Institutional Investors, Networking, and Sustainable Environmental Performance

By

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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 an examination, which has led to the award of a degree.

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Abstract

This Ph.D. thesis, comprising two empirical chapters, assesses the effect of institutional investors on a portfolio company's decisions about sustainability. I focus on sustainability outcomes that capture the actual performance of companies. In the first empirical study, I employ a setup of MSCI-ACWI index addition that increases institutional ownership through benchmarking and diversification for companies across forty-six countries worldwide. In the second empirical study, I employ a setup of the distance between institutional investors, which is an immutable factor to determine the strength of investor connections.

To examine whether Institutional Ownership (IO) mitigates ESG-Misbehavior (ESG-MVR), I examine two hypotheses based on two questions. Do cross-sectional and temporal variations in IO provide insight into future ESG-MVR variations for their portfolio firms? Second, does the impact of IO on ESG-MVR vary depending on the investor type? With a battery of robustness tests, I show that IO mitigates ESG-MVR. This empirical chapter illustrates that institutional investors (II) help promote positive sustainability practices and manage future cases of ESG-MVR.

In my second study, I investigate the impact of well-connected II on the portfolio company's carbon emissions. I examine three hypotheses based on the question: do well-connected II influence carbon emissions? How does well-connected II prioritize mitigating carbon emissions while promoting cohesion among their counterparts? I run a battery of robustness tests and show that well-connected II reduces carbon emissions. This empirical chapter illustrates that well-connected II promote sustainability practices through active monitoring and activism.

In my thesis, I emphasize that investors demonstrate responsibility in their investment decisions and prioritize the sustainable performance of their portfolio companies, which significantly influences their decision-making process.

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List of Abbreviations

Abbreviation	*Full Name*
2SLS	Two Stage Least Squares
Big Three	Blackrock, Vanguard, and State Street
BP	British Petroleum
CalPERS	California Public Employees Retirement Scheme
CDP	Climate Disclosure Project
CO_2	Carbon-di-oxide
E&S	Environment and Social
EPI	Environmental Performance Index
ESG	Environment Social Governance
ESG-MVR	ESG Misbehavior
FII	Foreign Institutional Investors
FPI	Foreign Portfolio Investors
GHG	Green House Gas
HHI	Herfindahl-Hirschman Index
ICAPM	International Capital Asset Management Pricing Model
ICB	Industry Classification Benchmark
II	Institutional Investors
IO	Institutional Ownership
ISIN	International Securities Identification Number
IV	Instrumental Variables
LSEG	London Stock Exchange Group
LT	Long-Term
MSCI-ACWI	Morgan Stanley Capital International All Country World Index

OLS	Ordinary Least Squares
PATSAT	World Patent Statistics Database
PPE	Plant, Property, and Equipment
PRI	Principles for Responsible Investment
RRI	Reputation Risk Index
S&P	Standard and Poor
ST	Short-Term
TEPCO	Tokyo Electric Power Company
UK	United Kingdom
USA	United States of America

1. Chapter 1: Introduction

I explore the influence of institutional investors on corporate sustainability behavior particularly focusing on ESG outcomes like ESG misbehavior and carbon emissions. It is divided into two key empirical chapters:

Firstly, institutional investors and ESG misbehavior. In this empirical chapter, I investigate the relationship between institutional investors and portfolio companies found to be engaging in ESG violations. To gain insight into investor behavior, I am exploring two fundamental questions. Do changes in institutional investor ownership explain future ESG misbehavior for portfolio firms? Also, which type of investor is more effective in lowering ESG misbehavior more effectively than others?

Secondly, institutional investor network and carbon emissions. The second empirical chapter explores how institutional investor networks influence corporate carbon emissions. By examining how institutional investors are interconnected, the chapter explores how their centrality in these networks influences firms' environmental impact. It aims to reveal whether highly connected investors foster better environmental outcomes.

Both chapters aim to shed light on the broader implications of investor influence on corporate sustainability and governance, contributing to the ongoing debate on the role of financial actors in addressing environmental challenges.

The thesis is structured as follows. Chapter 2 discusses the related literature and hypotheses section. Chapter 3 presents the data source, variables description, and summary statistics. Chapter 4 discusses the empirical results and strategy. Chapter 5 provides the conclusion and discusses the implications, limitations, and future suggestions.

1.1. Introduction: First Empirical Chapter - Do institutional investors mitigate ESG misbehavior?

Literature documents that institutional investors (II) apply various tools, such as engagement, divestment, and monitoring, to improve their portfolio firms' environmental, social, and governance (ESG) performance. Consequently, a growing body of empirical studies generally agree that *ceteris paribus*, the higher the ownership holdings of their portfolio firms, the better their endogenously determined ESG-related performance, such as carbon intensity and ESG rating (see Riedl & Smeets 2017; Dyck *et al.* 2019; Krueger *et al.* 2020; Azar *et al.* 2021; Pástor *et al.* 2021; Heath *et al.* 2023; Starks 2023).[1]

In this paper, I ask whether current II's holdings have any implications in explaining the exogenously revealed future ESG-related harmful incidents reported in the media. For the purpose, I term such adverse incidents as ESG-related misbehaviors (*ESG-MVR*), which refers to the material ESG violations of international standards by the portfolio firms reported in media that carry significant reputational, compliance, and financial consequences for the firms.[2] For example, recent studies highlight that *ESG-MVR* incites strong adverse reactions in the stock market and reduces future sales revenue (Derrien *et al.* 2021; Gantchev *et al.* 2022; Liu *et al.* 2022; Wong & Zhang 2022). Research also indicates that frequent incidents of *ESG-MVR* invoke spillover effects from parent to foreign subsidiary firms, damaging the overseas strategic advantage (Wang & Li 2019; Zhou & Wang 2020). For instance, Wang and Li (2019) find that the public disclosure of *ESG-MVR* harms the reputation-based foreign strategic advantages of multinational companies. Evidence also suggests that cases of *ESG-MVR* are

[1] ESG performance refers to the effort and assessment of firms' commitment and outcomes related to environmental (such as carbon footprint reductions, waste reduction, bio-diversity impact, air quality, energy, and fuel management), social (such as human rights, and community relations, customer welfare, fair labor practices, labor relations, diversity, and inclusion) and governance (such as risk management, compliance, ethical business practices, accounting integrity, and transparency) metrics. The measurement of ESG performance typically involves thorough assessments conducted by specialized agencies, providing investors with valuable insights into a company's commitment to ethical considerations and long-term risk mitigation in the form of ESG ratings. Generally, higher ratings indicate higher ESG performance.

[2] For a sample list of such incidents and their impact, please see the Table in Appendix A.

associated with lower growth opportunities, higher credit risk, and higher financial risks (Kölbel *et al.* 2017; Fafaliou *et al.* 2022). Media coverage of such instances also results in the dismissals of CEOs, highlighting the importance of *ESG-MVR* at the board level (Burke 2022; Colak *et al.* 2024).

Given the growing importance of II in driving endogenously determined ESG performance and the importance of ESG-MVR, this study answers two related issues. First, do cross-sectional and temporal variations in the ownership of II explain the variations in the future *ESG-MVR* for their portfolio firms*?* Second, does the impact of II on *ESG-MVR* vary depending on the investor type? I answer these questions by proposing two sets of hypotheses.

To answer the first question, I hypothesize that a higher current level of II's ownership should be associated with a lower future *ESG-MVR* of their portfolio firms. I draw the economic arguments from the literature linking II ownership and the portfolio firms' endogenously determined ESG performance. Several studies offer convincing theoretical arguments and empirical evidence on the positive link between ownership of II and portfolio firms' environmental performance. For example, Dyck *et al.* (2019) note that II are crucial in improving their investee firms' environmental and social (E&S) performance, mostly through private engagements. Further, a recent study suggests that the world's largest three II (Blackrock, Vanguard, and The State Street, henceforth denoted as 'Big Three') exhibit significant engagement with their investee firms, contributing to the abatement of their carbon footprint (Azar *et al.* 2021). Other studies also note that an active engagement with investee firms on environmental issues improves their sustainability practices and reduces their carbon footprint (Dimson *et al.* 2015; Krueger *et al.* 2020; Ilhan *et al.* 2023). Evidence also suggests that monitoring mechanisms employed by II also help ensure compliance with environmental regulations and encourage the adoption of sustainable practices (Kim *et al.* 2020).

Research also strongly indicates that II, mainly through active engagement, enhances investee firms' performance against social parameters, such as labor standards, human rights, diversity, inclusion, etc. (Renneboog *et al.* 2008; Hong & Kacperczyk 2009; Buchanan *et al.* 2018). A stream of studies also documents that monitoring mechanisms could also be an essential means employed by II to promote ethical standards and social responsibility among investee firms (Ghaly *et al.* 2020). Finally, a sizeable body of theoretical and empirical literature exhibits a strong causal link between higher II's ownership and the improved quality of their investee firm's corporate governance through engagement and monitoring (David *et al.* 1998; Gillan & Starks 2000; Ferreira & Matos 2008; Cheng *et al.* 2010; Ramalingegowda & Yu 2012).

To summarize, given their significant holdings, literature documents that II drives investee firms' ESG performance by employing various tools, such as engagement, monitoring, divestment, proxy voting, and collaborative initiative strategies (Gillan & Starks 2000; Azar *et al.* 2021; Dimson *et al.* 2023). Consequently, I argue that II-driven endogenously determined better ESG performance should translate into a lower propensity for media-reported future ESG-related adverse incidents. In other words, I expect firms to experience a lower propensity for future ESG-MVR when II's current holdings are higher.

To answer the second question, I propose a heterogeneity hypothesis whereby I argue that investor heterogeneity should differentially explain the link between current ownership of II and future *ESG-MVR*. I underpin the economic reasoning by broadly classifying II into *values-based* and *value* categories. Starks (2023) notes that *values-based* investors are driven by non-pecuniary preferences seeking real ESG impact. They may invest in firms that align with their values, such as avoiding businesses associated with objectionable products or supporting those that reflect their ethical beliefs, even at the cost of sacrificing some financial returns. By doing so, they indirectly incentivize corporations to align with higher ESG standards, thereby driving the abatement of greenhouse gas emissions and improving ESG performance (Gantchev *et al.*. 2022; De Angelis *et al.,* 2023).

Value II, on the other hand, focuses explicitly on managing a firm's financial value by incorporating the firm's ESG-related risk and return profiles (Starks 2023). They recognize that companies with strong ESG practices are often critical to long-term value (Edmans 2023; Starks 2023), encouraging firms to prioritize ESG factors to safeguard their financial performance.

Given the discussion, it is reasonable to argue that *values-based* investors have greater motivation to drive better ESG performance, even at the expense of some financial sacrifice, which is not the case for financially driven *value* investors. Thus, I propose that *values-based* II should have a more pronounced effect on lowering the future incidents of *ESG-MVR.*

To test the hypotheses, I use a firm-level time-varying quantitative metric that captures the comprehensive assessment of the media-reported incidents related to ESG. I use this metric to investigate the crucial role of II's ownership (*IO*, henceforth) in mitigating future *ESG-MVR*. the final sample comprises 14,906 II investing in 4,342 firms covering 34 countries from 2007 to 2021. Consistent with the proposed hypothesis, I find that higher levels of *IO* in a firm are associated with lower future instances of *ESG-MVR*. The estimated effect is economically meaningful as the estimation suggests that a one-standard-deviation increase in firm-level *IO* results in a 0.55 points reduction in the following year's *ESG-MVR*, approximately 5.43% of the mean *ESG-MVR* in the sample.

