find that on average, the change in treated firms' FIIs' ownership ranges between 7.5% and 8.5% (this translates into an average increase in the range of INR 6,502.5 billion to INR 7,369.5 billion).[4] Further analysis shows that CSR firms not only attract new FIIs, but existing FIIs increase their share of ownership in these firms in the post-CSR reform period.[5]

Second, I also find support for the *FIIs' heterogeneity* hypotheses as FIIs domiciled in civil law origin jurisdictions are more likely to increase their investments in treated firms in the post-CSR mandate period compared to the common law origin

[4] Applying the average market capitalization figure of INR 86,700 billion during the post-regulation period of three years.
[5] Using a mandatory CSR disclosure regulation in China, Yu and Zheng (2020) find that foreign institutional ownership increases following the regulation. My study is different from theirs as the CSR regulation in China does not require firms to actually engage in CSR, whereas S-135 specifically mandates firms to engage with and expend a minimum threshold of their profit on approved CSR projects (Dharmapala and Khanna, 2018). While CSR disclosure requirement may help reduce some level of information asymmetry for FIIs, I conjecture that actual CSR engagement should benefit FIIs more by providing them with easier access to capital, insurance against various risks, and overall better financial returns through the reputation and social capital channels of CSR (Albuquerque et al., 2019; Lins et al., 2017).

jurisdictions. In addition, and consistent with the argument that CSR mandate improves transparency and reduces monitoring costs as the regulator also has responsibilities in mandated CSR regulations, my results show that independent FIIs (who are generally active monitors) and pension funds who are FIIs (having long investment horizons) are more likely to invest in firms complying with the mandated CSR regulations. My results are robust to several robustness checks, including the use of alternative measures of FIIs' ownership (year-on-year change), alternative treatment groups based on actual CSR expenditure of the firms, and placebo tests.

Finally, despite the empirical evidence that mandatory CSR regulations may reduce market value in the short run (Grewal et al., 2019; Manchiraju and Rajgopal, 2017), I test the long-term value relevance for firms complying with CSR mandates and engaging (expending financial resources) in CSR activities. The empirical evidence reveals that in the long run mandated CSR firms tend to have higher market-based valuations compared to non-CSR firms. This finding supports the argument that CSR mandates could increase long-term firm value by improving governance through strict monitoring, attracting higher FIIs' ownership, and building firms' social and reputational capital (Aggarwal et al., 2011; Ferrell et al., 2016; Lins et al., 2017).

This study makes the following contributions to the literature. First, most of the existing studies, based on voluntary CSR practices and ESG indices, examine the effect of institutional investors on firms' CSR activities.[6] However, I show that

[6] For instance, Dyck et al. (2019) show that FIIs promote CSR activities as insurance against event risk and negative financial shocks. Hoepner et al. (2018) find that institutional investors reduce their downside risk by pushing their investee firms' CSR activities. Nguyen et al. (2020) empirically demonstrate that institutional investors drive better firm level CSR performance as it reduces the earnings volatility of firms. Finally, Chen et al. (2020) study whether institutional investors make responsible investments to generate a social impact.

improvement in CSR activities, in the form of complying with regulatory mandates and, more notably, actual expenditures on CSR projects, attracts higher levels of investment from FIIs.[7] Second, I demonstrate that conditional on their heterogeneity (depending on legal origin and/or institution type) there is a differential FIIs' reaction to the same mandated CSR regulations.[8] From an empirical point of view, to the best of my knowledge, this is the first study to exploit a CSR regulatory mandate and make use of unique actual firm-level CSR expenditure data to investigate the link between heterogeneous FIIs and firm-level CSR engagement.

Moreover, my study adds to the debate on the effects of CSR on firms' financial performance. Studies suggest that mandated CSR regulations could deteriorate shareholder wealth (Grewal et al., 2019; Manchiraju and Rajgopal, 2017). However, these studies either use data from developed markets[9] or employ short-term event study-based methods.[10] I argue that, in this emerging market set-up, where the

[7] Two important sources of bias may question the empirical credibility of results using rating indices. The first is *reverse causality* as studies show investors themselves could influence CSR activities (Chen et al., 2020). Second is the issue of *construct validity*, whereby these indices/ratings may capture other aspects of the firm. This is a similar problem to that of the governance index, as pointed out by Atanasov and Black (2016).

[8] Hartzmark and Sussman (2019) show that individual investors generally value sustainability as they tend to buy (sell) funds with higher (lower) sustainability ratings. My study is different from theirs as I investigate whether firms' mandatory CSR activities induce FIIs' investments and, more importantly, whether heterogeneous FIIs make differential investment choices in CSR firms following the CSR mandate.

[9] For example, using the European market set-up, Grewal et al. (2019) show that the market reacts negatively to mandatory CSR disclosures. The authors argue that firms already have their optimal level of CSR disclosure and any excess disclosure requirements may raise agency issues. I argue that this view should be more applicable to developed markets where numerous firms voluntarily engage in CSR activities driven by social and market forces and thus any regulatory burden may create additional deadweight costs. However, for emerging markets, this view is less relevant as firms tend to have weak or no CSR engagement.

[10] Manchiraju and Rajgopal (2017), who use stock market returns data around the S-135-related announcements prior to the actual enactment of S-135, document short-term negative market reactions for mandated CSR firms. However, I argue that since CSR activities generate payoffs in the long run, the real effect of mandated CSR engagement should be more pronounced and evident in the post-S-135 period when firms actually undertake CSR activities (Renneboog et al., 2008; Allen et al., 2015). In my setting, the window period is three years pre- and post-S135, thus captures the long-term value effect of firms' actual mandated CSR activities.

concept of stakeholder protection and CSR engagement was almost non-existent prior to the enforcement of the CSR regulation, mandatory CSR compliance should help firms to build their social and reputation capital leading to higher market value (Lins et al., 2017; Albuquerque et al., 2019; Turban and Greening, 1997). Using a longer window sample period (six years), I find compelling evidence that mandatory CSR engagement indeed boosts the long-term market value of CSR firms. Thus, my study contributes to the literature by showing the long-term value effect of firms' actual mandated CSR activities.

Finally, from a policy point of view, this study offers insights on whether mandated CSR regulation is able to attract (specific types) of FIIs and suggests that regulators should be sensitive to investor preferences. This is particularly important for capital-constrained emerging markets, as extensive evidence suggests that higher foreign investment flows lower the cost of capital, thus contributing to the real growth of the economy (Henry, 2000; Bekaert and Harvey, 2003).

The rest of the chapter is organized as follows. Section 2.2 offers a summary of the CSR regulatory shock, followed by a discussion of relevant literature and hypotheses development in Section 2.3. Detailed discussions on data and variables are presented in Section 2.4. Section 2.5 describes the empirical strategy (near randomization quasi-natural experiment technique) and Section 2.6 discusses the empirical findings. Finally, Section 2.7 concludes the chapter.

2.2 CSR regulation: Section 135

Section 135 (S-135) was introduced as part of India's Companies Act in 2013 (Dharmapala and Khanna, 2018). Initially, the Ministry of Corporate Affairs (MCA) issued voluntary CSR guidelines as part of the new Companies Bill in 2009. However, the voluntary CSR provision was a failure, as Indian firms were unfamiliar with socially responsible activities (Van Zile, 2012). As a result, it became essential for authorities to formulate a set of mandatory CSR regulations. Consequently, on 31st August 2010, the Parliamentary Standing Committee on Finance introduced the concept of mandatory CSR regulation as part of a Companies Bill, along with the thresholds above which companies will be mandated to undertake CSR activities (Manchiraju and Rajgopal, 2017).

Although there was substantial initial resistance from corporate bodies, the Government of India went ahead with the mandatory CSR reforms under S-135 of the revised Companies Bill in December of 2011. This bill was eventually passed by both Houses of Parliament and received consent from the President of India on 29th August 2013 to become the Companies Act 2013. The provisions of the S-135 became applicable from the fiscal year 2014-2015, beginning April 1, 2014.

Dharmapala and Khanna (2018) identify five important provisions of S-135 that may be relevant for outside investors: i) a CSR committee of three directors of which one should be independent; ii) disclose the conformation of the committee; iii) a CSR policy for the recommended CSR activities must be formulated by the committee; iv) the board should approve and publicize the CSR policy; and v) the board should ensure that the firm spends at least 2% of the previous three years' net profit on CSR activities, as approved by the MCA, or explain non-compliance. The first four of these provisions are compulsory whereas the CSR expenditure is on a "comply or explain" basis, which means a firm might choose not to spend the prescribed amount or might choose to spend a portion of the prescribed amount and explain its non-compliance or partial compliance.[11] Any violation of these provisions would result in severe penalties for the affected firms and the responsible personnel.

Schedule VII of S-135 provides strict guidelines for mandated CSR firms regarding spending in and reporting of MCA-approved CSR activities. The activities include those aimed at eradicating extreme hunger and poverty, promoting education, promoting gender equality and empowering women, reducing child mortality and improving maternal health, combating deadly diseases, ensuring environmental sustainability, employment enhancing vocational skills, and social business projects. It also includes contributions to the Prime Minister's National Relief Fund, or any other fund set up by the Central Government or the State Governments for socio-economic development, such as the welfare of the Scheduled Castes, the Scheduled Tribes, other backward classes, minorities, women, etc. These activities come under the umbrella of some of the UN sustainability goals.[12]

The main provision relevant to my study is that any company satisfying at least one of the three size thresholds (net worth of INR 5 billion or more, sales of INR 10 billion or more, or net profit of INR 50 million or more) in any specific year from the effective date of the Companies Act 2013 (i.e., April 1, 2014), would be obliged to comply with the provisions suggested in S-135. Thus, I take the calendar year 2014 as the effective year (or fiscal year ending 2015 in India). It is noteworthy that once a firm comes under the obligations of S-135, it will remain obligated under this rule for the succeeding three years, and only if none of the thresholds is satisfied in any of

[11] The "comply or explain" rule does not make CSR expenditure voluntary under S-135 primarily for two reasons. First, mandated firms must show credible reason and provide legitimate explanation if they are unable to spend the prescribed amount in CSR. Second, firms must expend their prescribed amount in MCA approved CSR projects only.
[12] See http://tinyurl.com/6hmf7tjd

these consecutive three years will the company not be required to apply S-135.[13] The term "net profit" implies "profit before tax", which means the previous three-year average profit will be calculated based on earnings before tax (EBT) and not profit after tax (PAT).[14]

2.3 Related literature and hypotheses development

In this section, I construct the testable hypotheses for my two research questions. For the first *CSR engagement attraction* hypothesis, I test whether mandatory CSR engagement leads to a higher level of investments from FIIs. Next, for the research question relating FIIs' heterogeneity to mandatory CSR engagement, I consider two aspects of FIIs' heterogeneity in the *FIIs' heterogeneity* hypotheses; firstly, based on the legal origins of the FIIs, and secondly on the monitoring role and investment horizon of FIIs.

2.3.1 CSR engagement attraction hypothesis: CSR and FIIs

There is debate in the literature on the effect of CSR on firm performance (Margolis et al., 2011; Servaes and Tamayo, 2017). The agency theory posits that CSR is merely a manifestation of a managerial agency problem and a waste of corporate resources (Tirole, 2001; Masulis and Reza, 2015). Agency concerns are manifested when managers make non-value-maximizing investment choices as well as when managerial compensation is not tied to performance (Bebchuk and Fried, 2003). This school of thought argues that managers undertake CSR activities to benefit themselves privately

[13] For instance, if a firm goes above any of the above-mentioned thresholds in 2015, it has to comply with the CSR rule in the consecutive fiscal years 2015, 2016, and 2017, and it will only be considered for non-compliance if it fails to satisfy any of the thresholds for any consecutive three years from 2016.
[14] See S-135 of India's Companies Act 2013 at http://www.mca.gov.in/Ministry/pdf/CompaniesAct2013.pdf for detailed provisions.

by pleasing crucial non-investing stakeholders such as politicians, NGOs, labor unions, and others, at the cost of other investors. As a result, CSR activities raise over-investment concerns which can be costly and value-destroying for the shareholders (Di Giuli and Kostovetsky, 2014; Masulis and Reza, 2015).

In addition, firms focusing on aggregate CSR activities might forgo potential value-enhancing investment opportunities and suffer losses in the long run (Bhandari and Javakhadze, 2017). Hence, CSR engagements are perceived as negative signals whereby markets react negatively to CSR-related news (Krüger, 2015). The negative perception of CSR holds even in a mandated CSR scenario as evidence suggests that firms lose short-term market value around mandatory CSR-related announcements (Grewal et al., 2019; Manchiraju and Rajgopal, 2017). Following the agency view, if FIIs are assumed to have a short-term view then they would be inclined to underinvest in mandated CSR firms (Bena et al., 2017).

In contrast, the CSR good governance theory argues that socially responsible firms are able to attain financial benefits through various channels as they maintain amicable relationships with key stakeholders, such as the government, local community, employees, customers, suppliers, and activists (Turban and Greening, 1997; Waddock and Graves, 1997). The underlying economic argument is that by being responsive to non-investing stakeholders firms manifest a positive impact in mitigating conflicts of interest between managers and non-investing stakeholders, which in turn should boost firms' financial performance (Allen et al., 2015; Magill et al., 2015). Empirical evidence supports this view as studies document that firms with higher CSR performance exhibit superior firm and stock market performance (Dimson et al., 2015; Ferrell et al., 2016).

I argue that in the case of FIIs in emerging markets, the good governance view should be more prevalent as there can be substantial differences in the investment choices of FIIs and DIIs, primarily driven by the argument that FIIs suffer significantly more from information asymmetry relative to DIIs (Tsang et al., 2019; Ferreira and Matos, 2008). Information asymmetry not only hinders FIIs from assessing the risk-adjusted economic value of overseas firms' equity, but also increases the monitoring costs of overseas investments, and these deadweight costs lead to inefficiency in asset allocation (Leuz et al., 2009). Such information asymmetry, which may originate from differences in language, culture, legal environments, and disclosure requirements between FIIs' and DIIs' jurisdictions, may induce FIIs to underweight foreign stocks relative to their theoretically prescribed weights (Baik et al., 2013; Coval and Moskowitz, 2001).

Several studies suggest that CSR activities could play a positive role in mitigating the friction of information asymmetry and its associated inefficiencies. For example, studies show that better CSR practices lead to a lower possibility of earnings smoothing, improved transparency, and better corporate disclosure (Dhaliwal et al., 2011; Kim et al., 2012). This in turn reduces the cost of capital and transaction costs and improves information quality (El Ghoul et al., 2011, 2017). All of these positive outcomes ultimately lead to the reduction in information asymmetry (Cui et al., 2018). Furthermore, in the case of a mandated CSR regulation, it becomes obligatory to produce information that improves firm-level disclosures and transparency (Ioannou and Serafeim, 2017). These additional CSR disclosures could reduce the information gap between FIIs and DIIs (Tsang et al., 2019).[15]

In addition, an emerging theme in the literature advocates that CSR activities build social capital and trust for the firms (Lins et al., 2017; Servaes and Tamayo, 2017). Social capital and trust expedite financial contracts by alleviating the potential negative outcomes of information asymmetry, i.e. adverse selection and moral hazard, which in turn leads to better financial performance and economic growth (Knack and Keefer, 1997; La Porta et al., 1997). Further, recent studies suggest that investment in CSR activities, which develops social capital, imparts valuable insurance against event risks, and helps in product market differentiation (Albuquerque et al., 2019).[16] As a result, institutional investors appear to promote CSR activities to develop firms' social capital as a potential risk management tool that accords natural insurance against various risks, particularly the unexpected negative financial shocks (Chen et al., 2020; Nguyen et al., 2020; Hoepner et al., 2018; Dyck et al., 2019).

I conjecture that if higher firm-level CSR engagement reduces information asymmetry, promotes good governance, develops social capital leading to better financial performance, and provides insurance against unexpected adverse shocks, then I would expect FIIs to be more attracted toward firms with higher levels of CSR engagement. Since S-135 mandates CSR-related disclosure and expenditure, I should

[15] DIIs may not gain any further advantage over such corporate disclosures as they are already better equipped to deal with the informational opacity of local firms through private channels, such as managers and local analysts (DeFond et al., 2011; Leuz et al., 2009).
[16] Studies empirically show that during economic turmoil (e.g. the 2008 financial crisis), firms with higher CSR performance had better financial performance than firms with lower social capital (Lins et al., 2017).

expect firms that need to comply with S-135 provisions to attract higher levels of FIIs' investment, as proposed in the following *CSR engagement attraction* hypothesis.

H_1: Firms that comply with the CSR mandate attract greater levels of FIIs' investments, relative to firms that do not comply.

2.3.2 FIIs' heterogeneity hypothesis: Legal origins

Liang and Renneboog (2017) show that a country's legal origin is a stronger institutional feature in explaining variations in CSR activities compared to other firm and country level characteristics, such as profitability, ownership structure, market institutions, and degree of globalization, among others. They find that firms belonging to civil law origin countries, particularly Scandinavian civil law, are engaged in higher levels of CSR activities compared to firms originating from common law origin countries.

Given the evidence linking legal origin influencing a firm's CSR activities, I am motivated to investigate whether the legal origin of the countries in which the FIIs are based influences their investment decisions toward overseas firms engaged in mandated CSR activities. I argue that FIIs from civil law countries should invest more in overseas CSR oriented firms, relative to FIIs from other legal origin jurisdictions.[17] This argument is built on two broader levels of the literature. First, studies note that the regulatory environment in common law countries mostly promotes private market

[17] The literature suggests that the differential investment philosophy and preferences originating from countries with different legal regimes are reflected in those countries' FIIs as well. For instance, common law countries tend to emphasize more on investor protection and shareholder wealth maximization (La Porta et al., 2008). Thus, having such shareholder oriented attitudes, FIIs from common law countries seem to promote better corporate governance (Aggarwal et al., 2011). Similarly, if civil law countries promote better stakeholder protection and are more CSR oriented (Liang and Renneboog, 2017), then FIIs from such countries should have more stakeholder oriented views and, consequently, invest more in mandated CSR firms.

outcomes through unrestricted private dealing, whereas civil law countries typically depend on "policy implementing" mechanisms through socially accustomed conventions (La Porta et al., 2008). This suggests that FIIs having a "socially accustomed" civil law background would be more familiar with CSR mandated provisions, compared to FIIs from common law countries. Studies show that familiarity with particular assets/markets stimulates greater investments (Huberman, 2001), which in turn implies that FIIs from civil law countries are likely to invest more in firms affected by a mandated CSR regulation.

In contrast, FIIs belonging to common law origins are less likely to differentiate firms based on a CSR mandate for making investments but would focus more on generating returns for their own investors following the philosophy of investor wealth maximization and stricter investor protection (La Porta et al., 1998; Liang and Renneboog, 2017). However, investors from civil law countries embrace, or are mandated to embrace, a more stakeholder-oriented philosophy owing to their legal heritage (La Porta et al., 2008). This suggests that the stakeholder-oriented CSR behavior of firms should attract more foreign investments from investors domiciled in civil law countries, relative to investors of all other legal origins.

Second, Dyck et al. (2019) show that cultural origins and social norms matter for FIIs' preference for CSR commitments. Thus, investors from high social norm backgrounds tend to be more demanding in driving-up investees' firm-level CSR activities. This may be attributable to the widely held view that FIIs headquartered in high stakeholder-oriented corporate social culture countries face greater social pressure to make socially responsible investments (Guiso et al., 2006). The evidence also indicates that social norms or ideals can significantly influence an asset manager's investment decisions (Akerlof and Kranton, 2005), whereby managers residing in societies with strong CSR ideology would be more likely to invest in foreign firms with better CSR performance.

Moreover, beneficiaries of investment firms who hold strong socially-oriented beliefs and ideologies may actively demand that their asset managers invest in domestic and overseas firms that undertake CSR activities (Hart and Zingales, 2017; Hartzmark and Sussman, 2019). The persistence of such beliefs and ideologies finds its way into the legal rules, macro-institutions, and education, and is then passed on from one generation to the next (La Porta et al., 2008). Evidence suggests that different legal origins capture such differences in cultural views (La Porta et al., 2008). Thus, CSR preferences of institutional investors due to cultural and social norms should be captured by legal origin. Dyck et al. (2019) provide evidence that investor ideologies and customs regarding CSR orientation vary across countries and generally investors from civil law countries maintain stronger CSR philosophies compared to those from common law countries.

Given the two complementary arguments on the preferences of investors from different legal origins, I expect FIIs from civil law countries to invest more in firms complying with CSR mandates. Accordingly, I propose the following as my first FIIs' heterogeneity hypothesis:

H_2: In comparison to FIIs from common law countries, FIIs from civil law countries invest more in firms that comply with the CSR mandate.

2.3.3 *FIIs' heterogeneity hypothesis: Monitoring role and investment horizon*

I further analyze the impact of the CSR engagement mandate on FIIs' heterogeneity based on their broad-based investment styles and horizons. In the first group, I classify FIIs into two major categories based on their investment styles; namely independent foreign investors (mutual funds and independent investment advisors), and grey foreign investors (banks, insurance companies, and other institutions) (Chen et al., 2007; Ferreira and Matos, 2008).[18]

It is argued that independent institutional investors tend to be "pressure-resistant", and grey institutional investors tend to be "pressure-sensitive" or loyal toward the corporate management of investee firms. The literature suggests that independent investors tend to be active monitors and influence the corporate governance mechanisms of firms (Chen et al., 2007; Ferreira and Matos, 2008). Furthermore, independent institutional investors compete for their financial capital by attracting higher inflows of funds not only through good financial performance, but also through social channels, such as networking and building a higher reputation (Dyck et al., 2019). As CSR can help build firms' reputation, by holding CSR-oriented firms in their portfolios, independent investors can also benefit by garnering a greater reputation themselves as socially responsible investors (Fombrun and Shanley, 1990; Turban and Greening, 1997). Consequently, such a reputation induces beneficiaries of FIIs to be more loyal toward more socially responsible investment funds (Hartzmark and Sussman, 2019; Renneboog et al., 2011). Additionally, with regard to mandatory CSR law S-135, these independent FIIs benefit further due to the reduction in their

[18] The literature collectively categorizes banks, insurance companies, and all other institutional investors who are not independent investment advisors as Grey institutional investors (Chen et al., 2007; Dyck et al., 2019; Ferreira and Matos, 2008).

monitoring costs. This is because having mandatory CSR requirements implies that there will be monitoring by the government/regulators and this reduces the need for monitoring by FIIs. Thus, the provisions of the S-135 should result in reduced ‘private information seeking and monitoring’ costs making it more attractive for FIIs to invest in these CSR firms, given the inherently difficult task of actively monitoring overseas investments.

In contrast, grey institutional investors tend to be reluctant in terms of being activist monitors of their investee firms as they have closer ties with the management and generally maintain docile business relationships with their investee firms (Chen et al., 2007; Ferreira and Matos, 2008). For example, Brickley et al. (1988) find that banks and insurance companies are more supportive of management actions than other types of institutional investors in antitakeover amendment proposals. Since grey investors, compared to independent investors, keep closer ties with insiders of firms and in turn have better access to inside information, they may not substantially benefit from the additional information generated by the mandated CSR activities. This implies that grey FIIs, relative to independent FIIs, should be indifferent to investing in mandated CSR and non-CSR firms. Thus, I conjecture that independent FIIs should invest more in firms with greater CSR engagement compared to grey FIIs, as proposed in the first *FIIs' heterogeneity* hypothesis:

H_{3a}: *In comparison to grey FIIs, independent FIIs invest more in firms that comply with the CSR mandate.*

I also classify FIIs into two groups based on their investment horizons; institutions with a long investment horizon such as pension funds, and those that have a relatively shorter investment horizon, such as hedge funds (Cella et al., 2013; Dyck et al., 2019).[19] Investments in investee firms that are sustainable enough to generate payoffs in the long run are considered to have a longer-term perspective (Renneboog et al., 2008). Studies argue that since CSR-oriented firms are able to better align their interests with those of non-investing stakeholders, they are able to acquire higher competitiveness, which in turn should help them generate enhanced financial returns in the long run (Allen et al., 2015; Magill et al., 2015). As a result, investors with a long-term investment horizon (such as pension funds) would be more likely to increase their investment stakes in firms that comply with the CSR regulation.

In addition, long-term-oriented investors tend to incur a considerable amount of monitoring expenses and are more prone to downside risks in the long run (Chen et al., 2007; Nguyen et al., 2020). Evidence indicates that mandated CSR engagements may help reduce the cost of monitoring through increased transparency and significantly mitigate downside risks (Hoepner et al., 2018). As a result, I should expect long-term-oriented FIIs (such as pension funds) to increase their investments in the firms affected by the CSR mandate. On the other hand, since short-term-oriented FIIs (such as hedge funds) have a myopic investment choice and a propensity to seek increased earnings in the short run (Bushee, 2001), they would be less likely to be attracted by CSR activities undertaken by the mandated firms. These short-term-oriented investors, potentially having superior private information, are interested in frequent trading, shorter profit horizons and turnaround, and are thus not willing to

[19] I obtain FIIs' ownership data from S&P Capital IQ (see Section 4.1 for details). Consistent with other institutional investor databases, Capital IQ classifies each FII based on its institution type. Following the literature, I use Capital IQ classifications to re-classify each FII into a broader category such as independent/grey investors (Ferreira and Matos, 2008; Dyck et al., 2019). Table 2-23 lists all the unique FIIs' types as classified by Capital IQ and the broad classifications to which they belong.

monitor a firm's management (Yan and Zhang, 2009). As a result, short-term-oriented FIIs, relative to long-term FIIs, may not materially gain from the mandatory CSR-induced information production and disclosure.

Given the argument that, relative to their short-term counterparts, long-term investors are more concerned with CSR engagement, I propose the second *FIIs' heterogeneity* hypothesis:

H_{3b}: In comparison with FIIs with a short-term investment horizon, FIIs with a long-term investment horizon invest more in firms that comply with the CSR mandate.

2.4 Data and descriptive statistics

My sample period spans a period of six years from the fiscal year-end 2012 to 2017 and comprises 23,694 firm-year observations, which includes 4,168 non-financial firms listed on either the Bombay Stock Exchange (BSE) or the National Stock Exchange of India Ltd. (NSE).[20] I obtain the ownership and financial data from S&P Capital IQ (CIQ) and the Prowess database, maintained by the Centre for Monitoring Indian Economy (CMIE).[21] In addition to using the exogenously imposed threshold to separate the treated and control groups, I also collect unique actual CSR expenditure data from several sources. These sources not only include CMIE Prowess but I also manually collect the CSR expenditure for the top 500 market capitalized companies from the Business Responsibility Report (BRR) and individual firms' annual reports

[20] The fiscal year begins on 1 April and ends on 31 March of the following calendar year.
[21] Prowess is a standard Indian firms' database and is widely used in the finance literature (Baghai and Becker, 2018; D'Acunto et al., 2019; Manchiraju and Rajgopal, 2017; Vig, 2013 among others). The S&P CIQ database is extensively used in finance empirical studies (Acharya et al., 2018; Cavagnaro et al., 2019; Rampini et al., 2020 among others).

for years prior to FY2015.[22] I further integrate the CSR data available from the MCA, Government of India website[23] for 7,334 companies for the fiscal year 2014-15, and 5,097 companies for the fiscal year 2015-16. Finally, I include the publicly available comprehensive CSR data of all the companies available on the CSR portal maintained by the Government of India for the fiscal years ending 2015, 2016, and 2017 (https://csr.gov.in).

2.4.1 Dependent variable

Data for my dependent variable are obtained from CIQ which tracks individual global institutional investors' ownership data. The set of variables includes investor identification, country of investor domicile (hence legal origin), investor types (such as hedge funds, pension funds, mutual funds, banks, etc.), and the name and domicile of the investee firms. At the individual investor level, I denote a particular foreign investor's holding as FIO_{jit}, whereby the foreign institutional investor (FII *j*) holds equity ownership (in the percentage of total share outstanding) of the Indian investee firm *i* for the fiscal year-end *t*.[24] In line with existing literature (Bena et al., 2017; Dyck et al., 2019) I use the investee firm-level aggregate measure as defined by equation (2.1):

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[22] 'The Security Exchange Board of India's (SEBI) Mandate' in 2012 requires the top 100 market capitalization companies listed on the NSE and BSE to file BRR. BRR follows the National Voluntary Guidelines on Social, Environmental and Economic responsibilities of business, as notified by the MCA, Government of India. It includes firms' responses to practices and performance on key principles defined by Regulation 34(2)(f) of SEBI (Listing Obligations and Disclosure Requirements) Regulations 2015, covering topics across environment, governance, and stakeholder relationships. I collect the top 500 market capitalization companies as I observed that companies with lower market capitalization prior to 2015 do not have publicly disclosed CSR expenditure details. I assume the expenditure value to be zero for all the companies with no CSR expenditure information.

[23] www.mca.gov.in/MinistryV2/csrdatasummary.html,

[24] I follow the FPI definition under SEBI regulations, and only consider FPIs as FIIs whose maximum holdings are not more than 10% of the equity capital of a company on a fully diluted basis. Holdings above 10% are considered to be foreign direct investments under SEBI regulations.

$$FIO_{it} = \sum_{j=1}^{n} FIO_{jit}, \tag{2.1}$$

where, FIO_{it} is the aggregated ownership (percentage of total shares outstanding) of FIO_{jit} for the year *t*. Moreover, and in the spirit of Tsang et al. (2019), I also take the year-on-year change in FIO_{it} (represented as ΔFIO_{it} hereafter) as any temporal trend, for example general over time growth in FIO_{it}, that may falsify or inflate the divergence I observe in the post-S-135 period for the level of FIO_{it}.[25]

2.4.2 Key independent variable

My main variable of interest reflecting the impact of S-135 on FIO_{it} is the interaction of two dummy variables $(Treat_i \times Post_t)$. $Treat_i$ is the treated group firms that satisfy at least one of the three size thresholds of S-135 requirements (net worth of INR 5 billion or more, sales of INR 10 billion or more, or net profit of INR 50 million or more) in any specific year from the effective date of the Companies Act 2013 (i.e. April 1, 2014). Firms that are not required to comply with S-135 are control firms.[26] The second dummy variable $Post_t$ takes the value of one for the post-CSR mandate period (i.e., 2015-2017) and zero otherwise (2012-2014).

[25] To compute ΔFIO_{it}, I first take the difference in total FIIs' ownership in firm *i* between year *t* and lag year *t-1* (FIO_{it} - FIO_{it-1}), and then express it as a percentage of FIO_{it-1}.

[26] A potential concern associated with S-135 is whether firms would endogenously choose to be affected or remain unexposed by the regulation. One scenario could be that firms might self-select to be affected or unaffected by the mandate by increasing or lowering their accounting figures above or below the threshold level. However, Manchiraju and Rajgopal (2017) do not find any strategic manipulation in the accounting data of Indian firms around the threshold levels.

2.4.3 Covariates

I use a number of covariates for two reasons. First, using the propensity score matching (PSM) approach I use the covariates to generate highly comparable control and treated groups before observing the changes in the outcome variable (FIO_{jit}) (Angrist and Pischke, 2008; Rosenbaum and Rubin, 1983, 1985). The credibility of causality depends on this important pre-estimation evaluation as I control for any heterogeneous expectations of the treated and control groups in the post-S-135 period (Rubin, 1997, 2007). This near randomization procedure controls for all possible time-varying and time-invariant factors within the DiD framework that may explain changes in *FIO* in the treated and control groups, in the post-S-135 period (Rubin and Waterman, 2006). Thus, even if I am unable to obtain any potential key variables that should be part of the model's estimation, particularly the unobserved time-varying ones, I attempt to lessen omitted variable and alternative explanation biases. This is because any potential factor should have homogeneous effects on the control and treatment groups in the post-S-135 period. The second reason for the use of the covariates is to include them in the regression estimations, potentially not as control variables, but to generate more precise estimates as the inclusion of covariates generates smaller residual variance (Angrist and Pischke, 2008). Drawing on the literature, I use a number of key covariates as briefly discussed below.

Dahlquist and Robertsson (2001) show that foreign investors prefer investing in firms that are larger in size and cash positions, have a greater presence in international markets, and exhibit less concentrated ownership. I expect larger firms and firms with a higher cash position to attract more investments of FIIs since large firms tend to be more visible and considered more trustworthy, whereas a greater cash position signals firms' financial strength to investors (La Porta et al., 1997). Similarly, investee firms with greater international presence, which induces greater innovation output, should attract higher levels of FIIs' investments (Salomon and Shaver, 2005). Concentrated ownership, denoting higher control over corporate resources, may motivate insiders to derive higher utility of private benefits, thus leading to poor corporate governance (Leuz et al., 2009). I expect FIIs' ownership to be lower when the ownership concentration is higher (Leuz et al., 2009; Ferreira and Matos, 2008).

I include firm size (*Size*) by taking the natural logarithm of total assets (Leuz et al., 2009), *Cash* as the sum of year-end cash and short-term securities scaled by total sales (Roy et al., 2022), the international presence using *Exports*, taking foreign sales as a percentage of total sales (Bena et al., 2017), and ownership concentration (*OwnCon*) as the proportion of total shares held by promoters (Koirala et al., 2020; Thapa et al., 2020).[27]

Furthermore, Leuz et al. (2009) suggest that leverage and growth potential are significant factors influencing the investment decisions of FIIs. Firms with higher leverage tend to be more financially vulnerable and, as a result, undertake less value-enhancing corporate risk-taking (Acharya et al., 2011). Thus, I expect the variable *Leverage*, taken as the ratio of the book value of debt-to-equity, to have a negative correlation with ownership of FIIs (Ferreira and Matos, 2008). Similarly, foreign investors appear to buy and hold growth stocks as such stocks tend to experience higher past intangible returns (Leuz et al., 2009). Thus, I include the book to market value of equity (*B/M*), calculated as the book value per share over the year-end market

[27] Promoters are dominant shareholders (including family owners) owning large controlling stakes in the firm.

share price, as a proxy for growth potential and expect it to have a negative association with ownership of FIIs (Leuz et al., 2009).

Following Aggarwal et al. (2005), I also incorporate return on asset (*ROA*), a proxy for profitability computed as earnings before interest and taxes (EBIT), scaled by the book value of total assets, and expect it to be positively associated with ownership of FIIs. Finally, Chen et al. (2015) note that any decline in analyst coverage should exacerbate agency problems and reduce the quality of a firm's governance, which should further lead to value-destruction activities. This should discourage FIIs from investing in such firms. I include the number of analysts covering the firm in any year (*Analyst*), which is expected to be positively associated with ownership of FIIs (DeFond et al., 2011). I include all the covariates in my empirical analysis by taking one-year lagged values (Bena et al., 2017).[28]

2.4.4 Descriptive statistics

Table 2-2 reports different summary statistics for the entire sample as well as the average values for the pre-CSR (2012-2014) and post-CSR (2015-2017) subsamples for all key variables. These statistics are presented at the investee firm (i) level in Panels A and B followed by the FII (*j)* level in Panel C.

Panel A of Table 2-2 shows the summary statistics of FIO_{it} and ΔFIO_{it}. For a typical listed Indian firm, the average FIO_{it} is approximately 2.30% of total outstanding shares.[29] In terms of pre- and post-CSR figures, with the difference being

[28] For definitions and sources of all key variables, see Table 2-1.

[29] For the US market, Baik et al. (2013) report a mean FIIs' ownership of 2.62% per firm. Thus, in relative terms and as FIIs are generally sophisticated investors and therefore selective in investing in foreign stocks, the average FIO of 2.30% per Indian equity is comparable and economically meaningful (Bekaert and Harvey, 2003). Further, and as noted earlier, FIIs are one of the major categories of outside

statistically significant at the 1% level, statistics suggest that the average FIO_{it} significantly increases from 2.16% to 2.43% in the post-CSR mandate period compared to the pre-CSR mandate period. This change represents an increase of 11.74% [(2.43-2.16)/2.30] compared to the overall average, or INR 10,178.58 billion in terms of market value for the sample period.[30] Further, there is also a significant positive difference observed in ΔFIO_{it} between the pre- and post-S-135 periods of 4.43% (increased from 7.11% to 11.54%) compared to the overall sample average of 9.31%.

Panel B of Table 2-2 reports the summary statistics for all the covariates as described in Subsection 4.3. The mean value of *Size* increases significantly in the post-CSR mandate period, suggesting that firms' net investment in assets increased (Cheng et al., 2014). On the other hand, three covariates, namely *B/M*, *Leverage* and *ROA*, decline in the post-CSR mandate period. The decline in *B/M* is indicative of the fact that the market value of firms could have increased in the post-CSR mandate period, suggesting that the increase in overall market value, at least partially, could be induced by the CSR mandate (Ferrell et al., 2016).

Further, the reduction in *Leverage* could be an indication that after the CSR mandate, CSR firms' reliance on debt capital reduced as they may have acquired easier access to equity capital (with a reduced cost of equity) (El Ghoul et al., 2011; Cheng et al., 2014). Moreover, the decline in profitability (*ROA*) in the post-S-135 period could be induced by the inclusion/increase in CSR expenditure in income statements

investors in India owning approximately 40% of the free float Indian market capitalization. Source: *Financial Times*, April 13, 2015.

[30] Applying the average market capitalization figure of INR 86,700 billion during the post-regulation period of three years.

by CSR firms (Chen et al., 2018). Although *ROA*, which is an accounting-based performance measure for firms, reduces on average in the post-CSR mandate period, the firms' market value increases significantly (Daniel and Titman, 2006). I also observe that the overall CSR expenditure has a mean value of INR 15.59 million, with this expenditure increasing significantly by 74.30% in the post-S-135 mandate. This provides us with a strong indication that mandated S-135 has led to a significant increase in CSR expenditure by firms. Finally, the rest of the covariates (*OwnCon*, *Cash*, *Analyst*, and *Exports*) remain almost unchanged in the post-CSR mandate period.[31]

Panel C of Table 2-2 exhibits the investor level statistics of the FIIs' heterogeneity based on legal origin (common vs. civil), investee-firm monitoring role (independent vs. grey investors), and investment horizon (short-term vs. long-term). At the aggregated firm level, I find that, on average, each firm receives about 1.62% (0.58%) of investments by common (civil) law origin FIIs. The pre- and post-S-135 differences of these averages across the heterogeneity show that, except for common law origin, grey, and short-term investors, the average investments significantly increase after the CSR S-135 mandate. These results provide us with some initial indication that S-135 may have influenced investments of FIIs in India.

[**Table 2-2 about here**]

[31] It can be observed that the standard deviation of most of these variables is large, suggesting wide variations in size, profitability, leverage, etc. Potentially, this also indicates that the treatment and control groups could vary significantly in their characteristics in the pre-treatment period (see Panel B of Table 2). Thus, applying DiD to the entire sample may lead to comparing treatment and control groups containing firms with wide variations and invalidate the identical expectation and common support assumption of near randomization. This leads us to generate a near-randomized approach using a standard and robust matching technique (see Section 5).

2.5 Propensity score matched (PSM) randomization

Although I exploit S-135 as an exogenous shock for my DiD approach, I need to have two highly comparable groups of treated and control firms which should, as far as plausible, have homogeneous expectations and be exposed to similar economic environments in the post-CSR reform period. To check the baseline differences in their characteristics, I run t-tests of mean differences in key covariates (*Size, OwnCon, B/M, Leverage,* and *Cash*) between treated and control firms for the pre-S-135 period (i.e., 2012-2014) to see if they are comparable. The results are presented in Panel A of Table 2-3.

[**Table 2-3 about here**]

As seen, the results in Panel A of Table 2-3 indicate that the treated and control group firms are significantly different in terms of the covariates' characteristics. Thus, I create near randomized treated and control groups using the PSM approach, in which I carry out the standard steps as prescribed in the literature (Bena et al., 2017; Koirala et al., 2020; Roy et al., 2022). I first run a probit regression in the pre-CSR mandate period (Fiscal Years 2012-2014) as per specification (2.2), where the $Treat_i$ dummy is the dependent variable. $\boldsymbol{X_{it}}$ is the vector of five key covariates for PSM matching, which comprises *Size, OwnCon, B/M, Leverage,* and *Cash*.[32] ϑ_k is the industry fixed effects using the Fama-French 17 industries classification in equation (2.2):

$$Treat_i = \alpha + \boldsymbol{X_{it}}.\boldsymbol{\beta}' + \vartheta_k + \varepsilon_{it} \tag{2.2}$$

[32] The PSM results do not alter in any significant manner when I include all the covariates instead of the five key covariates. However, I do include all the covariates in the DiD regression estimations to improve the quantitative accuracy of the estimates.

I apply the nearest neighbor caliper algorithm method with replacement to identify a matching set of highly comparable treated and control firms prior to the enforcement of the CSR mandate (Rosenbaum and Rubin, 1985; Smith and Todd, 2005).[33] The PSM outcome results in 469 pairs of matched treated and control firms. To test whether PSM decreases the potential noticeable variances amid treated and control firms prior to the mandate, I rerun specification (2.2) on the matched subsample. The results of both pre-matched and post-matched samples' probit estimations are shown in Panel B of Table 2-3.

As reported in Columns (1) and (2) of Panel B of Table 2-3, I observe that matched treated and control group firms are not significantly different from each other. The pseudo-R^2 drops significantly from 0.33 observed in the pre-match probit (Model [1]) to only 0.02 in the post-match diagnostics (Model [2]). This suggests that the explanatory power of the probit model having matched firms is significantly reduced. I also present the *z-score* and the *standardized bias* figures between unmatched and matched sample covariates in Figures 2-1a and 2-1b, respectively. The *z-scores* show whether the mean differences between the average values of all the five covariates between matched and unmatched firms are statistically significant. The *z-scores* close to zero indicate no significant differences in the covariates between treatment and

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[33] As treated firms are generally bigger in size, I do not apply an exact matching technique for PSM. Instead, I use a nearest neighbor matching algorithm with a highly restricted caliper radius of 0.01% to generate near-randomized and highly comparable treated and control groups. I refer to this as the NN-PSM-0.01% approach. I am able to apply such a restrictive approach for PSM as my sample contains a total of 1,916 treated and 2,070 control firms as exogenously determined by S-135 (almost evenly distributed). I acknowledge that the NN-PSM-0.01% approach significantly reduces the number of treated and control firms in my matched sub-sample. However, by following such a highly restrictive near-randomization process, I am able to obtain almost identical treated and control groups that are immune to size bias. Further, matching with replacement minimizes the PSM distance between the matched control group firms and the treatment group firms, thus helping in reducing bias (Dehejia and Wahba, 2002).

control groups. From Figure 2-1a, I observe that the PSM matched individual covariates' *z-scores* (small circled figures) are close to zero compared to much bigger absolute values of the similar *z-scores* (diamond-shaped figures) for the covariates in the pre-matched sample. This indicates that the PSM matched treated and control firms are very similar in terms of their characteristics.

One shortcoming of the two samples' z-score comparability is that it does not exhibit the potential reduction in bias that may be observed in the regression estimates before and after matching. One suitable indicator to assess such reduction is the standardized bias (SB) measure suggested by Rosenbaum and Rubin (1985). It evaluates the distance in marginal distribution of the covariates in pre- and post-matched samples. For each of the covariates, SB is defined as:

$$SB_{pre} = 100. \frac{(\bar{X}_1 - \bar{X}_0)}{\sqrt{0.5. [V_1(X) + V_0(X)]}} \tag{2.3}$$

$$SB_{post} = 100. \frac{(\bar{X}_{1M} - \bar{X}_{0M})}{\sqrt{0.5. [V_{1M}(X) + V_{0M}(X)]}} \tag{2.4}$$

where X_1 (V_1) is the average (variance) of the covariates in the treatment group before matching and X_0 (V_0) are the analogues for the control group. X_{1M} (V_{1M}) and X_{0M} (V_{0M}) are the corresponding values of each covariate post-matching. The larger these biases, the greater the differences in the treatment and control groups. I report such SBs for each covariate in Figure 2-1b and this shows there is a high level of bias (diamond-shaped figures) in the pre-matched covariates, indicating significant differences among treated and control firms. The bias figures of the covariates in the post-matched sample are close to zero, indicating there is no statistically significant difference between the treated and control firms of the matched sample.[34]

2.6 Empirical results

2.6.1 Mandated CSR engagement and FIIs: Difference-in-differences results

I begin my empirical examination by plotting the yearly mean value of FIO_{it} and the year-on-year change in FIO_{it}, i.e. ΔFIO_{it} for the PSM-matched treated and control firms. As presented in Figure 2-2, FIO_{it} and ΔFIO_{it} for PSM-matched treated and control firms move in tandem in the pre-CSR S-135 enactment period. However, this parallel trend has a significant divergence from the year 2015 (the fiscal year is April 1, 2014 to March 31, 2015) when the S-135 comes into force. Although FIO_{it} and ΔFIO_{it} continue to fall for the control group firms, I see an increase in the trend of FIO_{it} and ΔFIO_{it} for treated firms. I argue that the differential increment observed in FIO_{it} for the treated group is potentially attributed, at least partially, to the CSR reform S-135, thus offering some preliminary support in favor of the *CSR engagement attraction* hypothesis H_1.

Given the highly restricted PSM procedure described in Section 5, my PSM-DiD attempts to be as randomized as possible, and hence any time-invariant or time-variant factor, other than S-135, should affect the treated and control groups identically without disturbing the parallel trend. Such a credible set-up reduces the concern of my result being driven by any other alternative explanations to changes in FIO_{it} among treated firms post S-135.

[**Figure 2-2 about here**]

[34] A bias reduction below 5% is generally accepted as reasonable (Angrist and Pischke, 2008).

Next, I present the univariate DiD estimates for FIO_{it} and ΔFIO_{it} in Panel A of Table 2-4. The DiD estimates show, relative to control firms, what the differential change is in the average FIO_{it} and ΔFIO_{it} among the treated firms in the post-S-135 period. I find the univariate DiD coefficients of both FIO_{it} (0.331) and ΔFIO_{it} (10.581) to be positive and significant at the 1% level. When I compare the 0.33% increase relative to the average mean value of all firms in the pre-S-135 period, this is a material increase of almost 15% for the treated firms compared to control firms in the post-S-135 period. With the objective of improving the precision of the DiD estimates, I run the following multivariate DiD regression:

$$FIO_{it} = \alpha + \beta.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it} \quad (2.5)$$

where, FIO_{it} is the dependent variable (FIO_{it} or ΔFIO_{it}) and the key independent variable ($Treat_i \times Post_t$), the DiD term, is the interaction between the $Treat_i$ and $Post_t$ dummy variables. $\boldsymbol{X_{it-1}}$ is a vector of the covariates that include *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst,* and *Exports,* all lagged by a year and as defined in Subsection 4.3. γ_i and τ_t allow for firm and year fixed effects in the panel regressions. Standard errors are clustered at the firm level.

It could be credibly argued that the shorter the sample period the more precise should be the DiD estimates, as with the passage of time it is empirically challenging to isolate the effect of S-135 from other factors. However, once a firm meets the regulatory threshold of S-135 and becomes legally obliged, it remains obligated for the succeeding three years. We, therefore, estimate specification (2.5) for both shorter (2013-2016) and longer periods (2012-2017). Accordingly, the pre-CSR mandate period is 2013-14 for the shorter period and 2012-2014 for the longer period (i.e.,

$Post_t$ = 0), whereas the post-CSR mandate period is 2015-2016 for the shorter period and 2015-2017 for the longer period (i.e., $Post_t$ = 1). For each sample period and each measure of FIO_{it} and ΔFIO_{it}, I report the multivariate PSM-DiD regression results, in Panel B of Table 2-4.

Table 2-4 Panel B shows that in the post-S-135 CSR mandate period, on average, FIO_{it} significantly increases in the range of 0.316% to 0.431%, and the ΔFIO_{it} in the range of 7.505% to 8.465%, among the treated firms when compared to the control group firms. These results are generally significant at the significance levels of 5% or better. Overall, the results in Table 2-4 support CSR engagement attraction hypothesis H_1 that firms that comply with the CSR mandate attract more FIIs, relative to firms that do not comply.[35] Most of the covariates carry predicted signs.[36]

In an additional set of similar tests, I investigate how DIIs' ownership changes in the post S-135 period. The parallel trend graph for DII ownership, presented in Figure 2-4, shows no discernible difference in the post-S-135 period between the treated and control firms. These findings indicate that the mandated CSR disclosure does not seem to provide any additional information for the DIIs to influence their

[35] For robustness, I also run a regression in specification (2.5) where I take firm level yearly aggregate FIIs' ownership data from the CMIE Prowess database as the dependent variable. Presented in Table 2-5, the regression results are very similar, in terms of statistical significance and economic magnitude, to my main results in Table 2-4.

[36] It is plausible that some of the affected firms were already engaged in CSR and if so, investments by FIIs should not be affected by the CSR mandate. Indeed, an argument can be made that the impact for firms that were voluntarily engaged in CSR may have been negative. In order to address this concern, I conduct the following robustness test. I drop from the sample the firms that had voluntary CSR engagement prior to the enactment of S-135 and rerun my analysis on both the full and PSM samples. The empirical results presented in Table 2-6 are largely consistent with the main findings. This analysis confirms that the higher fund flows from FIIs are primarily attracted by the mandated CSR firms in the post-S-135 period and not by the firms that were already engaged in voluntary CSR activities prior to the enforcement of S-135.

investment levels, potentially corroborating the view that DIIs already had greater levels of information relative to FIIs (Ferreira and Matos, 2008; Tsang et al., 2019).

[**Table 2-4 about here**]

2.6.2 Does actual CSR expenditure matter to FIIs?

S-135 requires firms to either comply, by spending the required amounts on CSR projects, or explain their complete or partial non-compliance. In my empirical set-up under specification (2.5), the treated group may comprise those firms that may choose to explain their reason for non-compliance, and hence, their inclusion may generate biased estimates. In order to overcome this potential issue within the treated firms, I conduct a PSM-matched double difference-in-differences (DiDiD), using specification (2.6), whereby I exploit the cross-sectional variations in the actual CSR expenditure:

$$FIO_{it} = \alpha + \beta_1.(Treat_i \times Post_t \times CSR_{exp}) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it} \tag{2.6}$$

I follow two alternative approaches to estimate specification (2.6). In the first, I define CSR_{exp} as an indicator variable that takes the value of one if the firm's CSR expenditure is greater than zero, and the value of zero if the firm does not incur CSR expenditure. In the second alternative, I define CSR_{exp} as the natural logarithm of the actual value of the CSR expenditure in million Indian rupees (INR). All other variables are as per specification (2.5). I present the results of both these alternatives of specification (2.6) in Table 2-7.

[**Table 2-7 about here**]

The first alternative of specification (2.6) in which CSR_{exp} is a dummy variable is shown in columns [1] and [2], and the second alternative, based on actual scaled CSR expenditure value, in columns [3] and [4] of Table 2-7. I observe that the coefficient DiDiD is positive and significant across all specifications (at 5% or better levels of statistical significance). The positive signs of the estimates indicate that, on average and in the post-reform period, the higher the actual CSR expenditure the higher the FIO_{it} in the treated firms, relative to the control firms. In economic terms the additional attraction of FIO_{it} is 0.475% (0.371% for the alternative scaled CSR model) and that of ΔFIO_{it} is 9.162% (6.721% for the alternative scaled CSR model). The results provide evidence that FIIs place considerable importance on the actual CSR expenditure by firms, further supporting CSR engagement attraction hypothesis H_1.[37]

2.6.3 New and existing FIIs - CSR engagement attraction

To provide additional support for my CSR engagement attraction hypothesis, I investigate whether CSR firms attract new FIIs in the post S-135 period. As such, in specification (2.5), I consider three dependent variables which include (i) the total number of FIIs, (ii) the number of new FIIs as a proportion of the total number of existing FIIs, and (iii) the total ownership held by new FIIs for PSM-DiD regressions. Additionally, to see whether existing FIIs change their ownership in CSR firms, I also

[37] Higher levels of profits normally attract higher FIIs. The provisions of the S-135 mean that these firms will have higher CSR expenditure, and the relationship between CSR and FIIs could only be due to spurious correlation. In order to mitigate this concern, I conduct an additional empirical analysis to test the impact of excess CSR expenditure, i.e., CSR expenditure over and above the mandated amount under S-135, on attracting FIIs. The results indicate that mandated CSR (treated) firms that spend on CSR over and above the mandated (prescribed) amount attract higher levels of FIIs' ownership on average, relative to all other firms. The results are presented in Table 2-8.

set the total ownership by existing FIIs as the dependent variable and derive the estimates.

Table 2-9 shows that the DiD coefficients are positive and significant (at least at the 5% level) across all three proxies for new FIIs, indicating that S-135 significantly attracted new FIIs to invest in CSR firms in the post-S-135 period. Model (2) shows on average, when compared to non-CSR firms, there was an 11.9% increase in new FIIs among CSR firms post S-135. I also find in model (4) the DiD coefficients are positive and significant (at the 5% level) for the existing FIIs' ownership variable, whose proportion of ownership increased, on average, by 0.312% among CSR firms in the post S-135 period when compared to non-CSR firms. Overall, the results indicate that CSR firms obtained higher FIIs' ownership in the post S-135 period by attracting investments from both new and existing FIIs.

[**Table 2-9 about here**]

2.6.4 Robustness tests of hypothesis 1

I undertake several robustness checks to further validate my results in Table 2-4.

2.6.4.1 Placebo test

Although the findings suggest that the implementation of S-135 directly caused exogenous variation in FIIs' ownership, it is possible that these findings could have been due to cyclical trends or the persistence of prior exogenous variation. In order to address this concern, I conduct a placebo test by rerunning specification (2.5) for an alternative sample period of 2007-2012, with years 2007-2009 ($Post_t$=0) as the pre-shock period and years 2010-2012 ($Post_t$=1) as a false post-shock period. Here, in addition to capturing any past exogenous or cyclical events, I also assume that the S-

135 effective year is 2010, which is a false shock year. Columns [1] and [2] of Table 2-10 show that the DiD coefficients for both FIO_{it} and ΔFIO_{it} are insignificant, indicating that my main results presented in Table 2-4 are not confounded by other events, and lessens concerns of any pre-existing trends in FIO_{it} and ΔFIO_{it} .

[**Table 2-10 about here**]

2.6.4.2 Alternative treated and control groups

Apart from the S-135 treated firms, control firms that do not come under S-135 could voluntarily choose to undertake CSR expenditure.[38] Therefore I reclassify the matched treated and control firms based on actual CSR expenditure. The assumption is that firms within the alternative treatment group that actually incur CSR expenditure can be considered to be more "socially responsible" regardless of their compliance with the new, mandated CSR regulation. Therefore, I redefine the indicator variable $Treat_i$ value to be one for firms with CSR expenditure greater than zero, regardless of it satisfying the thresholds of S-135 (alternative treatment group firms), and those with no CSR expenditure take the value of zero (alternative control group firms). I test specification (2.5) using this alternative treatment group and present the results in Columns [3] and [4] of Table 2-10. I find that, in line with the main results, in the post-CSR mandate period, FIO_{it} (ΔFIO_{it}) increases significantly on average by 0.652% (7.350%) among treatment group firms when compared to alternative control group

[38] I find that 1,503 treated firms and 614 control firms actually expend on CSR activities in the post-S-135 period.

firms. These results provide further support to the *CSR engagement attraction* hypothesis (*H_1*).[39]

2.6.4.3 Multivariate regression discontinuity design (MRDD)

I supplement my PSM-DiD method with a regression discontinuity (RD) test around the cut-off thresholds of S-135 to estimate the localized effect of the treatment (i.e., the CSR mandate). However, as S-135 has multiple assignment thresholds that determine the treatment status, I use the binding-score MRDD (Manchiraju and Rajgopal, 2017; Reardon and Robinson, 2012). The binding-score MRDD technique results in generating a single rating score (M_{Score}) by collapsing multiple rating variables and estimating an average treatment effect for the entire sample using M_{Score}.

Following the standard approach of the MRDD, I first center each of the three rating variables, namely net worth, sales, and net profit (these are the thresholds-variables of S-135 as indicated in Section 2), on its cut-off (zero). Next, for each firm (i), I generate a single new rating variable ($M_{Score,i}$) by centering each variable score at its respective cut-off of INR 5 billion for net worth, INR 10 billion for sales, and INR 50 million for net profit (Reardon and Robinson, 2012; Wong et al., 2013).[40]

I take four different bandwidths (BWs) (i.e., 25%, 50%, 75%, and 100%) of the running variable $M_{Score,i}$ to determine the treatment effect around different

[39] Any time invariant changes, for example potential changes in weights of firms in Indian indices, effect of international acquisitions, family ownership and/or propensity for socially responsible investments, should affect both the highly comparable PSM groups identically. Therefore, exclusion of these changes in my econometric framework, if theoretically argued, should not affect the credibility of the estimates.
[40] I employ the following procedure, as outlined in Reardon and Robinson (2012) and Wong et al. (2013). For each firm (*i*), if the three rating variables net worth (W_i), Sales (S_i), and net profit (P_i) have a threshold cut-off of Wc, Sc and Pc respectively, then their centered values are $W_i^z=(W_i-Wc)/Wc$; $S_i^z=(S_i-Sc)/Sc$ and $P_i^z=(P_i-Pc)/Pc$. I then calculate M_{Score} using the following specification: $M_{Score,i}$ = minimum (W_i^z, S_i^z, P_i^z)

radiuses. Figure 3 reports the MRDD plots around $M_{Score,i}$ for the four different BWs. In all the figures of different BWs, I can see the discontinuities in the *FIO* variable at the cut-off where $M_{Score,i}$ is zero. These jumps offer further support to *CSR engagement attraction* hypothesis *H₁*.

[**Figure 3 about here**]

I further run the following regression-based MRDD (specification 2.7) test in the post-CSR mandate period (i.e., Fiscal Years 2015 to 2017):

$$FIO_{it} = \alpha + \omega . S_{135} + \boldsymbol{X_{it-1}} . \boldsymbol{\delta'} + \gamma_i + \tau_t + \varepsilon_{it} \qquad (2.7)$$

where S_{135} is a categorical variable that takes the value of one if the firm is treated, i.e., if $M_{Score,i}$ (running variable) ≥ 0 and zero otherwise. FIO_{it} and $\boldsymbol{X}_{it-1}$ are as defined under specification (2.5). γ_i and τ_t are the firm and year fixed effects, respectively. The key coefficient of interest ω, indicates the average treatment effect of S-135 on the ownership of FIIs.

Table 2-11 shows that, even at 25% BW radius, the treatment coefficient is positive and significant, at least at the 10% level of significance.[41] As I increase the BW radius further to 50% or more, the positive treatment effect becomes more pronounced and significant at least at the 5% level of significance. In economic magnitude terms, the coefficients indicate that the positive effect of treatment (S-135) on FIO_{it} is in the range of 0.425% to 0.764%. Thus, the MRDD analysis further

[41] The loss of efficiency, i.e., statistical power, in the form of reduced number of observations and lower t-statistics, is required to mitigate the higher degree of biasness when using RD models. Hence, for the BW of 25%, statistical significance even at the 10% level provides support for my argument.

confirms that firms affected by the CSR mandate attract more FIIs relative to unaffected firms and support the *CSR engagement attraction* hypothesis (H_1).

[**Table 2-11 about here**]

2.6.5 FIIs' heterogeneity hypotheses

To test the two *FIIs' heterogeneity* hypotheses (H_2 and H_{3} a and b), I use the cross-sectional heterogeneity of FIIs, which are based on time-invariant factors, such as country of domicile (legal origins) and types of FIIs, based on their investee-firm monitoring role (independent vs. grey investors) and investment horizon (hedge funds vs. pension funds). Since I use a PSM-based near-randomization procedure for my quasi-natural experiment, the regression-based DiD estimates are less likely to suffer from omitted variable and alternative explanation biases. Any potential forward-looking explanatory factor should have identical effects on the control and treatment groups in the post-S-135 period. Further, given the fact that in the DiD approach I exploit the disturbance in the parallel trend between treatment and control groups, the PSM-matched estimates, even in the absence of time-varying factors at the FIIs' level, should not be prone to omitted variable bias.

2.6.5.1 CSR and FIIs' heterogeneity: Legal origins

To test the causal effect of a CSR mandate on FIIs' ownership, based on their country of legal origin, I run different specifications of regression (2.8) using the PSM treated and control firms:

$$FIO_{jit} = \alpha + \beta_1.(Treat_i \times Post_t \times Legal_j) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \sigma.Legal_j + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_{ji} + \tau_t + \varepsilon_{jit} \tag{2.8}$$

where FIO_{jit} is the total percentage of ownership (at investor level) held by FII j of the investee firm i in the year t (see Subsection 4.1). $Treat_i$ and $Post_t$ are indicator dummy variables as defined earlier. $Legal_j$ is also a dummy variable that takes the value of one in different specifications, depending on whether the investor j is domiciled in a common, civil, or Scandinavian law jurisdiction and zero otherwise.[42] $\boldsymbol{X_{it-1}}$ is a vector of key firm-level lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst,* and *Exports*. γ_{ji} and τ_t are the investor-firm and year fixed effects respectively.[43] The triple interaction term ($Treat_i \times Post_t \times Legal_j$) is my primary DiDiD estimator that shows the causal effect of a CSR mandate on ownership of FIIs based on legal origin for treated firms in the post-CSR mandate period.

I report the regression results of different specifications of regression (2.8) in Table 2-12.[44] Column [1] reports the outcomes when the dummy variable takes the value of one for common law origin (*Common law*). The sign of the estimate indicates that the moderating effect of common law origin on the causal effect of CSR mandate on investments of FIIs is positive, but statistically insignificant compared to all FIIs from non-common legal origins. However, when I run a similar regression with a civil law dummy (*Civil law*), I find the regression coefficient to be positive and statistically significant at the 1% significance level. This suggests that in the post-CSR mandate

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[42] In my sample for the period 2012 to 2017, I have 73 unique foreign countries from which FIIs have invested in Indian firms. I categorize these unique investor countries into their legal origins following La Porta et al. (2008). An important issue that could arise is that the country of incorporation of the parent FII could be different from its subsidiary through which trades are executed. However, I argue that the investment policy is normally dictated by the parent company (Astley and Sachdeva, 1984). We, therefore, identify the legal origins of the FIIs based on their headquartered countries. Table 2-22 lists all the foreign investor countries and their legal origin.

[43] The inclusion of investor-firm fixed effect takes account of any investor-specific strategies/policies that do not change over time. Moreover, and as laid out earlier, in my PSM-DiD set-up, any other time-invariant or time-variant factor, other than S-135, should affect the treated and control groups identically without disturbing the parallel trend.

[44] Standard errors of all investor level regressions are clustered at the investor-firm (*ji*) level.

period, on average and relative to all other legal origins, FIIs from civil law origins differentially increase their ownership in treated firms by approximately 0.179% more, compared to control firms. Given the average ownership of 2.30% across all FIIs, as reported in Table 2-2, this 0.179% differential increment translates into a relative increase of approximately 7.8% (0.179/2.30).[45]

[**Table 2-12 about here**]

La Porta et al. (2008) suggest that the civil law origin is predominantly composed of French and German law origin countries, whereas the third constituent of civil law, i.e., Scandinavian law, contains only a few countries. However, even though considered as a part of the civil law family, Scandinavian law tends to be "distinct" from other civil laws in terms of legal rules and heritage (La Porta et al., 1998, 2008). Further, studies suggest that investors domiciled in Scandinavian countries could face greater social pressure to make socially responsible investments due to high stakeholder-oriented corporate social norms and culture (Dyck et al., 2019; Guiso et al., 2006). Thus, I investigate further to see whether the main results for civil law are primarily driven by Scandinavian law FIIs. To illustrate the difference in the moderating effects of Scandinavian legal origin versus other civil law origins (French and German), I modify specification (2.8) by including two DiDiD variables in a single regression. In the first case, the dummy variable $Legal_j$ takes the value of one if the investor j is domiciled only in a Scandinavian law country and zero otherwise. In the second case, the dummy variable $Legal_j$ takes the value of one if the investor j is

[45] The legal origin of countries in my sample is based on La Porta et al. (2008). Some of the countries in my sample are not in La Porta et al. (2008), and I am unable to determine their legal origins. Therefore columns [1] and [2] results are not mirror images of each other. I have different results in the two models as I am comparing common law FIIs with those from non-common law origins (primarily civil law origins) and civil law FIIs with those from non-civil law origins (primarily common law origins).

domiciled in any other non-Scandinavian civil law origin country and zero otherwise. The estimates of this regression are reported in column [3] of Table 2-12 (*Scandinavian vs. other civil law*).

The results indicate that compared to non-civil law origin FIIs, in the post-CSR mandate period, both Scandinavian and non-Scandinavian civil law origin FIIs significantly increase their investments by 0.172% and 0.180% among treated firms. Thus, it is apparent that there is no single driver within civil law origin FIIs in terms of making socially responsible investments, as all civil law FIIs are equally attracted toward increasing their ownership in CSR firms in the post-CSR mandate period. Overall, the results in Table 2-12 support the first *FIIs' heterogeneity* hypothesis (H_2).

2.6.5.2 CSR and FIIs' heterogeneity: Monitoring role and investment horizon

To test the second *FIIs' heterogeneity* hypothesis H_3, I run different specifications of regression equation (2.9) on the PSM sample firms:

$$FIO_{jit} = \alpha + \beta_1.(Treat_i \times Post_t \times Type_j) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \sigma.Type_j + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_{ji} + \tau_t + \varepsilon_{jit} \tag{2.9}$$

where $Type_j$ is an indicator variable that takes the value of one if FII j belongs to a particular investor group (i.e., independent investors, grey investors, pension funds, or hedge funds) and zero otherwise. Here the variable $Type_j$ represents four different dummy variables and depends on the investor $Type$ for which I run the regression, i.e., independent investors, grey institutions, pension funds, or hedge funds. Thus, $Type_j$ takes the value of one if investor j is one of these types and zero otherwise. Given that I have four different types of FII, I run four different regressions. All other variables are as per specification (2.5). The triple interaction term ($Treat_i \times Post_t \times Type_j$) is the primary DiDiD estimator that shows whether the change in FIIs' ownership for the treated firms, relative to control firms and in the post-S-135 period, depends on the heterogeneity of investor types based on monitoring role and investment horizon.

Results reported in column [1] of Table 2-13 shows that, relative to all other FIIs and in the post-S-135 period, independent FIIs differentially increase their ownership in treated firms more, i.e., by 0.191% (statistically significant at the 5% level). However, in the estimates in column [2], the DiDiD coefficients for grey FIIs are statistically insignificant, illustrating that the CSR mandate does not appeal to grey FIIs any more differentially than other FIIs. To summarize, independent investors, who are considered to be active monitors of investee firms, seem to be more attracted by more CSR engagements. These results are consistent with the *FIIs' heterogeneity* hypothesis (H_{3a}).

[**Table 2-13 about here**]

Further, the estimates in column [3] (significant at the 5% significance level) indicate that relative to all other FIIs, long-term FIIs and in the post-S-135 period, overweight their ownership in treated firms by around 0.291% compared to control firms. However, in Column [4], the DiDiD coefficients for short-term investors (foreign hedge funds) are statistically insignificant. These results for investors based on a time horizon of investments indicate that foreign long-term investors choose to invest more in the firms that comply with a CSR mandate, relative to firms that do not, supporting the *FIIs' heterogeneity hypothesis* (H_{3b}).[46]

2.6.5.3 Robustness test – legal origins and types of FIIs

On the same basis as Sections 6.4.1 and 6.4.2, I conduct a placebo test and an alternative treated and control group firms test as per equations (2.8) and (2.9). For the placebo test, $Post_t$ is an indicator variable that takes the value of one for the post-false shock period (FY 2010-2012) and zero for the pre-false shock period (FY 2007-2009). For the alternative treated and control group test, $Treat_i$ is an indicator variable that takes the value of one for firms with CSR expenditure greater than zero, regardless of it satisfying the thresholds of S-135, and firms with no CSR expenditure take the value of zero. All other variables are as defined under equations (2.8) and (2.9). I find insignificant results, as expected, for the placebo test and the results of the alternative treatment group test are in line with the findings in Tables 2-12 and 2-13. These results are presented in Tables 2-15 and 2-16, respectively.

2.6.6 Mandatory CSR engagement value relevance

The mandated CSR regulation not only requires firms to increase their CSR performance, but also to improve firm-level disclosures and transparency related to their CSR engagement. Such disclosures should be value-relevant, since it is evident

[46] I further analyze whether the CSR mandate attracts CSR/ESG oriented FIIs. To test this, I use the Principles of Responsible Investment (PRI) signatories' database. PRI is an international group of institutional investors that have a common agenda of incorporating ESG issues into their investment decisions, seeking appropriate ESG disclosures, and actively engaging in implementing ESG principles. I manually match the FII list with the PRI signatories (4,607 as of 18th December 2021) for my sample period and conduct a double DiD analysis. The results indicate that, compared to all other FIIs, CSR oriented FIIs (i.e., PRI signatories) significantly increased their ownership in mandated CSR firms (about 0.18% on average) relative to control firms in the post-S-135 period. This additional analysis confirms that the CSR mandate attracted CSR oriented FIIs in India. The results are presented in Table 2-14.

from the literature that greater transparency helps mitigate the friction of information asymmetry, which should further lead to lower cost of capital (Dhaliwal et al., 2011; El Ghoul et al., 2011). Further, CSR regulations requiring firms to only engage in prescribed CSR activities and implement strict monitoring, along with the penalties for any violation of the CSR regulatory provisions, should deter managers of CSR firms from engaging in opportunistic behaviors that may create agency problems associated with CSR (Tirole, 2001; Masulis and Reza, 2015). Thus, mandatory CSR regulation could improve CSR firms' corporate governance and, in turn, lead to higher long-term market value (Ferrell et al., 2016).

Moreover, since emerging markets generally lack the concept of stakeholder protection and CSR engagement, any obligatory CSR compliance should help firms in emerging markets to build their social and reputational capital, leading to higher firm value (Lins et al., 2017; Albuquerque et al., 2019; Turban and Greening, 1997). Further, by better aligning their interests with those of key non-investing stakeholders, mandated CSR firms should be able to obtain superior financial performance and value in the long run (Allen et al., 2015; Magill et al., 2015). To investigate whether mandatory CSR engagement induces firms to obtain long-term market-based valuations, I run the following multivariate DiD panel regression using my PSM-matched firms as specified in equation (2.10):

$$MV_{it} = \alpha + \beta_1.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it} \qquad (2.10)$$

where MV_{it} is the market value for firm *i* in the year *t*. I use two proxies for market-based values, namely Tobin's Q and equity's Market to Book (*MB*) ratio.[47] $Treat_i$, and $Post_t$ are as defined under specification (2.5). I also include $\boldsymbol{X}_{it-1}$, i.e., vector of covariates, all lagged by one year, to improve the precision of the regression estimates, i.e., *Size, OwnCon, Leverage, Cash, ROA, Analyst,* and *Exports*, all as defined in Subsection 4.3, along with firm and year fixed effects. For this analysis, the key coefficient of interest is from the interaction DiD term $(Treat_i \times Post_t)$ which estimates the long-term market-based value effect of mandated CSR on treated firms compared to control firms in the post-S-135 period. I report the multivariate PSM-DiD regression results as per specification (2.10) in Table 2-17.

[**Table 2-17 about here**]

In columns [1] and [2] of Table 2-17, I present the regression estimates using the primary treated and control group firms, whereas columns [3] and [4] report the estimates using my alternative treated and control group firms (based on actual CSR expenditure). It is seen that the DiD coefficients are positive and significant (at the 1% level) for both *Tobin's Q* and *MB* in all of my models. The results in columns [1] and [2] suggest that in the post-CSR mandate period, treated firms experience higher long-term market valuations (34.70% in terms of *Tobin's Q* and 6.099% in terms of *MB*) compared to control firms.[48] Thus, my PSM-DiD analysis provides evidence that firms

[47] Tobin's Q is defined as the sum of the book value of debt, preference stock, and market value of equity scaled by the book value of assets (Desai and Dharmapala, 2009). Dharmapala and Khanna (2013) note "*The book, rather than market, value of preferred stock is used because preferred stock is very thinly traded, if at all*."
[48] The DiD coefficients from alternative models are similar to my main results in terms of economic magnitude and statistical significance, as seen in columns [3] and [4].

that comply with the CSR mandate and spend on prescribed CSR activities are rewarded with higher long-term market valuations.[49]

One could argue that firms that are expected to do poorly in the long-term would currently have lower valuations and be more likely to be classified as control firms. Thus, the observed higher long-term market value of treated firms in the post-S-135 period is simply due to higher market expectations and not to the impact of the mandatory CSR engagement. However, such an endogeneity concern is unlikely in my robust PSM-DiD design as I take the book-to-market ratio (*B/M*), which is a proxy for market expectations, as one of the key covariates to generate the PSM matching pairs of treated and control groups. To further validate this, I include two analyst forecast measures, namely target price to book ratio (*P/B*) and 5 year forecasted earnings per share growth (*EPSGrowth*), in my PSM-DiD regressions as proxies for market expectations (Brown and Kim, 1991). The results are tabulated in Table 2-19. The results remain qualitatively similar even after controlling for market expectations.[50]

Nevertheless, in the case of S-135, event study-based papers do find that mandatory CSR firms lose firm value in the short run (Aswani et al., 2021; Manchiraju and Rajgopal, 2017). One plausible reason behind the contrasting results between these papers and my study could be that the market did not anticipate the mandatory CSR-

[49] As a further robustness test, I conduct an MRDD analysis to test the localized treatment effect of mandated CSR regulation on market value for treated firms in the post-S-135 period. Presented in Table 2-18, the results from my MRDD analysis indicate that the treatment effect of S-135 is positive and highly significant for both the market value proxies (Tobin's Q and MB), when applying all four different BWs (i.e., 25%, 50%, 75%, and 100%) of the $M_{Score,i}$. Overall, the MRDD estimates are in line with the PSM-DiD results.

[50] It could be argued that mandatory CSR firms are more profitable in general and hence the higher market value of these firms in the post-S-135 period is simply due to their higher profitability and not to their mandatory CSR engagement. Additional empirical results indicate that firms spending in excess of mandatory CSR prescribed amount generally obtained higher market-based valuations, compared to all other firms, thus alleviating this concern. The results are presented in Table 2-20.

induced higher fund flows from FIIs. It is well established in the literature that the growing presence of FIIs can improve firms' market-based value (Aggarwal et al., 2011; Ferreira and Matos, 2008). Such a value-enhancing effect is observed because greater FIIs' investments enhance international risk sharing, reduce home bias, lower the cost of capital, generate demand for better managerial performance, and promote greater firm-level micro and macro level transparency (Errunza, 2001; Bekaert and Harvey, 2003). This implies that the increased FIIs' investment, potentially induced by higher CSR engagement of the complying firms, could be an avenue through which mandated CSR regulation improves firms' market-based value in the long run.

To test this potential channel, following the literature, I conduct a mediation analysis (Francis et al., 2021; Roy et al., 2022). In particular, I want to show that FIIs' ownership acts as a mediator in the mandatory CSR – market value relationship. There are three prerequisites that need to be met for the mediation effect to be established. First, there should be a significant relationship between mandatory CSR engagement (in my case the interaction term $Treat_i \times Post_t$ or DiD) and market value ($Tobin's\ Q$ or MB), which is already shown in Section 6.6. Next, there should be a significant relationship between the DiD term and the mediator variable (FIO), which is shown in Section 2.6.1. Finally, to show the mediation effect, I regress the market value measures on both the DiD term and FIO alongside all other covariates and firm and year fixed effects. I present the results in Table 2-21. Models [1] and [3] reinstate the main DiD results as in Table 2-17, and Models [2] and [4] show the mediation effect of FIO on the mandatory CSR (DiD) induced market value.

If there is a mediation effect of FIO on the positive relationship between mandatory CSR engagement and market value, then the coefficients on FIO should be significant, which is observed for both *Tobin's Q* and *MB*. Further, the significance/magnitude of the DiD coefficients should be reduced after the mediator variable (*FIO*) is added to the regression. The reduction in the DiD coefficient captures the mediation effect of *FIO*. Indeed, I find the DiD coefficients to be reduced by 3.17% in terms of *Tobin's Q* and 5.33% in terms of *MB* with *FIO* being added to the regression. I run Sobel (1982) tests and find these mediation effects to be highly significant (p-value < 0.01). Overall, the mediation analysis confirms that mandatory CSR engagement is value relevant and that the mandatory CSR induced higher FIIs' ownership acts as a channel through which mandatory CSR engagement improves the long-term market value of mandated CSR firms.