Following existing literature, I address potential endogeneity concerns by exploiting the exogenous variation observed in *IO* after the inclusion of the investee firm in the most widely employed global diversification benchmark of Morgan Stanley Capital International All Country World Index (MSCI ACWI) (Bena *et al.* 2017; Kacperczyk *et al.* 2021). In line with the International Capital Asset Pricing Model (ICAPM), I observe a statistically significant uplift in the *IO* of investee firms after their inclusion in the MSCI-ACWI. Thus, the exogenous addition of investee firms to the MSCI-ACWI offers us a shock-based instrumental variable (IV) for *IO* (An *et al.* 2021). Consistent with the baseline results, the IV analysis results demonstrate that an exogenous increase in an investee firm's *IO* results in lower future *ESG-MVR*. Overall, the baseline regression and shock-based IV estimations corroborate the positive role of II in mitigating the future *ESG-MVR* of their investee firms.

Additionally, the granular investor-level dataset allows us to investigate the heterogeneous effect of investor-level *IO* on firm *ESG-MVR*.[3] I undertake several cross-sectional tests to examine the differential role of II heterogeneity in mitigating *ESG-MVR* based on *values-based* or *value* investor classifications. I exploit four criterias to classify II as a *values-based* investor.

First, I examine the link between *IO* and *ESG-MVR* through the lens of II's public commitment to follow responsible practices in their investment decision (Gibson Brandon *et al.* 2022). One such public commitment is launching the Principle of Responsible Investment (PRI) initiative, a network of investors supported by the United Nations. Investors signed up in the network are committed to promoting sustainable investments by incorporating ESG factors in their investment decisions, which aligns with the *values-based* investment principle.[4] Consistent with the conjecture, the estimation reveals that compared to non-signatories II, those who sign the PRI initiative demonstrate a more pronounced effect in lowering the future *ESG-MVR* of their investee firms.

Next, I classify II by the country's legal system– civil vs. common law (Porta *et al.* 1998). I expect II domiciled in civil law countries to have a higher impact on reducing future *ESG-MVR*, as they are more stakeholder-oriented (Aggarwal *et al.* 2011), and transplant social

[3] One of the uniqueness of the dataset is the availability of investor-level ownership data worldwide. Such granular dataset enables us to control for the time-invariant investor-level differences employing investor-fixed effects.
[4] For further details, see https://www.unpri.org/.

norms in the companies they invest in (Bena *et al.* 2017; Dyck *et al.* 2019), which is in line with the *values-based* investment style. In line with the expectation, I find that II from countries with civil law systems display a more substantial impact on mitigating future *ESG-MVR* when compared to those from common law systems, suggesting that the legal frameworks and enforcement mechanisms of the country of domicile matters in moderating the link between *IO* and *ESG-MVR*.

The third classification is based on the monitoring role of II, i.e., independent vs. grey (Chen *et al.* 2007). Literature notes that compared to grey, independent II with no amicable affiliations or ties with the incumbent management are more critically active in monitoring their investee firms, which is in line with the *values-based* investment style. Consistent with the theoretical expectation, I observe that independent II has a greater impact on mitigating the future *ESG-MVR* of their investee firms.

The final classification of *values-based* and *value* is based on the investment horizon criteria. Economic intuition from the existing literature implies that investors with long-term investment horizons (e.g., pension funds and endowments) are more concerned about ESG performance and associated risk compared to short-term investors (e.g., hedge funds) (Bena *et al.* 2017; Dyck *et al.* 2019; Marshall *et al.* 2022). Thus, long-term investors should be more concerned about the *ESG-MVR* of their investee firms, which is also in line with the *values-based* investment philosophy. the results, which support this conjecture, suggest that long-term II has a more significant impact on mitigating the future *ESG-MVR* than short-term II.

Our study adds to the following strands of the literature. Firstly, I contribute to the literature that identifies the drivers explaining the variations in *ESG-MVR*. For instance, Li and Wu (2020) find that the *ESG-MVR* is lower in firms with better corporate social responsibility (CSR) engagements, whereas Asante-Appiah and Lambert (2022) report that external auditors help manage *ESG-MVR* due to their expertise in assurance reporting. Likewise, He *et al.* (2023)

find that mutual funds' support for failed shareholders' E&S issue-related proposals predicts increased *ESG-MVR*. However, the literature is mixed, as Raghunandan and Rajgopal (2022) find that ESG funds hold a higher proportion of portfolio firms with worse track records for compliance with labor and environmental laws compared to non-ESG funds. I contribute by providing conclusive evidence that higher *IO* is important in mitigating the *ESG-MVR* of investee firms. This suggests that II plays an important role in explaining the variations in *ESG-MVR*.

Second, I contribute to the stream of studies identifying and explaining the differential effect of *values-based* and *value* II in mitigating *ESG-MVR*. the research complements the body of research that underscores the significance of discerning the motivations rooted in financial considerations (value) and non-pecuniary preferences (values-based) of investors (Starks 2023). Existing literature suggests that *values-based* investors can influence companies' sustainability practices (Pedersen *et al.* 2021; Starks 2023). Even *values-based* investors actively engage with companies to demand greater transparency on climate-related disclosures (Ilhan *et al.* 2023). However, values-based investors are willing to sacrifice some financial rewards for real ESG impact (Starks 2023). To the knowledge, ours is the first comprehensive and systematic investigation to demonstrate the differential role of *values-based* and *value* II in mitigating investee firms' *ESG-MVR*.

Finally, the study also extends the literature on the future implications of the role of II's engagement, divestment, and monitoring in driving improved sustainability outcomes of their portfolio firms. A plethora of studies exist documenting the impact of the II on positive ESG performance (Dyck *et al.* 2019; Pástor *et al.* 2021; Pedersen *et al.* 2021; Avramov *et al.* 2022), governance practices (Aggarwal *et al.* 2011; Ge *et al.* 2022), abatement of carbon emissions (Azar *et al.* 2021; Bolton & Kacperczyk 2021), and promotion of green innovations (Bena *et al.* 2017). However, the literature on the future implications of II's driven sustainability performance on their investee firms' exogenously reported ESG-related risk incidents is missing. I augment the implications of II and ESG outcomes literature by documenting the link between *IO* and exogenously media-reported *ESG-MVR*.

1.2. Introduction: Second Empirical Chapter - Birds of a feather: Do institutional investors flock together to reduce carbon emissions?!

"Collaboration is almost part of fiduciary duty.". While some asset managers claim they can engage independently, consistent and persistent messaging through collaborative efforts like Climate Action 100+ is crucial to ensure companies focus on meaningful actions.

- Head of Stewardship, Phoenix Group at ICGN Stewardship Forum

Well-connected institutional investors (II) are increasingly recognized as a powerful force in improving financial value and shaping corporate behavior (Bajo *et al.* 2020; Chen *et al.* 2023).[5] As the world grapples with the urgent challenge of climate change, the role of these interconnected market participants in greenhouse gas emissions reductions has emerged as a focal point of inquiry. The debate between II influence driven by their network over individual decision-making revolves around whether investors achieve greater impact through collective engagement within networks or by acting independently (Webb 2024). II independently can drive positive corporate performance by pressuring firms to lower emissions, increase gender diversity, improve reporting, and achieve better sustainability ratings, contributing to stronger governance practices and ultimately adding to firm value (Aggarwal *et al.* 2011; Dyck *et al.* 2019; Azar *et al.* 2021; Brandon *et al.* 2022; Gormley *et al.* 2023). However, little evidence exists about how networks of II affect the firms' environmental performance. This paper aims to fill this gap in the literature by exploring two underlying questions: Do II networks reduce carbon emissions? And what is the possible mechanism through which IIs' network reduce carbon emissions?

When ValueAct Capital, a low-profile activist investor owning less than 1% stock gained a board seat at Microsoft Corp., it showcased a notable shift in the behavior of some II

[5] For the purposes of this study, I use network, inter-connectedness, well-connected investors interchangeably.

who have traditionally remained passive (Benoit & Grind 2015). Jeffrey Ubben, the founder, and Mason Morfit, the president, contacted major stockholders who held a collective 6% of Microsoft's stock, such as Franklin Templeton Investments and Capital Research and Management Co., to gain their support in obtaining a board seat. The incident implies that II are willing to back change-making initiatives leading to greater challenges for the company's management and board (Vardi 2013). This shift in behavior is expected to continue as II faces pressure to outperform the market and seek an edge in its investments while also being climate conscious. I expect well-connected II to exert a substantial effect on corporate sustainability practices, such as reduction in carbon emissions, due to their potential to leverage their network position and influence other II towards shared sustainability goals.

II network is not just about connections but also about leveraging connections to optimize information flow and managing reputational risks through the certification effect. Investors' networks are an essential source of information collection and transmission. Investors in a network gather and process non-public information by exchanging company-specific information (Kang *et al.* 2018). This can include insights gleaned from direct engagement with companies where large investors might have opportunities for face-to-face meetings with management (Bushee *et al.* 2018; Xiong *et al.* 2021). It reduces the risk of free riding by other investors who benefit from actions without contributing. Maggio *et al.* (2019) find that II who rely on central brokers benefit from informational advantages because brokers have privileged access to order flow. However, this access allows other investors to free-ride by imitating the trades of informed investors. However, this free riding is reduced since they receive long-term benefits from brokers' selective sharing of future insights based on reciprocity, which enhances overall returns. Being aligned with other II can serve as a form of certification, reducing the risk of certain investment strategies. Bajo *et al.* (2020) find that when a prominent and well-connected investor invests in a company, it sends a strong signal of the firm's quality to the market, as they leverage their reputation and visibility to attest to its worth.

Building upon prior research that explores the influence of social networks on investment manager performance (Hochberg *et al.* 2007; Bajo *et al.* 2020), this study investigates the indirect network connections of II, known as centrality.[6] Centrality goes beyond direct connections – it's about who the investor knows, giving central players an information and performance advantage (Walden 2018).[7] I analyze the role of central institutions, which are prominent II that could act as hubs due to their diversified holdings, influence, or expertise, sharing information within the network (Hochberg *et al.* 2007; Bajo *et al.* 2016).

Previous research suggests that when II have overlapping portfolio holdings, it leads to more interactions between them, leading them to share information freely (Hong *et al.* 2005; Pool *et al.* 2015; Crane *et al.* 2019). Bushee *et al.* (2018) use corporate jet travel patterns to identify unobservable private meetings with investors, showing these meetings impact stock prices, trading activity, and analysts' forecasts. Participants who have access to non-public information about the firm may have an advantage over non-participants, which could influence their investment decisions (Bushee *et al.* 2018) even reducing corporate fraud (Xiong *et al.* 2021). II share information within networks to benefit from collective knowledge; therefore, I posit well-connected II facilitates the efficient processing of information related to climate change and risks.

[6] Direct connections between II are often informal and challenging to measure within the research setting. Therefore, I analyze the network structure through shared portfolio holdings (Bajo *et al.* 2020; Chen *et al.* 2023; Dissanaike *et al.* 2023).
[7] By identifying instances where II invests in the same companies, I construct centrality measures that capture the potential influence stemming from these indirect connections within the investment network. Being in the center of the network grants them access to information earlier, giving them an advantage over those on the periphery (Walden 2018).

Globalization has led to a rise of foreign II, which focuses on good governance and large firms improving companies' performance and valuations (Ferreira & Matos 2008; Bena *et al.* 2017), creating connections between II across different countries. In a questionnaire survey, Shiller and Pound (1989) find II to be swayed by the trading behavior of other investors. Investors compare and adopt investment strategies from their peers. While country-specific studies provide valuable insights, they only represent a limited portion of the network (Bajo *et al.* 2020; Dissanaike *et al.* 2023). I show the importance of II networks in the global space, which represents better portfolio diversification and risk management.