2.7 Conclusion

When assessing firms' financial and sustainability performance, institutional investors around the world boast of taking account of corporates' role in promoting better ESG activities seriously (Ioannou and Serafeim, 2015; Amel-Zadeh and Serafeim, 2018). If such arguments hold any relevance, then do FIIs prefer to invest more in firms that are legally mandated to spend a minimum threshold of their income on CSR activities? Further, and more importantly, do different types of FIIs react differentially to the same mandated CSR engagement regulation? I answer these questions by exploiting a CSR regulation in India which mandates listed firms to spend at least 2% of their net profit on CSR-related activities.

My PSM-DiD and MRDD empirical approach, on a sample of listed Indian non-financial firms for the period between the fiscal years 2012-2017, shows that in the post-CSR mandate period FIIs significantly increase their investment stakes in firms that comply with the mandated expenditure regulation compared to firms that do not. Additionally, I find that CSR firms not only attract new FIIs, but the existing FIIs increase their ownership in these firms in the post-CSR reform period. For the first time, to the best of my knowledge, I find that not all types of foreign investors are equally attracted to CSR activities. I provide evidence that FIIs from civil law origins are inclined to invest more in the post-CSR mandate period compared to FIIs from common law countries. Further, my results also reveal that independent and pension funds' FIIs materially boost their asset allocation in complying firms after the enforcement of the CSR mandate. Finally, my results also show that mandated regulations are value-relevant and those mandatory CSR activities help increase the firm value of CSR firms in the long run.

To conclude, although better CSR performance is seen as an attractive proposition by FIIs, not all types of foreign investors are symmetrically attracted. The empirical evidence in this study suggests that investors' legal origin and investment objectives significantly matter when responding to mandated CSR regulations.

2.8 Tables of Chapter 2

Table 2-1 Variable description

Variable		Description	Source
Foreign Institutional Ownership variables			
FIO_{it}		Total percentage of shares owned by foreign institutional investors (FIIs) in the firm *i* in the year *t*	S&P Capital IQ
ΔFIO_{it}		Change in total *FIO* in the firm *i* from year *t-1* to *t* expressed as a percentage of total *FIO* in year *t-1*	
FIO_{jit}		Total percentage of shares owned by an FII *j* in an Indian firm *i* for the year *t*	S&P Capital IQ
Key DiD and MRDD variables			
$Treat_i$		Indicator variable that takes the value of one if it satisfies any one of the thresholds of S-135 and zero otherwise	CMIE
$Post_t$		Indicator variable that takes the value of one for the years 2015-2017 and zero otherwise	CMIE
S_{135}		For MRDD analysis, takes the value of one if $M_{Score} \geq 0$ and zero if $M_{Score} < 0$.	Derived from CMIE
Covariates			
Size		Natural logarithm of total assets	Derived from CMIE
OwnCon		Proportion of total shares held by promoters	CMIE
B/M		Book value per share over the year-end market share price	CMIE
Leverage		Ratio of book value of debt-to-equity	CMIE
Cash		Sum of year end cash and short-term securities scaled by total sales	Derived from CMIE
ROA		Return on total assets computed as earnings before interest and taxes (EBIT) scaled by the book value of total assets	Derived from CMIE
Analyst		Number of analysts following the stock	S&P Capital IQ
Exports		Foreign sales as a percentage of total sales	Derived from CMIE
Other indicator dummy variables			
$Legal_j$	*Common*	If the investor *j* belongs to common law origin country, $Legal_j$ then takes the value of one and zero otherwise	S&P Capital IQ
	Civil	If the investor *j* belongs to civil law origin country, $Legal_j$ then takes the value of one and zero otherwise	S&P Capital IQ
	Scandinavian	If the investor *j* belongs to Scandinavian law origin country, $Legal_j$ then takes the value of one and zero otherwise	S&P Capital IQ
	Other civil	If the investor *j* belongs to non-Scandinavian civil law origin country, $Legal_j$ then takes the value of one and zero otherwise	S&P Capital IQ
$Type_j$	*Independent*	If the investor *j* is an independent investor, $Type_j$ then takes the value of one and zero otherwise	S&P Capital IQ
	Grey	If the investor *j* is a grey investor, $Type_j$ then takes the value of one and zero otherwise	S&P Capital IQ
	Long-term	If the investor *j* is a pension fund investor, $Type_j$ then takes the value of one and zero otherwise	S&P Capital IQ
	Short-term	If the investor *j* is a hedge fund investor, $Type_j$ then takes the value of one and zero otherwise	S&P Capital IQ

Table 2-2 Descriptive statistics

This table reports the mean values of all variables used in this study for the overall sample period (i.e., 2012 to 2017) and is also segregated into two periods, i.e., before the enforcement of S-135 (2012-2014) and after the enforcement of S-135 (2015-2017) for which the number of observations is presented in parentheses. Panels A and B respectively report the statistics for the main dependent variables (i.e., foreign institutional ownership variables) and firm level covariates. *FIO* is the total institutional ownership (% of total outstanding shares) of Indian firms held by all foreign institutional investors (FIIs). *ΔFIO* is the year-on-year change in total foreign institutional ownership (*FIO*). Covariates are as defined in Table 2-1. Panel C provides the summary statistics of aggregated ownership by heterogeneous FIIs. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. Data sources: S&P Capital IQ (CIQ) and the Centre for Monitoring Indian Economy (CMIE) database.

Variable	Observations	Mean	Median	Std. Deviation	Minimum	Maximum	Before S-135	After S-135	Diff	t-stat	p-value
Panel A: FIIs' ownership variables											
FIO	23,694	2.30	0.00	6.12	0.00	37.60	2.16	2.43	0.27***	3.37	0.001
							(11,974)	(11,720)			
ΔFIO	23,502	9.31	0.00	71.60	-100	864.15	7.11	11.54	4.43***	4.74	0.000
							(11,830)	(11,672)			
Panel B: Covariates and other independent variables											
Size	23,120	6.93	6.97	2.37	1.16	11.62	6.84	7.03	0.19***	6.17	0.000
							(11,736)	(11,384)			
OwnCon	20,116	49.20	35.77	21.30	0.62	85.27	48.98	49.41	0.44	1.46	0.144
							(9,913)	(10,203)			
B/M	18,554	0.92	0.15	2.49	-2.43	11.67	1.05	0.80	-0.24***	-6.69	0.000
							(9,047)	(9,507)			
Leverage	20,707	1.04	0.40	1.77	0.00	9.01	1.08	1.00	-0.08***	-3.56	0.000
							(10,590)	(10,117)			
Cash	20,309	0.26	0.04	0.69	0.00	3.50	0.27	0.25	-0.02*	-1.79	0.074
							(10,168)	(10,141)			
ROA	22,981	0.41	1.24	11.11	-45.52	27.29	0.72	0.09	-0.62***	-4.24	0.000
							(11,624)	(11,357)			
Analyst	23,694	1.25	0.00	5.09	0.00	51.00	1.25	1.24	-0.01	-0.21	0.833

							(11,974)	(11,720)			
Exports	23,123	11.38	0.00	30.42	0.00	100.00	11.73	11.02	-0.71*	-1.79	0.073
							(11,732)	(11,391)			
CSR Expenditures	23,694	15.59	0.00	108.30	0.00	1707.60	11.40	19.87	8.47***	6.02	0.000
							(11,974)	(11,720)			
Panel C: FIIs' ownership heterogeneity											
FIO (Common law)	23,694	1.62	0.00	4.47	0.00	24.05	1.59	1.65	0.06	1.00	0.315
							(11,974)	(11,720)			
FIO (Civil law)	23,694	0.58	0.00	2.39	0.00	14.74	0.49	0.67	0.18***	5.79	0.000
							(11,974)	(11,720)			
FIO (Scandinavian)	23,694	0.06	0.00	0.39	0.00	4.68	0.04	0.07	0.03***	6.03	0.000
							(11,974)	(11,720)			
FIO (Other civil)	23,694	0.51	0.00	2.31	0.00	9.83	0.43	0.59	0.16***	5.25	0.000
							(11,974)	(11,720)			
FIO (Independent)	23,694	1.26	0.00	3.55	0.00	18.96	1.20	1.32	0.12***	2.63	0.008
							(11,974)	(11,720)			
FIO (Grey)	23,694	1.04	0.00	4.91	0.00	16.65	1.45	1.44	-0.01	0.10	0.923
							(11,974)	(11,720)			
FIO (Long-term)	23,694	0.05	0.00	0.30	0.00	3.84	0.03	0.06	0.03***	8.69	0.000
							(11,974)	(11,720)			
FIO (Short-term)	23,694	0.15	0.00	0.86	0.00	7.39	0.15	0.16	0.01	0.76	0.444
							(11,974)	(11,720)			

Table 2-3 Propensity score matching (PSM)

Panel A reports the t-test of mean differences in covariates between treated and control firms in the pre-S-135 period and Panel B shows a probit model for PSM as per the following specification:

$$Treat_i = \alpha + \boldsymbol{X_{it}}.\boldsymbol{\beta}' + \vartheta_k + \varepsilon_{it}$$

where $Treat_i$ is a categorical variable that takes the value of one if the firm is affected by S-135 and zero otherwise. $\boldsymbol{X_{it}}$ is the vector of covariates comprising *Size, OwnCon, B/M, Leverage,* and *Cash* used for matching. *Size* is the natural logarithm of total assets, *OwnCon* is the proportion of total shares held by promoters, *B/M* is the book value per share over the year-end market share price, *Leverage* is the ratio of book value of debt-to-equity, *Cash* is the sum of year end cash and short-term securities scaled by total sales. ϑ_k is the industry fixed effects using the Fama-French 17 industries classification. Model [1] presents the probit model predicting the likelihood of being a treated firm from the entire sample of firms with no missing covariates in the pre-S-135 period. Model [2] presents the probit likelihood model for matched treated and comparison firms using PSM with replacement. Heteroskedasticity robust t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. Data sources: CIQ and CMIE database.

Panel A: Mean differences in covariates between treated and control firms in the pre-S-135 period

Variable	Control	Treated	Diff (T-C)	t-stat	p-value
Size	6.00	7.74	1.74***	41.97	0.000
	(1.72)	(2.70)			
	6,093	5,643			
OwnCon	46.69	51.29	4.60***	10.88	0.000
	(21.07)	(21.02)			
	4,979	4,934			
B/M	0.62	1.45	0.83***	15.49	0.000
	(2.01)	(2.93)			
	4,408	4,639			
Leverage	1.26	0.90	-0.36***	-10.37	0.000
	(1.99)	(1.49)			
	5,362	5,228			
Cash	0.30	0.23	-0.08***	-5.30	0.000
	(0.77)	(0.59)			
	5,996	4,172			

Panel B: Pre-match propensity score regression and post-match diagnostic regression

	Dummy = 1 if affected by S-135; 0 if unaffected	
	Pre-match [Model 1]	Post-match [Model 2]
Size	0.564***	0.010
	(21.79)	(0.29)
OwnCon	-0.001	-0.001
	(-0.55)	(-0.29)
B/M	-0.089***	-0.021
	(-4.63)	(-0.63)
Leverage	-0.208***	-0.007
	(-9.33)	(-0.24)
Cash	0.110**	-0.032
	(2.19)	(-0.46)
Constant	-3.841***	0.266
	(-17.92)	(0.98)
Industry FE	Yes	Yes
Pseudo R^2	0.33	0.02
p-value of χ^2	0.00	0.38
Observations	2,748	938

Table 2-4 Mandated CSR and FIIs: Propensity scored matched – DiD regression

This table reports the results from the propensity scored matched DiD regression as per the following specification:

$$FIO_{it} = \alpha + \beta.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where FIO_{it} (ΔFIO_{it}) is the institutional ownership (change in ownership), held by all FIIs, of Indian firm *i* for the year *t*. $Treat_i$ is an indicator dummy variable that takes the value of one for firms that are affected by S-135 and zero otherwise. $Post_t$ is a categorical variable that takes the value of one for the post-CSR mandate period (2015-2017) and zero for the pre-S-135 period (2012-2014). The DiD is the interaction between the $Treat_i$ and $Post_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of the one year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports,* all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

Panel A: Univariate DiD estimates of PSM-matched treated and control firms for 2012-2017

	Foreign Institutional Ownership (FIO)				*Change in Foreign Institutional Ownership (ΔFIO)*			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Treated	Control	Diff (T-C)	DiD	Treated	Control	Diff (T-C)	DiD
Before	3.486	0.895	2.590***	**0.331*** **	8.084	6.892	1.193	**10.581*** **
			(16.31)	**(2.79)**			(0.63)	**(3.88)**
After	3.624	0.702	2.921***		11.130	-0.643	11.773***	
			(19.58)				(6.29)	

Panel B: Multivariate PSM-DiD regression estimates:

	Foreign Institutional Ownership (FIO)		*Change in Foreign Institutional Ownership (ΔFIO)*	
	2013-2016	2012-2017	2013-2016	2012-2017
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	**0.316** **	**0.431** **	**7.505** **	**8.465*** **
	(2.10)	**(2.16)**	**(2.15)**	**(3.06)**
Size	0.347**	0.564***	-4.424	-3.027
	(2.22)	(2.85)	(-0.59)	(-0.79)
OwnCon	-0.030**	-0.050***	0.505**	0.386**
	(-2.56)	(-2.91)	(2.26)	(2.32)
B/M	0.002	-0.038	-5.793***	-2.592**
	(0.03)	(-0.48)	(-3.32)	(-2.27)
Leverage	-0.037	0.013	-0.943	-0.013
	(-0.68)	(0.24)	(-0.77)	(-0.02)
Cash	0.117	0.121	2.819	3.470
	(1.07)	(0.97)	(0.76)	(1.31)
ROA	0.663	-0.382	5.952	24.580
	(0.78)	(-0.43)	(0.30)	(1.62)
Analyst	0.315***	0.440***	2.951	0.274
	(3.31)	(3.13)	(1.18)	(0.13)
Exports	-0.001	-0.006	0.006	0.000
	(-0.09)	(-0.56)	(0.05)	(0.00)
R^2 (within)	0.026	0.025	0.017	0.009
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	863	903	863	903
Observations	3,162	4,706	3,162	4,706

Table 2-5 PSM-DiD robustness using CMIE database

This table reports the results from the PSM-DiD regression as per the following specification using the FIIs' ownership data from the CMIE database:

$$FIO_{it} = \alpha + \beta.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where FIO_{it} (ΔFIO_{it}) is the institutional ownership (change in ownership), held by all FIIs, of Indian firm i for year *t*. $Treat_i$ is an indicator dummy variable that takes the value of one for firms that are affected by S-135 and zero otherwise. $Post_t$ is a categorical variable that takes the value of one for the post-CSR mandate period (2015-2017) and zero otherwise. The DiD is the interaction between $Treat_i$ and $Post_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports,* all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

Panel A: Univariate DiD estimates of PSM-matched treated and control firms for 2012-2017

	Foreign Institutional Ownership (FIO)				*Change in Foreign Institutional Ownership (ΔFIO)*			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Treated	Control	Diff (T-C)	DiD	Treated	Control	Diff (T-C)	DiD
Before	3.774	3.328	0.446	**1.138****	-1.229	-2.222	0.993	**8.400*****
			(1.19)	**(2.12)**			(0.59)	**(3.45)**
After	4.453	2.869	1.585***		3.735	-5.659	9.393***	
			(4.11)				(5.35)	

Panel B: Multivariate PSM-DiD regression estimates:

	Foreign Institutional Ownership (FIO)		*Change in Foreign Institutional Ownership (ΔFIO)*	
	2013-2016	2012-2017	2013-2016	2012-2017
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	**0.841****	**0.813****	**8.578****	**8.116*****
	(2.16)	**(2.03)**	**(2.56)**	**(3.16)**
Size	0.257	0.556**	3.795	1.558
	(0.90)	(2.06)	(0.69)	(0.51)
OwnCon	-0.006	0.015	0.314	0.115
	(-0.25)	(0.55)	(1.12)	(0.63)
B/M	-0.153	-0.224*	-1.884	-3.029***
	(-0.86)	(-1.78)	(-1.31)	(-2.98)
Leverage	-0.002	0.045	-0.181	0.663
	(-0.02)	(0.54)	(-0.17)	(0.71)
Cash	0.030	0.1841	4.604*	3.396*
	(0.21)	(0.98)	(1.75)	(1.79)
ROA	0.392	-0.604	30.957*	31.513**
	(0.23)	(-0.35)	(1.76)	(2.23)
Analyst	0.317*	0.349**	0.379	-0.931
	(1.83)	(2.27)	(0.17)	(-0.55)
Exports	0.006	0.006	0.217	0.132
	(0.60)	(0.60)	(1.55)	(1.33)
R^2 (within)	0.008	0.010	0.013	0.012
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	851	899	851	899
Observations	3,105	4,650	3,105	4,650

Table 2-6 No voluntary CSR

This table reports the results from the DiD regression on the subsample of firms with no voluntary CSR expenditure prior to the enforcement of S-135 as per the following specification:

$$FIO_{it} = \alpha + \beta.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where FIO_{it} (ΔFIO_{it}) is the institutional ownership (change in ownership), held by all FIIs, of Indian firm *i* for the year *t*. $Treat_i$ and $Post_t$ are indicator variables as described in Table 2-4.The DiD is the interaction between $Treat_i$ and $Post_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of the one-year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects, respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Full sample		*PSM sample*	
	(FIO)	*(ΔFIO)*	*(FIO)*	*(ΔFIO)*
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	**0.264****	**7.447*****	**0.474****	**8.056*****
	(2.16)	**(4.49)**	**(2.43)**	**(2.83)**
Size	0.749***	0.878	0.599***	-2.467
	(4.73)	(0.44)	(2.97)	(-0.63)
OwnCon	-0.042***	0.394***	-0.046***	0.374**
	(-4.27)	(3.82)	(-2.96)	(2.17)
B/M	-0.173***	-1.976***	-0.017	-2.257**
	(-3.40)	(-3.51)	(-0.23)	(-2.00)
Leverage	-0.098**	-0.499	0.018	0.230
	(-2.24)	(-0.79)	(0.33)	(0.26)
Cash	0.009	2.634**	0.052	3.498
	(0.10)	(2.11)	(0.46)	(1.30)
ROA	0.476	22.300***	-0.136	25.390
	(0.75)	(2.79)	(-0.15)	(1.62)
Analyst	0.284***	-1.001***	0.451***	-0.974
	(6.55)	(-2.58)	(3.16)	(-0.50)
Exports	0.004	0.032	-0.004	0.032
	(0.67)	(0.54)	(-0.45)	(0.35)
R^2 (within)	0.044	0.007	0.032	0.008
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	2,539	2,539	835	835
Observations	13,041	13,041	4,317	4,317

Table 2-7 CSR expenditure and FIIs' ownership

This table reports the results from the propensity matched DiDiD regression as per the following specification:

$$FIO_{it} = \alpha + \beta_1.(Treat_i \times Post_t \times CSR_{exp}) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where FIO_{it} (ΔFIO_{it}) is the institutional ownership (change in ownership), held by all FIIs, of Indian firm *i* for the year *t*. The DiDiD is the interaction among $Treat_i$, $Post_t$ and CSR_{exp}. In columns [1] and [2], CSR_{exp} is an indicator variable that takes the value of one if a firm actually incurs CSR expenditure and zero otherwise. In columns [3] and [4], CSR_{exp} is the log of a firm's actual CSR expenditure. $Treat_i$ and $Post_t$ are indicator variables as in Table 2-4. $\boldsymbol{X}_{it-1}$ is a vector of the one year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	CSR_{exp} is an indicator variable		*CSR_{exp} is log of CSR expenditure*	
	(FIO)	*(ΔFIO)*	*(FIO)*	*(ΔFIO)*
	[1]	[2]	[3]	[4]
DiDiD ($Treat_i \times Post_t \times CSR_{exp}$)	**0.475****	**9.162*****	**0.371****	**6.721****
	(2.47)	**(2.83)**	**(2.38)**	**(2.37)**
DiD ($Treat_i \times Post_t$)	-	-	0.047	1.513
			(0.18)	(0.44)
Size	0.543***	-3.416	0.504**	-4.106
	(2.74)	(-0.88)	(2.55)	(-1.07)
OwnCon	-0.051***	0.366**	-0.051***	0.370**
	(-2.98)	(2.21)	(-2.97)	(2.24)
B/M	-0.034	-2.517**	-0.029	-2.419**
	(-0.44)	(-2.20)	(-0.37)	(-2.13)
Leverage	0.015	0.032	0.023	0.176
	(0.29)	(0.04)	(0.43)	(0.20)
Cash	0.127	3.585	0.123	3.502
	(1.01)	(1.36)	(0.97)	(1.32)
ROA	-0.326	25.750*	-0.428	23.750
	(-0.37)	(1.71)	(-0.48)	(1.58)
Analyst	0.433***	0.143	0.408***	-0.305
	(3.11)	(0.07)	(2.94)	(-0.15)
Exports	-0.006	-0.003	-0.005	0.004
	(-0.59)	(-0.04)	(-0.55)	(0.04)
R^2 (within)	0.025	0.009	0.028	0.012
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	903	903	903	903
Observations	4,634	4,634	4,706	4,634

Table 2-8 Excess CSR expenditure and FIIs' ownership

This table reports the results from the propensity matched DiDiD regression as per the following specification:

$$FIO_{it} = \alpha + \beta_1.(Treat_i \times Post_t \times CSR_{exc}) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where FIO_{it} (ΔFIO_{it}) is the institutional ownership (change in ownership), held by all FIIs, of Indian firm *i* for year *t*. The DiDiD is the interaction among $Treat_i$, $Post_t$ and CSR_{exc}. In columns [1] and [2], CSR_{exc} is an indicator variable that takes the value of one if a firm's CSR expenditure is above the mandated amount and zero otherwise. In columns [3] and [4], CSR_{exc} is the log of firm's excess CSR expenditure above the mandated amount. $Treat_i$ and $Post_t$ are indicator variables as in Table 2-4. $\boldsymbol{X}_{it-1}$ is a vector of the one year lagged covariates *Size*, *OwnCon*, *B/M*, *Leverage*, *Cash*, *ROA*, *Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	CSR_{exc} is an indicator variable		*CSR_{exc} is log of excess CSR expenditure*	
	(FIO)	*(ΔFIO)*	*(FIO)*	*(ΔFIO)*
	[1]	[2]	[3]	[4]
DiDiD ($Treat_i \times Post_t \times CSR_{exc}$)	**0.392****	**7.717****	**0.267****	**9.136*****
	(2.17)	**(2.04)**	**(2.08)**	**(2.89)**
DiD ($Treat_i \times Post_t$)	-	-	**0.449*****	3.811
			(2.94)	(1.36)
Size	0.567***	-2.963	0.426***	-4.204
	(2.86)	(-0.76)	(3.02)	(-1.09)
OwnCon	-0.051***	0.368**	-0.028***	0.379**
	(-2.97)	(2.21)	(-2.83)	(2.29)
B/M	-0.040	-2.625**	0.019	-2.421**
	(-0.51)	(-2.28)	(0.35)	(-2.12)
Leverage	0.009	-0.081	-0.007	0.234
	(0.17)	(-0.09)	(-0.18)	(0.27)
Cash	0.128	3.606	0.038	3.435
	(1.02)	(1.36)	(0.42)	(1.29)
ROA	-0.232	27.520*	-0.274	22.910
	(-0.26)	(1.81)	(-0.42)	(1.52)
Analyst	0.445***	0.377	0.333***	-0.013
	(3.19)	(0.18)	(3.10)	(-0.01)
Exports	-0.006	-0.002	-0.006	0.008
	(-0.58)	(-0.02)	(-0.89)	(0.09)
R^2 (within)	0.025	0.008	0.036	0.015
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	903	903	903	903
Observations	4,706	4,706	4,706	4,706

Table 2-9 CSR engagement and FIIs' ownership: New and existing FIIs

This table reports the DiD of propensity matched pairs of firms as per the following specification:

$$FIO_{it} = \alpha + \beta.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_i + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

depending on the model, FIO_{it} is either the total number of FIIs, the number of new FIIs as a proportion of the total number of existing FIIs, the total ownership held by new FIIs or the total ownership held by existing FIIs of Indian firm *i* for the year t. $Treat_i$ and $Post_t$ are indicator variables as defined in Table 2-4. The DiD is the interaction between the $Treat_i$ and $Post_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of the one-year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Total FIIs	*New FIIs /Existing FIIs*	*New FIIs' Ownership*	*Existing FIIs' Ownership*
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	**0.230*** **	**0.119*** **	**0.169** **	**0.312** **
	(4.10)	**(4.29)**	**(2.16)**	**(2.04)**
Size	0.373***	-0.033	-0.127	0.683***
	(4.43)	(-0.70)	(-1.18)	(2.96)
OwnCon	-0.007*	0.004*	0.006	-0.044***
	(-1.91)	(1.88)	(1.08)	(-3.57)
B/M	-0.073***	-0.045***	-0.017	0.060
	(-2.69)	(-3.00)	(-0.55)	(0.89)
Leverage	-0.063***	-0.009	-0.033	0.040
	(-3.12)	(-0.62)	(-1.53)	(0.81)
Cash	0.119**	0.031	0.050	0.027
	(2.41)	(1.30)	(0.93)	(0.27)
ROA	0.222	0.229	0.548	-0.918
	(0.84)	(1.31)	(1.48)	(-1.33)
Analyst	0.306***	-0.059***	0.030	0.377***
	(3.94)	(-2.71)	(0.53)	(2.75)
Exports	-0.002	-0.001	-0.002	-0.001
	(-0.51)	(-0.83)	(-0.74)	(-0.18)
R^2 (within)	0.068	0.014	0.005	0.037
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	903	903	903	903
Observations	4,706	4,706	4,706	4,706

Table 2-10 Placebo test and alternative treated and control groups

This table reports the DiD of propensity matched pairs of firms as per the following specification:

$$FIO_{it} = \alpha + \beta.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_i + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where FIO_{it} (ΔFIO_{it}) is the institutional ownership (change in ownership), held by all FIIs, of Indian firm *i* for the year *t*. For the placebo test presented in columns [1] and [2], the DiD term is the interaction between $Treat_i$ as defined in Table 2-4 and $Post_t$ which is an indicator variable that takes the value of one for the post-false shock period (2010-2012) and zero for the pre-false shock period (2007-2009). For the alternative treated and control group test presented in columns [3] an [4], the DiD term is the interaction between $Treat_i$ an indicator variable that takes the value of one for firms with CSR expenditure greater than zero regardless of it satisfying the thresholds of S-135 and firms with no CSR expenditure take the value of zero, and $Post_t$ as defined in Table 2-4. $\boldsymbol{X}_{it-1}$ is a vector of the one year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports* and these are as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2007 to 2012. Data sources: CIQ and CMIE database.

	Placebo test		*Alternative treated and control group firms test*	
	(FIO)	*(ΔFIO)*	*(FIO)*	*(ΔFIO)*
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	-0.100	-1.247	**0.652****	**7.350****
	(-0.17)	(-0.19)	**(2.32)**	**(2.49)**
Size	1.541*	-3.929	0.496*	-2.909
	(1.96)	(-0.66)	(1.94)	(-0.76)
OwnCon	-0.040**	0.0769	-0.056***	0.379**
	(-2.48)	(0.45)	(-2.70)	(2.27)
B/M	-0.016	-3.698*	-0.087	-2.577**
	(-0.11)	(-1.82)	(-0.87)	(-2.26)
Leverage	-0.005	0.0252	-0.001	-0.047
	(-1.14)	(0.79)	(-0.02)	(-0.05)
Cash	0.009	0.0272	0.125	3.555
	(1.50)	(0.37)	(0.92)	(1.35)
ROA	0.616	14.21	-1.194	26.380*
	(0.51)	(0.69)	(-1.00)	(1.74)
Analyst	0.225	-8.061**	0.442***	0.337
	(1.05)	(-2.05)	(3.13)	(0.16)
Exports	-0.008	0.0902	-0.008	0.002
	(-0.74)	(0.38)	(-0.68)	(0.02)
R^2 (within)	0.003	0.004	0.014	0.008
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	730	730	903	903
Observations	3,744	3,744	4,706	4,706

Table 2-11 Multivariate regression discontinuity design (MRDD)

This table reports the regression estimates as per the following specification:

$$FIO_{it} = \alpha + \omega . S_{135} + \boldsymbol{X}_{it-1} . \boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where FIO_{it} is the institutional ownership held by all FIIs of Indian firm *i* for the year *t*. S_{135} is an indicator variable that takes the value of one if $M_{Score,i} \geq 0$ and zero if $M_{Score,i} < 0$. $M_{Score,i}$ is the minimum (nearest to zero) of the three rating variables (net worth of INR 5 billion or more, sales of INR 10 billion or more, or net profit of INR 50 million or more) centered on zero. $\boldsymbol{X}_{it-1}$ is a vector of the one year lagged covariates *Size, OwnCon, B/M, Leverage*, *Cash*, *ROA*, *Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. We use four different bandwidths (BWs) of 25%, 50%, 75%, and 100% around M_{Score} to examine the treatment effect at various radiuses from the cut-off. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2015 to 2017. Data sources: CIQ and CMIE database.

	25% BW	50% BW	75% BW	100% BW
	[1]	[2]	[3]	[4]
S_{135}	**0.764***	**0.591****	**0.473****	**0.425*****
	(1.77)	**(2.50)**	**(2.83)**	**(3.02)**
Size	0.981	0.161	0.701**	0.445**
	(0.99)	(0.29)	(2.21)	(2.60)
OwnCon	-0.019	0.010	0.037	0.003
	(-0.28)	(0.19)	(0.70)	(0.18)
B/M	-0.289	-0.135**	-0.057	-0.121*
	(-1.62)	(-2.39)	(-1.01)	(-2.06)
Leverage	-0.155	-0.129	-0.057	-0.146*
	(-0.75)	(-1.33)	(-0.94)	(-1.85)
Cash	0.055	-0.024	-0.132	0.013
	(0.13)	(-0.12)	(-0.96)	(0.21)
ROA	-3.305	0.698	3.555	0.770
	(-0.65)	(0.25)	(1.23)	(0.73)
Analyst	0.235	0.409***	0.324***	0.332***
	(0.90)	(3.69)	(4.83)	(5.26)
Exports	0.004	-0.003	0.008	0.002
	(0.29)	(-0.31)	(1.37)	(0.68)
R^2 (within)	0.024	0.031	0.028	0.012
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	218	490	855	1,789
Observations	510	1,200	2,192	4,866

Table 2-12 CSR and FIIs' heterogeneity: Legal origins

This table reports the DiDiD regressions of propensity matched pairs of firms as per the following specification:

$$FIO_{jit} = \alpha + \beta_1.(Treat_i \times Post_t \times Legal_j) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \sigma.Legal_j + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_{ji} + \tau_t + \varepsilon_{jit}$$

where FIO_{jit} is the ownership held by an FII *j* in an Indian firm *i* for the year *t*. $Treat_i$ and $Post_t$ are indicator variables as described in Table 2-4. $Legal_j$ is an indicator variable that takes the value of one if investor *j* is domiciled in a specific country of legal origin (i.e., common law, civil law, or Scandinavian law). X_{it-1} is a vector of the key firm level lagged covariates *Size*, *OwnCon*, *B/M*, *Leverage*, *Cash*, *ROA*, *Analyst* and *Exports*, all as defined in Table 2-1. γ_{ji} and τ_t are the investor-firm level fixed effects and year fixed effects, respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the investor-firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

Dependent variable: FIO (Disaggregated at investor level)

	Common law	Civil law	Scandinavian vs. other civil law
	[1]	[2]	[3]
DiDiD $(Treat_i \times Post_t \times Legal_j)$	0.080	**0.179*** **	-
	(1.07)	**(2.72)**	
DiDiD $(Treat_i \times Post_t \times Scandinavian_j)$	-	-	**0.172** **
			(2.50)
DiDiD $(Treat_i \times Post_t \times Other\ Civil\ law_j)$	-	-	**0.180** **
			(2.56)
Size	0.134**	0.133*	0.133*
	(1.97)	(1.93)	(1.93)
OwnCon	-0.012***	-0.012***	-0.012***
	(-2.82)	(-2.81)	(-2.81)
B/M	-0.031*	-0.031*	-0.031*
	(-1.76)	(-1.79)	(-1.79)
Leverage	-0.002	-0.003	-0.003
	(-0.25)	(-0.33)	(-0.33)
Cash	0.033	0.035	0.035
	(0.73)	(0.79)	(0.79)
ROA	-0.174	-0.167	-0.167
	(-0.73)	(-0.74)	(-0.74)
Analyst	0.017***	0.017***	0.017***
	(3.00)	(2.91)	(2.90)
Exports	-0.001	-0.001	-0.001
	(-1.26)	(-1.29)	(-1.29)
Adj. R^2	0.56	0.56	0.56
Investor-Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
No. of Investor-Firms	3,661	3,661	3,661
Observations	19,233	19,233	19,233

Table 2-13 CSR and FIIs' heterogeneity: Monitoring role and investment horizon

This table reports DiDiD regressions of propensity matched pairs of firms as per the following specification:

$$FIO_{jit} = \alpha + \beta_1.(Treat_i \times Post_t \times Type_j) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \sigma.Type_j + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_{ji} + \tau_t + \varepsilon_{jit}$$

where FIO_{jit} is the ownership held by an FII *j* in an Indian firm *i* for the year *t*. $Treat_i$ and $Post_t$ are indicator variables as described in Table 2-4. $Type_j$ is an indicator variable that takes the value of one if FII *j* belongs to a particular investor group (i.e., independent investors, grey investors, long-term investors, or short-term investors). $\boldsymbol{X}_{it-1}$ is a vector of key firm level lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports*, all as defined in Table 2-1. γ_{ji} and τ_t are the investor-firm level fixed effects and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the investor-firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

Dependent variable: FIO (Disaggregated at investor level)

	Independent	Grey	Long-term	Short-term
	[1]	[2]	[3]	[4]
DiDiD ($Treat_i \times Post_t \times Type_j$)	**0.191****	0.015	**0.291****	-0.184
	(2.20)	(0.11)	**(2.55)**	(-0.92)
Size	0.129*	0.137**	0.138**	0.138**
	(1.88)	(2.00)	(1.99)	(2.00)
OwnCon	-0.012***	-0.012***	-0.012***	-0.012***
	(-2.83)	(-2.82)	(-2.82)	(-2.80)
B/M	-0.030*	-0.031*	-0.031*	-0.031*
	(-1.73)	(-1.79)	(-1.78)	(-1.78)
Leverage	0.002	-0.005	-0.005	-0.006
	(0.22)	(-0.61)	(-0.56)	(-0.68)
Cash	0.031	0.036	0.036	0.038
	(0.68)	(0.81)	(0.81)	(0.85)
ROA	-0.231	-0.143	-0.146	-0.134
	(-0.97)	(-0.63)	(-0.65)	(-0.60)
Analyst	0.016***	0.018***	0.018***	0.018***
	(2.62)	(3.05)	(3.09)	(3.01)
Exports	-0.001	-0.002	-0.002	-0.002
	(-1.20)	(-1.32)	(-1.33)	(-1.34)
Adj. R^2	0.56	0.56	0.56	0.56
Investor-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Investor-Firms	3,661	3,661	3,661	3,661
Observations	19,233	19,233	19,233	19,233

Table 2-14 PRI signatories

This table reports the DiDiD regressions of propensity matched pairs of firms as per the following specification:

$$FIO_{jit} = \alpha + \beta_1.(Treat_i \times Post_t \times PRI_j) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \sigma.PRI_j + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_{ji} + \tau_t + \varepsilon_{jit}$$

where FIO_{jit} is the ownership held by an FII *j* in an Indian firm *i* for year *t*. $Treat_i$ and $Post_t$ are indicator variables as described in Table 2-4. PRI_j is an indicator variable that takes the value of one if investor *j* is a PRI signatory and zero otherwise. $\boldsymbol{X_{it-1}}$ is a vector of key firm level lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports*, all as defined in Table 2-1. γ_{ji} and τ_t are the investor-firm level fixed effects and year fixed effects, respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the investor-firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

Dependent variable: FIO (Disaggregated at investor level)

	PRI Signatories
	[1]
DiDiD ($Treat_i \times Post_t \times PRI_j$)	**0.181*** **
	(2.92)
Size	0.132*
	(1.92)
OwnCon	-0.012***
	(-2.84)
B/M	-0.031*
	(-1.76)
Leverage	-0.001
	(-0.14)
Cash	0.031
	(0.68)
ROA	-0.208
	(-0.90)
Analyst	0.016***
	(2.80)
Exports	-0.002
	(-1.30)
Adj. R^2	0.56
Investor-Firm FE	Yes
Year FE	Yes
No. of Investor-Firms	3,661
Observations	19,233

Table 2-15 Placebo and alternative treated and control groups test - CSR and FIIs' legal origin

This table reports the DiDiD regressions of propensity matched pairs of firms as per the following specification:

$$FIO_{jit} = \alpha + \beta_1.(Treat_i \times Post_t \times Legal_j) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \sigma.Legal_j + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_{ji} + \tau_t + \varepsilon_{jit}$$

where FIO_{jit} is the ownership held by an FII j in an Indian firm i for year t . For the placebo test presented in columns [1] to [3], the DiDiD term is the interaction between $Treat_i$ as defined in Table 2-4, $Post_t$ which is an indicator variable that takes the value of one for the post-false shock period (F.Y. 2010-2012) and zero for the pre-false shock period (F.Y. 2007-2009) and $Legal_j$, an indicator variable as defined in Table 2-12. For the alternative treated and control group test presented in columns [4] to [6], the DiDiD term is the interaction among $Treat_i$ an indicator variable that takes the value of one for firms with CSR expenditure greater than zero regardless of it satisfying the thresholds of S-135 and firms with no CSR expenditure that takes the value of zero, and $Post_t$ as defined in Table 2-4. and $Legal_j$, an indicator variable as defined in Table 2-12. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst and Exports and are as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2007 to 2012. Data sources: CIQ and CMIE database.

	Placebo test			*Alternative treated and control group firms test*		
	Common Law	Civil Law	Scandinavian vs. other civil law	Common Law	Civil Law	Scandinavian vs. other civil law
	[1]	[2]	[3]	[4]	[5]	[6]
DiDiD $(Treat_i \times Post_t \times Legal_j)$	-0.182*	0.062		0.074	**0.224*** **	
	(-1.93)	(0.55)		(1.04)	**(3.43)**	
DiDiD $(Treat_i \times Post_t \times Scandinavian_j)$	-	-	0.198	-	-	**0.174** **
			(0.91)			**(2.49)**
DiDiD $(\mathrm{Treat_i} \times \mathrm{Post_t} \times \mathrm{Other\ Civil\ law_j})$	-	-	0.035	-	-	**0.232*** **
			(0.34)			**(3.29)**
Size	0.285***	0.283***	0.322***	0.133**	0.131*	0.131*
	(4.39)	(4.40)	(4.17)	(1.96)	(1.91)	(1.91)
OwnCon	-0.008***	-0.008***	-0.010***	-0.012***	-0.012***	-0.012***
	(-3.20)	(-3.24)	(-3.48)	(-2.82)	(-2.83)	(-2.82)
B/M	-0.046	-0.051	-0.050	-0.031*	-0.031*	-0.031*
	(-1.13)	(-1.27)	(-0.95)	(-1.76)	(-1.77)	(-1.77)
Leverage	-0.000	-0.000	-0.070*	-0.003	-0.002	-0.002
	(-0.60)	(-0.61)	(-1.86)	(-0.30)	(-0.28)	(-0.29)
Cash	-0.003	-0.003	0.211	0.033	0.035	0.035
	(-1.15)	(-1.17)	(1.02)	(0.74)	(0.79)	(0.79)
ROA	0.172	0.175	0.661	-0.171	-0.176	-0.175
	(0.82)	(0.84)	(1.45)	(-0.72)	(-0.78)	(-0.78)
Analyst	-0.025***	-0.028***	-0.030***	0.018***	0.018***	0.017***
	(-3.02)	(-3.26)	(-3.49)	(3.08)	(3.00)	(2.98)
Exports	0.000	0.000	-0.001	-0.001	-0.001	-0.001
	(1.03)	(1.07)	(-0.36)	(-1.25)	(-1.26)	(-1.26)
Adj. R^2	0.27	0.27	0.30	0.56	0.56	0.56
Investor-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Investor-Firms	3,105	3,105	3,105	3,661	3,661	3,661
Observations	16,462	16,462	16,462	19,233	19,233	19,233

Table 2-16 Placebo and alternative treated and control groups test - CSR and FIIs' type heterogeneity

This table reports the DiDiD regressions of propensity matched pairs of firms as per the following specification:

$$FIO_{jit} = \alpha + \beta_1.(Treat_i \times Post_t \times Type_j) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \sigma.Type_j + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_{ji} + \tau_t + \varepsilon_{jit}$$

where FIO_{jit} is the ownership held by an FII j in an Indian firm i for year t. For the placebo test presented in columns [1] to [4], the DiDiD term is the interaction between $Treat_i$ as defined in Table 2-4, $Post_t$ which is an indicator variable that takes the value of one for the post-false shock period (F.Y. 2010-2012) and zero for the pre-false shock period (F.Y. 2007-2009) and $Type_j$, an indicator variable as defined in Table 2-13. For the alternative treated and control group test presented in columns [5] to [8], the DiDiD term is the interaction among $Treat_i$ an indicator variable that takes the value of one for firms with CSR expenditure greater than zero regardless of it satisfying the thresholds of S-135 and firms with no CSR expenditure that takes the value of zero, and $Post_t$ as defined in Table 2-4 and $Type_j$ an indicator variable as defined in Table 2-13. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports* as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2007 to 2012. Data sources: CIQ and CMIE database.

	Placebo test				*Alternative treated and control group firms test*			
	Independent	Grey	Long-term	Short-term	Independent	Grey	Long-term	Short-term
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
DiDiD ($Treat_i \times Post_t \times Type_j$)	-0.115	-0.137	-0.074	-0.066	**0.180****	0.053	**0.287****	-0.169
	(-1.39)	(-1.10)	(-0.83)	(-0.37)	**(2.35)**	(0.39)	**(2.54)**	(-0.78)
Size	0.325***	0.326***	0.322***	0.323***	0.126*	0.136**	0.138**	0.139**
	(4.24)	(4.16)	(4.16)	(4.16)	(1.84)	(1.99)	(1.99)	(2.01)
OwnCon	-0.010***	-0.010***	-0.010***	-0.010***	-0.012***	-0.012***	-0.012***	-0.012***
	(-3.43)	(-3.48)	(-3.49)	(-3.49)	(-2.83)	(-2.83)	(-2.82)	(-2.80)
B/M	-0.049	-0.048	-0.050	-0.050	-0.030*	-0.031*	-0.031*	-0.031*
	(-0.93)	(-0.92)	(-0.95)	(-0.95)	(-1.72)	(-1.78)	(-1.78)	(-1.79)
Leverage	-0.071*	-0.071*	-0.070*	-0.071*	0.001	-0.004	-0.005	-0.006
	(-1.88)	(-1.87)	(-1.87)	(-1.87)	(0.13)	(-0.55)	(-0.56)	(-0.67)
Cash	0.201	0.210	0.210	0.210	0.031	0.035	0.036	0.038
	(0.97)	(1.01)	(1.01)	(1.01)	(0.69)	(0.79)	(0.81)	(0.84)
ROA	0.706	0.693	0.671	0.672	-0.230	-0.145	-0.146	-0.136
	(1.52)	(1.50)	(1.46)	(1.46)	(-0.96)	(-0.64)	(-0.65)	(-0.61)
Analyst	-0.027***	-0.030***	-0.029***	-0.029***	0.017***	0.018***	0.018***	0.018***
	(-3.19)	(-3.45)	(-3.43)	(-3.43)	(2.96)	(3.07)	(3.09)	(3.01)
Exports	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002
	(-0.35)	(-0.37)	(-0.35)	(-0.35)	(-1.17)	(-1.30)	(-1.33)	(-1.35)
Adj. R^2	0.30	0.30	0.30	0.30	0.56	0.56	0.56	0.56
Investor-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Investor-Firms	3,105	3,105	3,105	3,105	3,661	3,661	3,661	3,661
Observations	16,462	16,462	16,462	16,462	19,233	19,233	19,233	19,233

Table 2-17 Mandatory CSR engagement and firm value

This table reports the results from the propensity scored matched DiD regression as per the following specification:

$$MV_{it} = \alpha + \beta_1.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where MV_{it} is the market value for firm *i* in the year *t*. We take two proxies for examining the value effect of the CSR mandate, namely Tobin's Q and Market to Book (MB) ratio. $Treat_i$ and $Post_t$ are indicator variables as described in Table 2-4. $\boldsymbol{X}_{it-1}$ is a vector of the one year lagged key firm-level covariates *Size*, *OwnCon*, *Leverage*, *Cash*, *ROA*, *Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	Primary treated and control group firms		*Alternative treated and control group firms*	
	(Tobin's Q)	*(MB)*	*(Tobin's Q)*	*(MB)*
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	**0.347*** **	**6.099*** **	**0.343*** **	**4.778*** **
	(5.92)	**(3.79)**	**(5.92)**	**(3.17)**
Size	0.146	-8.939***	0.145	-8.779***
	(1.22)	(-2.98)	(1.21)	(-2.94)
OwnCon	0.010*	0.259***	0.010*	0.254***
	(1.79)	(2.97)	(1.79)	(2.91)
Leverage	-0.000	1.817*	-0.001	1.778*
	(-0.02)	(1.72)	(-0.03)	(1.68)
Cash	0.110*	1.052	0.113**	1.098
	(1.90)	(0.87)	(1.97)	(0.90)
ROA	0.620	-4.565	0.663*	-3.094
	(1.59)	(-0.36)	(1.72)	(-0.24)
Analyst	0.044**	0.973**	0.045**	1.034**
	(2.02)	(2.23)	(2.10)	(2.35)
Exports	0.003	0.030	0.003	0.031
	(1.55)	(0.51)	(1.60)	(0.52)
R^2 (within)	0.042	0.031	0.042	0.029
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	904	905	904	905
Observations	4,667	4,702	4,667	4,702

Table 2-18 Mandated CSR & firm value – MRDD estimates

This table reports the regression estimates as per the following specification:

$$MV_{it} = \alpha + \omega . S_{135} + \boldsymbol{X}_{it-1} . \boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where MV_{it} is the market value (Tobin's Q or MB as indicated) for firm i in year t. S_{135} is an indicator variable that takes the value of one if $M_{Score,i} \geq 0$ and zero if $M_{Score,i} < 0$. $M_{Score,i}$ is the minimum (nearest to zero) of the three rating variables (net worth of INR 5 billion or more, sales of INR 10 billion or more, or net profit of INR 50 million or more) centered on zero. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged covariates *Size*, *OwnCon*, *Leverage*, *Cash*, *ROA*, *Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. We use four different bandwidths (BWs) of 25%, 50%, 75%, and 100% around $M_{Score,i}$ to examine the treatment effect at various radiuses from the cut-off. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2015 to 2017. Data sources: CIQ and CMIE database.

	25% BW		50% BW		75% BW		100% BW	
	[*Tobin's Q*]	[*MB*]	[*Tobin's Q*]	[*MB*]	[*Tobin's Q*]	[*MB*]	[*Tobin's Q*]	[*MB*]
S_{135}	**0.116****	**3.936****	**0.106****	**6.324****	**0.126*****	**5.910****	**0.145*****	**5.787****
	(2.28)	**(2.47)**	**(2.82)**	**(2.19)**	**(4.32)**	**(2.56)**	**(4.23)**	**(2.76)**
Size	0.009	-3.099	-0.172	1.456	-0.034	0.095	-0.255**	5.238
	(0.05)	(-1.02)	(-1.52)	(0.56)	(-0.36)	(0.07)	(-2.39)	(1.71)
OwnCon	0.005	0.171	0.009	0.073	0.002	0.054	0.005	0.454
	(0.72)	(1.40)	(0.80)	(1.54)	(0.29)	(1.04)	(1.26)	(1.26)
Leverage	0.022	0.499	0.005	0.802**	0.005	0.121	0.039***	-2.515
	(1.40)	(1.18)	(0.23)	(2.62)	(0.44)	(0.42)	(3.09)	(-1.51)
Cash	0.047	-0.029	-0.015	-0.137	-0.023	0.136	0.018	0.355
	(0.97)	(-0.03)	(-0.38)	(-0.09)	(-0.95)	(0.17)	(1.42)	(0.22)
ROA	1.212	-14.53	0.659	3.071	0.312	-2.259	0.391	-16.40
	(1.17)	(-1.09)	(1.21)	(0.35)	(1.42)	(-0.38)	(0.96)	(-1.67)
Analyst	-0.019	-0.046	-0.040**	-0.587**	-0.019	-0.342*	-0.022	-0.564**
	(-0.36)	(-0.16)	(-2.37)	(-2.83)	(-1.15)	(-1.98)	(-1.22)	(-2.80)
Exports	-0.001	-0.029	0.002	-0.045*	0.002	0.003	0.003	-0.014
	(-0.47)	(-1.17)	(0.68)	(-1.79)	(1.36)	(0.22)	(1.31)	(-0.19)
R^2 (within)	0.023	0.023	0.019	0.030	0.009	0.025	0.009	0.019
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	223	222	499	491	868	856	1,879	1,783
Observations	520	518	1,220	1,203	2,227	2,198	5,121	4,876

Table 2-19 Controlling for market expectation

This table reports the results from the propensity scored matched DiD regression as per the following specification:

$$MV_{it} = \alpha + \beta_1.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where MV_{it} is the market value for firm *i* in year *t*. We take two proxies for examining the value effect of CSR mandate, namely Tobin's Q and Market to Book (MB) ratio. $Treat_i$ and $Post_t$ are indicator variables as described in Table 2-4. The DiD is the interaction between $Treat_i$ and $Post_t$ dummies. $\boldsymbol{X}_{it-1}$ is a vector of one year lagged key firm-level covariates *Size*, *OwnCon*, *Leverage*, *Cash*, *ROA*, *Analyst*, and *Exports*, *P/B* (Analyst target stock price scaled by book value of stock), and *EPSGrowth* (5-year analyst EPS growth estimate) all as defined in Table 2-1. γ_i and τ_t are firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	(Tobin's Q)	*(MB)*	*(Tobin's Q)*	*(MB)*
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	**0.333*** **	**5.887*** **	**0.343*** **	**6.049*** **
	(5.88)	**(3.71)**	**(5.90)**	**(3.77)**
Size	0.126	-9.248***	0.141	-9.013***
	(1.03)	(-3.08)	(1.17)	(-3.00)
OwnCon	0.010*	0.259***	0.010*	0.259***
	(1.76)	(2.96)	(1.78)	(2.96)
Leverage	-0.000	1.818*	-0.000	1.820*
	(-0.01)	(1.72)	(-0.00)	(1.72)
Cash	0.108*	1.027	0.110*	1.050
	(1.87)	(0.85)	(1.89)	(0.87)
ROA	0.591	-4.940	0.595	-4.848
	(1.55)	(-0.39)	(1.55)	(-0.38)
Analyst	-0.006	0.270	0.028	0.781*
	(-0.29)	(0.58)	(1.36)	(1.79)
Exports	0.003	0.029	0.003	0.029
	(1.54)	(0.49)	(1.54)	(0.49)
P/B	0.063**	0.959		
	(2.35)	(1.28)		
EPSGrowth			0.009*	0.118
			(1.75)	(1.15)
R^2 (within)	0.047	0.033	0.044	0.032
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	904	905	904	905
Observations	4,667	4,702	4,667	4,702

Table 2-20 Value effect of excess CSR expenditure

This table reports the results from the propensity matched DiDiD regression as per the following specification:

$$MV_{it} = \alpha + \beta_1.(Treat_i \times Post_t \times CSR_{exc}) + \beta_2.(Treat_i \times Post_t) + \lambda.Treat_i + \rho.Post_t + \boldsymbol{X}_{it-1}.\boldsymbol{\delta}' + \gamma_i + \tau_t + \varepsilon_{it}$$

where MV_{it} is the market value for firm *i* in year *t*. We take two proxies for examining the value effect of CSR mandate, namely Tobin's Q and Market to Book (MB) ratio. The DiDiD is the interaction among $Treat_i$, $Post_t$ and CSR_{exc}. In columns [1] and [2], CSR_{exc} is an indicator variable that takes the value of one if a firm's CSR expenditure is above the mandated amount and zero otherwise. In columns [3] and [4], CSR_{exc} is the log of firm's excess CSR expenditure above the mandated amount. $Treat_i$ and $Post_t$ are indicator variables as in Table 2-4. $\boldsymbol{X}_{it-1}$ is a vector of the one year lagged covariates *Size, OwnCon, B/M, Leverage, Cash, ROA, Analyst* and *Exports*, all as defined in Table 2-1. γ_i and τ_t are the firm and year fixed effects respectively. All covariates are winsorized at 1% and 99% levels. Standard errors are clustered at the firm level and t-stats are presented in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	CSR_{exc} is an indicator variable		*CSR_{exc} is log of excess CSR expenditure*	
	(Tobin's Q)	*(MB)*	*(Tobin's Q)*	*(MB)*
	[1]	[2]	[3]	[4]
DiDiD ($Treat_i \times Post_t \times CSR_{exc}$)	**0.272*** **	**5.663*** **	**0.118*** **	0.811
	(4.90)	**(3.76)**	**(3.96)**	(1.17)
DiD ($Treat_i \times Post_t$)	-	-	**0.283*** **	**5.672*** **
			(4.99)	**(3.64)**
Size	0.151	-8.841***	0.133	-9.014***
	(1.26)	(-2.95)	(1.11)	(-3.00)
OwnCon	0.010*	0.247***	0.010*	0.258***
	(1.76)	(2.85)	(1.78)	(2.97)
Leverage	-0.005	1.775*	0.002	1.837*
	(-0.25)	(1.69)	(0.12)	(1.73)
Cash	0.112*	1.095	0.109*	1.048
	(1.94)	(0.91)	(1.89)	(0.87)
ROA	0.768**	-2.516	0.601	-4.697
	(1.98)	(-0.20)	(1.55)	(-0.37)
Analyst	0.051**	1.048**	0.039*	0.939**
	(2.35)	(2.39)	(1.85)	(2.17)
Exports	0.003	0.029	0.003	0.031
	(1.51)	(0.50)	(1.60)	(0.52)
R^2 (within)	0.035	0.030	0.048	0.032
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	904	905	904	905
Observations	4,667	4,702	4,667	4,702

Table 2-21 Mediation analysis

This table presents the results on the mediation effect of foreign institutional ownership (*FIO*) on the relationship between mandatory CSR (DiD) and firm value. The dependent variable is either Tobin's Q (*Tobin's Q*) (Models 1 and 2) or Market to book (*MB*) ratio (Models 3 and 4) of firm i in year *t*. $Treat_i$ and $Post_t$ are indicator variables as described in Table 2-4. The DiD is the interaction between $Treat_i$ and $Post_t$ dummies. One year lagged key firm-level covariates that include *Size, OwnCon, Leverage, Cash, ROA, Analyst* and *Exports*, all as defined in Table 2-1, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The study period ranges from 2012 to 2017. Data sources: CIQ and CMIE database.

	(Tobin's Q)	*(Tobin's Q)*	*(MB)*	*(MB)*
	[1]	[2]	[3]	[4]
DiD ($Treat_i \times Post_t$)	**0.347*** **	**0.336*** **	**6.099*** **	**5.774*** **
	(5.92)	**(5.78)**	**(3.79)**	**(3.64)**
FIO		**0.013*** **		**0.346*** **
		(6.05)		**(3.64)**
Size	0.146	0.141	-8.939***	-9.123***
	(1.22)	(1.17)	(-2.98)	(-3.06)
OwnCon	0.010*	0.010*	0.259***	0.259***
	(1.79)	(1.82)	(2.97)	(2.95)
Leverage	-0.000	-0.001	1.817*	1.860*
	(-0.02)	(-0.07)	(1.72)	(1.76)
Cash	0.110*	0.110*	1.052	1.015
	(1.90)	(1.90)	(0.87)	(0.84)
ROA	0.620	0.604	-4.565	-2.980
	(1.59)	(1.55)	(-0.36)	(-0.24)
Analyst	0.044**	0.043**	0.973**	1.021**
	(2.02)	(2.03)	(2.23)	(2.37)
Exports	0.003	0.003	0.030	0.030
	(1.55)	(1.45)	(0.51)	(0.51)
R^2 (within)	0.042	0.054	0.031	0.040
Sobel test (p-value)	-	<0.01	-	<0.01
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. of Firms	904	905	904	905
Observations	4,667	4,702	4,667	4,702

Table 2-22 FIIs' countries and their legal origins (Based on La Porta et al., 2008)

Common	Civil	French	German	Scandinavian	Unknown[§]
Australia	Argentina	Argentina	Austria	Denmark	Andorra
Bahrain	Austria	Belgium	Bulgaria	Finland	British Virgin Islands
Bangladesh	Belgium	Brazil	China	Iceland	Guernsey
Barbados	Brazil	Chile	Croatia	Norway	Isle of Man
Bermuda	Bulgaria	France	Czech Republic	Sweden	Jersey
Canada	Chile	Greece	Estonia		Liechtenstein
Cayman Islands	China	Indonesia	Germany		Monaco
Cyprus	Croatia	Italy	Hungary		
Hong Kong	Czech Republic	Kuwait	Japan		
Ireland	Denmark	Lithuania	Poland		
Israel	Estonia	Luxembourg	Slovenia		
Malaysia	Finland	Macedonia	South Korea		
Nepal	France	Malta	Switzerland		
New Zealand	Germany	Mauritius	Taiwan		
Pakistan	Greece	Mexico			
Saudi Arabia	Hungary	Netherlands			
Singapore	Iceland	Oman			
South Africa	Indonesia	Philippines			
Thailand	Italy	Portugal			
UAE	Japan	Qatar			
UK	Kuwait	Russia			
USA	Lithuania	Spain			
Zimbabwe	Luxembourg	Turkey			
	Macedonia	Yemen			
	Malta				
	Mauritius				
	Mexico				
	Netherlands				
	Norway				
	Oman				
	Philippines				
	Poland				
	Portugal				
	Qatar				
	Russia				
	Slovenia				
	South Korea				
	Spain				
	Sweden				
	Switzerland				
	Taiwan				
	Turkey				
	Yemen				

§ Not covered by La Porta et al. (2008)

Table 2-23 FIIs' type with classification based on S&P Capital IQ definitions

Independent Investor	Grey Institutions	Long-term investors Pension Fund	Short-term investors Hedge Fund
Corporate Pension Plan Sponsor	Bank/Investment Bank	Corporate Pension Plan Sponsor	Hedge Fund Manager/CTA
Real Estate Investment Manager/REIT	Endowment Fund Sponsor	Government Pension Plan Sponsor	
Structured Finance Pool Manager	Family Office/Family Trust	Union Pension Plan Sponsor	
Traditional Investment Manager	Foundation Fund Sponsor		
Government Pension Plan Sponsor	Insurance Company		
Hedge Fund Manager/CTA	Sovereign Wealth Fund		
Union Pension Plan Sponsor	Unclassified		
	Venture Capital/Private Equity Firm		

2.9 Figures of Chapter 2

Figure 2-1 Pre- and post-matched firms' mean differences in covariates

Figure 2-1a

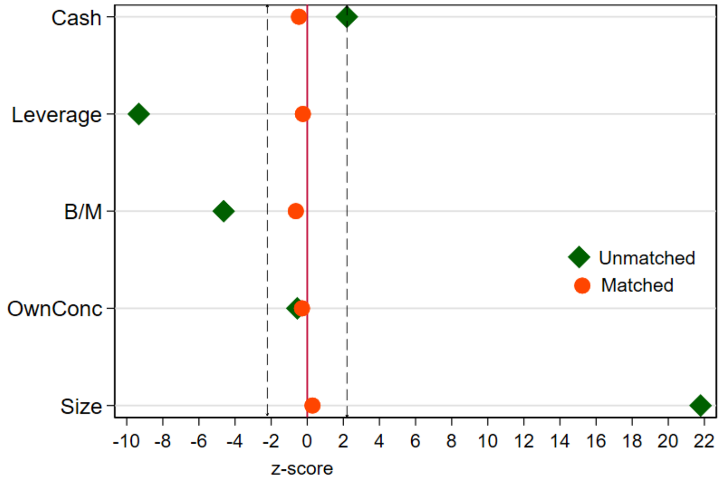

Figure 2-1b

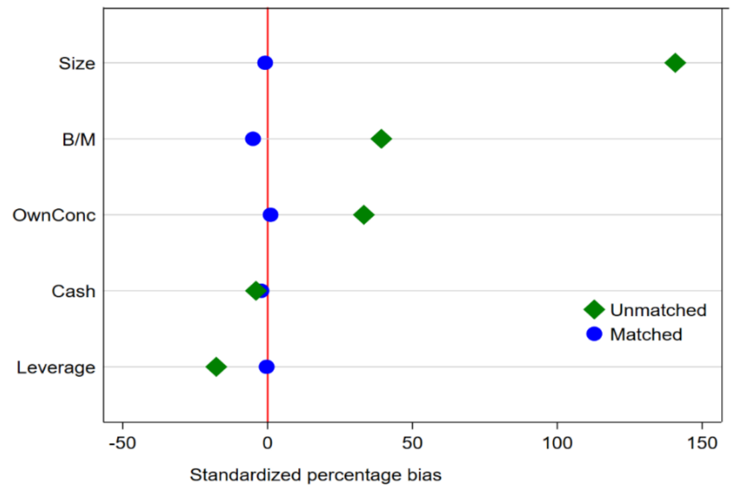

Figure 2-1a shows the z-score of the covariates *Cash, Leverage, B/M, OwnCon* and *Size* of the treated and control group firms before and after PSM. We observe very high z-scores pre-matching, indicating significant differences among treated and control firms. The z-score post-matching is close to zero indicating that there is no significant difference between treated and control firms. The sample period for matching ranges from 2012 to 2014, which is the period before the introduction of CSR mandate reform. Data source: CMIE database.

Figure 2-1b shows the standardized percentage bias of the covariates *Cash, Leverage, B/M, OwnCon* and *Size* of the treated and control group firms before and after PSM. We observe very high bias pre-matching, indicating significant differences among treated and control firms. The bias post-matching is close to zero indicating that there is no significant difference between treated and control firms. The sample period for matching ranges from 2012 to 2014, which is the period before the introduction of CSR mandate reform. Data source: CMIE database.

Figure 2-2 Treated and control firms' annual mean values of foreign institutional ownership

Figure 2-2a

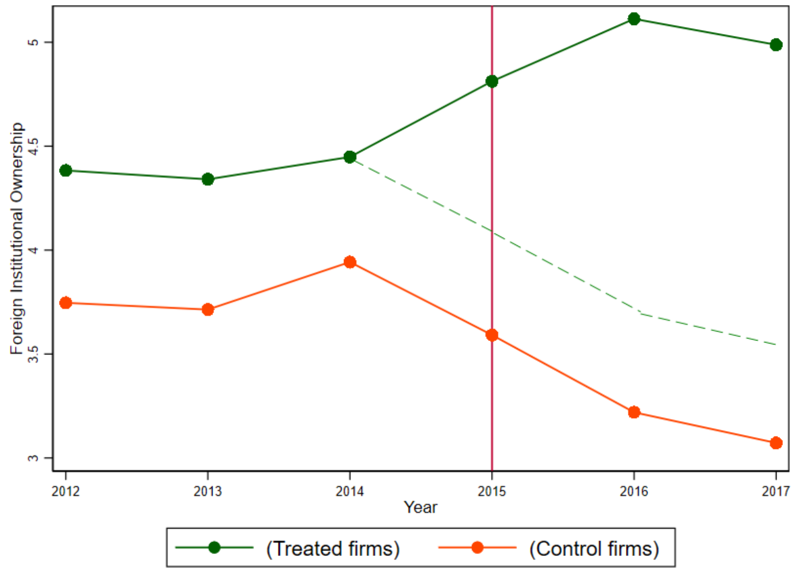

Figure 2-2b

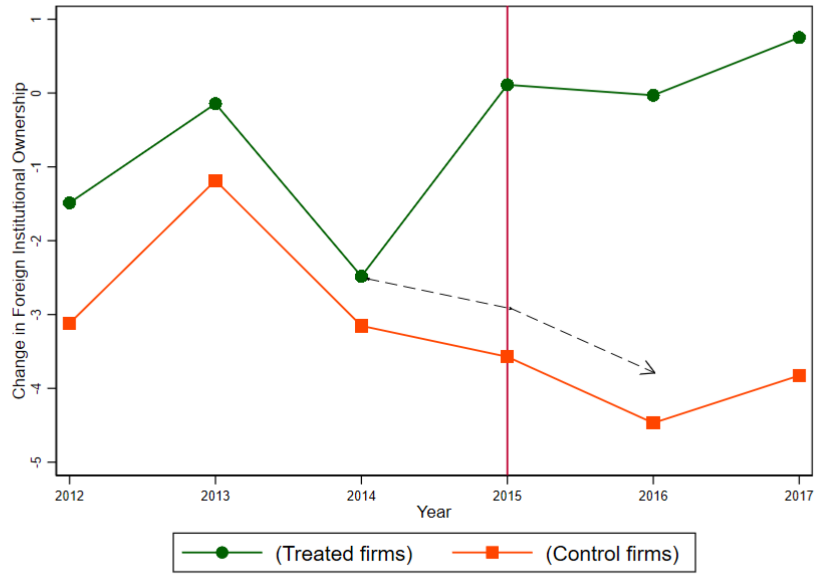

Figure 2-2 shows the trend of the annual mean values of Foreign Institutional Ownership of treated and control firms before and after the introduction of CSR mandate reform enforced from year 2015. Figure 2-2a shows the trend for the Foreign Institutional Ownership (FIO_{it}) and Figure 2-2b shows the trend for changes in foreign institutional ownership (ΔFIO_{it}). The dashed arrow in Figure 2-2a and 2-2b shows the expected path of the treated firms' trend line in the absence of S-135 shock. The sample period is 2012 to 2017. Data sources: CIQ and CMIE database.

Figure 2-3 MRDD plots

Figure 2-3a

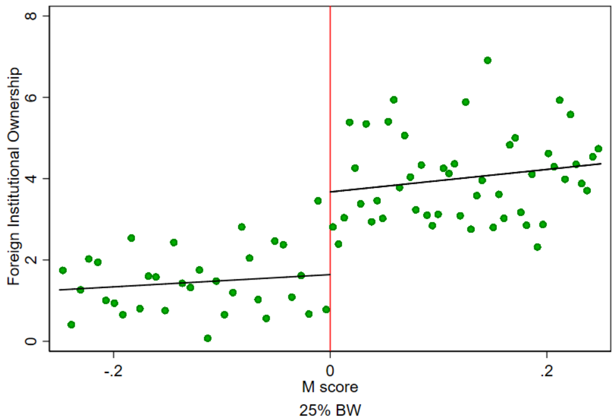

Figure 2-3b

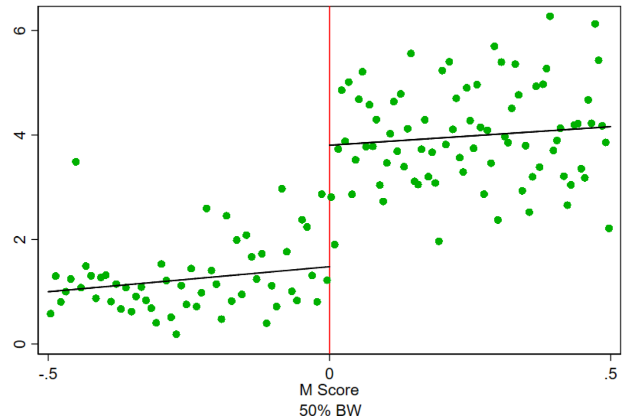

Figure 2-3c

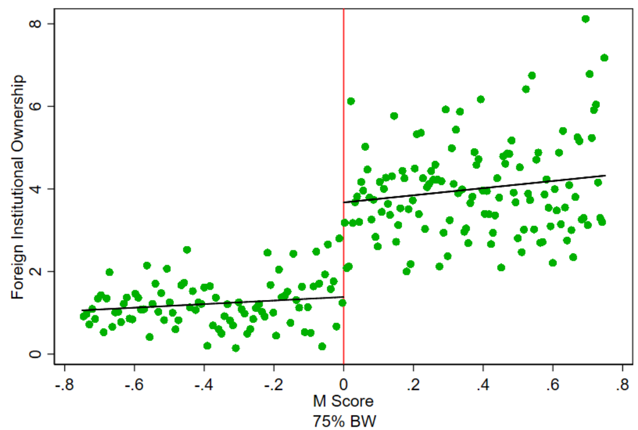

Figure 2-3d

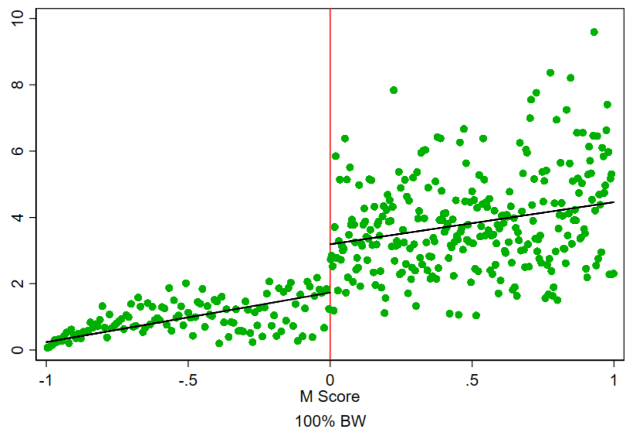

Figure 2-3 shows the Regression discontinuity of Foreign Institutional Ownership around the M-Score value of zero under 25% bandwidth (Figure 2-3a), 50% bandwidth (Figure 2-3b), 75% bandwidth (Figure 2-3c) and 100% bandwidth (Figure 2-3d). Data sources: CIQ and CMIE database.

Figure 2-4 Domestic institutional ownership for treated and control group firms

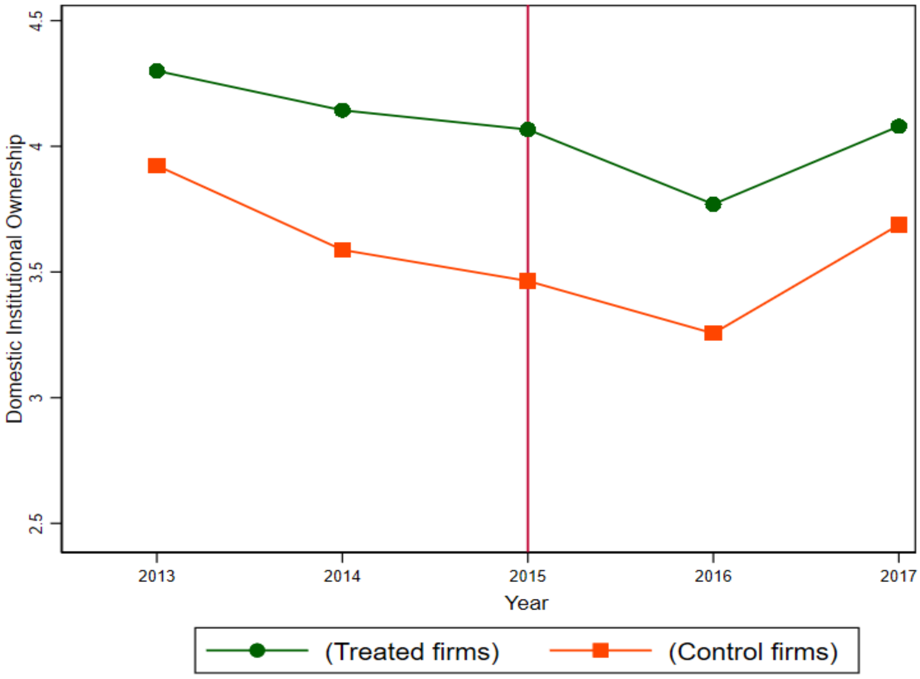

Figure 2-4 shows the trend of the annual mean of Domestic institutional ownership of treated and control firms before and after the introduction of CSR mandate reform enforced from year 2015. We observe no change in the trend for both treated and control firms. Data sources: CIQ and CMIE.

3. Chapter 3: Extreme Rainfall and Institutional Investor Behavior

3.1 Introduction

From an economic perspective, climate change is seen as one of the biggest challenges to investors, regulators, and governments around the world (Nordhaus, 2019). A major impact of the increase in global temperatures is more extreme rainfall conditions, with intense rainfalls and flooding in some regions, but in other regions increased drought (Hardwick Jones et al., 2010). Some countries, including India, are experiencing both more frequent excess and deficit rainfall conditions. Climate models predict that a continuous increase in rainfall extremes for most of the world will persist for the foreseeable future (Kharin et al. 2013). The finance literature suggests that capital markets are inefficient in terms of fully reflecting long-run extreme weather risks, resulting in problems in fully pricing risks (Hong et al., 2019). Extreme rainfall conditions, including both deficit and excess rainfall, can cause severe uncertainty for rain-sensitive firms (industries that are negatively impacted by extreme rainfall conditions). This can result in decreasing firm value due to reduced economic activity and output and this can influence investor behavior (Huang et al., 2018; Rao et al., 2022).

Motivated by the growing importance of institutional investors in international capital markets (Stambaugh, 2014) and increased saliency risk in their portfolio choices (Alok et al., 2020; Bordalo et al., 2012), I examine how institutional investors make investment decisions in rain sensitive firms when faced with exogenous extreme rainfall-induced risks. Although extreme rainfall conditions can have a negative impact on rain sensitive firms, the two extremes of abnormal rainfall conditions could have different signals for investors, due to differential market conditions and divergent corporate strategies (Rao et al., 2022). Therefore, institutional investors may opt for different investment strategies in rain sensitive firms following heterogeneous extreme rainfall episodes which I refer to as the differential response hypothesis. Also, as extreme rainfall events become more common, in line with saliency theory, through frequently experiencing and greater knowledge of the impact of extreme rainfall conditions, institutional investors should be able to make more rational investment choices in rain sensitive firms (Bordalo et al., 2012). This is supported in the finance literature which suggests that institutional investors exhibit superior trading and stock-picking skills due to superior information (Baker et al., 2010; Huang et al., 2020).

I further analyze in a geographical proximity hypothesis whether institutional investors geographical proximity (domestic (DIIs) and foreign institutional investors (FIIs)) affects investment allocations in rain sensitive firms following extreme rainfall episodes. I contend that both DIIs and FIIs can make their investment choices quickly during excess rainfall due to greater investor attention and the immediate market reaction (Da et al., 2014; Ben-Rephael et al., 2017). In contrast, the deficit rainfall-induced slower market reaction and longer periods of uncertainty can impose greater challenges for institutional investors in making their investment choices.

Using Indian monsoon data, I use extreme rainfall conditions as ongoing natural experiments (Dell et al., 2014) and employ an empirical set-up similar to a difference-in-differences (DiD) approach. I find support for a differential response hypothesis as during excess (deficit) rainfall conditions, institutional investors significantly increase (decrease) their ownership in rain sensitive firms. Despite these extreme rainfall conditions, my empirical analysis indicates that institutional investors gain from investments in rain sensitive firms following excess rainfall as these firms have higher market-based valuations and profitability, relative to control firms. This improvement in performance could be driven by the sudden mispricing impact of the excess rainfall on stock prices, the strategic investment choices and higher risk-taking by the rain sensitive firms during these periods (Rao et al., 2022).

When I consider the geographical proximity of institutional investors, I find that both DIIs and FIIs significantly increase their ownership in rain sensitive firms in excess rainfall conditions, whereas only DIIs significantly reduce their ownership in rain sensitive firms during deficit rainfall conditions. DIIs could have better knowledge of local climatic conditions and the actions of the rain sensitive firms, and therefore choose to divest from these firms (Baik et al., 2010; Coval and Moskowitz, 2001). The future performance of rain sensitive firms following deficit rainfall conditions tends to be uncertain due to slower market reactions, lower trading liquidity and reduced corporate risk-taking during deficit periods.