Network theory examines how mechanisms and processes within network structures lead to outcomes helping overcome information asymmetry through information diffusion (Hochberg *et al.* 2007). This mechanism can be attributed to two mechanisms: the flow of information and the management of reputational risks through the certification effect.

First, the network establishes an information channel. Information asymmetry between II and firms regarding a company's operations can impede effective decision-making. Evidence shows that funds investing in similar firms share information (Pareek 2012), aligning with findings that institutional investors communicate with others holding the same stock (Shiller & Pound 1989). At the center of the network, II has direct access to valuable information, allowing for timely insights into corporate operations (Bajo *et al.* 2020; Fan *et al.* 2023). II networks enhance information flow by sharing corporate insights, improving monitoring of ESG risks, and protecting long-term portfolio value while reducing negative external impacts (Dimson *et al.* 2015).

Secondly, well-connected II within a network creates a certification effect (Bajo *et al.* 2020; Chen *et al.* 2023). I argue that when the II invests in the portfolio firm, it provides a credible signal to other investors regarding its credibility. Well-connected II can act as a certification mechanism, reducing concerns about adverse selection. Their investment signals to the market attach their reputation to the firm's, encouraging other investors to invest with greater confidence.

In addition to reducing the risk of adverse selection, certification also helps to mitigate the possibility of moral hazard. Managers may pursue risky or self-serving opportunistic behavior, knowing that passive investors won't exert influence (Appel *et al.* 2016). However, these investors pressure companies to improve governance and encourage managers to focus on long-term value creation instead of short-term gains (Gillan & Starks 2000; Bena *et al.* 2017). Well-connected II leverages its resources to oversee management and align its incentives with shareholder interests. Therefore, the first hypothesis is well-connected II exhibits stronger monitoring practices to reduce carbon emissions in their portfolio companies.

However, the question of how the II network enables a better environmental outcome for a firm remains unanswered. I argue that reducing information asymmetry should enhance the monitoring effect and shareholder activism, reducing carbon emissions. Through enhanced monitoring, well-connected II are better positioned to monitor the firm's environmental performance (Ferreira & Matos 2008; Azar *et al.* 2021). Their position provides them with greater access to information and resources (Gillan & Starks 2000; Fich *et al.* 2015), enabling them to identify and address risks more effectively. California Public Employees' Retirement Scheme (CALPERS), a prominent II, exerts strong monitoring influence due to its large asset base and active engagement policies (Smith 1996). Foreign II acts as a powerful external force to promote innovation amongst portfolio firms (Luong *et al.* 2017). By facilitating information diffusion and knowledge transfer, well-connected investors and firm network help increase innovation levels in their portfolio firms (Chuluun *et al.* 2017; Fan *et al.* 2023). Therefore, I hypothesize that well-connected II exhibits stronger monitoring practices, increasing environmental innovations and reducing carbon emissions.

I also argue that by being well-connected, II are empowered to engage in effective activism (Appel *et al.* 2018; Gantchev & Jotikasthira 2018). A strong position enhances their influence and ability to mobilize other investors and stakeholders to demand greater accountability (Tsang *et al.* 2019; Cohen *et al.* 2023; Ilhan *et al.* 2023). The Norwegian Wealth Funds global reach and substantial investments position it as a key advocate for climate-related issues on a global scale (Vasudeva 2013).

II may enhance the E&S performance of their portfolio firms due to financial and social motivations. Connected investors might push firms to consider long-term financial risks, pushing for actions and ensuring long-term sustainability (Kang *et al.* 2018; He *et al.* 2023). Well-connected II impact firms by actively scrutinizing, engaging in activism, and advocating for portfolio firms based on their perceived exposure to climate change. II are incentivized to thoroughly scrutinize the environmental practices of the firms in their portfolios (Marti *et al.* 2024). Therefore, I hypothesize that well-connected II exhibit stronger scrutiny, engage in activism, and advocate practices leading to increased climate change exposure, consequently reducing carbon emissions.

Our study relies on Trucost data, which covers around 1,000 companies since 2005, and over 2,900 listed companies since 2016. I match these data with institutional ownership data with publicly listed firms from S&P Capital IQ from 2004 to 2020 and then build the centrality graph. Carbon emissions from a company's operations are grouped into three categories: direct emissions from the company's operations (scope 1), indirect emissions from purchased energy sources like electricity, heat, or steam (scope 2), and other indirect emissions that are outside the company's direct control such as use of product, waste disposal, or outsourced activities (scope 3). Scope 1 and 2 are widely reported while scope 3 emissions are largely estimated using an input-output model. Scope 3 emissions are separated into downstream (from customers) and upstream (from suppliers) indirect emissions.

To examine how the II network might encourage or discourage environmental innovation to impact a firm's carbon footprint, I use a dataset provided by Thapa *et al.* (2023). Environmental innovations are essential for developing cleaner technologies and reducing the negative environmental impact of economic activities (Haščič & Migotto 2015). Patents related to environmental technologies from the World Patent Statistical Database (PATSAT) are identified, reflecting sustainable investment by companies (See section 3.2).

I capture a firm's perceived climate change exposure using the dataset made available by Sautner *et al.* (2023a). Climate change exposure is an example of an externality—a cost or benefit of a company's actions that falls outside the market system and affects others. The authors quantify climate change exposure by counting the frequency of climate-related word pairs (bigrams) within company earnings call transcripts. Current literature provides evidence that firms face significant consequences from climate change exposure. Expectations of climate change on a company impact stock markets' reaction to climate risk disclosures (Matsumura *et al.* 2024). CEOs of companies facing greater climate change risks receive more compensation in the form of equity stocks and options (Hossain *et al.* 2023).

Our empirical models are in line with Chuluun *et al.* (2017) and Cohen *et al.* (2023). I employ fixed effect ordinary least squares (OLS) regressions, estimating the impact of well-connected II using network centrality measures (*II_centrality*) – *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality* on carbon emissions (*Ln_GHG_Abs_Scp1*). the empirical analysis reveals a significant negative relationship between well-connected II and carbon emissions, suggesting that the influence of well-connected II effectively mitigates portfolio firms’ emissions reduction. A one standard deviation increase in *Degree_centrality* (0.04089) leads to a 0.00094 point reduction in *Ln_GHG_Abs_Scp1* in the following year, which is about 0.094% of the mean (10.652).[8]

I conduct a series of robustness tests to validate the findings. I employ alternative fixed effects models, use alternative measures of carbon emissions from Trucost and LSEG, and alternative measures of well-connected II by aggregating centrality measures using Larcker *et al.* (2013) N-score, factor analysis, PCA, and orthogonalization techniques. I then use an instrumental variable set up by using the average distance between investors as an instrument. Finally, I use a bootstrapping technique, indicating the relationship I find is not merely an artifact of randomness. I find that the results are robust, and the findings hold.

I examine the nuances of well-connected II by differentiating them based on investment style, institutional type, and commitment to responsible investment. The investment strategies of active and passive investors can result in varying impacts on the firm (Appel *et al.* 2016, 2018). The decision to hold or purchase equity depends on factors such as the duration it is held, the resources allocated for engagement, and access to private information. I find that well-connected II classified as active reduce carbon emissions than those classified as passive. II that are categorized as independent are autonomous and are pressure-resistant to the management of their portfolio firm, promoting corporate social responsibility (Chen *et al.* 2007; Ferreira & Matos 2008). Grey II's association with corporate management can lead to prioritizing loyalty to management and enabling corporate actions that may not align with the shareholders' interests (Ferreira & Matos 2008; Aggarwal *et al.* 2011). I find that well-connected II classified as independent, have a stronger effect in reducing carbon emissions than those classified as grey investors. Focussing on their commitment for responsible investment, II that have signed up as a Principles for Responsible Investment (PRI) signatory, emphasizing

[8] USA having 6.5 million metric tons of GHG emissions and $51 per metric ton of CO2 as the social cost of carbon in the year 2019, the potential reduction in carbon taxes amount to over $311,610 eliminating 6,110 metric tonnes.

long-term sustainable strategies aligned with PRI principles (Dikolli *et al.* 2022; Liang *et al.* 2022). I find that well-connected II that are signatory to the PRI are found to reduce carbon emissions than non-PRI signatories.

I find a positive association between well-connected II and green innovations, which eventually plays a mediating role and reduces carbon emissions. I also observe a positive association between well-connected II and climate change exposure, aligning with the notion that these investors are more attuned to climate-related risks. Consequently, these investors reduce carbon emissions by increasing their portfolio firms' climate change exposure.

Our contribution is twofold. Firstly, I extend the literature on well-connected II impacting carbon emissions. Bolton and Kacperczyk (2023b) show higher carbon emissions are associated with higher stock returns in developing economies with fewer regulations, but the trend is reversing in countries with strict regulations. Bolton and Kacperczyk (2021) show that investor behavior is shifting towards demanding compensation for companies with high carbon footprints. Investor demand for climate risk disclosures, as reflected by firms' joining CDP (Climate Disclosure Project), is associated with increased disclosures and lower future carbon emissions (Cohen *et al.* 2023). While the short-term relationship between carbon emissions and stock returns remains debated (Aswani *et al.* 2023a, b; Bolton & Kacperczyk 2023a), well connected II may look beyond trends and pressure companies for long-term sustainability strategies that mitigate climate risk. I investigate the influence of well-connected investors on the carbon emissions of their portfolio companies. I also contribute to the literature by investigating the link between investor connectedness and green innovations, which eventually mitigates carbon emissions. I also investigate the link between investor connectedness and the portfolio firms climate change exposure through which investors scrutinize, advocate, and engage with portfolio companies to eventually make real world sustainable outcomes of reducing carbon emissions.

Secondly, the research builds on the growing body of work exploring social networks within financial markets. Well-connected investors receive valuable information faster, with central investors trading earlier than peripheral investors (Ozsoylev *et al.* 2013), leading to better investment decisions (Hochberg *et al.* 2007) and higher investor flows (Rossi *et al.* 2018). Brokers at the center of the network can view more informed trades, potentially profiting from the information and informing investors, leading to faster price discovery that impacts investment returns (Maggio *et al.* 2019). Networks can also function as a reputation system. Bajo *et al.* (2016) show that a strong underwriter network helps them attract investor attention and potentially improve IPO performance. Well-connected boards achieve higher future returns and profitability and outperform analyst forecasts by leveraging their networks for valuable information, resources, and access to capital (Larcker *et al.* 2013). They also improve monitoring through financial reporting quality (Intintoli *et al.* 2018), and gender bias in connections benefits careers, where men gain advantages in both performance and perception (Fang & Huang 2017).

On the contrary, CEOs with strong business networks make more acquisitions that destroy value, suggesting better access to private information is outweighed by their power and influence over boards (El-Khatib *et al.* 2015). Their indirect connections to board members influence them to receive higher compensation and job security (Balsam *et al.* 2017). Social connections within the CEO’s network impede the audit committee's function and reduce audit oversight (Bruynseels & Cardinaels 2014).

Dharwadkar *et al.* (2008) analyze the portfolio-level characteristics of the largest institutional investor and find that the portfolio characteristics can significantly offset the monitoring benefits associated with the firm level. I analyze the II network, which encompasses the composition and diversification of the equity investment portfolio worldwide, providing a more comprehensive understanding of their monitoring incentives and potential influence. I examine how an investor's position within the network influences their access to information, potentially shaping their engagement with companies, and impacting carbon emissions.

2. Chapter 2: Related Literature Review and Hypotheses Development

Institutional investors have dominated and played an essential role in the global financial markets for several decades (Chemmanur *et al.* 2021), with both apparent and imperceptible interactions with target firms in their portfolios (McCahery *et al.* 2016). They are often challenged to meet their goals in promoting better corporate practices in target companies (Becht *et al.* 2009).