My study primarily contributes to the literature in three ways. First, I add to the nascent yet growing body of literature on climate risk and institutional investors (Alok et al., 2020; Krueger et al., 2020), by investigating the impact of extreme rainfall conditions as an exogenous weather anomaly on the investment behavior of institutional investors and showing a differential response of institutional investors to extreme excess and deficit rainfall. Second, my study contributes to the literature on information-based stock selection and trading skills of institutional investors (Baker et al., 2010; Huang et al., 2020; Nofsinger and Sias, 1999). I complement these studies by suggesting that institutional investors can exhibit superior investment skills not only because of better information about their investee firms but also because they are now considering the impact of exogenous climatic conditions. Finally, I also contribute to the literature on the institutional investors' location-based information advantage (Baik et al., 2010; Coval and Moskowitz, 2001). I find that geographically proximate DIIs behave differently from FIIs in deficit rainfall conditions.

The rest of the chapter is organized as follows. In Section 3.2, I develop the testable hypothesis supported by literature, followed by Section 3.3 where I describe the data and empirical strategy, discussion of the empirical results in Section 3.4, and finally, the conclusion in Section 3.5.

3.2 Related literature and hypotheses development

3.2.1 Differential response hypothesis

Although it is clear extreme rainfall conditions have a negative impact on rain-sensitive firms, the two extreme ends of abnormal rainfall conditions could have different signals for investors. Excess rain-induced flooding and landslides can cause direct physical damage to infrastructure and tangible assets of rain-sensitive firms leading to reduced production and earnings capacity during excess rainfall events (Huang et al., 2018; Rehse et al., 2019). Further, excess rainfall events are typically sudden and have greater climate-related physical risks, and as market prices tend to reflect future cash flow uncertainty due to the climate risk and incorporate appropriate discount rates for valuation, extreme rainfall-induced lower production and earnings should be translated into lower stock prices for rain-sensitive firms (Bansal et al., 2016). Consequently, in the immediate aftermath of extreme rainfall conditions, rain-sensitive firms could lose market value leading to higher book to market (*B/M*) ratios (Rao et al., 2022). Moreover, the market could also overreact to the suddenness of excess rainfall conditions leading to mispricing, higher trading liquidity, and volatility (Alok et al., 2020; Kruttli et al., 2020).

On the contrary, deficit rainfall conditions are less likely to cause damage to tangible assets (i.e., physical risk). However, lack of rainfall and in some cases, drought conditions may lead to lower yields and profitability, and increasing operational costs due to underutilized operational and production capacity (Hong et al., 2019; de Sherbinin et al., 2011). Rao et al. (2022) suggest that markets could only realize the full impact of deficit rainfall conditions on rain sensitive firms over the span of the whole monsoon season. Further, markets are typically slow to incorporate deficit rainfall-induced information, and market overreactions and mispricing of rain-sensitive stocks are more unlikely during deficit periods. This suggests that deterioration in the performance of the rain sensitive firms should occur gradually over time. Consequently, such information is slowly incorporated by the market as the impact is less conspicuous to investors (Da et al., 2014). The longer periods of uncertainty and information asymmetry could result in lower stock trading liquidity and higher volatility for rain sensitive firms' stocks following deficit rainfall conditions (Rehse et al., 2019).

These differing signals on rain sensitive firms following extreme rainfall are important to institutional investors in their investment choices. institutional investors tend to invest in stocks with higher liquidity, volatility, and high book to market (*B/M*) ratios as such stocks tend to generate higher returns in the subsequent period (Gompers and Metrick, 2001). The literature also suggests that institutional investors having superior information and the ability to detect mispriced stocks trade aggressively to exploit such mispricing to generate higher returns and divest from stocks that underperform (Baker et al., 2010; Huang et al., 2020). Such superior information could originate from private channels such as analyst recommendations or public channels such as news (Brown et al., 2014; Huang et al., 2020). As a result, information related to extreme rainfall conditions and rain sensitive firms should play a key role in institutional investors' investment choices.

The literature suggests that institutional investors tend to engage in momentum or positive feedback trading where they buy (sell) past winner (loser) stocks (Brown et al., 2014; Nofsinger and Sias, 1999). Therefore, it can be inferred that some of the institutional investors' trading is based on past experience or saliency. Under salience theory, investment choices are context-dependent where investors should increase (decrease) their investments during favorable (unfavorable) conditions (Bordalo et al., 2012).

Institutional investors also have a significant positive preference for corporate risk-taking behavior of their investee firms, as such additional risk could increase the value of their investments (Faccio et al., 2011). Rao et al. (2022) show that excess rainfall leads to a sudden drop in stock prices and higher risk-taking by the corporates. In contrast, the future performance of rain sensitive firms following deficit rainfall conditions tends to be uncertain due to slower market reactions and lower trading liquidity. Moreover, rain sensitive firms reduce their corporate risk-taking during deficit periods. Therefore, I suggest that the heterogeneous extreme rainfall conditions most likely create differential preferences among institutional investors for investing in rain sensitive stocks.

Thus, I conjecture that excess rainfall conditions could create favorable investment windows for institutional investors in rain sensitive firms due to mispricing, higher B/M ratios, stock liquidity, volatility, and greater risk-taking at the firm level. On the contrary, during deficit rainfall conditions, as there is no sudden decrease in stock price, the B/M effect would be less pronounced for rain sensitive stocks. Together with lower trading liquidity and risk-taking at the firm level could make rain sensitive firms unattractive to institutional investors. Thus, my differential response hypothesis predicts that:

H_1: Institutional investors invest differentially in rain sensitive firms following excess and deficit extreme rainfall episodes.

3.2.2 Geographical proximity hypothesis

A contrary view to all institutional investors having superior trading and stock-picking skills is that there is heterogeneity in their abilities (Carhart, 1997). Such divergence in trading skills among institutional investors can result from differences in relevant information available to them and their experience of the impact of extreme weather conditions (Alok et al., 2020). Studies show that institutional investors who are more geographically proximate to their investee firms are better monitors (Ayers et al., 2011), and possess better investment-related information relative to others (Baik et al., 2010; Coval and Moskowitz, 2001). Geographical proximity enables formal and informal communication and collaboration between the institutional investors and the firm, lower coordination and monitoring costs, and closer social ties (Kim et al., 2019).

The literature also suggests that better informed institutional investors such as DIIs may rely less on public information compared to less informed investors such as

FIIs (Kacperczyk and Seru, 2007). As such, having better information about local climatic conditions, DIIs might be able to distinguish between favorable and unfavorable stocks following extreme rainfall episodes. Moreover, as not all institutional investors experience similar climatic conditions, under saliency theory it can be expected that some institutional investors trade irrationally during extreme rainfall conditions (Alok et al., 2020). Therefore, I investigate whether geographical proximity plays any role in institutional investors' investment choices in rain sensitive firms during extreme rainfall periods. I conjecture a geographical proximity hypothesis that DIIs have a better knowledge of local climatic conditions due to past experience and are better informed of the rain sensitive firms' response following extreme rainfall conditions compared to FIIs (Baik et al., 2010; Coval and Moskowitz, 2001). As such, I formulate the following hypothesis:

H_2: The differential response to excess and deficit rainfall conditions is more pronounced in DIIs than in FIIs with regard to investments in rain sensitive firms.

3.3 Data and empirical strategy

3.3.1 Sample dataset

I use the rainfall deviation data provided by the Indian Meteorological Department (IMD) from the 36 meteorological subdivisions belonging to different states of India to capture the rainfall variations. This data is based on the daily rainfall data obtained from 3,500 ground stations spread across India. I map the firms to specific rainfall subdivisions based on their location in specific districts within these subdivisions. The primary database for obtaining firm-level financial parameters for this study is Prowess, maintained by the Centre for Monitoring Indian Economy (CMIE).

Integrating the Prowess data with IMD rain data, I have 51,764 firm-year observations between 2001-2017.

3.3.2 Dependent variable

I use annual firm ownership by institutional investors as my key dependent variable (IO) to proxy institutional investors investment choices (Bena et al., 2017; Nofsinger and Sias, 1999). I obtain institutional ownership data from the Centre for Monitoring Indian Economy (CMIE) Prowess database. Prowess calculates institutional ownership as the percentage of total shares of a company held by all institutional investors in a given year (Nofsinger and Sias, 1999). I treat institutional ownership as zero if firm shares are not held by any institutional investors in a given year (Gompers and Metrick, 2001). To examine whether geographical proximity I segregate firm institutional ownership by DIIs and FIIs. The total percentage of shares held by DIIs (FIIs) as my dependent variable for domestic (foreign) institutional ownership (DIO and FIO).

3.3.3 Control variables

I control for several key firm-level characteristics that could explain cross-sectional and temporal variations in institutional ownership (Alok et al., 2020; Baik et al., 2010; Brown et al., 2014; Gompers and Metrick, 2001). These include firm size (*Size*), calculated as the natural logarithm of the year-end book value of total assets, ownership concentration (*OwnCon*), calculated as the total percentage of share ownership held by promoters (individuals that were active at the time of establishing the firm and currently in control of the firm) (Koirala et al., 2020), the book to market (*B/M*) ratio, computed as the book value of equity divided by the market value of equity, leverage (*Leverage*), calculated as the book value of debt to equity, firm's cash holdings (*Cash*), which is the total year-end cash and other short term securities scaled by total sales, analyst (*Analyst*) as the number of analysts following the firm. Control variables are obtained from the CMIE Prowess database, except *Analyst* data is from the S&P Capital IQ (CIQ) database. I winsorize all continuous variables at the 2% and 98% level and lag all control variables by one year (Bena et al., 2017).

3.3.4 Empirical set-up

I use the rainfall deviation data obtained from IMD to identify the normal and extreme rainfall conditions. I generate quintiles of rainfall deviation observations and classify the top quintile as excess and the lowest quintile observations as deficit conditions. The mid quantile observations are classified as normal rainfall. Rainfall extremities (*excess* or *deficit* rainfall) can have a differential impact on rain sensitive industries. I follow Rao et al. (2022) to identify excess and deficit rain sensitive industries for my study. Firms belonging to rain sensitive industries are grouped as *treated* firms and those belonging to other non-rain sensitive industries are grouped as *control* firms. The treatment variable is a dummy that takes the value of 1 for *treated* firms and a value of 0 for *control* firms. My identification strategy allocates treated and control groups based on their industry rain-sensitivity and are assigned to either excess, normal, or deficit rainfall conditions based on their exposure to different rainfall episodes.

3.4 Empirical results

3.4.1 Descriptive statistics

Panel A of Table 3-1 reports the descriptive statistics summary for *Rainfall departure, IO, DIO, FIO, Size, OwnCon, B/M, Leverage, Cash,* and *Analyst*. Rainfall departure is the percentage deviation of the monsoon rainfall from the long-term normal mean rainfall, as obtained from the IMD. The variation in rainfall departure has a very high standard deviation with the maximum deficit rainfall departure of an extreme of -68% and maximum excess rainfall departure of 126%, illustrating the extremes in rainfall conditions in India. The average institutional ownership is 21.39%, 16.55% is owned by DIIs, and 4.75% by FIIs.

[**Table 3-1 about here**]

Panel B of Table 3-1 indicates 9,814 observations belong to the excess treatment, 4,766 observations are in deficit treatment, and 41,950 control group observations (firms that are not sensitive to rainfall). Some industries are sensitive only to excess rainfall conditions (Rao et al., 2022).[51] Panel C of Table 3-1 reports the differences in the dependent and independent variables among the treated (excess and deficit rain sensitive) and control firms. I observe a significant difference in IO among excess and deficit rain sensitive firms in comparison to control group firms. Further, although DIIs have significantly higher ownership in rain sensitive firms, FIIs seem to have higher holdings only among excess rain sensitive firms when compared to control firms.

3.4.2 Extreme rainfall and stock market characteristics

My preliminary analysis begins by examining if institutional investors invest in stocks with higher liquidity, volatility, and high book to market (*B/M*) ratios, and whether the impact of extreme rainfall on rain sensitive firm are important in their investment

[51] It is to be noted here that the deficit treatment group is a sub-sample of the excess treatment group as some of the rain sensitive industries are only affected by excess rainfall and not by deficit rainfall.

choices. I consider two liquidity measures, namely the Amihud illiquidity ratio (*Amihud*) of Amihud (2002) and the zero trading days (*Zeros*) measure of Lesmond et al. (1999) all estimated using daily stock trading data. Further, I construct volatility measures by taking the monthly standard deviation of both daily stock prices (*Price Volatility*) and daily stock returns (*Return Volatility*) (Schwert, 1989). Finally, I use daily market capitalization and the daily book value of equity outstanding to calculate the monthly average book to market (*B/M*) ratio for each stock. I run a t-test of mean differences between the treated and control group stocks for both the monsoon season (June to September) and the post-monsoon period (October to January) of extreme rainfall years.

[Table 3-2 about here]

From Table 3-2 I find that, during excess (deficit) rainfall years, *Amihud* and *Zeros* significantly decline (increase) for rain sensitive firms in both monsoon and post-monsoon seasons suggesting an increase (decrease) in liquidity. I also find that *Price Volatility* and *Return Volatility* increase significantly for rain sensitive stocks during both excess and deficit rainfall years. Although *B/M* ratio significantly increases for rain sensitive stocks in both seasons of excess rainfall years, I find weak significance only in the post-monsoon season for deficit rainfall years.

The results suggest that trading liquidity significantly improves for rain sensitive stocks during excess rainfall years leading to increased stock volatility (Jones et al., 1994). In contrast, the deficit rainfall induced periods of uncertainty and information asymmetry lead to lower trading activity and liquidity, and higher volatility for rain sensitive stocks (Rehse et al., 2019). Further, the increased *B/M* ratio for rain sensitive stocks in excess rainfall years indicates that rain sensitive firms significantly lose market value during excess rainfall years. Combined with increased liquidity and volatility this could provide institutional investors with a favorable investment opportunity to invest in rain sensitive stocks. In contrast, the weak significance of increased B/M ratio only in post-monsoon during deficit rainfall years suggests that markets are slow to fully reflect the effect of deficit rainfall on rain sensitive stocks. Together with the higher illiquidity, lower trading activity, and slower market reaction, this could discourage institutional investors from investing in rain sensitive stocks during deficit rainfall periods.

3.4.3 Differential response hypothesis

To test the extreme rainfall differential response hypothesis (H_1), I run regressions in equation (3.1) on excess and deficit rainfall subsamples separately:

$$IO_{it} = \alpha + \beta.(Treat_{RSi} \times AR_t) + \boldsymbol{X_{it-1}}.\boldsymbol{\delta}' + \tau.Time + \gamma_i + \epsilon_{it} \qquad (3.1)$$

where the key dependent variable IO_{it} is the total percentage of share ownership by institutional investors in firm *i* and year *t*. $Treat_{RSi}$ is an indicator dummy variable that takes the value of one if firm *i* belongs to a rain sensitive industry (excess or deficit) and zero otherwise. AR_t is also an indicator variable that takes the value of one if year *t* experiences extreme rainfall condition (excess or deficit) and zero otherwise. $\boldsymbol{X_{it-1}}$ is a vector of one-year lagged control variables namely *Size, OwnCon, B/M, Leverage, Cash,* and *Analyst*. The *Time* variable absorbs long-running trends in rainfall conditions (Rao et al., 2022).[52] γ_i controls for firm fixed effects and ϵ_{it} is the error

[52] I do not include time fixed effects in the analysis since the temporal fluctuations in the rainfall-departure would be neutralized due to its time-varying nature. To account for any long-term patterns in rainfall conditions, I include the *Time* control variable in the model.

term. The key variable of interest is the interaction term $(Treat_{RSi} \times AR_t)$, which is my DiD estimator that shows the causal impact of extreme rainfall conditions (excess or deficit) on firm institutional ownership.

Estimates of specification (3.1) presented in Table 3-3 indicate that the DiD coefficients are significantly positive (negative) at 1% level of significance for excess (deficit) rainfall conditions. The economic magnitude indicates an increase (decrease) in institutional investors ownership on an average by around 2.465% to 2.587% (in the range of -2.126% to -2.830%) during excess (deficit) rainfall conditions in rain sensitive firms relative to non-rain sensitive control firms. These results support the extreme rainfall differential response hypothesis (H_1) that following excess (deficit) rainfall conditions, institutional investors invest (divest) in rain sensitive firms.

[Table 3-3 about here]

3.4.4 Robustness tests of hypothesis 1

I conducted several robustness tests including an alternative measure of institutional ownership, subsample analysis using single location firms, and an alternative definition of extreme rainfall years which support my primary differential response hypothesis (H_1). These tests are briefly discussed below.

3.4.4.1 Alternative measure of institutional ownership

I take a year-on-year change in institutional ownership (ΔIO) as my alternative measure for institutional ownership. This first difference alternative measure helps address the issue of any temporal trends in institutional ownership. I run regressions as per specification (3.1) with ΔIO as the dependent variable on the excess and deficit rainfall subsamples separately. I present the results using ΔIO in Table 3-4. Similar to my main findings in section 3.4.3, I see that the coefficients of the DiD interaction term are significant (at 1% level) and positive (negative) for excess (deficit) rainfall conditions.

3.4.4.2 Sub-sample analysis: Single location firms

The firms in my sample are assigned to treated and control groups based on the location of their headquarters in a specific rainfall subdivision. I follow Rao et al. (2022) filtration process to identify the subsample. I run regressions on the sub-sample of single location firms as per specification (3.1). The regression estimates are tabulated in Table 3-5. Similar to my main findings in section 3.4.3, I find the DiD coefficient signs to be significant and positive (negative) for excess (deficit) rainfall conditions.

3.4.4.3 Alternative extreme rainfall measure

IMD characterizes deviations in rainfall of above (below) 19% (-19%) to be excess (deficit) rainfall conditions each year. Using this cutoff of ±19% of rainfall deviation, I redefine my extreme rainfall years as an alternative measure (IMD_AR_t). I use this alternative measure of extreme rainfall conditions in the specification (3.1) and run regressions to test the impact of extreme rainfall conditions on institutional ownership. I present the results in Table 3-6. In line with section 4.3 I see that the DiD coefficients are significant (at 1%) and positive (negative) for excess (deficit) rainfall conditions.

3.4.5 Do institutional investment strategies following extreme rainfall pay off?

Based on their experience and investment skills if institutional investors invest in rain sensitive stocks, I should see an increase in firm performance in the period following excess rainfall conditions. Also, I find these stocks have increased *B/M* ratios, increased liquidity and volatility, this should result in higher returns for rain sensitive stocks in the following periods. Further, if excess rainfall conditions increase corporate risk-taking this should lead to higher future performance (Koirala et al., 2020; Rao et al., 2022). Thus, to examine whether rain sensitive firms obtain superior performance in the year following excess conditions, I run regressions as per specification (3.2):

$$PI_{it+1} = \alpha + \beta.(Treat_{RSi} \times ER_t) + \boldsymbol{X_{it}}.\boldsymbol{\delta'} + \tau.Time + \gamma_i + \epsilon_{it} \qquad (3.2)$$

where the dependent variable PI_{it+1} is the performance indicator for firm *i* in the lead year *t+1*, which are *Tobin's Q*, market to book (*MB*) ratio of firm's equity, or return on equity (*ROE*), measured as profit as a percentage of the book value of equity. ER_t is also a dummy variable that takes the value of one if year *t* encounters excess rainfall conditions and zero if rainfall conditions are normal. Other variables are as defined in specification (3.1).

Table 3-7 shows that the DiD coefficients are significant (at the 1% level of significance) and positive across all three performance measures. The results indicate that rain sensitive firms obtain higher market-based valuations (around 8.0% to 9.9% for *Tobin's Q* and 2.667% to 3.166% for *MB*) and profitability (around 2.644% to 2.780% for *ROE*) compared to non-rain sensitive firms in the lead year following excess rainfall conditions. The results are consistent with institutional investors being skilled in timing their investments in rain sensitive firms following excess rainfall conditions. They use information on the excess rainfall-induced economic and market conditions and the actions of the firms to gain from their investments in rain sensitive firms.[53]

[Table 3-7 about here]

[53] I also run similar regressions as specification (3.2) for deficit rainfall subsample. The performance measures in the lead years following deficit rainfall conditions are insignificant.

3.4.6 Does geographical proximity matter?

Table 3-8 finds that during excess rainfall conditions, both DIIs and FIIs significantly increase their investments in rain sensitive firms. The positive and significant (at the 1% level of significance) DiD coefficients indicate that DIIs (FIIs) increase their ownership by around 1.514% to 1.852% (0.566% to 0.986%) in rain sensitive firms following excess rainfall periods relative to non-rain sensitive firms. In contrast, for deficit rainfall conditions, I find the DiD coefficients to be significant only for DIIs. The results indicate that DIIs significantly decrease their ownership by around -1.801% to -2.314% during deficit rainfall periods compared to control firms. The negative but insignificant DiD coefficients for FIIs suggest that my main results for deficit rainfall periods in section 3.4.3 are primarily driven by DIIs, which supports the proximity hypothesis (H_2).

[Table 3-8 about here]

As a robustness check, I take a year-on-year change in institutional ownership (ΔIO) as the alternative measure for institutional ownership for both domestic institutional ownership (ΔDIO) or foreign institutional ownership (ΔFIO). This first difference alternative measure helps address the issue of any temporal trends in institutional ownership. I run regressions as per specification (3.1) with either domestic institutional ownership (ΔDIO) or foreign institutional ownership (ΔFIO) as the dependent variable for on the excess and deficit rainfall subsamples separately. I present these results in Table 3-9. Similar to my main findings with the primary measures, I see that the coefficients of the DiD interaction term are significant (at 1% level) and positive (negative) for excess (deficit) rainfall conditions for ΔDIO. For

ΔFIO the coefficients of my DiD interaction term are significant (at 1% level) and positive for excess rainfall conditions, however, they are insignificant for deficit rainfall conditions.

Therefore, although DIIs and FIIs make similar investment choices in rain sensitive firms during excess rainfall conditions, FIIs do not follow the same investment strategy as DIIs during deficit rainfall periods. I conjecture that the immediate and extreme nature of excess rainfall conditions quickly attracts the attention of all institutional investors (Da et al., 2014; Ben-Rephael et al., 2017). As a result, both DIIs and FIIs can time their investment similarly in the immediate period following excess rainfall conditions (Huang et al., 2020). In contrast, the gradual nature of the impact of deficit rainfall conditions could be less prominent in the investment decisions of institutional investors (Da et al., 2014). However, DIIs having superior information and knowledge about local climatic conditions, can make better divestment choices on these rain sensitive firms (Baik et al., 2010). On the contrary, having more limited access to information on local climatic conditions, FIIs are slow to react to deficit rainfall-induced market conditions (Coval and Moskowitz, 2001).

3.5 Conclusion

In this chapter, I investigate the impact of extreme rainfall conditions on the institutional investors' ownership patterns in rain sensitive firms. I use the Indian monsoon setup, where I exploit the extreme rainfall variations as exogenous shocks. Using the theoretical arguments based on saliency theory including information asymmetry, and institutional investors' superior trading skills, I show that institutional investors significantly increase (decrease) their ownership in rain sensitive firms during the excess (deficit) rainfall years. This finding is important as institutional investors seem to gain from investing in rain-sensitive firms during excess rainfall years as these firms tend to have better performance in the following years, relative to non-rain sensitive firms.

Further analysis shows that although both DIIs and FIIs increase their ownership in rain sensitive firms following excess periods, only DIIs significantly divest from rain sensitive firms in deficit periods. I contend that both DIIs and FIIs can make their investment choices quickly during excess rainfall conditions, but the deficit rainfall conditions prompt a slower market reaction and longer periods of uncertainty which impose greater challenges for institutional investors in making their investment choices. However, the more geographically proximate DIIs could have superior information and better knowledge of local climatic conditions and the reactions of rain sensitive firms to those conditions.

Although it is suggested in the finance literature that capital markets are inefficient in terms of fully reflecting long-run extreme weather risks, the evidence suggests that institutional investors, particularly DIIs, are taking into account the impact of extreme rainfall on market conditions and the response of rain sensitive firms in their investment decisions.

3.6 Tables of Chapter 3

Table 3-1 Descriptive statistics

Panel A reports the summary statistics of variables *Rainfall departure, IO, DIO, FIO, Size, OwnCon, B/M, Leverage, Cash,* and *Analyst*. *Rainfall departure* is the percentage deviation of the monsoon rainfall from the long-term normal mean rainfall. *IO* is the total percentage of share ownership by institutional investors, *DIO* (*FIO*) is the total percentage share ownership by domestic (foreign) institutional investors, *Size* is the natural logarithm of the total assets, *OwnCon* is the total percentage of ownership by promoter ownership, *B/M* is the book to market ratio calculated as the book value of equity as a percentage of the market value of equity, *Leverage* is the debt to equity ratio, *Cash* is the cash and other short term securities scaled by sales, *Analyst* is the number analysts following the firm. The total sample period ranges from 2001 to 2017. Data source: IMD, CMIE, and CIQ databases.

Panel A

Variables	No. of Obs.	Mean	Std. Dev.	Minimum	Median	Maximum
Rainfall departure	51,762	-1.69	22.33	-68.00	-1.60	126.60
IO	51,764	21.39	26.95	0.00	7.05	91.72
DIO	51,764	16.55	22.75	0.00	4.08	84.28
FIO	51,764	4.75	13.3	0.00	0.00	74.51
Size	51,731	6.65	2.18	1.84	6.60	11.44
OwnCon	51,764	49.56	20.21	2.58	51.16	88.2
B/M	42,706	45.97	79.77	0.00	12.87	317.65
Leverage	51,531	0.83	2.26	-4.92	0.40	10.61
Cash	44,182	0.09	0.27	0.00	0.01	1.55
Analyst	51,764	0.89	4.09	0.00	0.00	51.00

Panel B reports the number of treatment group observations for rainfall departure for the sample period

Panel B

Rainfall departure	Treatment	Control	Total Observations
Excess	9,814	41,950	51,764
Deficit	4,766	41,950	46,716

Panel C reports the differences in variables *control* firms with both *excess*-rain sensitive *treated* firms and *deficit*-rain sensitive *treated* firms for the entire sample period.

Panel C

	Excess rain sensitive firms					*Deficit* rain sensitive firms			
Variable	*control* firms	*treated firms*	Diff	t-stat	p-value	*treated firms*	Diff	t-stat	p-value
IO	20.82	23.85	3.03	10.05	0.000	23.87	3.06	7.46	0.000
DIO	16.03	18.76	2.73	10.72	0.000	18.85	2.83	8.20	0.000
FIO	4.70	4.97	0.27	1.83	0.067	4.88	0.18	0.90	0.366
Size	6.55	7.05	0.50	20.42	0.000	7.08	0.52	15.80	0.000
OwnCon	48.94	52.19	3.25	14.37	0.000	51.79	2.84	9.23	0.000
B/M	45.15	49.44	4.29	4.35	0.000	45.70	0.55	0.41	0.678
Leverage	0.79	0.97	0.18	7.06	0.000	1.02	0.23	6.54	0.000
Cash	0.09	0.10	0.01	2.88	0.004	0.06	-0.03	7.86	0.000
Analyst	0.82	1.17	0.35	7.56	0.000	1.23	0.41	6.53	0.000

Table 3-2 Extreme rainfall and stock market characteristics

This table reports the t-test of mean differences of stock market characteristics induced by extreme rainfall conditions. *Amihud* is Amihud (2002) illiquidity ratio. *Zeros* is the Zeros spread measure of Lesmond et al. (1999). *Price Volatility* and *Return Volatility* are monthly averages of daily stock price and stock return volatility, respectively. *B/M* is the monthly average book to market ratio. t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017.

	Excess Rainfall						*Deficit Rainfall*					
	Monsoon			Post-Monsoon			Monsoon			Post-Monsoon		
Variable	Control	Treated	Diff	Control	Treated	Diff	Control	Treated	Diff	Control	Treated	Diff
Amihud	10.50	7.25	-3.25***	7.48	6.16	-1.32**	9.78	11.23	1.45**	9.86	10.80	0.94*
			(-4.07)			(-2.18)			(2.27)			(1.67)
Zeros	0.20	0.17	-0.03***	0.18	0.16	-0.02***	0.21	0.22	0.01**	0.21	0.22	0.01***
			(-6.87)			(-5.98)			(2.29)			(2.61)
Price Volatility	5.32	7.15	1.84***	5.59	7.23	1.64***	5.50	5.83	0.33**	5.54	5.91	0.37**
			(14.97)			(13.31)			(2.21)			(2.27)
Return Volatility	3.37	4.40	1.03***	3.51	4.55	1.04***	3.55	3.83	0.29**	3.32	3.74	0.42***
			(12.53)			(12.66)			(2.01)			(3.19)
B/M	0.92	1.17	0.24***	0.84	1.05	0.21***	0.95	1.05	0.10	0.93	1.06	0.13*
			(4.69)			(4.55)			(1.48)			(1.73)

Table 3-3 Extreme rainfall and institutional ownership

This table reports the regression estimates as per the following specification:

$$IO_{it} = \alpha + \beta.(Treat_{RSi} \times AR_t) + \boldsymbol{X_{it-1}}.\boldsymbol{\delta'} + \tau.Time + \gamma_i + \epsilon_{it}$$

Where the dependent variable IO_{it} is the total percentage of share ownership by institutional investors in firm *i* and year *t*. $Treat_{RSi}$ is an indicator variable that takes the value of one if firm *i* is rain-sensitive (excess or deficit) and zero otherwise. AR_t is a dummy variable that takes the value of one if year *t* experiences extreme rainfall (excess or deficit) and zero otherwise. The interaction term $(Treat_{RSi} \times AR_t)$ is the DiD. $\boldsymbol{X_{it-1}}$ is a vector of one year lagged control variables namely *Size*, *OwnCon*, *B/M*, *Leverage*, *Cash*, and *Analyst*, all defined in Table 3-1. $Time$ is the long-running time trend and γ_i controls for firm fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017. Data source: IMD, CMIE, and CIQ databases.

	Excess Rainfall		*Deficit Rainfall*	
	[Model 1]	[Model 2]	[Model 1]	[Model 2]
DiD $(Treat_{RSi} \times AR_t)$	**2.465***	**2.587***	**-2.126***	**-2.830***
	(4.80)	**(4.35)**	**(-3.80)**	**(-4.33)**
Size		2.281***		1.569***
		(5.63)		(3.69)
OwnCon		0.217***		0.174***
		(9.95)		(8.98)
B/M		0.047***		0.049***
		(3.22)		(3.76)
Leverage		-0.431***		-0.445***
		(-3.83)		(-4.15)
Cash		-3.407***		-1.730**
		(-4.06)		(-1.96)
Analyst		0.798***		0.949***
		(10.52)		(12.01)
Time		2.318***		2.225***
		(30.73)		(31.61)
R^2 (within)	0.001	0.325	0.000	0.406
Firm FE	Yes	Yes	Yes	Yes
No. of Firms	3,722	2,790	3,748	2,866
Observations	21,911	14,649	26,467	17,444

Table 3-4 Alternative measure of institutional ownership

This table reports the regression estimates as per the following specification:

$$\Delta IO_{it} = \alpha + \beta.(Treat_{RSi} \times AR_t) + \boldsymbol{X_{it-1}}.\boldsymbol{\delta}' + \tau.Time + \gamma_i + \epsilon_{it}$$

Where the dependent variable ΔIO_{it} is the year-on-year change in institutional ownership (IO) in firm *i* and year *t*. $Treat_{RSi}$ and AR_t are indicator variables as in Table 3-3. The interaction term $(Treat_{RSi} \times AR_t)$ is the DiD. $\boldsymbol{X_{it-1}}$ is a vector of one-year lagged control variables. All other variables are as defined in Sections 3.2 and 3.3. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017. Data source: IMD, CMIE, and CIQ databases.

	Excess Rainfall		*Deficit Rainfall*	
	[Model 1]	[Model 2]	[Model 1]	[Model 2]
DiD $(Treat_{RSi} \times AR_t)$	**3.708*** **	**3.141*** **	**-1.804*** **	**-1.766*** **
	(8.88)	**(6.55)**	**(-3.96)**	**(-3.31)**
Size		-0.711***		-0.588***
		(-3.25)		(-4.09)
OwnCon		0.008		-0.013
		(0.64)		(-1.53)
B/M		-0.000		0.005
		(-0.00)		(1.28)
Leverage		-0.006		0.012
		(-0.06)		(0.29)
Cash		-1.529***		-0.437
		(-2.84)		(-1.02)
Analyst		0.102***		0.004
		(4.82)		(0.34)
Time		-0.504***		-0.074***
		(-14.92)		(-4.10)
R^2 (within)	0.004	0.033	0.001	0.008
Firm FE	Yes	Yes	Yes	Yes
No. of Firms	3,722	2,790	3,748	2,866
Observations	21,911	14,649	26,467	17,444

Table 3-5 Subsample analysis – Single location firms

This table reports the regression estimates for a sub-sample of single location firms as per the following specification:

$$IO_{it} = \alpha + \beta.(Treat_{RSi} \times AR_t) + X_{it-1}.\delta' + \tau.Time + \gamma_i + \epsilon_{it}$$

Where the dependent variable IO_{it} is the total percentage of share ownership by institutional investors in firm *i* and year *t*. $Treat_{RSi}$ and AR_t are indicator variables as in Table 3-3. The interaction term $(Treat_{RSi} \times AR_t)$ is the DiD. $\boldsymbol{X_{it-1}}$ is a vector of one-year lagged control variables. All other variables are as defined in Sections 3.2 and 3.3. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017. Data source: IMD, CMIE and CIQ databases.

	Excess Rainfall		*Deficit Rainfall*	
	[Model 1]	[Model 2]	[Model 1]	[Model 2]
DiD $(Treat_{RSi} \times AR_t)$	**2.465*** **	**2.587*** **	**-2.126*** **	**-2.830*** **
	(4.80)	**(4.35)**	**(-3.80)**	**(-4.33)**
Size		2.281***		1.569***
		(5.63)		(3.69)
OwnCon		0.217***		0.174***
		(9.95)		(8.98)
B/M		0.047***		0.049***
		(3.22)		(3.76)
Leverage		-0.431***		-0.445***
		(-3.83)		(-4.15)
Cash		-3.407***		-1.730**
		(-4.06)		(-1.96)
Analyst		0.798***		0.949***
		(10.52)		(12.01)
Time		2.318***		2.225***
		(30.73)		(31.61)
R^2 (within)	0.001	0.325	0.000	0.406
Firm FE	Yes	Yes	Yes	Yes
No. of Firms	3,722	2,790	3,748	2,866
Observations	21,911	14,649	26,467	17,444

Table 3-6 Alternative measure of extreme rainfall and institutional investors

This table reports the regression estimates as per the following specification:

$$IO_{it} = \alpha + \beta.(Treat_{RSi} \times IMD\_AR_t) + X_{it-1}.\delta' + \tau.Time + \gamma_i + \epsilon_{it}$$

Where the dependent variable IO_{it} is the total percentage of share ownership by institutional investors in firm *i* and year *t*. $Treat_{RSi}$ is an indicator variable that takes the value of one if firm *i* is rain sensitive (excess or deficit) and zero otherwise. IMD_AR_t is a dummy variable that takes the value of one if year *t* defined as extreme rainfall year (excess or deficit) by IMD and zero otherwise. The interaction term $(Treat_{RSi} \times IMD\_AR_t)$ is the DiD. $\boldsymbol{X_{it-1}}$ is a vector of one-year lagged control variables. All other variables are as defined in Sections 3.2 and 3.3. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017. Data source: IMD, CMIE, and CIQ databases.

	Excess Rainfall		*Deficit Rainfall*	
	[Model 1]	[Model 2]	[Model 1]	[Model 2]
DiD ($Treat_{RSi} \times IMD\_AR_t$)	**2.556*** **	**2.093*** **	**-2.228*** **	**-2.605*** **
	(5.52)	**(4.57)**	**(-4.02)**	**(-4.44)**
Size		2.771***		2.111***
		(7.59)		(5.49)
OwnCon		0.206***		0.172***
		(11.51)		(9.74)
B/M		0.044***		0.047***
		(3.56)		(3.88)
Leverage		-0.414***		-0.428***
		(-4.22)		(-4.32)
Cash		-3.066***		-1.440*
		(-4.07)		(-1.71)
Analyst		0.864***		0.919***
		(12.33)		(11.93)
Time		2.250***		2.176***
		(34.48)		(33.34)
R^2 (within)	0.001	0.350	0.000	0.384
Firm FE	Yes	Yes	Yes	Yes
No. of Firms	4,075	3,223	3,856	2,999
Observations	38,610	26,030	34,732	23,210

Table 3-7 Excess rainfall and firm performance

This table reports the regression estimates as per the following specification:

$$PI_{it+1} = \alpha + \beta.(Treat_{RSi} \times ER_t) + \boldsymbol{X_{it}}.\boldsymbol{\delta}' + \tau.Time + \gamma_i + \epsilon_{it}$$

Where the dependent variable PI_{it+1} is the performance indicator for firm *i* in the lead year *t+1*. We take three firm performance measures namely Tobin's Q, Market to Book (MB) ratio, and Return on Equity (ROE) for our regressions. $Treat_{RSi}$ is an indicator variable that takes the value of one if firm *i* is rain-sensitive (excess or deficit) and zero otherwise. ER_t is a dummy variable that takes the value of one if year *t* experiences excess rainfall and zero otherwise. The interaction term $(Treat_{RSi} \times ER_t)$ is the DiD. $\boldsymbol{X_{it}}$ is a vector of control variables namely *Size*, *OwnCon*, *B/M*, *Leverage*, *Cash*, and *Analyst*, all defined in Table 3-1. $Time$ is the long-running time trend and γ_i controls for firm fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017. Data source: IMD, CMIE, and CIQ databases.