Existing literature on II has been growing with an increased focus on their role in shaping corporate governance and sustainability practices (Aggarwal *et al.* 2011; Dyck *et al.* 2019). Research also documents that equity investors, particularly II, may change their investee firm behavior on different issues by divestment, voting on shareholder proposals, monitoring, and voicing their concerns by engaging with the management (Donaldson & Davis 1991; Shleifer & Vishny 1997; Gillan & Starks 2000; Aggarwal *et al.* 2011; Boone & White 2015; Luong *et al.* 2017; Ramalingegowda *et al.* 2020; Azar *et al.* 2021; Kacperczyk *et al.* 2021; Gibson Brandon *et al.* 2022; Lewellen & Lewellen 2022). However, the relationship between II and ESG outcomes remains complex. Given the increasing significance of sustainability as a financial risk and the role of II in influencing portfolio firms, I investigate their impact on ESG misbehavior.

Increased awareness of climate change as a significant financial risk has increased investor interest in environmental, social, and governance factors. II leverages its strategic positioning with the network to capitalize on its information advantage (Chen *et al.* 2023). Furthermore, research on II network indicates they influence portfolio firms' corporate practices (Bajo *et al.* 2020; Chen *et al.* 2023). Given the increasing significance of corporate carbon emissions and the role of II network, I investigate their impact on reducing carbon emissions.

2.1. Hypotheses: First Empirical Chapter

2.1.1. Ownership of II and ESG Performance

This section discusses the economic mechanisms through which II may mitigate their investee firms' future *ESG-MVR*. An overwhelming body of general equilibrium theoretical frameworks and the associated empirical evidence document that equity investors, particularly II, may change their investee firm behavior on different issues by employing diverse means: divesting/exiting (or not purchasing) the stock (Crane *et al.* 2019; Blanco *et al.* 2024), voting on shareholder proposals (Gillan & Starks 2000; Iliev *et al.* 2015; Marti *et al.* 2024), monitoring investee firms' activities and performance (Aggarwal *et al.* 2011; Boone & White 2015; Luong *et al.* 2017; Ramalingegowda *et al.* 2020; Kacperczyk *et al.* 2021), and voicing their concerns by engaging with the management (Shleifer & Vishny 1997; Azar *et al.* 2021; Brandon *et al.* 2022; Lewellen & Lewellen 2022). Given the recent and growing importance of instituting ESG-related behavioral changes among firms, I commence my economic arguments by focusing on related theories and empirical evidence demonstrating how II drives their investee firms' ESG performance and other ESG-oriented behavioral changes.

2.1.1.1 II and Environmental Performance

The existing literature highlights that II promotes their investee firms' environmental policies, practices, and performance through various mechanisms such as active monitoring (stewardship), engagement, and exercising their voting rights. In line with stewardship theory, evidence suggests that II fosters engagement with their portfolio firms by providing valuable resources and expertise that enables them to implement environmentally friendly practices (Guadalupe *et al.* 2012). Recent evidence suggests that the world's three prominent II (BlackRock, State Street, and Vanguard, referred to as the big three) play an active role in lowering the carbon emissions of their investee firms (Azar *et al.* 2021). Given their significant stake, such direct environmental impact results from the big three's active engagement with the management of their investee firms. Krueger *et al.* (2020) note that ESG-focused investors are more inclined to engage, rather than divest, in climate risk management of their portfolio firms.

Evidence also implies that II may employ exit and voice tools. For example, Dyck *et al.* (2019) find that II influences firms to better their environmental performance through exit and voice channels. Recent studies on voting rights indicate that II supports more than half of E&S proposals, encouraging firms to adopt environmentally and socially friendly practices (see Kim *et al.* 2019; He *et al.* 2023). Ilhan *et al.* (2023) imply that firms with higher *IO* are more likely to disclose information on their carbon footprints, responding to II's demand or preferences to invest in firms with increased climate risk disclosures.

To summarize, the economic arguments and empirical evidence discussed above support the conjecture that II is important in positively driving investee firms' environmental policies, practices, and performances by applying varied means such as screening/divestment investment strategies, engagements, and voting.

2.1.1.2 II and Social Performance

Compared to evidence of II's driving portfolio firms' environmental performance, literature documenting changes in social practices and policies is scant. Nonetheless, a growing strand of studies suggests that II promote its investee-firm social policies and profiles through shareholder activism, proxy voting, and collaborative initiatives, leading to significant improvements in practices such as employee health and safety, gender diversity, employee productivity, and CSR investments (Nofsinger *et al.* 2019; Brandon *et al.* 2022; Gormley *et al.* 2023). II initiate such changes through risk assessment, demanding transparent reporting, and through collaborative initiatives (Bebbington & Larrinaga 2014; Borghesi *et al.* 2014; Dimson *et al.* 2023). For example, being a signatory of a collaborative initiative (such as PRI), II may push companies toward socially responsible behavior (Dimson *et al.* 2023).[9] Furthermore, the framework of legitimacy theory proposes that II enhance their investee firms' reputation and legitimacy by encouraging and promoting their CSR efforts via monitoring and engagement tools (Kim *et al.* 2019).

Studies further note that II drives a company's approach to addressing social issues beyond traditional CSR activities, such as reducing labor inefficiencies (Ghaly *et al.* 2020). Using a comprehensive dataset of publicly listed companies from over 30 countries, Bena *et al.* (2017) find that foreign II (FII) contribute to their investee firms' human and organizational capital growth through active monitoring, direct involvement, and divestment threats. Likewise, in the Chinese context, Yi *et al.* (2023) find that foreign II promotes ethical and sustainable activities within the supply chains of the investee firms.

Evidence also suggests that the Big Three II (Black Rock, State Street, and Vanguard) boost gender diversity on corporate boards by employing campaigning and voting mechanisms (Gormley *et al.* 2023). Likewise, Johnson and Greening (1999) show that II promotes corporate social performance related to community engagement, diversity, employee relations, and environmental responsibility by using their voting power to impact portfolio firms' management decisions

In light of the above-noted discussions and in general, I conclude that most studies support II's positive influence on instigating a better social profile of their investee firms, employing screening, engagement, monitoring, voting, and divestment tools.

[9] PRI signatories may employ various approaches, including ESG integration, active ownership, impact investing, screening, and ESG thematic investing (Brandon *et al.* 2022; Liang *et al.* 2022; Dimson *et al.* 2023).

2.1.1.3 II and Governance Performance

A significant body of empirical studies demonstrates II's role in shaping their investee firms' corporate governance and structure. For example, evidence suggests that II, at an individual level, influences the corporate board's decision-making by actively monitoring and engaging with their portfolio companies. For instance, Aggarwal *et al.* (2011) show that II promotes good governance practices worldwide, especially in countries with weak shareholder protection, by directly monitoring their investee firms or indirectly via their trading activities. For example, the authors note that II signals their dissatisfaction by voting with their feet, i.e., selling the stocks, which depresses the stock price of their investee firm. Likewise, several other studies also note that companies with higher *IO* exhibit higher levels of board independence, better executive compensation structure, and improved risk oversight (see Cheng *et al.* 2010; Schnatterly & Johnson 2014; McCahery *et al.* 2016).

Focusing specifically on foreign portfolio investors' (FPI) role in emerging markets, Errunza (2001) argues that FPI, which includes FII, may play a crucial role in monitoring the activities of their investee firms, which in turn boosts firm performance. Similarly, Boone and White (2015) find that certain types of II, especially quasi-indexers that closely mimic a specific index, affect corporate governance practices by demanding timely and adequate information production and transparency, ultimately reducing monitoring costs for outside investors. Kacperczyk *et al.* (2021) show that II can enhance the firms' pricing efficiency in capital markets by enhancing the informational environment and advocating for transparent information disclosures.

Studies also note that II connectedness and collaborations among themselves also play a pivotal role in shaping the corporate governance of their common investee firms. They wield significant influence through coordinated activities, collective voting, and improving monitoring effectiveness (Huang & Kang 2017; Crane *et al.* 2019). Such collaborative power enables the group to exert collective pressure on firms advocating improved governance practices (Hong *et al.* 2005; Huang & Kang 2017; Crane *et al.* 2019; Dimson *et al.* 2023).

To summarize, theoretical framework and empirical evidence support the idea that II influences investee firms' governance practices by employing various methods, such as screening/divestment, investment strategies, engagements, and voting.

2.1.1.4 Hypothesis: II and ESG-MVR

Given the above discussions, the current evidence suggests that II actively promotes positive ESG practices and the performance of their firms. However, I have yet to learn about the implications or the outcome of initiating such sustainable practices and performances of investee firms. It is reasonable to argue that if II drives positive ESG performances, then in equilibrium, investee firms in which II holds a higher level of ownership, the likelihood of these investee firms' future adverse and exogenously reported ESG-related incidents should be lower. Thus, better ESG performance, driven by higher II ownership, should mitigate the investee firms' future *ESG-MVR*. Accordingly, in this study, I hypothesize and test the following hypothesis:

H_1: Ceterus Paribus, firms with higher levels of IO are associated with lower future incidents of ESG-MVR.

2.1.2 Differential Role of Values-based vs. Value II

Here, I argue that II's *value vs. values-based* investment philosophy should exhibit differential effects in mitigating the future *ESG-MVR* of their portfolio firms. *Value* investors prioritize financial considerations and optimize the risk-return profiles of their portfolios (Starks 2023). They generally believe that firms incorporating ESG factors should improve a company's financial performance and help manage risk. For example, a value-oriented investor might invest in a company with strong environmental practices, believing it reduces regulatory risk and attracts environmentally conscious customers, leading to long-term profitability. However, in addition to financial returns, *values-based* investors prioritize their personal non-pecuniary values in investment decisions, seeking ethical, social, and environmental alignment with companies. *Values-based* investors often take a long-term view, recognizing that sustainable business practices should contribute to long-term profitability and have a positive societal impact (Dimson *et al.* 2015; Starks 2023). For example, an investor who values environmental sustainability might choose to invest in renewable energy companies and avoid those involved in fossil fuels. Unlike traditional value-oriented investors, *values-based* II are willing to accept lower returns for real positive ESG impact (Pedersen *et al.* 2021).

As discussed below, I distinguish *value* and *values-based* II against their preference for alignments with ESG goals, long and short-term perspectives, and active/passive engagement strategies. I argue that *values-based*, relative to value II, should play a more significant role in mitigating the future *ESG-MVR* of the companies they invest in.

2.1.2.1 PRI vs. Non-PRI Investors

Our first categorization of *value vs. values-based* II is related to their public commitment to promoting responsible investments that entail real ESG-oriented impact. One such initiative is the launch of the UN-supported initiative called Principle of Responsible Investment (PRI).[10]

[10] PRI is a UN initiative launched in 2006 to encourage II to incorporate ESG factors into their investment strategies. The main objective is to promote sustainable investments and contribute to the stability of financial markets. To be a signatory, it is required to follow PRI's six principles, which include analyzing and deciding investments based on ESG factors, integrating ESG issues into ownership policies and practices, encouraging the adoption of internationally recognized reporting standards, collaborating to enhance the effectiveness of PRI principles, promoting the principles within the investment industry, and reporting progress on activities. II can join the PRI initiative and become part of the global network of investors, provided they express a commitment to responsible investment, demonstrate their willingness to incorporate the six principles, and commit to reporting on their activities and progress. For more information on PRI principles, please visit the PRI website at https://tinyurl.com/UN-PRI [Accessed on 15/Oct/2023 15:06 BST]

Evidence suggests that II who sign up for the UN-PRI initiative are more committed to responsible investment practices (Liang *et al.* 2022). They are expected to actively engage with companies they invest in actively, encouraging the incorporation of ESG-related performance yardsticks in the portfolio firms' business practices. Empirical evidence supports such conjectures. For example, Dyck *et al.* (2019) find that higher ownership by PRI signatories improves the E&S performance of their portfolio firms. Relatedly, Liang *et al.* (2022) and Kim and Yoon (2023) document that when II becomes a PRI signatory, they either steer clear of firms with low ESG ratings or choose to invest in firms with high ESG ratings.