	Tobin's Q (lead year)		*MB* (lead year)		*ROE* (lead year)	
	[Model 1]	[Model 2]	[Model 1]	[Model 2]	[Model 1]	[Model 2]
DiD $(Treat_{RSi} \times ER_t)$	**0.099*** **	**0.080*** **	**3.166*** **	**2.667*** **	**2.644*** **	**2.780*** **
	(3.90)	**(3.43)**	**(3.55)**	**(3.30)**	**(3.36)**	**(3.55)**
Size		-0.161***		-8.758***		-5.064***
		(-5.86)		(-13.80)		(-8.76)
OwnCon		0.001		0.098***		0.113***
		(1.22)		(3.35)		(3.99)
B/M						-0.255***
						(-3.86)
Leverage		-0.014***		1.918***		-2.076***
		(-3.82)		(9.34)		(-5.99)
Cash		-0.094**		-1.086		-2.222**
		(-2.03)		(-0.82)		(-2.27)
Analyst		0.007		0.083		0.011
		(1.25)		(1.64)		(0.19)
Time		0.036***		0.364***		-0.440***
		(10.77)		(4.14)		(-4.89)
R^2 (within)	0.001	0.026	0.001	0.067	0.001	0.082
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,561	3,245	3,116	2,924	3,304	2,724
Observations	20,568	17,594	17,707	15,784	18,664	14,371

Table 3-8 Extreme rainfall and domestic and foreign institutional investors

This table reports the regression estimates as per the following specification:

$$IO_{it} = \alpha + \beta.(Treat_{RSi} \times AR_t) + X_{it-1}.\delta' + \tau.Time + \gamma_i + \epsilon_{it}$$

Where the dependent variable IO_{it} is the total percentage of share ownership by either domestic institutional investors ownership (*DIO*) or foreign institutional investors ownership (*FIO*) in firm *i* and year *t*. $Treat_{RSi}$ and AR_t are indicator variables as in Table 3-3. The interaction term $(Treat_{RSi} \times AR_t)$ is the DiD. $\boldsymbol{X_{it-1}}$ is a vector of one year lagged control variables namely *Size*, *OwnCon*, *B/M*, *Leverage*, *Cash*, and *Analyst*, all defined in Table 3-1. $Time$ is the long-running time trend and γ_i controls for firm fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017. Data source: IMD, CMIE, and CIQ databases.

	Excess Rainfall				*Deficit Rainfall*			
	DIO	*DIO*	*FIO*	*FIO*	*DIO*	*DIO*	*FIO*	*FIO*
DiD	**1.852*** **	**1.514*** **	**0.566*** **	**0.986*** **	**-1.801*** **	**-2.314*** **	-0.305	-0.497
$(Treat_{RSi} \times AR_t)$	**(4.10)**	**(2.94)**	**(2.61)**	**(3.33)**	**(-3.53)**	**(-3.91)**	(-1.29)	(-1.46)
Size		0.690*		1.576***		0.052		1.514***
		(1.85)		(7.39)		(0.13)		(6.82)
OwnCon		0.150***		0.062***		0.134***		0.035***
		(7.50)		(4.36)		(7.36)		(3.16)
B/M		0.027*		0.020***		0.032**		0.016***
		(1.91)		(2.58)		(2.47)		(2.89)
Leverage		-0.152		-0.276***		-0.194*		-0.241***
		(-1.56)		(-3.94)		(-1.92)		(-3.54)
Cash		-3.362***		-0.155		-2.755***		0.927
		(-4.07)		(-0.31)		(-3.28)		(1.57)
Analyst		0.353***		0.433***		0.410***		0.535***
		(4.33)		(6.67)		(4.60)		(7.79)
Time		1.941***		0.366***		1.887***		0.325***
		(28.39)		(8.62)		(28.89)		(8.41)
R^2 (within)	0.001	0.268	0.000	0.091	0.000	0.330	0.000	0.125
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,722	2,790	3,722	2,790	3,748	2,866	3,748	2,866
Observations	21,911	14,649	21,911	14,649	26,467	17,444	26,467	17,444

Table 3-9 Alternative measures of domestic and foreign institutional ownership

This table reports the regression estimates as per the following specification:

$$\Delta IO_{it} = \alpha + \beta.(Treat_{RSi} \times AR_t) + X_{it-1}.\delta' + \tau.Time + \gamma_i + \epsilon_{it}$$

Where the dependent variable ΔIO_{it} is the year-on-year change in either domestic institutional ownership (*ΔDIO*) or foreign institutional ownership (*ΔFIO*) in firm *i* and year *t*. $Treat_{RSi}$ and AR_t are indicator variables as in Table 3-3. The interaction term $(Treat_{RSi} \times AR_t)$ is the DiD. $\boldsymbol{X_{it-1}}$ is a vector of one-year lagged control variables. All other variables are as defined in Sections 3.2 and 3.3. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively. The sample period ranges from 2001 to 2017. Data source: IMD, CMIE, and CIQ databases.

	Excess Rainfall				*Deficit Rainfall*			
	ΔDIO	*ΔDIO*	*ΔFIO*	*ΔFIO*	*ΔDIO*	*ΔDIO*	*ΔFIO*	*ΔFIO*
DiD	**2.607*****	**2.187*****	**0.658*****	**0.668****	**-1.084*****	**-1.004*****	-0.232	-0.232
$(Treat_{RSi} \times AR_t)$	**(9.65)**	**(7.15)**	**(3.26)**	**(2.50)**	**(-3.49)**	**(-2.68)**	(-1.27)	(-0.92)
Size		-0.406***		-0.272**		-0.226**		-0.393***
		(-2.81)		(-2.45)		(-2.41)		(-4.79)
OwnCon		-0.016*		0.021***		-0.018***		0.009**
		(-1.90)		(3.08)		(-3.27)		(2.51)
B/M		-0.000		0.002		0.004*		-0.002
		(-0.04)		(0.54)		(1.67)		(-1.06)
Leverage		-0.024		-0.031		-0.033		0.057**
		(-0.43)		(-0.73)		(-1.31)		(2.21)
Cash		-1.037***		-0.620***		-0.259		-0.463**
		(-2.84)		(-3.07)		(-0.94)		(-2.48)
Analyst		-0.019		-0.062***		-0.040***		-0.047***
		(-0.98)		(-2.76)		(-2.92)		(-3.71)
Time		-0.331***		-0.116***		-0.048***		0.004
		(-14.82)		(-6.90)		(-3.95)		(0.40)
R^2 (within)	0.004	0.036	0.001	0.011	0.001	0.008	0.000	0.005
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Firms	3,722	2,790	3,722	2,790	3,748	2,866	3,748	2,866
Observations	21,911	14,649	21,911	14,649	26,467	17,444	26,467	17,444

Table 3-10 Variable description and sources

Variable	Description	Source
Institutional ownership variables		
IO	Total percentage of share ownership by all institutional investors	CMIE
DIO	Total percentage of share ownership by DIIs	CMIE
FIO	Total percentage of share ownership by FIIs	CMIE
Independent variables		
Rainfall departure	Percentage deviation of the monsoon rainfall from the long-term normal mean rainfall	IMD
Excess	Takes the value of one for periods with *Rainfall departure* belonging to the upper quintile and zero otherwise	Derived from IMD
Deficit	Takes the value of one for periods with *Rainfall departure* belonging to the lower quintile and zero otherwise	Derived from IMD
Treat	Takes the value of one if the firm belongs to rain sensitive industry and zero otherwise	Rao et al. (2022)
Key firm-level control variables		
Size	Natural logarithm of total assets	CMIE
OwnCon	Proportion of total shares held by promoters	CMIE
B/M	Book value per share over the year-end market share price	CMIE
Leverage	Ratio of book value of debt-to-equity	CMIE
Cash	Sum of year end cash and short-term securities scaled by total sales	CMIE
Analyst	Number of analysts following the stock	CIQ

4. Chapter 4: Immigration Fear, Populism, and Institutional Investors

4.1 Introduction

Neoclassical economic theory advocates an "open border" policy for immigrants as such cross-border movement of people tends to boost global productivity through various channels (Hayter, 2000).[54] However, despite these potential positive economic consequences, immigrants are seen as a source of threat and socioeconomic concerns by the local populace within the host countries (De Vreese and Boomgaarden, 2005). Such immigration induced fear and anxiety seem to have intensified significantly in recent years by the rapid rise in refugees and asylum seekers in numerous countries (Baker et al., 2015).[55] Consequently, immigration has become a central theme in the political discussion in several countries where such heightened immigration fear and anti-immigration sentiments play key roles such as fueling support for anti-immigrant right-wing populist (RWP) parties and impacting on crucial electoral outcomes (De Vreese and Boomgaarden, 2005; Mughan and Paxton, 2006).[56]

Recent studies demonstrate that fear plays a significant role in the financial decision-making of investors by triggering greater levels of risk-aversion (Guiso et al., 2018; Kuhnen and Knutson, 2011). In addition, investors tend to decrease their overall

[54] A global report by McKinsey in 2016 shows that immigrants contribute about 9.4% to global GDP, and about 40-80% of the labor force in top destinations without harming the long-run employment or wages of native workers. For details, see https://rb.gy/7djk40

[55] The number of refugees (asylum seekers) worldwide has increased from almost 10.50 million (0.94 million) in 2012 to almost 26.67 million (4.91 million) by mid-2022 (Source: UNHCR - https://www.unhcr.org/globaltrends).

[56] The 2016 presidential election win of Donald Trump in the US, the 2016 Brexit referendum, and its subsequent implementation in 2020 in the UK, and strong support for Front National and Alternative für Deutschland (AfD) parties in the 2017 French presidential election and 2017 German general election, respectively are some of the major recent events linked directly with the increased immigration fear and anti-immigration sentiments.

financial risk exposures during periods of increased fear and uncertainty by taking precautions like divesting risky assets and investing in relatively safer assets (Lee and Andrade, 2011; Wang and Young, 2020). Motivated by this literature on how negative emotions such as fear and anxiety affect the investment decisions of investors, and by the upsurge and prominence of immigration related fear sentiments in several countries in recent years, in this study I examine whether immigration fear causes variations in the investment behavior of institutional investors.[57]

Higher immigration inflow is perceived as a threat to national and personal security by some of the local populace due to the belief that immigrants engage in various terrorist and criminal activities (Helbling and Meierrieks, 2020; Reid et al., 2005). Such immigration induced threat, beyond the control of the general public, could further intensify the fear and anxiety among local citizens causing greater levels of risk-aversion (Johnson and Tversky, 1983; Lerner and Keltner, 2001). Moreover, the economic and cultural threat dimensions of immigration fear may erode social capital and trust within the society leading to higher information asymmetry, reduced stock market liquidity, and slower macroeconomic and financial development (Guiso et al., 2008, 2004; Ziller et al., 2019). Thus, I conjecture that the heightened immigration fear induced greater risk-aversion and degrading market conditions owing to the deteriorating social capital and trust should all lead institutional investors to deter their investments from their investee firms. I refer to this as the *investment deterrence* hypothesis, my primary research question in this study.

[57] I focus on institutional investors for their dominance in international capital markets in terms of owning majority of the market capitalizations (DeVault et al., 2019).

As the investment preferences and choices differ considerably among different groups of institutional investors (Ferreira and Matos, 2008; Marshall et al., 2022), I further investigate whether heterogenous institutional investors respond differentially to increased immigration fear sentiments. As such, I formulate and test a set of three *institutional investor heterogeneity* hypotheses as follows. Firstly, studies suggest that domestic institutional investors (DIIs) tend to have greater risk exposures to local market conditions due to holding more local stocks compared to foreign institutional investors (FIIs) (Baik et al., 2013; Choe et al., 2005). As immigration fear sentiments primarily accumulate within the local populace where DIIs are domiciled in, I conjecture that increased immigration fear would trigger greater risk-aversion in DIIs leading them to divest their local stocks more than FIIs. I refer to this as the *geographic proximity-based heterogeneity* hypothesis.

Secondly, being active monitors, independent institutional investors (independent investment advisers) tend to invest in riskier portfolios compared to grey institutional investors (i.e., banks, insurance companies and others) who tend to make safer investments by keeping closer ties with their investee firms' management (Bennett et al., 2003; Chen et al., 2007). Thus, I hypothesize that compared to their grey counterparts, independent institutional investors would be more susceptible to increased immigration fear, which should induce them to divest from their investee firms (I refer to this as the *investment style-based heterogeneity* hypothesis). Thirdly, I hypothesize that short-term institutional investors having greater risk profiles, information, and behavioral biases (DeVault et al., 2019; Yan and Zhang, 2009) would be more inclined towards reducing their investment stakes amidst heightened immigration fear than long-term institutional investors (I refer to this as the *investment horizon-based heterogeneity* hypothesis).

Finally, I also study whether RWP moderates the association between immigration fear and institutional investors' investment choices. Studies argue that RWP parties promote xenophobia by activating more immigration fear and anti-immigration sentiments among the local populace (De Vreese and Boomgaarden, 2005; Rydgren, 2008). Further, RWP parties tend to implement protectionist economic policies that may impede economic growth and create deadweight costs for investors (Rodrik, 2018). Taken together, I hypothesize that the proposed relation between immigration fear and institutional investors' divestments would be more prominent in RWP regimes (I refer to this as the *populism* hypothesis).

I test these hypotheses by utilizing data from four developed countries: namely the United States (US), the United Kingdom (UK), France, and Germany. I use a sample of all publicly-traded non-financial firms in these four economies for the sample period 2005–2019. To proxy for immigration fear sentiments in my analyses, I rely on the immigration fear index (*IFI*) developed by Baker et al. (2015). As for empirical strategy, I use pooled OLS regressions alongside 2SLS instrumental variable (IV) approach that mitigates endogeneity issues and establishes causality.[58] To further support the findings, I exploit an exogenous shock (the 2015 European refugee crisis or ERC) that caused an exponential rise in immigration fear sentiments in an empirical setup similar to a difference-in-differences approach.

[58] Section 4 provides detailed description and explanation of the empirical design and strategy utilized in this study.

My robust empirical investigation reports the following findings. First, in line with the primary *investment deterrence* hypothesis, I find that institutional investors significantly reduce their investment stakes in their investee firms amidst heightened immigration fear. In specific terms, a one standard deviation increase in *IFI* is seen to be associated with almost 0.95% reduction in institutional ownership (*IO*) on average. In economic terms, the 0.95% decline in *IO* translates into 267.84 million USD of annual divestment by institutional investors.[59] Second, I also find evidence in support of all the three institutional *investor heterogeneity* hypotheses as increased immigration fear sentiments significantly induce domestic, independent, and short-term institutional investors to deter their investments from their respective investee firms more than foreign, grey, and long-term institutional investors.

Finally, the empirical results also support the *populism* hypothesis as I find that countries with RWP parties in power (RWP countries) tend to deter investments from institutional investors more than non-RWP countries during periods of increased immigration fear. This finding is further supported by my exogenous shock-based analysis that shows that institutional investors reduced their ownership by 1.57% to 1.88% more on average in firms domiciled in RWP countries relative to the ones based in non-RWP countries in the three-year post-ERC period (with increased immigration fear sentiments). The main findings are robust to a series of robustness tests that include alternative measures/definitions of institutional investor preferences.

Extending the study, I further investigate whether institutional investors make their divestment choices amidst heightened immigration fear due to their risk-aversion

[59] Applying average annual market capitalization of USD 2,819.41 million across all firms in the four countries over the sample period.

nature or because they possess the information that a surge in immigration fear leads to lower future firm performance and returns, as suggested in some studies (Baik et al., 2010; Gompers and Metrick, 2001; Yan and Zhang, 2009). From my analysis, I find that immigration fear does not affect future firm performance which contradicts the information-based explanation and reinforces my fear-based risk-aversion explanation.

My study makes several contributions to literature. First, I contribute to the literature on the effects of fear as a negative emotion on the risk-aversion and investment behavior of investors (Guiso et al., 2018; Kuhnen and Knutson, 2011; Lee and Andrade, 2011). Although most of the research in this area is conducted on individual investors in different experimental settings, my study shows how institutional investors respond to fear sentiments originating from immigration.[60] To this end, I conjecture and show that immigration fear sentiments trigger greater risk-aversion in institutional investors inducing them to divest from their investee firms. To the best of my knowledge, this is the first study to investigate and show this negative association between institutional investors and immigration fear.

Further, the literature predominantly emphasizes on the superior information gathering, stock picking, and trading skills of institutional investors (Baker et al., 2010; Gompers and Metrick, 2001). Contrary to this view, recent studies demonstrate that institutional investors are susceptible to psychological and behavioral biases including herding, salient, and irrational trading behavior (Alok et al., 2020; DeVault et al., 2019;

[60] An exception to this is Wang and Young (2020), who show that individual investors in the US shift from risky assets (mutual funds) to relatively safer assets (bond portfolios) as a response to terrorism induced fear. My study is different from theirs as I study the investment behavior of institutional investors with regard to fear sentiments induced by immigration in a multi-country setup.

Sias, 2004). I add to this literature by showing that institutional investors also exhibit risk-aversion due to increased immigration fear. Moreover, I also contribute to the literature on the heterogenous nature of institutional investors by demonstrating that different groups of institutional investors respond differentially to immigration induced fear sentiments (Ferreira and Matos, 2008; Marshall et al., 2022). Finally, my study adds to the literature relating political ideologies to financial markets and investors by showing that RWP intensifies the negative impact of immigration fear on the investments of institutional investors (Addoum and Kumar, 2016; Bonaparte et al., 2017).

The rest of the chapter is organized as follows. Section 2 provides a review of related literature and develops hypotheses. Section 3 describes the data and variables. Section 4 illustrates the empirical design and strategy. Section 5 reports all empirical findings. Finally, Section 6 concludes the chapter.

4.2 Related literature and hypotheses development

4.2.1 Immigration fear

In recent years, immigration has become a major global phenomenon in economic, social, and political issues, especially in the developed democratic countries (Mughan and Paxton, 2006). Civil wars, genocide, terrorism, oppression, changing political regimes, famine, and natural disasters all lead to increased outmigration resulting in huge influx of uninvited immigrants into countries that have superior social and economic prospects (Moore and Shellman, 2004). Recent events such as the European refugee crisis of 2015, the uprising of the Taliban group in Afghanistan in 2021, and the war in Ukraine in 2022 have all gained global media attention as a large number of people had to move from the conflict zones to Europe and other parts of the world to seek refuge and asylum.

Immigration, particularly uninvited immigration in the form of refugees and asylum seekers, could lead to heightened fear and anxiety among the local population (De Vreese and Boomgaarden, 2005). The literature documents three primary sources of such immigration related fear sentiments; namely personal and national security threats, economic threats, and cultural threats (Bove et al., 2021; Mughan and Paxton, 2006). Although a matter of debate, it is well established in the literature that uninvited immigration is seen as a threat to national and personal security as local citizens perceive higher immigrant inflows to be associated with more terrorist and criminal activities (Helbling and Meierrieks, 2020; Reid et al., 2005). However, studies document that there is almost no relation between immigration and terrorism or crime (Forrester et al., 2019; Ousey and Kubrin, 2018). Thus, the fear and anxiety among the local populace due to immigration induced personal and national security concerns could be considered as "perceived" rather than "actual" (Huddy et al., 2005; Nunziata, 2015).

The economic and cultural threat dimensions of immigration fear could be explained by the theories of intergroup relations, conflict, and social identity (Hogg, 2016; Tajfel and Turner, 1979). These theories posit that the existence of migrants raises the salience of inner and outer groups based on different ethnicities, thereby promoting (perceived) competition between these groups for economic resources and cultural supremacy (Esses et al., 1998; Ziller et al., 2019). In other words, local citizens fear that immigrants would compete and take over their property, jobs, education, tax benefits, and other limited resources as well as deteriorate their cultural integrity as it is their perception that immigrants are culturally “more distant” from them, and are economically “weaker” (Alesina et al., 2018).

The immigration induced perceived cultural and economic threats have significant consequences on the society at large. In particular, intergroup conflict and competition lead to outgroup threat and distrust (Stolle et al., 2008; Ziller et al., 2019). Further, Putnam’s “constrict hypothesis” contends that such perceptions of fear due to immigration could also “spill over” to distrust in others within the same society by triggering feelings of social anomie and insecurity (Putnam, 2007). Such feelings of social isolation and insecurity could result from differences in norms and moral principles between locals and immigrants resulting in people becoming more cynical and distrusting. This, coupled with intergroup conflict and competition, should all lead to a significant decrease in social capital and trust, owing to the heightened immigration induced fear sentiments (Ziller, 2015; Ziller et al., 2019).

4.2.2 Immigration fear and institutional investors

Extant literature suggests that negative emotions such as fear and anxiety could result in pessimistic judgments and risk-aversion (Johnson and Tversky, 1983; Kuhnen and Knutson, 2011). Under the appraisal tendency framework, this effect becomes even more pronounced as individuals face more ambiguous and/or uncontrollable threat (Lerner and Keltner, 2001). In fact, studies suggest that fearful individuals try to reduce their risk exposures by taking behavioral and intellectual actions such as taking precautionary measures, selecting safer bets, and processing information more carefully (Lerner et al., 2003; Raghunathan and Pham, 1999; Tiedens and Linton, 2001). If uninvited immigration results in increased perceived threat and fear among the local populace, then such fear and anxiety should lead to higher risk-aversion among investors (Loewenstein, 2000).

Further, social projection theories predict that investors may use their current mental state or emotions to forecast not only their own future preferences, but also the ideas, beliefs, and actions of other investors (Loewenstein et al., 2003). Thus, immigration related fear sentiments may spill over among all investors in a financial market triggering their fear-based action tendencies to divest from risky assets such as stocks. Recent studies provide empirical evidence that fear acts as a substantial mechanism in financial decision making. For instance, in a market simulation based experimental study, Lee and Andrade (2011) show that fear significantly induce investors to divest from stocks. In a similar manner, Guiso et al. (2018) demonstrate that fear leads to heightened risk-aversion in households as following the financial crisis they substantially divest stocks. Also, Wang and Young (2020) show that the aggregate fear induced by terrorism leads individual investors to shift from risky assets (mutual funds) to safer assets (bond portfolios). Taken together, I can predict from these studies that the fear and anxiety caused by uninvited immigration should lead to higher levels of risk-aversion among investors where they would be more inclined towards divesting stocks.

Institutional investors are currently the most dominant investors in international capital markets owning the majority of the market capitalizations (DeVault et al., 2019). A prominent view in the literature is that institutional investors are more rational and that they possess superior trading and stock picking skills (Baker et al., 2010; Gompers and Metrick, 2001). Nevertheless, recent literature emphasizes that psychological characteristics such as political orientation and home bias could affect the investment decisions of institutional investors (Chan et al., 2005; DeVault and Sias, 2017). In fact, institutional investors tend to be prone to behavioral biases where they exhibit herding, salient, and even irrational trading behavior driving up market sentiment (Alok et al., 2020; DeVault et al., 2019; Sias, 2004). If immigration related fear sentiments cause emotional distress and anxiety to all investors including institutional investors triggering their risk-aversion, then I should expect institutional investors to divest from their investee firms during periods of increased immigration fear (Loewenstein, 2000).

The immigration fear induced deterioration in aggregate social capital and trust has further consequences in financial markets. In particular, such decline in social capital and trust should impede financial transactions by triggering issues associated with information asymmetry such as adverse selection and moral hazard (Knack and Keefer, 1997; La Porta et al., 1997). This in turn should lead to less stock market participation by all investors leading to lower stock market liquidity, poorer stock market performance, and sluggish macro-economic and financial development (Guiso et al., 2008, 2004). Under such degrading market conditions, potentially driven by immigration fear sentiments, I should expect institutional investors to “herd out” and decrease their investment stakes in their investee firms as fear tends to trigger greater levels of herding behavior among investors (Economou et al., 2018).

From the above discussion, I conjecture that if heightened immigration fear sentiments cause emotional distress and anxiety among investors leading to greater risk aversion, and impede social capital and trust leading to worsening market conditions, then I should expect to see a negative association between immigration fear and investments from institutional investors. As such, I propose the following *investment deterrence* hypothesis:

H_1: Immigration related fear sentiments lead institutional investors to reduce their investment stakes in their investee firms.

4.2.3 Institutional investor heterogeneity hypotheses

The literature suggests that there is a substantial level of heterogeneity within institutional investors in terms of their origins, institution type, investment styles and objectives, and investment horizons (Ferreira and Matos, 2008; Marshall et al., 2022). As diverse types of institutional investors have differences in their risk profiles, investment preferences, and investment related information, I conjecture that different types of institutional investors would react differentially to increased immigration related fear sentiments.

It is well documented in the literature that geographic proximity plays a key role in institutional investors' investment choices and strategies (Baik et al., 2010; Coval and Moskowitz, 2001). In particular, domestic institutional investors (DIIs), being geographically more proximate to their investee firms, tend to possess better information about local firms and market conditions compared to foreign institutional investors (FIIs) (Baik et al., 2013; Ferreira and Matos, 2008). Such information advantage leads DIIs to hold more local stocks in their portfolios resulting in more risk exposures to local market conditions compared to FIIs who generally invest in fewer selective local stocks (Choe et al., 2005). As a result, I predict that the declining market conditions, potentially induced by heightened immigration fear sentiments, would affect DIIs more than FIIs.

Furthermore, a sudden influx of uninvited immigration generally triggers fear and anxiety among the local populace and, as a result, such immigration fear should primarily channel towards the DIIs where they are domiciled in (Wang and Young, 2020). As information can flow more quickly to DIIs and as DIIs tend to have more risk exposures to local market conditions, I conjecture that immigration related fear sentiments should trigger risk aversion behavior more in DIIs than in FIIs. Taken together, I hypothesize that the negative nexus between immigration fear and institutional investments should be more pronounced in DIIs than in FIIs. As such, I formulate the following *geographic proximity-based heterogeneity* hypothesis:

H_{2a}: Immigration related fear sentiments lead DIIs to reduce their investment stakes more than FIIs in their respective investee firms.

The differences in investment decisions and choices within institutional investors could also stem from the heterogeneity based on their investment styles, objectives, and horizons. For instance, independent institutional investors (mutual funds, hedge funds, and other independent investment advisors) tend to be more active in monitoring firms and general market conditions compared to grey institutional investors (banks, insurance companies, and others) (Chen et al., 2007; Ferreira and Matos, 2008). Moreover, independent institutional investors tend to invest in riskier portfolios compared to grey institutional investors who generally pick stocks that are considered to be “safer” (Bennett et al., 2003; DeVault et al., 2019). Due to their active monitoring and greater risk-taking nature, independent institutional investors should be more sensitive to immigration related fear sentiments, which should consequently trigger their risk-aversion at a greater level.

Further, grey institutional investors tend to be more loyal to their investee firms when it comes to their investment preferences as they keep closer ties with the management of such firms (Brickley et al., 1988; Chen et al., 2007). On the contrary, independent institutional investors tend to compete for capital, and fund flows significantly affect their investment decisions and strategies. It is expected that individual investors would divest from independent institutional investors (mutual/hedge funds) during periods of increased immigration fear resulting in lower fund flows (Wang and Young, 2020). Under such circumstances, I should expect independent institutional investors to reduce their investment stakes in their investee firms more than grey investors who are less likely to divest from their investee firms and deteriorate the close relationships with them. Hence, I hypothesize that immigration related fear sentiments would trigger greater risk-aversion among independent institutional investors compared to grey investors. As such, I develop the following *investment style-based heterogeneity* hypothesis:

H_{2b}: Immigration related fear sentiments lead independent institutional investors to reduce their investment stakes more than grey investors in their respective investee firms.

Institutional investors having different investment horizons may also react differently to immigration related fear sentiments. To categorize institutional investor based on their investment horizons, I follow the literature and classify pension funds as long-term investors, and hedge funds as short-term investors (Cella et al., 2013; Marshall et al., 2022). The literature suggests that short term investors such as hedge funds are frequent traders possessing better information and attentiveness to general market conditions compared to long-term investors (Yan and Zhang, 2009). Further, compared to their long-term counterparts, such short-term investors tend to invest in more risky stocks forming riskier portfolios.

The literature also suggests that short-term investors tend to exhibit behavioral bias and irrational trading behavior such as "bubble riding" which drives up market sentiment (Brunnermeier and Nagel, 2004; DeVault et al., 2019). In contrast, long-term investors tend to hold comparatively "safer" stocks in their portfolios over long horizons and do not make frequent adjustments to them. Thus, I predict that short-term institutional investors having higher risk profiles, more information and attentiveness, and greater behavioral biases would be more reactive to heightened immigration fear sentiments compared to long-term investors. Consequently, such immigration fear should result in greater risk-aversion behavior among short-term institutional investors compared to their long-term counterparts. As such, I formulate the following *investment horizon-based heterogeneity* hypothesis:

H_{2c}: Immigration related fear sentiments lead short-term institutional investors to reduce their investment stakes more than long-term investors in their respective investee firms.

4.2.4 Populism hypothesis

It is well established in the literature that the actual or perceived threats of immigration result in greater levels of anti-immigration sentiments, which fuel support for RWP parties (Helbling and Meierrieks, 2020; Mughan and Paxton, 2006). Populism could be considered as an ideology of societal cleavage between "pure people" and "corrupt elites", where politics should reflect the will of the majority "pure people" whose opinions and interests have been ignored by the "corrupt elites" (Mudde, 2004). In right-wing populism, immigrants are seen as “nefarious minorities”, who form a major portion of the “corrupt elites” whereby taking the rights and advantages away from the more “deserving” local people (Lockwood, 2018). As such, right-wing populism has been a well-established aspect of politics in Europe and other Anglophone countries (Brubaker, 2017; Mudde, 2004).

Extant literature on right-wing populism suggests that RWP parties thrive on anti-immigration sentiments together with economic threats and cultural concerns that are brought on the society by immigrants (Mughan and Paxton, 2006; Rodrik, 2018). In fact, by utilizing such anti-immigration sentiments, RWP parties exert xenophobia for the purpose of electoral success and survival resulting in additional immigration induced fear and anxiety among the local populace (De Vreese and Boomgaarden, 2005; Rydgren, 2008). Consequently, RWP parties tend to obtain greater public support by promising to impose stringent immigration and security policies together with anti-globalization strategies (Lerner et al., 2003; Rodrik, 2018).

Studies suggest that the composition of political parties at the government level and the overall political climate significantly affect financial markets and investors (Addoum and Kumar, 2016; Bonaparte et al., 2017). If increased anti-immigration sentiments fuel support for RWP parties resulting in their subsequent electoral success, then I should expect such changes in the political environment to affect institutional investors. In particular, by triggering further immigration related fear and anxiety, RWP parties in power may induce institutional investors to divest more from their investee firms based in RWP regimes.

Moreover, RWP parties tend to possess strong nationalistic views and pursue protectionist policies (i.e., create international trade barriers, prevent foreign labor, and hinder capital flow and innovation among others) that may impede economic growth and development (Rodrik, 2018; Serdar Dinc and Erel, 2013). This may result in greater economic uncertainties potentially inducing deadweight costs for investors. Thus, from the above discussion, I conjecture that, amidst heightened immigration fear and anti-immigration sentiments, countries with RWP parties in power (RWP countries) may deter institutional investors' investments more by fostering additional immigration related fear sentiments and economic uncertainties than countries governed by non-RWP parties (non-RWP countries). As such, I develop the following *populism* hypothesis:

H_3: The negative nexus between immigration related fear sentiments and institutional investors' investments is more pronounced in RWP countries than in non-RWP countries.

4.3 Data and variables

4.3.1 Sample and data sources

My primary research question in this study is related to immigration fear sentiments across different countries which I capture by utilizing a migration-related fear index (immigration fear index or *IFI*) developed by Baker et al. (2015). At the time of this study, this index was only available for four major developed countries with large financial markets, namely the United States (US), the United Kingdom (UK), France, and Germany. Thus, my sample consists of all publicly listed non-financial firms that are based in these four countries. I obtain institutional ownership data of these firms from the S&P Capital IQ (CIQ) database following Marshall et al. (2022). Firm-level financial variables including analyst following data alongside industry classifications are also sourced from CIQ database. The study period ranges from the year 2005 to 2019.[61] Overall, the study sample comprises of 15,498 unique firms (10,035 US, 3,248 UK, 1,076 French, and 1,139 German firms) with 157,266 firm-year observations.

I further obtain country-level macro variables (i.e., GDP per capita, and annual GDP growth rate) from the World Bank's World Development Indicators (WDI) database. Moreover, I source time varying country-level governance indicators from Kaufmann et al. (2011).[62] In addition, for my instrumental variable (IV) analysis, I acquire terrorist attacks data from the Global Terrorism Database (GTD).[63] Finally, I procure country-level government composition data from the Comparative Political Data Set (CPDS) maintained by Armingeon et al. (2022).[64]

4.3.2 Key dependent variable

The key dependent variable for this study is firm-level institutional ownership (*IO*) computed at annual intervals which proxies for institutional investors' investment choices. CIQ tracks percentage share ownership by institutional investors of each individual firm. Following the literature, I aggregate the total percentage share ownership by all institutional investors of each firm annually to obtain the firm-level institutional ownership (*IO*) (Ferreira and Matos, 2008; Marshall et al., 2022). I treat

[61] Even though *IFI* data is available from 1995, I consider my sample from 2005 as institutional ownership data in CIQ prior to 2005 is very scarce or non-existent. I also restrict the study period to 2019 to ensure that my results and findings do not suffer from any confounding effects of the Covid-19 global pandemic.
[62] This data is maintained by the World Bank's Worldwide Governance Indicators (WGI) database available at https://info.worldbank.org/governance/wgi/
[63] GTD data is available at https://www.start.umd.edu/gtd/
[64] The data is publicly available at https://www.cpds-data.org/index.php/data

institutional ownership as zero if firm shares are not held by any institutional investor in a given year (Gompers and Metrick, 2001).

For my institutional investor heterogeneity analysis, I segregate firm-level institutional ownership by institutional investors' geographic location or institution type. Accordingly, I take the total percentage of shares held by domestic (foreign) institutional investors as the dependent variable for domestic (foreign) institutional ownership *DIO* (*FIO*) (Ferreira and Matos, 2008). Similarly, I also compute the total percentage share ownership by different types of institutional investors following Marshall et al. (2022). Accordingly, I denote total ownership by independent, grey, long-term (i.e., Pension funds), and short-term (i.e., Hedge funds) institutional investors as *Indep_IO, Grey_IO, Pension_IO,* and *Hedge_IO*, respectively.

4.3.3 Key independent variable

As noted earlier, the key independent variable of interest of my study is the country-level immigration fear index (*IFI*), which tracks levels of immigration related fear sentiments across each of the four countries (US, UK, France, and Germany) over time. The index is compiled on a quarterly basis by counting the number of news reports that contain at least one keyword associated with the words "Migration" and "Fear".[65] For each country and year-quarter, a proportionate measure of migration fear (*IFI*) is generated by dividing the number of news articles by the total number of news articles. As the rest of the data and variables are obtained on an annual basis (including

[65] For "Migration" the related terms are: "border control", "Schengen", "open borders", "migrant", "migration", "asylum", "refugee", "immigrant", "immigration", "assimilation", "human trafficking". And for "*Fear*", the terms are: "anxiety", "panic", "bomb", "fear", "crime", "terror", "worry", "concern", "violent". The counts are obtained from "Le Monde" for France, "Frankfurter Allgemeine Zeitung" and "Handelsblatt" for Germany, the "Financial Times" and the "Times of London" for the UK, and US newspapers indexed by the Access World News Newsbank database for the US.

institutional ownership), I obtain yearly measures of *IFI* from the year-quarter data for each country to conduct my analysis. For easier interpretation of the results, I normalize *IFI* from 0 to 100, where 0 (100) represents the lowest (highest) levels of immigration fear sentiments in my sample dataset.

4.3.4 Control variables

To help improve the accuracy of my regression estimates, following the literature, I control for several key firm and country level characteristics that are associated with institutional ownership in my analysis. Studies suggest that institutional investors have a significant preference for stocks of large firms as such firms tend to be more visible, trustworthy, and transparent (Gompers and Metrick, 2001). Hence, I control for firm size (*Size*), computed as the natural logarithm of year end book value of total assets expressed in millions of US dollars (USD) (Tsang et al., 2019). Next, firms' leverage levels tend to indicate their default risks and may create agency conflicts between creditors and investors (Jensen and Meckling, 1976). As such, I control for firms' leverage levels (*Leverage*), taken as the ratio of the book value of debt to equity (Marshall et al., 2022). Further, institutional investors tend to prefer firms that are financially less constrained and are more liquid (Dahlquist and Robertsson, 2001). Hence, I control for firms' current ratio (*CurRatio*), defined as the ratio of current assets to current liabilities (Koirala et al., 2020).

Block holders may influence institutional investors as they tend to actively monitor firm managers, influence corporate governance mechanisms, and promote value enhancing corporate investments (Faccio et al., 2011; Maug, 1998). Thus, I control for block holder ownership (*BlockOwn*), which is the percentage share ownership of the largest shareholder of the firm. As firms' growth potential could influence institutional investors' investment choices, I also control for firms' market to book ratio (*MB*), calculated as the year-end total market capitalization scaled by the total book value of equity (Baik et al., 2013). Moreover, as firms' payout policies seem to affect institutional investors' investment preferences, I control for dividend yield (*DivYield*), taken as the ratio of total dividends to market value of equity at year end (Bennett et al., 2003). Further, since there tends to be a strong association between firm innovation and institutional investors, I control for firms' research and development intensity (*R&D*), taken as the total research and development expenditure scaled by total assets (Aghion et al., 2013; Baik et al., 2013). Finally, analyst recommendations seem to significantly affect institutional investors' investment choices (Brown et al., 2014). Thus, I control for analyst following (*Analyst*) as the number of analysts following the firm (Roy et al., 2022).

I also control for several country-level characteristics following the literature (DeFond et al., 2011; Ferreira and Matos, 2008). Namely, I control for countries' GDP growth rate (*GDP_Gr*), GDP per capita (*GDP_PC*), taken as the natural logarithm of GDP per capita, and country governance index (*CGI*).[66] I provide a summary of all key variable details and their sources in Table 4-1. To mitigate the issues associated with outliers, I winsorize all continuous variables at the 1% level on both tails. Further, to

[66] For measuring *CGI*, I follow Kaufmann et al. (2011) who track yearly governance indicators across six dimensions for over 200 countries starting from 1996. The six dimensions are namely "Voice and Accountability", "Political Stability and Absence of Violence/Terrorism", "Government Effectiveness", "Regulatory Quality", "Rule of Law", and "Control of Corruption". For each country, I take the yearly average of the estimates across these six dimensions and then normalize the values between 0 to 100 to generate *CGI*.

alleviate any concerns of reverse causality, I lag all control variables in my regressions by one year.