Although, as noted above, PRI II makes a public commitment to promoting positive ESG practices as a group, the literature demonstrates heterogeneity among PRI investors regarding their investment preferences and impact. For instant, Brandon *et al.* (2022) find that PRI signatories from the United States have a differentially lower impact on improving the ESG scores of their portfolio firms compared to PRI signatories from other countries. Likewise, Kim and Yoon (2023) find that US mutual funds do not improve their fund-level ESG scores after becoming. Liang *et al.* (2022) show that despite attracting large fund inflows, PRI signatory hedge funds underperform. However, such underperformance is attributed to their exposure to lower-ESG firms. Dikolli *et al.* (2022) I find that most PRI signatories' non-ESG funds do not back E&S proposals as much as PRI signatories' ESG funds, highlighting the inconsistency between the public claims and the voting behavior of PRI signatories, depending on the type of funds.

In summary, the literature generally supports the view that PRI signatories exert positive ESG-related sustainability practices. Thus, given the above discussion, I arguably conclude that PRI signatories, as a group, generally align with the characteristics and motivations of *values-based II* as defined by Starks (2023). Given that *values-based* investors are more inclined to support firms in their ESG-related performance, such an approach should lead to lower frequencies of future ESG-MVR. Accordingly, I propose and test the following hypothesis:

H_{2a}: PRI investors exhibit a greater ESG-MVR mitigating impact on their portfolio firms than non-PRI investors.

2.1.2.2 Civil vs. Common Legal Jurisdiction of II

The second criterion I employ to differentiate between *value and values-based* II is against investors' origin of legal jurisdiction. Here, I focus on the legal jurisdictions that seem more oriented toward protecting stakeholders' vs. shareholders' rights. Extensive evidence suggests that relative to common law legal jurisdiction that focuses on the sole objective of maximizing the wealth of shareholders, civil law legal jurisdiction promotes the legal rights and responsibilities of multiple stakeholders (creditors, employers, outside minority investors, customers, and the community) and design regulations for more inclusive corporate governance (Porta *et al.* 1998; Liang & Renneboog 2017; Marshall *et al.* 2022).[11]

Evidence suggests that II from civil law countries exhibit a significant influence in exporting their own legal jurisdiction's inclusive governance practices (Aggarwal *et al.* 2011) and enhancing human capital through active monitoring (Bena *et al.* 2017). Studies note that *values-based II* emphasizes stakeholder engagement and is more long-term-oriented (Aggarwal *et al.* 2011). Within my economic framework, I thus expect II domiciled in civil law countries to have a higher impact on reducing future *ESG-MVR*, as they are more stakeholder-oriented (Aggarwal *et al.* 2011) and transplant their social norms when investing in the investee firm (Bena *et al.* 2017; Dyck *et al.* 2019). Thus, II originating from civil law

[11] The legal system of Civil law countries relies on comprehensive legal codes and statutes. The legal system of Common law countries relies on judicial decisions and precedents set by courts to interpret and apply the law.

jurisdictions are classified as more *values-based* investors compared to the *value* approach of those originating from common law jurisdictions. Accordingly, I propose and test the following hypothesis.

H_{2b}: II, originating from civil law jurisdictions, have a greater ESG-MVR mitigating impact on their portfolio firms than those from common law.

2.1.2.3 Independent vs. Grey II

I also differentiate values-based and value II centered on their level of active oversight and monitoring of the portfolio firms. Against such criteria, the literature classifies II as independent or grey investors (Chen *et al.* 2007; Ferreira & Matos 2008). Independent II is more involved in impartially monitoring the company's management as it is autonomous and has a reputation for being a "pressure-resistant" investor. Such "pressure-resistant" activities influence the investee firms' management to be more accountable and sustainable in managing the business (Chen *et al.* 2007; Ferreira & Matos 2008; Marshall *et al.* 2022).[12] Studies also recognize that independent II is more E&S-conscious (Luong *et al.* 2017; Dyck *et al.* 2019).

On the other hand, grey II's potential amicable association with corporate management often makes them more sensitive to pressure. They prioritize loyalty to management over responding to corporate actions that may not align with the shareholders' and other stakeholders' interests (Ferreira & Matos 2008; Aggarwal *et al.* 2011).[13] They avoid critical monitoring due to the risk of damaging their relationships with firm management, potentially leading to the loss of existing or potential business (Chen *et al.* 2007).

[12] Independent II are mutual funds and independent investment advisors that manage investment portfolios not directly affiliated with banks, insurance companies, or financial institutions (Chen *et al.* 2007; Ferreira & Matos 2008). They operate more autonomously and prioritize clients' interests and performance.

[13] Grey II are banks, insurance companies, and other institutions that manage investment portfolios as part of their business operations (Chen *et al.* 2007; Ferreira & Matos 2008). Their various business interests likely disadvantage them in monitoring.

In light of the above discussion, I argue that by actively engaging with companies on ESG issues, particularly corporate governance matters, I can classify independent II as more *values-based*. Their active monitoring of the management should help mitigate the likelihood of future adverse ESG-related incidents. As such, I propose to test the following hypothesis:

H_{2c}: Independent II has a greater ESG-MVR mitigating impact on their portfolio firms than grey II.

2.1.2.4 Long vs. Short-Term II

Finally, the last *value vs. values-based* II classification relates to investors' investment horizons. Driven by ethical principles, *values-based* investors adopt a long-term perspective, cultivating lasting impact and sustainable growth (Kim & Yoon 2023). Several studies show that pension funds and hedge funds have distinct investment strategies that primarily focus on long-term and short-term financial goals, respectively (Chen *et al.* 2007; Caglayan *et al.* 2018b; Marshall *et al.* 2022).[14]

Pension funds and endowments aim to grow and preserve assets over an extended period to ensure sufficient funds to meet future pension obligations, leading to a long-term investment horizon (Woidtke 2002). Chen *et al.* (2007) show that firms with a long-term view experience lower monitoring costs due to their extensive knowledge of the organization and its managers, which allows them to process new information and make informed decisions effectively. Pension funds are essential in corporate governance as they actively monitor and promote changes within targeted companies (Guercio & Hawkins 1999) and strongly engage

[14] Pension funds are an excellent representation of long-term investment strategies prioritizing stability and sustainability, as they follow strict standards and exercise careful judgment (Derrien *et al.* 2013). Hedge funds are private investment funds managed by professional portfolio managers to generate superior returns for their investors by employing mainly speculative and riskier approaches, as they are not bound by regulation compared to other II (Caglayan *et al.* 2018b).

on E&S issues (Dimson *et al.* 2015). On the other hand, the basic structure of a hedge fund aligns with a focus on generating short-term profits by exploiting performance-based fees, which incentivizes delivering short-term positive returns (French 2008).

I expect long-term investors (pension funds and endowments), relative to short-term investors (hedge funds), to be more influential in promoting investee firms' ESG practices following engaging investment strategies (Guercio & Hawkins 1999; Appel *et al.* 2016). Accordingly, following the literature (Starks 2023), I classify long-term investors as *values-based* and short-term horizon investors as *value* investors, and propose to test the following hypothesis.

H_{2d}: Long-term II have a greater ESG-MVR mitigating impact on their portfolio firms than short-term II.

2.2 Hypotheses: Second Empirical Chapter

2.2.1 Information Flow and Signaling

It is generally accepted in theoretical and empirical research that information asymmetry exists among transaction parties in the financial market that impedes decision-making (Akerlof 1970). This could lead to non-optimal economic outcomes for investors who display weaker interconnectedness compared to other investors. These non-optimal outcomes result in adverse selection, such as a risk of selecting a portfolio company that does not align with the investor's values, and moral hazard, such as the risk of investing in a company with poor environmental outcomes. Network theory, which refers to the mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups (Borgatti & Halgin 2011), suggests that networks help overcome information asymmetry as it facilitate the distribution of information across all nodes within a network (Hochberg *et al.* 2007). This may occur due to two mechanisms: information flow, and managing reputational risks through certification effect.

First, the network establishes an information channel. Pareek (2012) finds evidence of information flow between funds that have investments in similar firms, which is consistent with Shiller and Pound (1989) who find that II actively communicate with other II holding the same stock. II possess a unique information advantage by leveraging the strategic position and extensive connections (Hong *et al.* 2005; Chen *et al.* 2023). Being positioned at the center of the network, II can have enhanced access to a wealth of valuable information, enabling them to gather comprehensive and timely insights into various aspects of corporate operations, including financial performance, market trends, and governance practices (Bajo *et al.* 2020; Fan *et al.* 2023). II networks enhances information flow by sharing insights on corporate practices strengthening their monitoring capabilities address ESG risks effectively, safeguarding long-term portfolio value and reducing impact of negative externalities (Dimson *et al.* 2015). Site visits allow small blockholders to gather information and trade strategically, putting pressure on companies to perform better (Cao *et al.* 2022) who then pay higher cash dividends to mitigate the threat of exit.

Secondly, well-connected II within a network creates a certification effect (Bajo *et al.* 2020; Chen *et al.* 2023). I argue that once the II invests in the portfolio firm, it offers a credible signal/ certification to other investors regarding the credibility of the firm that they invest in. II with large network, with their extensive resources and expertise, can signal promising investment opportunities (Gillan & Starks 2000). Association with monitoring institutions attracts other investors, improving the firm's credibility when accessing capital markets for finance (Ferreira & Matos 2008; Aggarwal *et al.* 2011; Boone & White 2015).

The presence of well-connected II can serve as a certification mechanism that alleviates concerns of adverse selection. By investing in the company, it sends a positive signal to the market implying the firm passing scrutiny and due diligence, encouraging other investors to invest with greater confidence. Li *et al.* (2020) establishes in their study that venture capital financing helps mitigate information asymmetry between entrepreneurs and external shareholders, increasing the perceived value of a start-up and reducing investor uncertainty (Li *et al.* 2020). Boone and White (2015) find that II participation in Initial Public Offering (IPO) leads to greater investor demand and lower underpricing due to reduced perceived risk of adverse selection. This either reduces information asymmetry between investors and the company or sends a signals to other investors addressing the concern of adverse selection.

Further to alleviating adverse selection, certification alleviates the potential for moral hazard.[15] Although, some managers might pursue strategies that are riskier or more self-serving knowing that passive investors are unlikely to exert significant influence, Appel *et al.* (2016)

[15] Moral hazard is a fundamental concept in finance that arises when one party takes on excessive risk because they do not fully bear the consequences of their actions (Holmström 1979).

find that passive investors apply pressure on companies to improve governance practices. The presence of II drive managers to prioritize long-term value creation over short-term gains (Bena *et al.* 2017). Well-connected II utilize their resources and expertise to oversee managerial actions mitigating managerial opportunism, aligning managerial incentives to shareholder interests and reducing value-destroying actions such as excessive risk-taking or misallocation of resources.

II in a network without sufficient resources or expertise can benefit from the confidence instilled by a reputable II due diligence on potential investments (Bajo *et al.* 2020; Chen *et al.* 2023). This creates the risk of free-riding, where some benefit from these actions without contributing. Maggio *et al.* (2019) find that individuals using central brokers gain informational advantages due to brokers' privileged access to order flow. This access allows investors to mimic each other's trades. The challenge of free-riding becomes less significant as investors begin to reap long-term benefits from brokers' exclusive sharing of insights grounded in reciprocity contributing to improved overall returns.

In this study, I postulate that the information flow and the certification effect of the network of II reduces information asymmetry related to the environmental performance of the portfolio firms. The II could take advantage of the privileged position within a network to influence a firm’s environmental performance such as reducing carbon emissions. Hence, I propose the following baseline hypothesis:

H1: Ceteris paribus, the higher II network in a firm is associated with reduced carbon emission.

However, it remains unanswered how the II network enable a better environmental outcome for a firm. I argue that reducing information asymmetry should enhance the monitoring effect and shareholder activism, resulting in the reduction of carbon emissions. Interconnectedness of II impact the scrutiny, activism and advocacy directed toward portfolio companies (Marti *et al.* 2024). By sharing information and best practices, well-connected II identify and highlight shortcomings in corporate climate strategies. This can lead to increased scrutiny of companies' environmental practices, inspire activist campaigns pushing for change, and promote broader advocacy efforts that pressure policymakers to enact stricter climate regulations. For instance, socially responsible II are more likely to closely monitor progress and hold companies accountable for achieving their commitments (Heath *et al.* 2023). With a long-term view and push for broader sustainability practices or ambitious goals beyond emissions reduction, firms with a higher proportion of well-connected investors will experience more frequent discussions through shareholder activism and ongoing monitoring regarding their climate goals, even if their targets are met.

2.2.1.1 Enhanced Monitoring

Lewellen and Lewellen (2022) find that II have a financial incentive to be engaged monitors. II pressure companies directly through vocal communication with management or indirectly by selling their shares or by field building (Ferreira & Matos 2008; Marti *et al.* 2024). Monitoring activities require substantial effort, encompassing information gathering, analysis, and potential actions to influence others (Chen *et al.* 2007). Extensive connections provide a market edge and influence over ethical practices within companies. The network of II reflects the degree of information flow and their influence on the decisions of others through certification effect (Crane *et al.* 2019; Bajo *et al.* 2020). II that are central in the network can share environmental related goals with other II in the network to play a significant role in monitoring opportunistic behavior throughout the implementation of corporate sustainability strategies.

Due to its prominent network position, II can leverage its extensive connections to enforce better governance to quickly disseminate information, and exert pressure on management leading to better financial value (Gillan & Starks 2000; Aggarwal *et al.* 2011; Boone & White 2015). Large investors are generally effective monitors but their diverse holdings can reduce their monitoring effectiveness (Dharwadkar *et al.* 2008). The effectiveness of individual investors' firm monitoring increases when they join a network that pools resources and information, overcoming individual limitations (Brav *et al.* 2022). The ability to unite the interests of stakeholders increases pressure on firm management to prioritize their needs.

II are better equipped to monitor companies due to the potential gains from effective monitoring outweighing the associated monitoring costs that improve firm performance (Gillan & Starks 2000). Multiple block holdings that increases the presence of II can enhance monitoring effectiveness by providing II with greater capabilities and incentives to monitor due to reduced monitoring costs and information uncertainties (Kang *et al.* 2018) enhancing firm value. For instance, prominent investors like California Public Employees' Retirement Scheme (CalPERS) closely monitor companies advocating for changes in governance (Smith 1996). Fich *et al.* (2015) find that when a firm represents a significant portion of an investor's portfolio, the investor is more likely to intervene, leading to higher deal completion rates, higher bid premiums, and lower acquirer returns.

Well-connected II reduce value-destroying acquisitions, improve deal quality, and boost innovation due to superior information (Bajo *et al.* 2020; Fan *et al.* 2023). This pressure stems from the desire to access capital and avoid divestment by climate-conscious investors (Brandon *et al.* 2022; Angelis *et al.* 2023). As companies that are susceptible to climate change risks are likely to experience a growing demand to reduce their emission levels, these firms face heightened investor scrutiny due to their elevated risk profiles. Investors increasingly prioritize ESG considerations, and firms occupying central positions within the network face greater pressure to reduce their carbon emissions. I thus argue that the enhanced monitoring of its portfolio firm facilitated by its network with other II is a potential channel through which the firm's carbon emission is reduced.

However, testing this channel is not straightforward as the collective monitoring of II network may not be observable. I provide indirect evidence to support the enhanced monitoring argument by investigating the real environmental outcome of a firm such as green innovation. Previously literature has already shown that certain II, such as foreign and well-connected II, acts as a powerful external monitor to promote innovation in economies facing internal challenges boosting innovation (Bena *et al.* 2017; Luong *et al.* 2017; Fan *et al.* 2023). Jiang and Yuan (2018) show II monitor managers by observing manager's behavior and firm's operations through site visits, which improves the managers' incentive to increase firm innovation. In line with this evidence, Zhao *et al.* (2023) investigate the real environmental outcome of II and find that II play a crucial role in increasing firm's green innovation.

Firms with a more central position within an interfirm network experience a higher level of innovation, particularly in intangible industries (Chuluun *et al.* 2017). They find connected and diverse networks play a crucial role in helping firms stay innovative by facilitating information diffusion and knowledge transfer. Stronger network connections allow investors to engage more effectively with portfolio companies. Through monitoring and engagement, investors can encourage companies to invest in green technologies and processes, ultimately driving innovation (Bena *et al.* 2017; Thapa *et al.* 2023). This suggests that well-connected II could facilitate the sharing of best practices and knowledge related to environmental innovations, aligning with the concept of network effects.

H2a: Well-connected II exhibits stronger monitoring practices, leading to increased green innovation consequently reducing carbon emissions.

2.2.1.2 Enhanced Shareholder Activism

Shareholder activism is a strategy used to put pressure on companies that are not prioritizing wealth maximization (Karpoff *et al.* 1996), governance (Appel *et al.* 2018), and E&S goals (Dyck *et al.* 2019). Private channels effectively allow II to achieve E&S changes through activism (Becht *et al.* 2009; Dyck *et al.* 2019). For instance, Norwegian Government through the Norwegian Sovereign Wealth Fund, uses public ethical standards to encourage responsible behavior by companies beyond using just regulations (Vasudeva 2013).

Shareholder activism struggles due to free-riding, conflicts of interest, and institutional differences (Becht *et al.* 2009). Shi et al. (2022) argue that after being targeted by activist investors with conservative-leaning political ideology, firms tend to discount the interests of non-shareholder stakeholders and demonstrate that such firms exhibit elevated workplace injuries and illnesses. Companies with high levels of selling by II are more likely to be targeted by activist investors as they can hide their share purchasing from the selling, allowing them to accumulate shares quickly and cheaply (Gantchev & Jotikasthira 2018). This enables them to launch campaigns that might not be viable otherwise. Although Song and Szewczyk (2003) find shareholder activism did not improve the company value of targeted companies, Becht *et al.* (2017) examine international hedge fund activism and find that success depends on specific engagements.

Short-term financial pressures might tempt companies to prioritize immediate profits over long-term environmental costs. Appel *et al.* (2018) find that passive investors owning a large portion of stocks help activist investors push for changes in companies to increase their value. When passive investors dominate stocks, activist investors are more likely to use expensive methods to push for company changes, reflecting lower campaign costs or higher expected benefits (Appel *et al.* 2018). Gillan and Starks (2000) find that coordinated efforts from institutions and II have a stronger bargaining position with companies despite some negative stock market responses.

With their extensive access to information and shared concerns about climate change, II, with strong connections, are more likely to closely examine their portfolio firms' environmental practices (Marti *et al.* 2024). This scrutiny could translate into activism, where investors push for changes in a firm's operations or strategy to reduce its climate impact. Their certifications and positive evaluation of a company's climate efforts serve as valuable signals to other stakeholders (Vasudeva 2013; Chen *et al.* 2023), leading for investors to influence industry norms and public expectations about environmental responsibility. Firms seeking to attract capital or maintain a good reputation might be more responsive to pressure from well-connected investors who prioritize climate action.

Connected, long-term investors push for stricter emission reduction timelines and broader sustainability practices (Kang *et al.* 2018; Azar *et al.* 2021; He *et al.* 2023). Climate change poses significant long-term risks to businesses, and these investors might be more likely to push for actions that mitigate those risks and ensure the long-term sustainability of their portfolio companies. This heightened focus on climate change signifies corporate discourse and prioritization under the influence of activism.

However, testing this channel is not straightforward as the collective activism of II may not be observable. I provide indirect evidence to support the enhanced activism argument by investigating the market perception of a firm's climate change exposure as captured during a conference call.[16] Increased awareness of climate change as a significant financial risk has increased investor interest in ESG factors (Pedersen *et al.* 2021; Heath *et al.* 2023). Investors anticipate a positive risk premium when considering downside risks and opportunities linked to climate change (Sautner *et al.* 2023a; Sautner *et al.* 2023b).

II may enhance E&S performance of their portfolio firms due to both financial and social motivations (Dyck *et al.* 2019). The authors find that II often push for improved E&S performance driven by long-term financial returns as well as social pressure shaped by social norms. This can lead to coordinated activism efforts to influence firm behavior. Improved network connections enable investors to interact more effectively with their portfolio companies. Through activism, investors encourage companies to meet their climate targets, ultimately driving climate change exposure. This suggests that well-connected II could facilitate the scrutiny, advocacy, and activism of climate change related discussion, aligning with the concept of network effects.

H3a: Well-connected II exhibit stronger activism practices leading to increased climate change exposure, reducing carbon emissions.

[16] I acknowledge that climate change exposure is a soft activism measure reflecting the underlying pressure from II that influences firms to discuss or take action on climate related issues. It is unlike the direct measure of shareholder activism like proxy voting or public campaigns.

3 Chapter 3: Data and Variables

This chapter provides an outline of the key data and variables used to study the impact of institutional investors on corporate sustainability outcomes regarding ESG misbehavior and the impact of the institutional investor network on carbon emissions. I merge information from multiple databases that are reputable and robust as detailed in the respective empirical chapter below. The chapter then identifies key variables of interest, key control variables outlining their methodological construction.

I also emphasize the importance of including control variables to account for potential confounding factors that might influence the relationship of study. I carefully select and control for these variables to ensure robust and reliable findings. I also present the summary statistics highlighting their distribution within the sample and period of study. It includes a breakdown of the key variable of interest by industry and country to provide insights into how it varies across them emphasizing the heterogeneity within the data.

3.1 Data Sources, Variables, and Summary Statistics: First Empirical Chapter

3.1.1 Data Sources

I use multiple databases to test the hypotheses. First, I collect annual institutional ownership (*IO)* data at the firm-investor level from the S&P Capital IQ database for 2007-2021. This dataset provides the equity ownership holdings of individual II for their investee firms. Following Ferreira and Matos (2008) and Kacperczyk *et al.* (2021), I use the last reported holding value for each calendar year. I also obtain firm-level accounting information from LSEG (London Stock Exchange Group formerly Refinitiv) – Worldscope and Datastream databases. I obtain country-level information from World Bank and Yale Center for Environmental Law and Policy. To capture investee firms' *ESG-MVR*, I use the widely employed RepRisk dataset available from 2007 until 2021 (Wang & Li 2019; Zhou & Wang 2020; Dai *et al.* 2021; Dogru *et al.* 2022).