4.3.5 Descriptive statistics

I provide a brief summary statistics of all the key variables from my study sample in Table 4-2. Panel A shows the overall sample summary statistics of all key variables. It is seen that institutional investors own around a third of all sample firms' shares (*IO* Mean = 33.48; Std. Deviation = 36.55) on average annually with the median ownership being 16.95%. DIIs seem to hold the majority of these shares (*DIO* Mean = 26.84) on average annually whereas the average annual foreign institutional ownership (*FIO*) is 6.97%. Similarly, independent investment advisers own the majority of all firm shares with a mean of 29.08% (*Indep_IO* Mean), and grey investors have an average yearly ownership of 4.53% (*Grey_IO* Mean) of all sample firms. Finally, when comparing pension fund ownership (*Pension_IO*) with hedge fund ownership (*Hedge_IO*), hedge funds own a larger stake on average with a mean annual ownership of 3.50% compared to pension funds with a mean ownership of just over 1%.

[Table 4-2 about here]

The mean *IFI* (normalized values between 0 to 100) is 11.02 with a standard deviation of 14.13 across the sample. Further, the annual averages of leverage (*Leverage*), current ratio (*CurRatio*), and block holder ownership (*BlockOwn*) are 0.57, 3.14, and 13.46%, respectively for the overall sample. The overall average yearly market to book ratio (*MB*) is 1.75 whereas the mean dividend yield (*DivYield*) is 1.30. Finally, among country level controls, the average annual GDP growth rate (*GDP_Gr*) across the four countries is 1.70%, whereas the mean country governance index (*CGI*) is 47.08 having normalized values ranging from 0 to 100.

Panel B, C, D, and E of Table 4-2 provide country wise sample distribution and summary statistics of all variables for the US, UK, France, and Germany, respectively. The US and the UK have higher levels of institutional ownership with mean *IO* values of 37.48 and 36.83, respectively. the average institutional ownership is lower in France and Germany with mean *IO* values of 14.63% and 13.34%, respectively. US firms' shares are predominantly owned by DIIs as the mean *DIO* for the US is 33.64%, whereas the mean *FIO* is only 4.38%.[67] The ownership of DIIs and FIIs is comparatively more balanced in the UK and France with mean *DIO* (*FIO*) being 22.78% (14.11%) and 8.13% (6.40%), respectively. Germany is the only country in the sample to have a higher mean *FIO* of 8.21% compared to a mean *DIO* of 4.99%. Finally, hedge funds have a greater presence in the US having a mean ownership of 5.09% compared to other countries in the sample whose mean *Hedge_IO* is below 1.40%.

Finally, I look at the differences in *IFI* and other country-level controls across the four countries. The US has the lowest levels of mean *IFI* (5.57) with values ranging from 0 to 19.41. In comparison, France seems to have a stable but higher level of average *IFI* (Mean = 11.93; Std Deviation = 5.38) over the sample years. However, the average *IFI* levels seem to be significantly higher for Germany (*IFI* Mean = 26.92) followed by the UK (*IFI* Mean = 20.18) in the sample. It is also noteworthy to mention here that both Germany and the UK experienced greater levels of *IFI* fluctuations over

[67] It is worth mentioning here that US has the lowest level of mean *FIO* among the four countries in the sample.

the years as *IFI* values for Germany (UK) range from 3.06 to 100 (0.51 to 54.58) with a standard deviation of 29.82 (14.87). Among other variables, research and development intensity (*R&D*) is seen to be significantly higher in the US with a mean of 0.05 compared to the rest of the countries, each of which has a mean of 0.01 only. Finally, among country-level controls, the US (France) is seen to have the highest (lowest) average annual GDP growth rate of 1.87% (1.17%). For *CGI* Germany has the highest yearly average of 82.73 followed by the UK with an annual mean of 68.72.[68]

4.4 Empirical design and strategy

To assess the relation between immigration fear sentiments and institutional investors' investment preferences, I run pooled OLS regressions with firm and year fixed effects as specified in specification (4.1). I use specification (4.1) to test both my primary *investment deterrence* hypothesis as well as my *institutional investor heterogeneity hypotheses*. The general form of the specification is as follows:

$$IO_{ict} = \alpha + \beta . IFI_{ct} + \boldsymbol{X_{it-1}} . \boldsymbol{\delta}' + \boldsymbol{Z_{ct-1}} . \boldsymbol{\theta}' + \gamma_i + \tau_t + \varepsilon_{ict} \qquad (4.1)$$

where the dependent variable IO_{ict} is the total institutional ownership or the institutional ownership by institutional investors' geographic location or institution type, as defined in Section 3.2, of firm *i* in country *c* in year *t*. IFI_{ct} is the key independent variable, immigration fear index, of country *c* in year *t*, as defined in Section 3.3. $\boldsymbol{X_{it-1}}$ and $\boldsymbol{Z_{ct-1}}$ are vectors of one year lagged key firm-level and country-

[68] Even though my study sample covers only four countries, from the summary statistics I can observe that there are substantial variations in the key variables across these four countries.

level control variables, respectively, that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *MB*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Section 3.4. Finally, γ_i and τ_t are firm and year fixed effects, respectively whereas ε_{ict} denotes the error term. Standard errors are clustered at the firm-level in all regressions. The key coefficient of interest from specification (4.1) is β, which captures the effect of immigration fear sentiments on institutional investors.

I acknowledge that the estimates from specification (4.1) could suffer from endogeneity issues, particularly from omitted variable bias. To mitigate such endogeneity concerns, I resort to an instrumental variable (IV) approach where I use terrorist attacks in the geographic region surrounding a country as an exogenous instrument. My choice of such geographical terrorist attacks as an IV relies primarily on three major factors. First, terrorist attacks tend to be politically motivated and are purely exogenous in nature (Wang and Young, 2020). Second, studies suggest that such unexpected terrorist attacks significantly and exponentially increase immigration fear and anti-immigration sentiments (Branton et al., 2011; Helbling and Meierrieks, 2020). Third, I consider all terrorist attacks in the geographic region excluding the attacks within the country of interest as the IV because such transnational terrorism should primarily affect that country's immigration fear of the local populace without having other confounding effects that country-level terrorist attacks might have on institutional investors (Bove et al., 2021; Legewie, 2013). Thus, such regional terrorist attacks should not have any direct or indirect effect on institutional investors, fulfilling the exclusion restriction criterion of the IV approach. As such, to establish a causal relationship between immigration fear and institutional investors' investment choices, I estimate the following 2SLS IV specification (4.2):

$$IFI_{ct} = \alpha + \lambda.Terror\_Geo_{cgt-1} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta'} + \boldsymbol{Z_{ct-1}}.\boldsymbol{\theta'} + \gamma_i + \tau_t + \varepsilon_{ict}$$

$$IO_{ict} = \alpha + \beta.\widehat{IFI_{ct}} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta'} + \boldsymbol{Z_{ct-1}}.\boldsymbol{\theta'} + \gamma_i + \tau_t + \varepsilon_{ict} \quad (4.2)$$

In the first stage of the 2SLS IV specification, I regress the immigration fear index IFI_{ct}, as specified in specification (4.1), on the one year lagged exogenous instrumental variable $Terror\_Geo_{cgt-1}$, which is the total number of terrorist attacks in the geographic region g surrounding the country c, and all other firm-level and country-level control variables alongside firm and year fixed effects. In the second stage, I regress my key dependent variable IO_{ict}, as specified in specification (4.1), on the fitted values of immigration fear index ($\widehat{IFI_{ct}}$) obtained from the first stage, and all other firm-level and country-level control variables alongside firm and year fixed effects. The key coefficient of interest from my 2SLS IV specification (4.2) is β, which shows the causal relation between immigration fear and institutional investors.

Finally, to test my third hypothesis on the moderating role of populism on the association between immigration fear sentiments and institutional investors investment preferences, I run regressions as the per the following specification (4.3):

$$\begin{aligned} IO_{ict} = \alpha + \beta.(IFI_{ct} \times RWP_{ct}) + \omega.IFI_{ct} + \rho.RWP_{ct} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta'} \\ + \boldsymbol{Z_{ct-1}}.\boldsymbol{\theta'} + \gamma_i + \tau_t + \varepsilon_{ict} \end{aligned} \quad (4.3)$$

where the variables IO_{ict} and IFI_{ct} are as per specification (4.1). RWP_{ct} is a time varying indicator variable that takes the value of one if majority of the government composition of country *c* consists of RWP parties in year *t* and zero otherwise. I rely on Armingeon et al. (2022) and define RWP_{ct} in two ways. First, RWP_{ct} is set to one if country *c*'s right-wing parties as percentage of total cabinet posts is greater than 50% in year *t* and zero otherwise.

Second, RWP_{ct} is set to one if country c's cabinet composition is either "hegemony of right/center parties" or "dominance of right/center parties" and zero otherwise. $\boldsymbol{X_{it-1}}$ and $\boldsymbol{Z_{ct-1}}$ are vectors of one year lagged key firm-level and country-level control variables, respectively, as specified in specification (4.1). γ_i and τ_t control for firm and year fixed effects, respectively. The key coefficient of interest from specification (4.3) is β, which shows the moderation effect of RWP on the nexus between immigration fear sentiments and institutional investors' investments.

4.5 Empirical results

4.5.1 The effect of immigration fear on institutional investors

I begin my empirical investigation by conducting tests relating to my primary hypothesis H_1. To do so, I run pooled OLS regression with firm and year fixed effects as per specification (4.1) alongside conducting the IV analysis as per specification (4.2). The estimates from the first stage of the 2SLS IV regression is presented in Model [1] of Table 4-3. As predicted, there seems to be a significant positive relationship between the IV (*Terror_Geo*) and *IFI*, reflected by the highly significant (at the 1% level) positive coefficient on *Terror_Geo* in Model [1]. I run additional diagnostic tests to further validate my IV. These include the Kleibergen-Paap rank LM statistic under-identification test, and the Kleibergen-Paap rank Wald F statistic weak identification test (Kleibergen and Paap, 2006). I obtain a Kleibergen-Paap rank LM statistic of 3,569.72 (Chi-square p-value = 0.000) indicating that the IV (*Terror_Geo*) does not suffer from under identification issue and is highly correlated with *IFI*. Next, the Kleibergen-Paap rank Wald F statistic of 4,918.75 exceeds the Stock and Yogo

(2005) test with a maximal IV size of 10% (Critical value = 16.38), which indicates that the IV (*Terror_Geo*) strongly captures exogenous variations in *IFI*.[69]

[Table 4-3 about here]

I tabulate the estimates obtained from the OLS regression in Model [2] of Table 4-3. It is observed that the key coefficient of interest from the variable *IFI* is negative with a magnitude of -0.067 and is highly significant at the 1% level. Thus, the results indicate that there is a significant negative relation between *IFI* and institutional ownership (*IO*), and that a one standard deviation increase in *IFI* results in almost 0.95% decrease in *IO* on average across all firms.[70] The 0.95% reduction in *IO* translates into 267.84 million USD of divestment by institutional investors on average which is also economically significant.[71] Most of the control variables generally carry the expected signs.

Model [3] of Table 4-3 reports the estimates from the second stage of the 2SLS IV specification. Similar to my OLS results, the second stage of the IV estimates also show a highly significant (at the 1% level) negative association between *IFI* and *IO*. More importantly, the IV analysis mitigates the concerns of endogeneity in my OLS estimates and establishes a causal relationship between immigration fear sentiments and investments from institutional investors. Overall, the results from my OLS and IV analyses support the primary *investment deterrence* hypothesis H_1 that higher

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[69] It is important to note here that I only report the estimates and test statistics from the first stage of the 2SLS IV specification (4.2) using *Terror_Geo* as the IV in Model [1] of Table 2. I do not repeat reporting these in the subsequent 2SLS IV analyses with *Terror_Geo* as the IV since the first stage results remain the same.

[70] Using standardized regression coefficient of -0.026 for *IFI*, and *IO* overall sample standard deviation of 36.55%. One standard deviation increase in *IFI* would lead to (-0.026×36.55%) = -0.95% reduction in *IO* on average.

[71] Applying average annual market capitalization of USD 2,819.41 million across all firms in the four countries over the sample period.

immigration fear sentiments lead institutional investors to divest from their investee firms.

4.5.2 Alternative measures/definitions of institutional investor preferences

To further validate my main findings in Section 5.1 and to provide additional support to the primary hypothesis H_1, I conduct a robustness test with alternative measures or definitions that proxy institutional investors' investment preferences or choices. I take four alternative measures/definitions of institutional investors' investment preferences following the literature (Marshall et al., 2022; Tsang et al., 2019). These include year-on-year change in institutional ownership (*ΔIO*), the annual total number of institutional investors in a firm (*Total_II*), the annual total number of existing institutional investors in a firm as a percentage of one year lagged *Total_II* (*Ext_II/Total_II*), and the annual total percentage share ownership by existing institutional investors of a firm (*Ext_IO*). I use these alternative measures/definitions as the dependent variables in the OLS specification (4.1) and the 2SLS IV specification (4.2) and derive the regression estimates. The results are presented in Table 4-4. Models [1] ([2]), [3] ([4]), [5] ([6]), and [7] ([8]) report the estimates from the pooled OLS (second stage of the 2SLS IV) specification for *ΔIO*, *Total_II*, *Ext_II/Total_II*, and *Ext_IO*, respectively.

[Table 4-4 about here]

It is seen that the regression coefficient on *IFI* remains negative and highly significant (at the 1% level) across all the measures in all the Models. From Model [1], I interpret that a one standard deviation increase in *IFI* leads to almost 8.27% reduction in *ΔIO* on average, which in line with my main results for *IO* in Section 5.1. Further, the highly significant negative coefficient on *IFI* for *Total_II* indicates that the total number of institutional investors decreases with higher levels of *IFI*, meaning existing institutional investors leave their investee firms amidst heightened immigration fear. This is further validated in Models [5] to [8], as I find that the number of existing institutional investors and their share ownership (*Ext_IO*) reduce by 1.43% and 0.64%, respectively on average when *IFI* increases by one standard deviation.[72] Further and consistent with the OLS results, the estimates from the IV analyses maintain the negative causal relationship between *IFI* and institutional investors. Overall, these results shed light on the fact that institutional investors deter their investments either by leaving or by reducing their investment stakes in their investee firms during periods of higher immigration fear sentiments, providing further support to my primary *investment deterrence* hypothesis H_1.

4.5.3 Heterogeneity hypothesis: Geographic proximity

I begin my *institutional investor heterogeneity* hypotheses testing by first considering geographic proximity as the source of heterogeneity among institutional investors. Specifically, I test whether DIIs and FIIs react differentially to immigration fear sentiments. To do so, I take *DIO* (*FIO*), which proxies for domestic (foreign) institutional investors' investment preferences, as the dependent variables in both the OLS specification (4.1) and 2SLS IV specification (4.2) and run the regressions. The results are presented in Table 4-5.

[Table 4-5 about here]

[72] Using standardized regression coefficients on *IFI* from the OLS Models.

Models [1] and [2] of Table 4-5 respectively show the OLS and the second stage of the IV estimates for *DIO*. In line with my predictions, I find highly significant (at the 1% level) negative coefficients on *IFI* in both the Models. From the OLS results in Model [1], I estimate that a one standard deviation increase in *IFI* leads DIIs to reduce their ownership by almost 1.26% in their investee firms which is economically highly significant. The IV estimates, in line with the OLS results, in Model [2] provide additional support to this and further suggest that the negative effect of *IFI* on *DIO* is causal. In contrast, the regression coefficients on *IFI* for *FIO* seem to be insignificant in both the OLS and IV specifications, as seen in Models [3] and [4], respectively. This suggests that immigration fear sentiments have a highly significant deteriorating effect on DIIs' investments but have no significant effect on FIIs' investments. Overall, the results support my *geographic proximity-based heterogeneity* hypothesis H_{2a} that immigration fear sentiments have a more pronounced negative impact on DIIs than on FIIs.

4.5.4 Heterogeneity hypothesis: Institution type

To test the set of *institutional investor heterogeneity* hypotheses, I take total institutional ownership by institution type (i.e., *Indep_IO*, *Grey_IO*, *Pension_IO*, and *Hedge_IO*) as dependent variables and run regressions using both the pooled OLS specification (4.1) and 2SLS IV specification (4.2). I report the results from these regressions in Table 4-6.

[Table 4-6 about here]

Models [1] ([2]) and [3] ([4]) of Table 4-6 report the regression results from the pooled OLS (second stage of the 2SLS IV) for *Indep_IO* and *Grey_IO*, respectively. It is seen that the coefficients on *IFI* remain negative and highly significant (at the 1% level) for *Indep_IO* in both the Models, indicating that immigration fear sentiments significantly induce independent institutional investors to divest from their investee firms. On the contrary, coefficients on *IFI* remain insignificant across both the Models for *Grey_IO* suggesting that grey institutional investors' investment preferences do not get affected by immigration fear sentiments. Overall, these results support my conjecture that immigration fear leads independent institutional investors to reduce their investment stakes more than grey investors in their respective investee firms and provide support to my *investment style-based heterogeneity* hypothesis H_{2b}.

Finally, I report the pooled OLS (second stage of the 2SLS IV) estimates for *Pension_IO* and *Hedge_IO* in Models [5] ([6]) and [7] ([8]), respectively. I find the coefficients on *IFI* to be insignificant across all the Models for *Pension_IO* implying that immigration fear sentiments do not affect the investment behavior of pension funds (long-term institutional investors) in general. However, the highly significant (at the 1% level) negative coefficients on *IFI* in both the Models for *Hedge_IO* indicate that heightened immigration fear significantly triggers risk-aversion behavior among hedge funds (short-term institutional investors) as they choose to divest from their investee firms. Overall, these results provide support to my *investment horizon-based heterogeneity* hypothesis H_{2c}.[73]

[73] I conduct additional robustness tests using alternative measures/definitions to further validate the findings in Section 4.5.3 and 4.5.4. The results from these robustness tests remain consistent and in line with my main findings in Section 4.5.3 and 4.5.4, providing further support to all the *institutional investor heterogeneity* hypotheses.

4.5.5 The role of populism

I run regressions as per specification (4.3) to test my third hypothesis H_3 related to the role of populism. I present the results in Table 4-7. As noted earlier, I define the time-varying indicator variable *RWP* in two ways. Accordingly, in Model [1], *RWP* takes the value of one if a country's right-wing parties as percentage of total cabinet posts is greater than 50% in a year and zero otherwise.[74] In Model [2], *RWP* is set to one if a country's cabinet composition is either "hegemony of right/center parties" or "dominance of right/center parties" in a year and zero otherwise. In both the Models, I find the coefficients on the interaction term ($RWP \times IFI$) to be negative and highly significant at the 1% level. This suggests that populism does play a significant moderating role in the relationship between immigration fear sentiments and institutional ownership as RWP countries seem to deter investments from institutional investors more amidst heightened immigration fear than non-RWP countries. The coefficients on *IFI* in both the Models remain negative and highly significant (at the 1% level), consistent with the main results in Section 5.1. Overall, these results support my *populism* hypothesis H_3.

[Table 4-7 about here]

4.5.6 Evidence from an exogenous shock on investment deterrence and the role of populism

To provide more evidence to support my findings, I use an exogenous event (shock) that caused an exogenous increase in immigration fear sentiments in an empirical analysis similar to a difference-in-differences approach. For this, I exploit the 2015 European refugee crisis (ERC) as the exogenous event, which undoubtedly caused an

[74] My results do not change qualitatively when I increase this threshold to 55%, 60%, and 65%.

exponential spike in immigration fear among the local populace of Europe and the US (Greenhill, 2016; Holmes and Castañeda, 2016).[75] In line with my predictions, I assign a treatment status to firms by allocating them into more affected (less affected) groups if they are based in countries with RWP (non-RWP) parties in power. Accordingly, I run regressions as per the following specification (4.4):

$$IO_{ict} = \alpha + \beta.(RWP_{ct} \times ERC_t) + \rho.RWP_{ct} + \boldsymbol{X_{it-1}}.\boldsymbol{\delta}' + \boldsymbol{Z_{ct-1}}.\boldsymbol{\theta}' + \gamma_i + \tau_t + \varepsilon_{ict} \quad (4.4)$$

where the variables IO_{ict} and RWP_{ct} are as per specification (4.3). ERC_t is a categorical variable that is set to one if year *t* falls within the three-year post-ERC period (i.e., Years 2015-2017) and zero if year *t* falls within the three-year pre-ERC period (i.e., Years 2012-2014). $\boldsymbol{X_{it-1}}$ and $\boldsymbol{Z_{ct-1}}$ are vectors of one year lagged key firm-level and country-level control variables, respectively, as specified in specification (4.1). γ_i and τ_t control for firm and year fixed effects, respectively. The key coefficient of interest is from the interaction term ($RWP_{ct} \times ERC_t$) or β, which captures the differential causal impact of ERC (i.e., heightened immigration fear sentiments) on institutional ownership in RWP countries, relative to non-RWP countries.

[Table 4-8 about here]

I present the results from the exogenous shock-based analysis in Table 4-8. In Model [1], *RWP* takes the value of one if a country's right-wing parties as percentage of total cabinet posts is greater than 50% in a year and zero otherwise. In Model [2], *RWP* is set to one if a country's cabinet composition is either "hegemony of right/center parties" or "dominance of right/center parties" in a year and zero otherwise. I find the coefficients

[75] For a visual reference, see https://www.policyuncertainty.com/immigration_fear.html

on the interaction term (*RWP×ERC*) in both the Models to be negative and generally significant (at least at the 5% level). The results suggest that compared to the pre-ERC period, in the post-ERC period (with heightened immigration fear sentiments) institutional investors reduce their investment stakes between 1.57% to 1.88% in firms based in RWP countries, relative to the ones in non-RWP countries. Overall, these results re-validate the negative causal relation between immigration fear sentiments and institutional ownership and that the relation is more pronounced in RWP countries than in non-RWP countries. Thus, the findings provide additional support to my primary *investment deterrence* hypothesis H_1 and *populism* hypothesis H_3.

4.5.7 Fear or information – Which do institutional investors respond to?

So far, the findings in this study are primarily based on the notion that higher immigration fear sentiments trigger greater risk-aversion in institutional investors as a response to the emotional distress and anxiety caused by the fear and this influences them in their decision to divest from their investee firms. Even though there is ample evidence in the literature that suggests that institutional investors are prone to psychological and behavioral biases (Alok et al., 2020; DeVault et al., 2019; Sias, 2004), an alternative view contends that institutional investors make their investment decisions based on relevant information related to future returns (Baik et al., 2010; Gompers and Metrick, 2001; Yan and Zhang, 2009). Thus, institutional investors reducing their investment stakes in their investee firms due to higher immigration fear sentiments could be based on the information that such increased immigration fear leads to lower firm performance and, consequently, lower future returns.

The literature also provides some support to this information-based explanation. For instance, higher levels of immigration fear sentiments could trigger policy changes at the government level, particularly to immigration related policies resulting in greater migration policy uncertainties (Baker et al., 2015). Such government policy uncertainties may reduce stock prices and increase risk-premia resulting in lower future returns for the investors (Pástor and Veronesi, 2013, 2012). Further, such macro-level uncertainties could also increase discount rates resulting in poorer firm performance (Bansal et al., 2014).

To better understand the channel through which immigration fear sentiments induce institutional investors to divest from their investee firms, I take an approach similar to Alok et al. (2020) and test the relation between immigration fear sentiments and future firm performance. If higher levels of immigration fear lead to lower firm performance, then it is plausible that institutional investors make their divestment choices based on information under such circumstances. However, if no such relationship is observed, then the apparent negative relationship between immigration fear and institutional investors' investments could be attributed to the fear-based psychological response of increased risk-aversion in institutional investors. To test this, I run regressions as per the following specification (4.5):

$$FP_{ict+1} = \alpha + \beta . IFI_{ct} + \boldsymbol{X_{it}} . \boldsymbol{\delta'} + \boldsymbol{Z_{ct}} . \boldsymbol{\theta'} + \gamma_i + \tau_t + \varepsilon_{ict} \qquad (5)$$

where the dependent variable FP_{ict+1} is the firm performance, proxied by either Tobin's Q (*TobinQ*), market to book ratio (*MB*), or return on asset (*ROA*), of firm *i* in the lead year *t+1*. IFI_{ct} is as per specification (4.1). $\boldsymbol{X_{it}}$ and $\boldsymbol{Z_{ct}}$ are vectors of key firm-level and country-level control variables, respectively, that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Section 3.4. γ_i and τ_t control for firm and year fixed effects, respectively. The key coefficient of interest is β, which shows the association between immigration fear sentiments and future firm performance.

[Table 4-9 about here]

Alongside the pooled OLS specification (4.5), I also conduct 2SLS IV analysis on firm performance by instrumenting *IFI* with my primary IV (*Terror_Geo*). All the regression results are presented in Table 4-9. Models [1] ([2]), [3] ([4]), and [5] ([6]) report the results from the pooled OLS (second stage of the 2SLS IV) regressions for *TobinQ*, *MB*, and *ROA*, respectively. I find the coefficients on *IFI* to be insignificant across all the performance measures in all the Models. This suggests that immigration fear does not affect future firm performance in general which refutes the information-based explanation of institutional investors' divestments and immigration fear relationship. Thus, I conclude that it is the fear-based psychological response of greater risk-aversion in institutional investors that induces their divestment behavior amidst heightened immigration fear sentiments.

4.6 Conclusion

Immigration has become a highly salient political issue in several countries in the recent decades (Baker et al., 2015). Perceived by the local populace as a source of security, economic, and cultural threat, immigrants are now significantly influencing electoral outcomes and driving up right-wing populism via the route of heightened immigration fear and anti-immigration sentiments (De Vreese and Boomgaarden, 2005; Mughan and Paxton, 2006). Given the significance of this issue, in this study I investigate whether immigration fear affects the investment choices and preferences of institutional investors. In line with the conjectures that immigration related fear sentiments trigger greater risk-aversion in investors and degrade market conditions through deteriorating social capital and trust, the empirical results credibly show that institutional investors significantly reduce their investment stakes in their investee firms during periods of heightened immigration fear.

Further analyses show that heterogenous institutional investors react differentially to increased immigration fear as the results show that only domestic, independent, and short-term institutional investors make divestment choices amidst heightened immigration fear sentiments. Moreover, right-wing populism amplifies the impact of immigration fear on institutional investors as results indicate that countries with RWP parties in power (RWP countries) deter institutional investors' investments more than non-RWP countries during times of elevated immigration fear sentiments. I utilize instrumental variables (IVs) and employ an exogenous shock in my empirical analyses to show causal associations and reinforce my findings. Finally, I demonstrate that institutional investors divest amidst heightened immigration fear due to their risk-aversion behavior and not because of having better information related to future firm performance.

4.7 Tables of Chapter 4

Table 4-1 Variable description and sources

Variable	Description	Source
Institutional ownership variables		
IO	Total percentage of share ownership by all institutional investors	CIQ
DIO	Total percentage of share ownership by DIIs	CIQ
FIO	Total percentage of share ownership by FIIs	CIQ
Indep_IO	Total percentage of share ownership by independent institutional investors	CIQ
Grey_IO	Total percentage of share ownership by grey institutional investors	CIQ
Pension_IO	Total percentage of share ownership by pension funds (Long-term institutional investors)	CIQ
Hedge_IO	Total percentage of share ownership by hedge funds (Short-term institutional investors)	CIQ
Key independent variable		
IFI	Immigration fear index of Baker et al. (2015) normalized between 0 to 100	Baker et al. (2015)
Key firm-level control variables		
Size	Natural logarithm of total assets	CIQ
Leverage	The ratio of the book value of debt-to-equity	CIQ
CurRatio	Ratio of current assets to current liabilities	CIQ
BlockOwn	Annual additions to property, plant, and equipment scaled by total assets	CIQ
DivYield	Ratio of total dividends to market value of equity	CIQ
MB	Market capitalization scaled by book value of equity	CIQ
R&D	Research and development expenditure scaled by total assets	CIQ
Analyst	Total number of analysts following the firm	CIQ
Key country-level control variables		
GDP_Gr	Country's annual GDP growth rate	WDI
GDP_PC	Natural logarithm of country's GDP per capita	WDI
CGI	Annual mean of country's six governance indicators of Kaufmann et al. (2011) normalized between 0 to 100	WGI
Instrumental variable		
Terror_Geo	Total number of terrorist attacks surrounding the country	GTD

Table 4-2 Descriptive statistics

Table 4-2 provides the summary statistics of all key variables. Panel A reports the overall sample summery statistics whereas Panels B, C, D, and E reports the summery statistics for US, UK, France, and Germany, respectively. *IO* is the total percentage share ownership by institutional investors. Similarly, *DIO*, *FIO*, *Indep_IO*, *Grey_IO*, *Pension_IO*, and *Hedge_IO* are the total percentage share ownership by domestic, foreign, independent, grey, pension fund, and hedge fund institutional investors, respectively. *IFI* is the immigration fear index of Baker et al. (2015) normalized between 0 to 100. *Size* is the natural logarithm of total assets. *Leverage* is the ratio of the book value of debt-to-equity. *CurRatio* is the ratio of current assets to current liabilities. *BlockOwn* is the percentage share ownership of the largest shareholder. *MB* is the market capitalization scaled by book value of equity. *DivYield* is the ratio of total dividends to market value of equity. *R&D* is the total research and development expenditure scaled by total assets. *Analyst* is the number of analysts following the firm. *GDP_Gr* is the year-on-year GDP growth rate. GDP_PC is the natural logarithm of GDP per capita. Finally, CGI is the yearly mean of the six governance indicators of Kaufmann et al. (2011) normalized between 0 to 100. See Table 4-1 for detailed description and sources of the variables. The sample period of study ranges from 2005 to 2019. Data sources: S&P Capital IQ (CIQ), Baker et al. (2015), World Bank's World Development Indicators (WDI) and Worldwide Governance Indicators (WGI) databases.

Variable	Observations	Mean	Std. Deviation	Min	P25	Median	P75	Max
Panel A: Overall sample summary statistics								
IO	157,266	33.48	36.55	0	0	16.95	67.75	100
DIO	157,266	26.84	31.99	0	0	10.07	51.45	100
FIO	157,266	6.97	12.34	0	0	0.86	9.01	63.69
Indep_IO	157,266	29.08	34.22	0	0	11.69	56.76	100
Grey_IO	157,266	4.53	9.49	0	0	0.52	4.43	55.78
Pension_IO	157,266	1.05	1.99	0	0	0	1.32	10.45
Hedge_IO	157,266	3.50	7.26	0	0	0	3.46	38.74
IFI	157,266	11.02	14.13	0	2.09	6.89	12.07	100
Size	157,266	5.10	2.84	0	3.03	5.26	7.13	11.64
Leverage	152,754	0.57	2.10	-7.33	0	0.18	0.77	13.19
CurRatio	151,000	3.14	6.59	0	0.67	1.41	2.71	49.33
BlockOwn	157,266	13.46	18.52	0	0.01	7.4	16.31	87.55
MB	152,754	1.75	6.25	-28	0	1.03	2.29	37.41
DivYield	157,266	1.30	2.43	0	0	0	1.80	12.30
R&D	151,170	0.04	0.14	0	0	0	0	1
Analyst	157,266	2.90	5.52	0	0	0	3	50
GDP_Gr	157,266	1.70	1.62	-5.69	1.54	2.16	2.56	4.18
GDP_PC	157,266	10.76	0.10	10.57	10.65	10.79	10.82	10.93
CGI	157,266	47.08	19.59	0	35.91	40.01	59.8	100
Panel B: Summary statistics for US								
IO	97,354	37.48	38.32	0	0	22.45	76.74	100
DIO	97,354	33.64	35.1	0	0	19.42	67.62	100
FIO	97,354	4.38	7.24	0	0	0.66	6.98	63.69
Indep_IO	97,354	33.47	36.49	0	0	16.67	68.42	100
Grey_IO	97,354	4.24	9.09	0	0	1.08	3.97	55.78
Pension_IO	97,354	1.17	1.96	0	0	0	1.93	10.45
Hedge_IO	97,354	5.09	8.35	0	0	1.03	6.72	38.75
IFI	97,354	5.57	5.41	0	1.75	3.32	6.89	19.41

Size	97,354	5.20	3.01	0	2.88	5.67	7.40	11.64
Leverage	93,897	0.55	2.13	-7.34	0	0.2	0.82	13.19
CurRatio	93,007	2.84	5.85	0	0.35	1.35	2.72	49.33
BlockOwn	97,354	12.07	16.28	0	0.72	7.51	14.48	87.57
MB	93,897	1.83	7.25	-28	0.26	1.11	2.46	37.37
DivYield	97,354	1.31	2.51	0	0	0	1.70	12.3
R&D	91,956	0.05	0.17	0	0	0	0	1
Analyst	97,354	3.21	5.59	0	0	0	4	50
GDP_Gr	97,354	1.87	1.45	-2.54	1.64	2.25	2.85	3.51
GDP_PC	97,354	10.83	0.04	10.77	10.8	10.82	10.86	10.93
CGI	97,354	37.56	7.52	14.05	34.11	37.03	41.49	51.76

Panel C: Summary statistics for UK

IO	34,078	36.83	36.05	0	0	29.45	70.74	100
DIO	34,078	22.78	24.6	0	0	15.76	41.14	100
FIO	34,078	14.11	18.67	0	0	4.65	23.41	63.69
Indep_IO	34,078	31.08	32.68	0	0	20.64	58.51	100
Grey_IO	34,078	5.94	9.68	0	0	1.75	7.9	55.78
Pension_IO	34,078	1.13	2.33	0	0	0	0.9	10.45
Hedge_IO	34,078	1.30	4.56	0	0	0	0.06	38.75
IFI	34,078	20.18	14.87	0.51	9.61	15.11	32.66	54.58
Size	34,078	4.67	2.46	0	2.91	4.55	6.26	11.64
Leverage	33,536	0.43	1.91	-7.34	0	0.06	0.48	13.19
CurRatio	32,849	4.20	8.65	0	0.86	1.45	3	49.33
BlockOwn	34,078	11.66	15.08	0	0	7.24	16.43	87.57
MB	33,536	1.63	4.48	-28	0	0.89	2	37.37
DivYield	34,078	1.31	2.34	0	0	0	2	12.3
R&D	33,579	0.01	0.07	0	0	0	0	1
Analyst	34,078	2.22	4.98	0	0	0	1	47
GDP_Gr	34,078	1.50	1.77	-4.25	1.46	1.92	2.43	3.18
GDP_PC	34,078	10.62	0.03	10.57	10.6	10.62	10.65	10.69
CGI	34,078	68.72	11.47	49.44	62.83	66.18	77.24	88.79

Panel D: Summary statistics for France

IO	12,793	14.63	20.90	0	0	4.60	21.96	100
DIO	12,793	8.13	14.61	0	0	1.65	9.98	100
FIO	12,793	6.40	12.01	0	0	0.22	7.32	63.69
Indep_IO	12,793	9.99	15.87	0	0	2.36	13.84	100
Grey_IO	12,793	4.37	11.04	0	0	0	1.03	55.78
Pension_IO	12,793	0.66	1.73	0	0	0	0.11	10.45
Hedge_IO	12,793	0.29	2.15	0	0	0	0	38.75
IFI	12,793	11.93	5.38	6.88	7.96	8.94	13.88	25.08
Size	12,793	5.40	2.57	0	3.45	5.07	7.04	11.64
Leverage	12,645	0.82	2.09	-7.34	0.09	0.41	0.98	13.19
CurRatio	12,570	2.47	5.18	0	0.99	1.4	2.13	49.33
BlockOwn	12,793	21.77	26.72	0	0	7.5	39.63	87.57
MB	12,645	1.61	3.97	-28	0.18	1	2.06	37.37
DivYield	12,793	1.43	2.40	0	0	0	2.20	12.3

R&D	12,658	0.01	0.07	0	0	0	0	1
Analyst	12,793	2.96	6	0	0	0	2	38
GDP_Gr	12,793	1.17	1.32	-2.87	0.58	1.51	2.19	2.45
GDP_PC	12,793	10.64	0.03	10.6	10.62	10.63	10.64	10.7
CGI	12,793	25.60	13.73	0	9.66	26.69	39.59	43.56

Panel E: Summary statistics for Germany

IO	13,041	13.34	20.44	0	0	2.00	19.95	100
DIO	13,041	4.99	12.14	0	0	0.25	4.36	100
FIO	13,041	8.21	14.37	0	0	0.11	10.59	63.69
Indep_IO	13,041	9.84	16.06	0	0	0.97	14.08	100
Grey_IO	13,041	3.20	9.88	0	0	0	0.05	55.78
Pension_IO	13,041	0.35	1.05	0	0	0	0	10.45
Hedge_IO	13,041	0.46	2.45	0	0	0	0	38.75
IFI	13,041	26.92	29.82	3.06	5.50	11.34	37.64	100
Size	13,041	5.16	2.6	0	3.40	4.88	6.64	11.64
Leverage	12,676	0.89	2.3	-7.34	0	0.25	0.88	13.19
CurRatio	12,574	3.30	6.45	0	1.05	1.64	2.77	49.33
BlockOwn	13,041	20.35	26.98	0	0	5.43	32.22	87.57
MB	12,676	1.69	3.51	-28	0	1.08	2.12	37.37
DivYield	13,041	1.10	2.06	0	0	0	1.6	12.3
R&D	12,977	0.01	0.06	0	0	0	0	1
Analyst	13,041	2.29	5.67	0	0	0	1	39
GDP_Gr	13,041	1.48	2.34	-5.69	0.56	1.49	2.98	4.18
GDP_PC	13,041	10.68	0.06	10.57	10.63	10.69	10.72	10.77
CGI	13,041	82.73	7.27	73.28	76.28	82.23	87.45	100

Table 4-3 Immigration fear and institutional investors

Table 4-3 reports the regression results from the pooled OLS specification (4.1) and the 2SLS IV specification (4.2). Model [1] shows the first stage estimates of the 2SLS IV specification (4.2), where immigration fear index (*IFI*), as defined in Table 4-2, is instrumented by one year lagged *Terror_Geo*, which is the total number of terrorist attacks surrounding the country. Models [2] and [3] show the pooled OLS and second stage of the 2SLS IV estimates, respectively where the dependent variable is institutional ownership (*IO*), as defined in Table 4-2. One year lagged firm-level and country-level control variables that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *MB*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Table 4-2, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The sample period of study ranges from 2005 to 2019. Data sources: CIQ, Baker et al. (2015), WDI, WGI, and Global Terrorism Database (GTD) databases.