Following existing literature, I apply several filters to clean the dataset (Kacperczyk *et al.* 2021). First, I exclude all investee firms in the financial sector from the sample as they are extensively regulated (INDM – Finance; typically comprising of supersectors like Banks, Financial services, and Insurance).[17] Second, I only keep investee firms with non-zero ownership of II, non-missing accounting information, and a market capitalization of more than $1 million. Third, I drop observations from countries with less than twenty firms. Fourth, I

[17] INDM is mapped 1:1 with Industry Classification Benchmark (ICB) subsector classification level (see https://www.ftserussell.com/data/industry-classification-benchmark-icb [Accessed 16th Sept 2023, 13:15 BST]). ICB is a taxonomy developed by Dow Jones and FTSE (Financial Times Stock Exchange) to categorize markets into sectors within the macroeconomy. It organizes industries into 11 categories, further divided into 20 supersectors, 45 sectors, 173 subsectors and is used by London Stock Exchange, NASDAQ and NYSE among others. It is better suited for financial analysis and investment decision-making as it focuses on a company's principal business activity based on revenues and earnings. When a company conducts multiple types of business, the predominant sector is determined by reviewing the audited accounts and the directors' report. The SIC (Standard Industry classification) system focuses on production processes, lacking the specificity needed to capture diverse business activities and financial characteristics resulting in inconsistent classifications (Kahle & Walkling 1996; Chan *et al.* 2007). These inconsistencies lead to mismatches in industry groups (Bhojraj *et al.* 2003), making it less reliable for analyzing II portfolios and risks.

restrict II to those that hold more than 0.01%.[18] Finally, I exclude investee firms reportedly having negative ownership and ownership greater than 100%, as this could result from short selling or data errors that cause bias to investor preferences (Asquith *et al.* 2005; Pan *et al.* 2022).[19]

I use the common identifier International Securities Identification Number (ISIN) to merge the yearly S&P Capital IQ, LSEG, and RepRisk database firms. I use the INDM series code from LSEG Datastream to identify and group industries. After merging all the different II, investee-firm, and country-level datasets, the final sample consists of 14,906 II from 97 countries investing in 4,342 firms domiciled in 34 countries. The sample period covers 2007 to 2021. In the following section, I describe all the variables used.

3.1.2 Variables

3.1.2.1 Outcome variable

Our primary outcome variable is the measure of firm-level ESG media reported misbehavior ($ESG - MVR_{it+n}$) where *i* denotes the investee firm, *t* denotes the year, and *n* takes the value of one or two, reflecting lead years. *ESG-MVR* is proxied using the Reputation Risk Index (RRI) developed by database firm RepRisk. Using artificial intelligence, algorithms, and human interaction, RepRisk screens over a diverse range of public sources and stakeholders including print media, online media, social media, blogs, government bodies, regulators, think tanks, newsletters and other online sources spanning 23 languages to identify relevant ESG risk incidents. These incidents involve ESG violations and controversies associated with twenty

[18] I impose this restriction because firms allocate more resources to engage with large II rather than small investors (Tosun 2020). Small II take longer to collect private information and possibly need more incentive to exit in the short term (Ekholm & Maury 2014). Therefore, I argue that small institutional holdings should be considered less relevant to company decision-making, having little impact on market outcomes.

[19] The reason for ownership above 100% information in the S&P Capital IQ database is acknowledged and justified by the S&P Capital IQ knowledgebase – https://spglobal.my.site.com/s/article/4361 [Accessed 26th Sept 2023, 13:13 BST].

eight parameters. For example, environmental issues encompass violations of the company's environmental impact, such as pollution, greenhouse gas emissions, water usage, etc. Social issues pertain to violations related to a company's treatment of its employees, communities, and other stakeholders, such as human rights, labor issues, etc. Governance parameters involve violations of a company's internal corporate governance practices, such as executive compensation, anti-competitive practices, and fraud. Based on these parameters Reprisk creates an indicator variable for violations categorized into environment, social, governance and cross-cutting domains that are linked to international standards, taking the values of one and zero. For the full details of the specific ESG parameters, scope, and how the violations are linked with these parameters, see https://tinyurl.com/5n83e5v9.

Each risk incident is then analyzed according to three dimensions: severity (harshness), reach of the information source, and novelty (newness). The severity or harshness is determined based on three sub-dimensions: consequences (such as health and safety, injury, or death), extent of the impact (such as number of people affected), and cause of the risk incidents (such as accident, negligence, or intent). It is then classified as low, medium, or high severity. The reach of the information source is classified as low (reported in local media, social media, local government bodies), medium (reported in national or regional media, international NGO, state, national or international government bodies), or high reach (truly global media outlets). Finally, novelty measures whether the incident is the first time a firm is exposed to a specific issue in a given location. Each risk incident is documented in a risk incident brief and is recorded only once in the dataset unless its risk profile changes due to a new development relating to the same issue, source escalation to a more influential source, or recurrence after a six-week period which could increase the risk of the incident.

Once the media-reported incidents are gathered, RepRisk quantifies the risk incidents using its proprietary standard and customized risk metrics to generate a firm's RRI.[20] This index score ranges from 0 to 100, with a higher score reflecting a greater level of ESG-related reputation risk, which I term ESG media-reported misbehavior (*ESG-MVR)*.[21] For details on the methodology of how ESG-related incidents are converted into the quantitative measure of *ESG-MVR*, please see Appendix D.

3.1.2.2 Key independent variable

Our main independent variable is IO_{it}, measured at two different levels. The first measure of IO_{it} is the aggregate investee firm level (FL_IO_{it}). For each year-end (t), FL_IO_{it} is the total ownership holdings in a firm (i) by all II ($j = 1 \ldots n$). The second measure is the pair investor-investee level ownership (Inv_IO_{jit}). For each year, Inv_IO_{jit} is the ownership holding of an individual institutional investor (j) in an investee firm (i) for the year-end t. I further classify all individual institutional investors into four different categories based on their *value* or *values-based* orientation. A brief definition of such classification is reported in Appendix C.

3.1.2.3 Control variables

Following the existing literature, I control for observable firm-level characteristics that could simultaneously be associated with the firms' *ESG-MVR* and the variations in the two different measures of *IO (i.e* FL_IO_{it} and Inv_IO_{jit}, see Li and Wu (2020); Asante-Appiah and Lambert (2022); Raghunandan and Rajgopal (2022); He *et al.* (2023)). First, I control for the organizational scope and size as evidence indicates that large firms are more likely to face

[20] For further information on calculations, see https://tinyurl.com/42dkz2fa [Accessed on 13th Sept 2024, 17:25 BST].

[21] Financial Times reported that Punjab National Bank processed $1.77 billion in fraudulent transactions in Mumbai, India falling under investigation (https://tinyurl.com/pnb18). [Accessed on 13th Sept 2024, 17:28 BST] The incident is rated with a severity (2) due to the significant amount of alleged fraud and was awarded an RRI of 83.

higher heightened media scrutiny, potentially elevating the level of *ESG-MVR* (Li & Wu 2020) and could be an important factor in attracting II because bigger firms are more visible, exhibit a higher level of transparency, and are more liquid in the capital market. I use the natural logarithm of a firm's revenue (*Ln_Firm_Size*) as a proxy of the scale and reach of its operations.[22]

Next, I consider operational liquidity, proxied by the level of cash holdings. I expect a negative relationship between the availability of cash and *ESG-MVR,* as firms with higher cash holdings should engage in greater levels of ESG initiatives, which should potentially be reflected in a lower likelihood of experiencing *ESG-MVR* (He *et al.* 2023). Further, cash holdings could also be positively related to *IO*. I proxy for cash holdings by using the natural logarithm of the ratio of total cash to total assets (*Ln_Cash*).

Likewise, I take account of a firm's reliance on debt financing.[23] I argue that high debt levels may elevate a firm's *ESG-MVR* by diverting resources from sustainable initiatives and practices. I proxy for a firm's indebtedness using the ratio of total debt to total assets (*Leverage*). I further control capital market-based growth opportunities. Firms with higher capital market-based growth opportunities would be more conscious of their ESG reputation and hold greater financial muscle to manage such misbehavior more prudently. Simultaneously, higher growth opportunities should also attract higher *IO*. To proxy for the market's performance and growth opportunities, I employ the investee firm's ratio of market to book value of equity (*MTB*).

I further address a firm's business growth potential that could attract II and potentially be associated with future *ESG-MVR*. Better business growth opportunities signify improved

[22] In the same spirit as Gürkaynak *et al.* (2022), I deflate the firm revenue by the consumer price index (a general purpose index suitable for estimating trends in real terms) using 2005 as the base year. Deflation of a monetary value reveals growth in relative terms (measures in constant dollars) and stabilizes the variance of random or seasonal fluctuations.
[23] Profitability, proxied by return on assets (ROA), is found to be highly correlated with leverage (88%). I have excluded it in the regressions to avoid over-identification.

financial performance and capacity to invest in ESG initiatives, indicating a firm's ability to allocate higher resources for ESG management and potentially exhibiting a lower likelihood of experiencing *ESG-MVR* (He et al., 2023). To proxy a firm's business growth opportunity, I use the annual change in revenue (*Revenue_Growth)*. Next, I control for the firm's experience and adaptability. I argue that older firms gather more knowledge and higher resources, enabling them to manage *ESG-MVR* better than younger firms. Further, thanks to their greater visibility and size, older firms should also attract higher *IO*. I proxy for a firm's experience and adaptability using *Firm Age*, calculated as the natural logarithm of the years since the firm was publicly listed (*Ln_Age*).

Given that the sample includes data from different countries, I also incorporate country characteristics that may affect firm-level *ESG-MVR* and *IO*. First, I control the level of economic development in the region where the firm operates, as studies suggest that economically developed countries tend to have higher ESG incidents (Li & Wu 2020). Further, higher economic development is likely to attract higher levels of *IO*. I proxy for a country's economic development by using GDP per capita, which is calculated as the natural logarithm of a country's GDP over its population in year *t* (*Cntry_Ln_GDPPC*).

Lastly, I control for the aggregate environmental performance of the country where the firm is domiciled. The rationale is that companies operating in countries with higher environmental performance encounter stricter environmental regulatory frameworks and institutions, which should help them boost their own environmental performance and thus help in mitigating future firm-level *ESG-MVR*. Higher environmental performance should also attract higher *IO*.

I proxy for the country's environmental performance (*Cntry_EPI*). by using the environmental performance index (EPI) constructed from the Yale Center for Environmental Law & Policy, constructed by Wolf *et al.* (2022). EPI is a global tool that assesses the environmental performance of 180 countries based on forty indicators in eleven issue areas. It offers a scorecard for environmental performance, measuring a country's proximity to established environmental targets. The composite measure of environmental health and ecosystem vitality across countries scoring each on a scale from 0 to 100. Higher values indicate better environmental performance, with scores closer to 100 reflecting stronger sustainability practices, robust environmental health, and well-preserved ecosystems. For more details, please see www.epi.yale.edu.

To address issues related to obvious outliers in such an extensive cross-country dataset, I winsorize all the continuous variables at the 1st and 99th percentiles.[24] Appendix B also offers a brief description of all the variables.

3.1.3 Summary Statistics

Table 1.1 reports the distribution statistics of all the variables discussed above.