Dependent variable:	*IFI*	*IO*	
	First Stage	OLS	IV
	[1]	[2]	[3]
IFI		**-0.067***** **(-5.90)**	**-0.173***** **(-8.80)**
Size	-0.821*** (-13.31)	4.661*** (25.85)	4.538*** (25.04)
Leverage	-0.0151 (-1.07)	-0.327*** (-6.31)	-0.329*** (-6.34)
CurRatio	0.021*** (3.69)	0.016 (1.18)	0.020 (1.43)
BlockOwn	-0.020*** (-6.28)	0.178*** (21.98)	0.177*** (21.96)
MB	0.004 (1.03)	0.203*** (15.99)	0.203*** (15.99)
DivYield	-0.034* (-1.90)	0.431*** (8.39)	0.424*** (8.27)
R&D	-0.171 (-0.76)	-0.395 (-0.41)	-0.413 (-0.43)
Analyst	0.055*** (3.03)	1.350*** (24.93)	1.354*** (25.50)
GDP_Gr	-0.684*** (-18.55)	-0.189** (-2.45)	-0.449*** (-5.26)
GDP_PC	75.290*** (24.23)	-14.940** (-1.97)	-4.524 (-0.58)
CGI	0.513*** (110.92)	0.032*** (2.95)	0.083*** (6.05)
Terror_Geo	0.124*** (70.13)		
Adj. R^2	0.81	0.81	-
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	3,569.72***	-	-
Kleibergen–Paap rk Wald F statistic	4,918.75	-	-
Observations	132,211	132,211	132,211

Table 4-4 Alternative measures/definitions of institutional investor preferences

Table 4-4 reports the regression results from the pooled OLS specification (4.1) and the second stage of the 2SLS IV specification (4.2), as indicated in each Model. Depending on the Model, the dependent variable is either year-on-year change in institutional ownership (*ΔIO*), total number of institutional investors (*Total_II*), total number of existing institutional investors as a percentage of one year lagged *Total_II* (*Ext_II/Total_II*), or total percentage of share ownership by existing institutional investors (*Ext_IO*). *IFI* is the immigration fear index, as defined in Table 4-2. In the IV Models, *IFI* is instrumented by one year lagged *Terror_Geo*, as shown in Table 4-3. One year lagged firm-level and country-level control variables that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *MB*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Table 4-2, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The sample period of study ranges from 2005 to 2019. Data sources: CIQ, Baker et al. (2015), WDI, WGI, and GTD databases.

Dep. Var:	*ΔIO*		*Total_II*		*Ext_II/Total_II*		*Ext_IO*	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
IFI	**-0.585*** **	**-0.687*** **	**-1.082*** **	**-1.431*** **	**-0.101*** **	**-0.224*** **	**-0.045*** **	**-0.075*** **
	(-4.91)	**(-3.40)**	**(-21.56)**	**(-21.42)**	**(-6.62)**	**(-9.56)**	**(-4.29)**	**(-4.58)**
Size	-17.310***	-17.420***	10.990***	10.580***	5.625***	5.483***	4.622***	4.589***
	(-8.11)	(-8.10)	(16.08)	(15.54)	(25.51)	(24.76)	(28.21)	(27.91)
Leverage	3.475***	3.474***	-0.650***	-0.654***	-0.427***	-0.429***	-0.373***	-0.373***
	(4.06)	(4.06)	(-3.99)	(-4.02)	(-7.25)	(-7.28)	(-8.05)	(-8.06)
CurRatio	-0.780***	-0.777***	0.007	0.018	0.030*	0.034*	0.038***	0.039***
	(-3.99)	(-3.97)	(0.22)	(0.56)	(1.67)	(1.90)	(2.97)	(3.04)
BlockOwn	-3.298***	-3.298***	-0.102***	-0.103***	0.465***	0.465***	0.242***	0.242***
	(-31.71)	(-31.73)	(-4.88)	(-4.92)	(37.04)	(37.01)	(27.36)	(27.35)
MB	-1.670***	-1.671***	0.739***	0.739***	0.278***	0.278***	0.212***	0.212***
	(-6.97)	(-6.98)	(11.61)	(11.64)	(12.96)	(12.97)	(17.18)	(17.18)
DivYield	-6.757***	-6.764***	0.849***	0.827***	1.029***	1.021***	0.579***	0.577***
	(-11.73)	(-11.74)	(4.09)	(3.99)	(15.36)	(15.25)	(11.32)	(11.29)
R&D	72.67***	72.65***	8.525***	8.466***	1.427	1.407	-2.417***	-2.422***
	(4.19)	(4.19)	(4.04)	(3.97)	(1.00)	(0.98)	(-3.01)	(-3.02)
Analyst	-12.92***	-12.91***	11.80***	11.82***	0.976***	0.980***	1.776***	1.777***
	(-27.72)	(-27.64)	(25.49)	(25.74)	(21.11)	(21.60)	(29.58)	(29.75)
GDP_Gr	-2.388	-2.640	-0.733***	-1.590***	0.117	-0.184	-0.174**	-0.246***
	(-1.54)	(-1.64)	(-3.20)	(-6.12)	(0.85)	(-1.26)	(-2.50)	(-3.06)
GDP_PC	565.70***	575.70***	171.20***	205.50***	19.900*	31.950***	-48.880***	-46.000***
	(6.78)	(6.84)	(7.23)	(8.43)	(1.86)	(2.89)	(-7.26)	(-6.47)
CGI	0.330**	0.380**	0.606***	0.774***	0.097***	0.156***	0.039***	0.053***
	(2.27)	(2.18)	(17.72)	(18.12)	(6.17)	(8.00)	(4.07)	(4.71)
Adj. R^2	0.07	-	0.92	-	0.59	-	0.82	-
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,211	132,211	132,211	132,211	132,211	132,211	132,211	132,211

Table 4-5 Institutional investor heterogeneity: DIIs and FIIs

Table 4-5 reports the regression results from the pooled OLS specification (4.1) and the second stage of the 2SLS IV specification (4.2), as indicated in each Model. Depending on the Model, the dependent variable is either domestic institutional ownership (*DIO*) or foreign institutional ownership (*FIO*), all as defined in Table 4-2. *IFI* is the immigration fear index, as defined in Table 4-2. In the IV Models, *IFI* is instrumented by one year lagged *Terror_Geo*, as shown in Table 4-3. One year lagged firm-level and country-level control variables that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *MB*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Table 4-2, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The sample period of study ranges from 2005 to 2019. Data sources: CIQ, Baker et al. (2015), WDI, WGI, and GTD databases.

Dependent variable:	*DIO*		*FIO*	
	OLS	IV	OLS	IV
	[1]	[2]	[3]	[4]
IFI	**-0.089*** **	**-0.223*** **	0.010	0.019
	(-9.95)	**(-13.85)**	(1.52)	(1.61)
Size	3.477***	3.323***	1.236***	1.227***
	(22.55)	(21.51)	(14.95)	(13.28)
Leverage	-0.259***	-0.261***	-0.088***	-0.089***
	(-5.85)	(-5.90)	(-4.12)	(-3.98)
CurRatio	0.027**	0.031***	-0.016**	-0.018
	(2.37)	(2.73)	(-2.05)	(-1.30)
BlockOwn	0.144***	0.144***	0.033***	0.036***
	(20.93)	(20.80)	(8.32)	(7.52)
MB	0.164***	0.163***	0.045***	0.048***
	(14.86)	(14.84)	(7.86)	(7.01)
DivYield	0.229***	0.220***	0.182***	0.185***
	(5.34)	(5.15)	(7.76)	(6.74)
R&D	-2.069**	-2.091**	1.443**	1.548**
	(-2.44)	(-2.47)	(2.46)	(2.48)
Analyst	0.872***	0.877***	0.477***	0.486***
	(20.51)	(21.21)	(20.84)	(19.76)
GDP_Gr	-0.229***	-0.557***	-0.008	-0.032
	(-3.95)	(-8.50)	(-0.18)	(-0.53)
GDP_PC	8.533	21.65***	-10.70**	-8.877*
	(1.51)	(3.72)	(-2.38)	(-1.76)
CGI	0.046***	0.110***	-0.015**	-0.019**
	(5.40)	(10.10)	(-2.49)	(-2.05)
Adj. R^2	0.81	-	0.64	-
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	132,211	132,211	132,211	132,211

Table 4-6 Institutional investor heterogeneity: Institution type

Table 4-6 reports the regression results from the pooled OLS specification (4.1) and the second stage of the 2SLS IV specification (4.2), as indicated in each Model. Depending on the Model, the dependent variable is either independent institutional ownership (*Indep_IO*), grey institutional ownership (*Grey_IO*), pension fund institutional ownership (*Pension_IO*), or hedge fund institutional ownership (*Hedge_IO*), all as defined in Table 4-2. *IFI* is the immigration fear index, as defined in Table 4-2. In the IV Models, *IFI* is instrumented by one year lagged *Terror_Geo*, as shown in Table 4-3. One year lagged firm-level and country-level control variables that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *MB*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Table 4-2, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The sample period of study ranges from 2005 to 2019. Data sources: CIQ, Baker et al. (2015), WDI, WGI, and GTD databases.

Dep. Var:	*Indep_IO*		*Grey_IO*		*Pension_IO*		*Hedge_IO*	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
IFI	**-0.075*****	**-0.187*****	0.007	0.013	-0.001	-0.001	**-0.033*****	**-0.068*****
	(-7.54)	**(-10.97)**	(1.57)	(1.44)	(-1.13)	(-0.45)	**(-12.88)**	**(-13.29)**
Size	3.967***	3.838***	0.741***	0.747***	0.113***	0.113***	0.498***	0.457***
	(25.14)	(24.22)	(10.32)	(10.27)	(12.10)	(12.00)	(9.77)	(8.88)
Leverage	-0.351***	-0.353***	0.018	0.018	-0.008***	-0.008***	-0.030**	-0.031**
	(-7.64)	(-7.67)	(0.86)	(0.87)	(-3.22)	(-3.22)	(-2.00)	(-2.03)
CurRatio	0.021*	0.025**	-0.008	-0.008	-0.001	-0.001	0.015***	0.016***
	(1.75)	(2.04)	(-1.45)	(-1.48)	(-1.29)	(-1.30)	(3.73)	(4.03)
BlockOwn	0.107***	0.106***	0.067***	0.067***	0.002***	0.002***	0.019***	0.019***
	(16.67)	(16.61)	(16.77)	(16.77)	(5.91)	(5.91)	(10.88)	(10.83)
MB	0.200***	0.200***	0.008	0.008	0.004***	0.004***	0.016***	0.016***
	(17.49)	(17.47)	(1.55)	(1.55)	(5.69)	(5.69)	(4.11)	(4.10)
DivYield	0.409***	0.402***	0.017	0.017	0.035***	0.035***	-0.061***	-0.064***
	(8.80)	(8.65)	(0.87)	(0.88)	(9.78)	(9.78)	(-4.53)	(-4.69)
R&D	-1.204*	-1.223*	0.374	0.375	0.100***	0.100***	-1.238***	-1.244***
	(-1.65)	(-1.67)	(0.67)	(0.67)	(2.61)	(2.61)	(-3.74)	(-3.76)
Analyst	1.431***	1.435***	-0.049***	-0.049***	0.077***	0.077***	0.110***	0.111***
	(27.20)	(27.88)	(-3.37)	(-3.38)	(23.89)	(23.89)	(10.25)	(10.51)
GDP_Gr	-0.125**	-0.400***	-0.085**	-0.071*	-0.022***	-0.022***	-0.056***	-0.143***
	(-2.01)	(-5.71)	(-2.34)	(-1.80)	(-4.32)	(-3.63)	(-3.39)	(-7.41)
GDP_PC	-16.370***	-5.361	2.770	2.228	1.926***	1.907***	12.570***	16.030***
	(-2.58)	(-0.83)	(0.86)	(0.66)	(3.60)	(3.40)	(8.66)	(10.41)
CGI	0.045***	0.099***	-0.019***	-0.021***	-0.005***	-0.005***	0.010***	0.027***
	(5.00)	(8.73)	(-3.66)	(-3.02)	(-6.15)	(-4.60)	(4.15)	(8.65)
Adj. R^2	0.83	-	0.52	-	0.71	-	0.60	-
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,211	132,211	132,211	132,211	132,211	132,211	132,211	132,211

Table 4-7 The role of populism

Table 4-7 reports the regression results from specification (4.3). The dependent variable is institutional ownership (*IO*), as defined in Table 4-2. *IFI* is the immigration fear index, as defined in Table 4-2. *RWP* is an indicator variable and, in In Model [1], it takes the value of one if the country's right-wing parties as percentage of total cabinet posts is greater than 50% and zero otherwise and in Model [2], it is set to one if the country's cabinet composition is either "hegemony of right/center parties" or "dominance of right/center parties" and zero otherwise. One year lagged firm-level and country-level control variables that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *MB*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Table 4-2, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The sample period of study ranges from 2005 to 2019. Data sources: CIQ, Baker et al. (2015), Comparative Political Data Set (CPDS), WDI, and WGI databases.

Dependent variable:	*IO*	
	[1]	[2]
IFI×RWP	**-0.017*** **	**-0.015*** **
	(-4.19)	**(-4.77)**
IFI	**-0.061*** **	**-0.064*** **
	(-5.97)	**(-5.90)**
RWP	0.485	-0.083
	(1.64)	(-0.32)
Size	4.517***	4.418***
	(24.97)	(24.72)
Leverage	-0.322***	-0.317***
	(-6.23)	(-6.20)
CurRatio	0.014	0.014
	(1.04)	(0.99)
BlockOwn	0.172***	0.166***
	(21.26)	(20.72)
MB	0.201***	0.197***
	(15.74)	(15.62)
DivYield	0.395***	0.381***
	(7.68)	(7.49)
R&D	-0.512	-0.499
	(-0.53)	(-0.53)
Analyst	1.341***	1.320***
	(24.89)	(24.62)
GDP_Gr	-0.010	-0.227***
	(-1.41)	(-3.37)
GDP_PC	-14.160**	-5.082
	(-2.06)	(-0.76)
CGI	0.016	0.018*
	(1.48)	(1.71)
Adj. R^2	0.81	0.81
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	132,211	132,211

Table 4-8 Evidence from an exogenous shock

Table 4-8 reports the regression results from specification (4.4). The dependent variable is institutional ownership (*IO*), as defined in Table 4-2. *RWP* is an indicator variable and, in In Model [1], it takes the value of one if the country's right-wing parties as percentage of total cabinet posts is greater than 50% and zero otherwise and in Model [2], it is set to one if the country's cabinet composition is either "hegemony of right/center parties" or "dominance of right/center parties" and zero otherwise. *ERC* is a categorical variable that takes the value of one for the three-year post-ERC period (2015-2017) and zero for the three-year pre-ERC period (2012-2014). One year lagged firm-level and country-level control variables that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *MB*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Table 4-2, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The sample period of study ranges from 2012 to 2017. Data sources: CIQ, CPDS, WDI, and WGI databases.

Dependent variable:	*IO*	
	[1]	[2]
RWP×ERC	**-1.571****	**-1.878*****
	(-2.43)	**(-5.19)**
RWP	-0.494	1.605***
	(-0.54)	(3.30)
Size	4.954***	4.956***
	(18.00)	(18.00)
Leverage	-0.189**	-0.189**
	(-2.54)	(-2.54)
CurRatio	0.046***	0.045***
	(2.59)	(2.58)
BlockOwn	0.131***	0.131***
	(12.43)	(12.44)
MB	0.126***	0.126***
	(7.05)	(7.04)
DivYield	0.286***	0.285***
	(4.06)	(4.05)
R&D	-2.677*	-2.669*
	(-1.80)	(-1.79)
Analyst	1.225***	1.228***
	(16.50)	(16.62)
GDP_Gr	-0.108	-0.391***
	(-0.88)	(-3.32)
GDP_PC	123.20***	149.80***
	(6.66)	(9.43)
CGI	-0.056***	-0.051***
	(-3.53)	(-3.14)
Adj. R^2	0.86	0.86
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	56,548	56,548

Table 4-9 Immigration fear and future firm performance

Table 4-9 reports the regression results from specification (4.5). The dependent variable is one year lead firm performance proxied by either Tobins' Q (*TobinQ*), market to book ratio (*MB*), or return on assets (*ROA*). *IFI* is the immigration fear index, as defined in Table 4-2. In the IV Models, *IFI* is instrumented by one year lagged *Terror_Geo*, as defined in Table 4-3. Firm-level and country-level control variables that include *Size*, *Leverage*, *CurRatio*, *BlockOwn*, *DivYield*, *R&D*, *Analyst*, *GDP_Gr*, *GDP_PC*, and *CGI*, all as defined in Table 4-2, are included in all regressions alongside firm and year fixed effects. Standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively. The sample period of study ranges from 2005 to 2019. Data sources: CIQ, Baker et al. (2015), WDI, WGI, and GTD databases.

Dep. Var:	*TobinQ (lead)*		*MB (lead)*		*ROA (lead)*	
	OLS	IV	OLS	IV	OLS	IV
	[1]	[2]	[3]	[4]	[5]	[6]
IFI	-0.001	-0.003	0.002	-0.003	0.023	-0.010
	(-1.14)	(-1.19)	(0.81)	(-0.84)	(1.34)	(-0.27)
Size	-0.519***	-0.521***	-0.003	-0.009	5.257***	5.216***
	(-13.45)	(-13.43)	(-0.08)	(-0.25)	(11.03)	(10.84)
Leverage	-0.009	-0.009	0.074***	0.074***	0.113	0.111
	(-1.60)	(-1.61)	(3.95)	(3.94)	(1.51)	(1.49)
CurRatio	-0.008***	-0.008***	0.005**	0.005**	0.021	0.022
	(-3.29)	(-3.27)	(2.21)	(2.27)	(0.80)	(0.85)
BlockOwn	0.013***	0.013***	0.013***	0.013***	-0.052***	-0.053***
	(8.43)	(8.43)	(7.14)	(7.12)	(-2.72)	(-2.75)
DivYield	0.004	0.004	-0.017**	-0.017**	-0.083**	-0.085**
	(1.20)	(1.19)	(-2.23)	(-2.25)	(-2.48)	(-2.54)
R&D	3.445***	3.444***	-0.803*	-0.807*	-78.590***	-78.610***
	(6.79)	(6.79)	(-1.75)	(-1.76)	(-11.37)	(-11.38)
Analyst	0.056***	0.056***	0.077***	0.077***	-0.189***	-0.188***
	(15.61)	(15.75)	(9.87)	(9.94)	(-5.53)	(-5.52)
GDP_Gr	0.034***	0.032***	0.013	0.007	0.250	0.212
	(3.12)	(2.87)	(0.66)	(0.36)	(1.56)	(1.29)
GDP_PC	-0.604	-0.525	0.479	0.706	-14.540	-12.940
	(-0.69)	(-0.59)	(0.39)	(0.57)	(-1.50)	(-1.28)
CGI	0.003**	0.003**	0.003	0.005*	0.039**	0.049**
	(2.10)	(2.26)	(1.52)	(1.94)	(1.96)	(2.31)
Adj. R^2	0.61	-	0.24	-	0.66	-
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131,530	131,530	131,356	131,356	117,857	117,857

5. Chapter 5: Discussion and conclusion

This thesis consists of three major empirical chapters exploring institutional investors' investment behavior and preferences in their investee firms under various exogenous factors. In this regard, the first empirical chapter (Chapter 2) studies the investment choices and preferences of heterogeneous foreign institutional investors (FIIs) based on different legal origins and/or different investment styles and objectives firms following mandatory CSR regulatory interventions. Next, in Chapter 3, I examine institutional investors' differential investment responses in rain-sensitive firms under the two extreme ends of extreme rainfall conditions (i.e., flooding vs. drought conditions). Finally, in the third empirical chapter (Chapter 4), I investigate how different institutional investors make investment decisions in their respective investee firms amidst heightened immigration-induced fear sentiments.

In the following sections, I summarize each empirical study's key findings and contributions, discuss the implications, identify some limitations of the thesis, and offer possible future research directions.

5.1 Summary of key findings and contributions

5.1.1 Mandatory CSR engagement and FIIs

Institutional investors claim to genuinely consider firms' efforts to better ESG activities when evaluating businesses' financial and sustainability performance (Amel-Zadeh and Serafeim, 2018; Ioannou and Serafeim, 2015). If that is the case, do FIIs prefer to invest more in companies legally required to spend a certain amount of their profits on CSR initiatives? Furthermore, FIIs from different legal origins, investment styles, and objectives may have differential preferences for their investee firms' CSR/ESG performance (Dyck et al., 2019; Liang and Renneboog, 2017). Thus, how do heterogeneous FIIs based on different legal origins and/or investment styles and objectives respond to such mandatory CSR interventions? In this empirical study, I answer these inquiries by utilizing Section 135 of India's Company's Act 2013, which requires certain listed companies meeting specific size thresholds to devote at least 2% of their net profits to CSR-related endeavors in a natural experiment setup.

By utilizing a novel hand-collected mandatory CSR expenditure dataset and employing PSM-DiD and MRDD as empirical identification strategies on a sample of listed Indian non-financial firms for the period between the fiscal years 2012-2017, I find that in the post-CSR mandate period, FIIs significantly increase their investment stakes in firms that comply with the mandated CSR engagement regulation compared to firms that do not. Economically speaking, I find that the average increase in FIIs' ownership in mandated CSR firms ranges from 7.5% to 8.5% more than non-CSR firms in the post-CSR regulatory period. Furthermore, I uncover that in the post-CSR reform period, firms complying with the CSR mandate attract investments from both new and existing FIIs. Moreover, I conduct additional tests and offer insights that mandated CSR firms that actually expend on the regulation-prescribed CSR activities tend to attract greater investments from FIIs than other firms.

I extend my investigation deeper and discover that not all categories of foreign investors draw to CSR initiatives similarly. As predicted by the literature, I offer proof that FIIs with civil law origin backgrounds are more likely to invest in mandated CSR firms than FIIs with common law backgrounds following the CSR reform. Furthermore, my findings show that independent and long-term FIIs (i.e., pension funds) significantly increase their asset allocations in the mandatory CSR law-compliant companies following the implementation of the CSR intervention. I also find evidence that Principles of Responsible Investment (PRI) signatory FIIs tend to invest more in CSR firms than non-signatory FIIs.

Finally, I test whether mandatory CSR engagement is value-relevant. The findings indicate that mandatory CSR activities tend to increase the market value of complying firms in the long run. In economic terms, it is observed that mandated CSR firms obtain 6.10% (*MB*) to 34.70% (*Tobin's Q*) more long-term market-based valuations than non-CSR firms in the post-CSR mandate period. Moreover, I show that mandatory CSR-induced higher FIIs' ownership acts as a channel through which the CSR mandate improves the long-term market value of CSR firms. To sum up, even though FIIs find higher CSR performance appealing, not all foreign investor types are equally drawn to such CSR efforts. The empirical findings in this study suggest that when reacting to mandatory CSR legislation, investors' legal origin and investment goals matter greatly.

This empirical study contributes to the literature in numerous ways. First, by using ESG indices as a proxy for voluntary CSR practices, the majority of the current research investigates how institutional investors affect firms' CSR efforts (Chen et al., 2020; Dyck et al., 2019; Nguyen et al., 2020). In this line of research, I am the first to investigate whether firms' mandatory CSR engagement attracts greater investments from FIIs. More importantly, by exploiting a CSR reform and utilizing a unique firm-level CSR expenditure data in a natural experiment setup, my study is the first to show the causal relationship between mandatory CSR activities and heterogenous FIIs' investment preferences. Last but not least, my study adds to the ongoing debate over firms' CSR initiatives and financial performance. Contrary to the short-term market reaction-based studies that show that mandatory CSR could deteriorate investor wealth (Grewal et al., 2019; Manchiraju and Rajgopal, 2017), I provide compelling evidence that mandatory CSR engagement increases the long-term market value of CSR firms.

5.1.2 Extreme rainfall and institutional investors

In this study, I examine the ownership patterns of institutional investors in rain-sensitive firms following extreme rainfall episodes. For this, I utilize the Indian monsoon setup and exploit the extreme rainfall variations as exogenous shocks in ongoing natural experiments. The two extreme ends of extreme rainfall conditions (i.e., excess and deficit) could create very different scenarios for institutional investors to invest in rain-sensitive firms (Rao et al., 2022). Drawing on the literature on saliency theory, information asymmetry, and institutional investors' superior trading, stock picking, and investment skills, I show that institutional investors significantly increase (decrease) their ownership in rain-sensitive firms during the excess (deficit) rainfall years. This outcome is significant because institutional investors appear to benefit from investing in rain-sensitive firms during the years of excess rainfall conditions since these firms often perform better than non-rain-sensitive firms in the following years.

I conduct further analysis to see whether the geographic proximity of institutional investors matters when investing in rain-sensitive firms during extreme rainfall conditions. The investigation reveals that while DIIs and FIIs grow their ownership stakes in rain sensitive firms during excess rainfall, only DIIs tend to sell rain-sensitive stocks during deficit periods. I conjecture that both DIIs and FIIs can make quick investment decisions when there is excess rainfall due to greater investor attention. However, during deficit rainfall years, the market reacts more slowly, and there are longer periods of uncertainty, making it harder for institutional investors to promptly make their investment decisions. Nevertheless, the geographically closer DIIs may have a more in-depth understanding of the local meteorological conditions and how rain-sensitive companies respond to them. To sum up, while the finance literature proposes that capital markets may not efficiently incorporate long-term extreme weather-induced risks, my empirical results indicate that institutional investors, specifically DIIs, consider the influence of extreme rainfall on market dynamics and the reactions of rain-sensitive companies when making their investment choices.

This study contributes to the existing body of literature in multiple ways. I contribute to the emerging field of research on climate risk and institutional investors (Alok et al., 2020; Krueger et al., 2020) by examining the distinct responses of institutional investors to varying levels of extreme rainfall. Specifically, I investigate how these investors make investment decisions in companies susceptible to extreme rainfall conditions. To this end, my study is the inaugural examination of the effects of extreme rainfall conditions, serving as an exogenous meteorological anomaly, on the investment choices of institutional investors. Furthermore, this study contributes to the existing body of literature on the superior trading information and stock-picking skills of institutional investors (Baker et al., 2010; Huang et al., 2020) by showing that institutional investors demonstrate enhanced investment abilities, not solely due to their access to superior information about the companies they invest in, but also because they possess superior information and knowledge pertaining to external climatic conditions. This enables them to generate higher returns from rain-sensitive stocks. Finally, my study makes a valuable contribution to the existing body of literature on the effects of geographic location on institutional investors' knowledge and investment decisions (Baik et al., 2010; Coval and Moskowitz, 2001). I show that DIIs located close to their rain-sensitive investee firms in a particular geographic region possess superior information, expertise, and understanding of local meteorological and rainfall conditions compared to FIIs.

5.1.3 Immigration fear and institutional investors

Immigration has gained significant attention in several countries during the past few decades (Baker et al., 2015). Immigrants are currently exerting a notable impact on electoral results and fueling the rise of right-wing populism through the amplification of concerns surrounding immigration and the promotion of anti-immigration sentiments. The local population perceives this phenomenon as threatening security, economic stability, and cultural cohesion (De Vreese and Boomgaarden, 2005; Mughan and Paxton, 2006). Considering the substantial importance of this issue, this study aims to examine the potential impact of immigration fear sentiments on institutional investors' investment decisions and preferences. Consistent with the economic conjectures positing that immigration fear sentiments induce heightened risk aversion among investors and negatively impact financial markets by eroding social capital and trust, my empirical results convincingly demonstrate that institutional investors substantially decrease their investment holdings in their investee companies during heightened immigration fear.

Additional investigation indicates that heterogeneous institutional investors react differently to heightened immigration fear sentiments. Specifically, the findings reveal that immigration fear-induced divestment decisions are made primarily by domestic, independent, and short-term institutional investors. Furthermore, right-wing populism seems to substantially influence the nexus between immigration fear and institutional investors' investment decisions. The results suggest that countries governed by right-wing populist parties (RWP countries) see a greater decline in investments from institutional investors compared to non-RWP countries in times of increased immigration fear. This study ultimately establishes that institutional investors engage in divestment activities in response to increased immigration fear sentiments primarily due to their risk-averse nature and not because of possessing superior information regarding future firm performance.

This empirical chapter makes several notable contributions to the existing body of literature. First, my study contributes to the existing literature by expanding our understanding of the adverse consequences of fear and anxiety on investors' inclination to avoid risk and their subsequent investment decisions (Guiso et al., 2018; Kuhnen and Knutson, 2011). I illustrate that institutional investors exhibit an elevated level of risk aversion in reaction to concerns about immigration, resulting in a decrease in their investments in the enterprises they have invested in. To my knowledge, I am the first to investigate and show this inverse relationship between immigration fear and institutional investors. Additionally, I add to the growing literature on institutional investors exhibiting psychological and behavioral biases by demonstrating immigration fear triggers risk aversion in institutional investors (Alok et al., 2020; DeVault et al., 2019). I also contribute to the literature on the heterogeneity in institutional investors by illuminating how various institutional investors display differing responses to immigration fear (Ferreira and Matos, 2008; Marshall et al., 2022). Finally, I also add to the literature studying the relationship between political ideologies and financial markets by demonstrating how RWP amplifies the adverse effects of immigration fear on institutional investors' investments (Addoum and Kumar, 2016; Bonaparte et al., 2017).

5.2 Implications

My thesis has several implications, particularly for institutional investors, corporate managers, and policymakers. The first empirical chapter (Chapter 2) on mandatory CSR engagement and FIIs concludes that mandatory CSR regulations requiring firms to expend and disclose their CSR activities could potentially attract foreign investments from FIIs in emerging markets. This is crucial for such capital-constrained emerging markets where foreign investments could significantly promote economic development and growth (Bekaert and Harvey, 2003; Henry, 2000). As such, policymakers and regulators, particularly in emerging economies where CSR is still not practiced widely, should take into account that institutional investors are increasingly considering ESG/CSR and other sustainable financial practices for their investment decisions and portfolio allocations (Amel-Zadeh and Serafeim, 2018). To this end, such CSR/ESG-related regulations could act as tools for attracting greater investments from institutional investors, particularly from foreign investors, in financial markets. Nevertheless, policymakers and regulators should ensure that their CSR interventions enhance the ESG/CSR performance of complying firms by imposing strict rules, regulations, and penalties. Furthermore, my study sheds light on the fact that heterogeneous FIIs, based on their legal origins and/or investment styles/objectives, hold different preferences for their investee firms' CSR engagement. Thus, regulators and policymakers should consider such investor preferences before implementing CSR-related legislation.

My study has further implications for investors and firm managers. Market reaction-based studies indicate that mandatory CSR interventions induce short-term negative market reactions (Grewal et al., 2019; Manchiraju and Rajgopal, 2017). However, this should not discourage investors from investing in CSR firms, as Krüger (2015) shows that any CSR-related events lead to such negative short-term market reactions. Moreover, investors should keep in mind that CSR tends to generate payoffs in the long run, supported by findings that mandatory CSR engagement increases the long-term market value of CSR firms. Furthermore, I show that firms complying with the CSR mandate and spending in CSR activities tend to attract more FIIs' investments than other firms. Thus, corporate managers should also consider investor preferences and try to comply with the laws accordingly.

Next, Chapter 3 reveals that extreme rainfall conditions as a weather anomaly affect the investment choices of institutional investors in rain-sensitive firms. Since the two extreme ends of extreme rainfall conditions (excess and deficit) provide institutional investors with opposing signals for investing in rain-sensitive firms, investors should closely monitor extreme weather and climatic conditions and identify the firms that could be sensitive to severe weather. Even though financial markets might be inefficient in pricing long-term weather-induced risks, my findings suggest that investors could potentially gain from rain-sensitive firms if they time their investments strategically in such firms with regard to varying rainfall conditions. As such, investors should better understand weather and climate-related risks in their investment portfolios. Furthermore, managers of rain-sensitive firms should also be strategic in utilizing their resources and making necessary corporate investments during heterogeneous extreme rainfall episodes to generate higher long-term value

(Rao et al., 2022). Thus, managerial expertise on extreme weather conditions and their potential impact on firms is also recommended.

Finally, from Chapter 4, it is seen that institutional investors significantly divest from their investee firms in times of heightened immigration fear. This effect seems to be more pronounced among institutional investors who are more susceptible to local market conditions (i.e., DIIs), and investors with greater risk profiles (i.e., independent and short-term institutional investors). This implies that negative emotions such as fear and anxiety induce differential psychological responses in different groups of institutional investors. As such, depending on the circumstances, institutional investors may want to better equip themselves to restrain their psychological biases and try to be rational and factual when making investment decisions. Moreover, additional tests suggest that immigration fear sentiments tend to have little to no effect on future firm performance and, consequently, on investors' returns. Thus, institutional investors should try to understand the effects of immigration better and make investments accordingly. Finally, RWP countries tend to deter investments from institutional investors more than non-RWP countries amidst increased immigration fear. As such, investors should also gather knowledge on how the overall political climate affects financial markets and ensure that irrelevant political sentiment does not affect their investment choices.

5.3 Thesis limitations

I identify some limitations of my thesis in this section. Like many other empirical studies, my thesis also suffers from data availability issues. For instance, in the first empirical chapter (Chapter 2), the data of socially responsible investment (SRI) funds could not be procured for India. It would have been interesting to see whether SRI funds increased their investments in mandated CSR firms following the mandatory CSR intervention. I have tried to address this by identifying and utilizing FIIs that are PRI signatories in my empirical investigation.

Moreover, I also did not have access to fund flow data for India. It would have been interesting to see whether general investors value sustainability by investigating the fund flows to FIIs that invest in mandated CSR firms in the post-CSR reform period, as Hartzmark and Sussman (2019) suggested. Finally, the empirical investigation in Chapter 2 is conducted in a single emerging market setup. Thus, the findings may not be generalized, particularly for developed economies with less severe information asymmetry and agency issues than emerging markets. Thus, further investigation relating to this in developed markets is necessary.

Similar to Chapter 2, Chapter 3 also focuses on a single emerging market (i.e., India). Moreover, the study relies on extreme rainfall conditions (i.e., large variations in rainfall from normal conditions), which is primarily relevant for the countries with a Monsoon season, when most of the rainfall takes place and rainfall extremities are plausible. Thus, the findings from this study may not be generalized for countries that do not have a specific Monsoon season where rainfall departures are not an issue. Moreover, the Indian economy is heavily dependent on rainfall, which allows me to identify numerous firms in rain-sensitive industries in India. However, many economies are not so dependent on rainfall conditions that such an investigation may not be applicable. Finally, there is also the possibility that certain firms within rain-sensitive industries are implementing coping strategies and innovations to protect themselves from extreme rainfall conditions better (Dell et al., 2012). This could potentially weaken the significance of my findings.

Finally, in Chapter 4, the immigration fear index data obtained from Baker et al. (2015) is only available for four developed economies (i.e., the United States, United Kingdom, France, and Germany). For this reason, the study could not have been extended to other countries where immigration is also a salient issue and where RWP is on the rise (i.e., Australia and some other Eastern European countries). Thus, if data were available, including such countries in the empirical investigations would have made the study wholesome, and the findings could have been better generalized. In addition, I exploit the 2015 European refugee crisis or ERC as an exogenous shock, assuming that the ERC only increased the immigration fear in my sample countries. However, the 2015 ERC may have other confounding effects which could influence my results. Moreover, any other macro-level shock in the three-year pre- and post-ERC period in any of the sample countries could also affect the outcome observed. Nevertheless, the employed firm and year-fixed effects should have mitigated this issue to a certain extent.

5.4 Suggestions for future research

In this section, I provide some directions for potential future research. With respect to mandatory CSR regulations, it would be interesting to investigate whether SRI funds emerged in India after the CSR law was enacted and whether such funds and other institutional investors that invest in mandated CSR firms attract greater fund flows from individual investors. Furthermore, it would be interesting to search for similar mandated CSR regulations, particularly in developed countries, and investigate whether the findings from my study could be generalized in developed economies as well. Finally, given my finding that mandatory CSR engagement attracts greater investments from FIIs, together with the finding of Roy et al. (2022) that such mandated CSR activities lead to higher stock market liquidity, it is expected that mandated CSR interventions may reduce the cost of capital of CSR compliant firms. Thus, it would be interesting to investigate how mandatory CSR laws may affect CSR firms' corporate investments, innovation, and risk-taking.

With regard to extreme rainfall conditions, the examination of firms' adaptation and coping mechanisms in response to such extreme weather conditions could be enlightening. The inquiry into whether there is any relationship between severe weather events and heightened innovation levels, specifically in research and development (R&D) activities and patent applications, remains a topic that warrants additional exploration. This could be studied in the context of extreme rainfall conditions. Finally, it would be interesting to investigate how institutional investors with different investment styles and objectives shape their investment strategies with respect to extreme rainfall conditions.

Lastly, in relation to immigration fear sentiments, it would be interesting to investigate individual investors' reactions to immigration fear using fund flows data. Further, the study could be extended to more countries where immigration and RWP are becoming more salient. Finally, as the literature suggests that immigration fear sentiments may erode social capital and trust in financial markets (Ziller, 2015; Ziller et al., 2019), it would be interesting to investigate how such immigration fear and RWP affect stock market liquidity (Guiso et al., 2004, 2008).

5.5 Concluding remarks

The process of making investment decisions could be complex and sophisticated. The literature suggests that institutional investors tend to possess superior trading and investment skills where they obtain relevant investment information from both private and public sources (Brown et al., 2014; Huang et al., 2020). To this end, this thesis investigates the investment choices and preferences of institutional investors under various exogenous factors. Based on the findings, it can be deduced that institutional investors may demonstrate distinct investment behavior in varying circumstances. Moreover, it is noteworthy that heterogenous institutional investors, characterized by varying attributes, investment approaches, and goals, exhibit contrasting reactions under different conditions. The divergent results observed in various contexts indicate that heterogeneous institutional investors not only possess distinct investment preferences, but also exhibit varying investment reactions in response to different exogenous factors.

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