<Insert Table 1.1>

Panel A shows that the mean (median) level of *ESG-MVR* of a firm over the sample period is 10.134 (6.750), similar to those reported by other studies employing the same dataset (see Asante-Appiah and Lambert (2022) and Hasan *et al.* (2022)). These scores suggest substantial variation among firms which demonstrates significant ESG misbehavior. The inter-quartile range (0, 18.333) highlights that many firms have minimal ESG misbehavior, but some display significantly higher levels.[25] The average (median) level of *Peak-ESG-MVR* is 22.746 (26.0), which is also similar to the 20.25 reported by Hasan *et al.* (2022). These scores are

[24] Winsorization is a standard practice of dealing with extreme outliers and eliminating events with likely data errors (See Gopalan *et al.* (2014); Chuprinin *et al.* (2015); DeAngelo and Roll (2015); Dougal *et al.* (2015); Erel *et al.* (2015)).
[25] I construct a simple example to demonstrate ESG-MVR decaying to zero, see Appendix D.

expected to be bigger than those of *ESG-MVR* as it represents the highest value of *ESG-MVR* in the last two years. *ESG-MVR* has components *Env-ESG-MVR* (1.830), *Soc-ESG-MVR* (3.418), and *Gov-MVR* (3.188). If *ESG_MVR* decays to zero, it is consequential for its components to be zero as they contribute to the overall score, and for peak score to be zero as *ESG_MVR* has been zero for the last two years indicating no observations to record. Violations (mean 5.716 standard deviation 22.228) indicate that many firms report minimal violations, while some face serious issues. When these values are zero, it suggests that the firm has not been involved in any reported non-compliances during the observed period. Social violations (mean 2.515) are higher on average than environmental (mean 1.807) and governance violations (mean: 1.393). Social issues often involve multiple stakeholders, covering a wider range of incidents, and have a broader public impact, potentially leading to more reported incidents.

Panel B reports the characteristics of *IO* and its classifications. The mean (median) firm-level *IO* (*FL_IO*) is 42.155% (35.191%) with a wide-spread (standard deviation 28.940) indicating that IO varies significantly across firms. The average ownership is similar to Azar *et al.* (2021), who report an average *IO* of 45%. Additionally, the mean (median) investor *IO* (*Inv_IO*) holding is 0.459% (0.072%), indicating that most investors hold smaller stakes while a few own significantly more equity. The average investor-level ownership is similar to Blanco *et al.* (2024) who report an average holding of 0.40%.

When examining by their commitment to responsible investment, *Inv_PRI_IO* (0.765%) exceeds that of *Inv_Non_PRI_IO* (0.402%). Interestingly *Inv_PRI_High_ESG_IO* focused investors hold more ownership (0.863%) than *Inv_PRI_Low_IO* (0.668%). II that are PRI signatories and with high-ESG portfolio scores may be more selective, focusing on fewer firms meeting ESG criteria. Meanwhile, those with low-ESG portfolio scores may take positions across a broader range of firms, regardless of ESG performance. Amongst other categories of investor country's legal system, institution type, and investor horizon, I observe low differences (*Inv_Civil_IO* 0.419%, *Inv_Common_IO* 0.471%, *Inv_Independent_IO* 0.438%, *Inv_Grey_IO* 0.687%, *Inv_LT_IO* 0.401%, *Inv_ST_IO* 0.474%).[26] When examining IO by their country of domicile, *Inv_Foreign_IO* hold a smaller average stake (0.329%) compared to *Inv_Domestic_IO* (0.601%). Finally, I compare II by their size. Large II wield greater influence and resources whereas smaller investors have limited market influence in comparison (*Inv_Large_IO* 0.886%, *Inv_Small_IO* 0.031%).

Panel C provides firm-level characteristics for companies in the sample. On average, a company has revenue of $7.627 billion, has 0.103 times cash-to-total-assets ratio, has leverage of 25.435%, a market-to-book ratio of 3.026, a revenue growth rate of 0.842%, and is 21.054 years old. Panel D presents country-level characteristics. The average per capita income is $39,829, and the average EPI score is 65.399.

<Insert Table 1.2>

In Table 1.2, Panel A summarizes *FL_IO* based on geographical location, while Panel B summarizes based on industry. In the sample, the two highest levels of *FL_IO* are domiciled in the USA (75.16%) and the UK (72.73%), exhibiting the highest number of unique II being 7,781 and 4,571, respectively. The Technology (49.63%) and Healthcare (47.44%) sectors have the highest average *FL_IO* by industry. However, the highest number of unique II were from the Consumer Discretion (8,909) and Industrials (8,876) sectors. In the regressions I control for country-specific factors, industry sector-specific characteristics, and temporal changes and fluctuations over time by using country, industry, and year-fixed effects. Additionally, I capture

[26] While the averages for independent and grey investors differ, I cross check the median values and conclude they are low differences (for *Inv_Independent_IO* (0.072) and *Inv_Grey_IO* (0.066) (See Table 1.1)).

the interaction between country and industry (country × industry) highlighting how IO varies across different geographical and industrial contexts.[27] These high-definition fixed effects ensure that the estimates reflect true variations in ESG misbehavior due to IO rather than confounding factors related to industry or geographical exposure (Blanco *et al.* 2024). In the investor-level analysis, I include investor fixed effects to control for differences between individual investors. I also capture the interaction between investor, country and industry by including investor × country × industry fixed effects. This high-dimensional setup allows us to ensure the estimates reflect investor behavior rather than confounding factors like geographical practices or sector specific exposure or between investors themselves.

[27] Incorporating investee company fixed effects subsumes all variations in the regression models.

3.2 Data Sources, Variables, and Summary Statistics: Second Empirical Chapter

3.2.1 Data Sources

Our primary database covers the 2004-2020 period by using firm-level carbon emissions obtained from the data provider Trucost.[28] I then match data sets from S&P Capital IQ, which provides institutional holdings data. I collect granular institutional ownership data at the firm-investor level from fifty-six countries collected for publicly listed companies with II holdings. I then match datasets with LSEG (London Stock Exchange Group) Workspace (Datastream and Worldscope), which provides corporate fundamentals. Further, I merge the dataset with publicly available data on climate change exposure (Sautner *et al.* 2023a), and self-collected data on green innovation metrics (Thapa *et al.* 2023). I perform matching using the S&P Capital IQ identification number and International Securities Identification Number (ISIN).

I restrict the sample to those with complete information, having ownership above 0.1%, firms with at least four years of consecutive data, and firms with above $1 million market capitalization.[29] I exclude all investee firms in the financial sector from the sample as they are extensively regulated (INDM – Finance; typically comprising of supersectors like Banks, Financial Services, and Insurance).[30] I also exclude those with negative ownership, and those

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[28] Trucost is a go-to source for corporate carbon emissions data. Carbon emissions data provided by Trucost is trusted by major players including financial institutions like MSCI and S&P who incorporate it into their indexes as well as international organizations like UNEP FI (United Nations Environment Program Finance Initiative) and even academic research (Azar *et al.* 2021; Bolton & Kacperczyk 2021; Cohen *et al.* 2023).

[29] Even tiny holdings can create a connection; a 0.1% threshold might help prioritize connections that are more likely to reflect significant investor influence, thereby focusing on potentially more impactful relationships. Investors with larger holdings might have a stronger incentive to monitor companies, engage with management, or even coordinate with other investors as they have more resources to allocate (Tosun 2020; Thapa *et al.* 2024). Limiting the data reduces the matrix size as the algorithm analyses a massive network of investors and their holdings, making the calculations faster and more manageable (Ozsoylev *et al.* 2013).

[30] INDM is mapped 1:1 with Industry Classification Benchmark (ICB) subsector classification level (see https://www.ftserussell.com/data/industry-classification-benchmark-icb [Accessed 16th Sept 2023, 13:15 BST]). ICB is a taxonomy developed by Dow Jones and FTSE (Financial Times Stock Exchange) to categorize markets into sectors within the macroeconomy. It organizes industries into 11 categories, further divided into 20 supersectors, 45 sectors, 173 subsectors and is used by London Stock Exchange, NASDAQ and NYSE among others. It is better suited for financial analysis and investment decision-making as it focuses on a company's principal business activity based on revenues and earnings. When a company conducts multiple types of business, the predominant sector is determined by reviewing the audited accounts and the directors' report. The SIC (Standard Industry classification) system focuses on production processes, lacking the specificity needed to capture diverse business activities and financial characteristics resulting in inconsistent classifications (Kahle &

with ownership over 100%.[31] I use the INDM series provided by LSEG to group the companies into the industries they belong to. the final sample data set consists of 13,682 firms domiciled worldwide.

3.2.2 Variable Description

3.2.2.1 Dependent Variable

Trucost gathers carbon emission data for companies through various channels, including readily available sources like company websites and reports, along with specialized databases like the Climate Disclosure Project (CDP). Trucost utilizes an environmental profiling model to estimate emissions for companies that do not publicly disclose this information. Some countries have implemented stricter guidelines or even recommended independent verification. Bolton and Kacperczyk (2021) find a very high correlation between Trucost data and other providers like CDP and Sustainalytics.

I focus on unscaled scope 1 and scope 2 carbon emissions, as it is a direct measure of how much a company pollutes and their risk from future climate change regulations.[32] Based on Bolton and Kacperczyk (2023a), I posit that absolute emissions are a measure that directly implicates total pollution, offering a more robust measure due to their direct alignment with the ultimate goal of achieving net-zero emissions. Also, carbon disclosure regulations emphasize absolute emissions, making it a practical choice for assessing a company's exposure to future regulations and potential vulnerability to financial risks. While using unscaled emissions may not capture firm-level efficiency improvements, as discussed by Aswani *et al.*

Walkling 1996; Chan *et al.* 2007). These inconsistencies lead to mismatches in industry groups (Bhojraj *et al.* 2003), making it less reliable for analyzing II portfolios and risks.

[31] The S&P Capital IQ knowledgebase documents reasons where institutional ownership percentages exceed 100% of common shares outstanding– https://spglobal.my.site.com/s/article/4361 [Accessed 26th April 2024, 09:35 GMT]

[32] I acknowledge the valuable discussion raised regarding efficiency considerations as highlighted by Bolton and Kacperczyk (2023a) and Aswani *et al.* (2023b).

(2023b), I need to consider the risk for smaller emitters with limited reduction potential. Absolute emissions offer a valuable starting point for this analysis recognizing further research into incorporating efficiency metrics.

3.2.2.2 Other Dependent Variables

I build on prior work by Thapa *et al.* (2023) that measures green innovation using patent data. Environmental innovations are crucial for developing cleaner technologies and processes, ultimately reducing the negative environmental impact of economic activity and potentially lowering costs (Haščič & Migotto 2015). Patents are a good way to identify environmentally friendly technologies because it is widely available, uses quantitative metrics, allows comparison across different innovations, and directly links to a specific output – patented technology (Haščič & Migotto 2015).[33] Using the World Patent Statistical Database (PATSAT), patents relating to four environmental goals were searched: human health, water scarcity, ecosystem health, and climate change mitigation.[34] PATSAT does not link patents to specific companies, which I address through a fuzzy matching process comparing company names to S&P Capital IQ using string searching algorithms verifying by name and location.[35] Green patent reflects each company's relative investment in green innovation in a year. Patents take time to be granted, so recent inventions might not appear in databases, skewing results toward older innovations. To address this truncation bias, the data reflects innovations based

[33] However, not all inventions are patented and the number of patents alone might not reflect the true importance or environmental impact of an innovation. Despite these limitations, patent data remains advantageous with its technical nature, offering rich characterization and having an international reach. Patenting though reserved for inventions with commercial potential reflects level of environmental innovation activity that focuses on commercially viable solutions with detailed technical descriptions.

[34] PATSAT is a rich resource for patent information. It has been collecting data on patent applications from companies in over 90 countries since 1844, covering filings from more than forty intellectual property offices around the world, including major ones like the US Patent and Trademark Office (USPTO), European Patent Office (EPO), Japan Patent Office (JPO), and World Intellectual Property Organization (WIPO).

[35] PATSAT provides details like the titles and abstracts of patent applications, names of the applicant companies and inventors, filing dates, and whether the patent was granted, including the classification according to international systems like International Patent Classification (IPC) and Cooperative Patent Classification (CPC), allowing the identification of green technologies (Haščič & Migotto 2015; Thapa *et al.* 2023).

on the date applications were submitted (Luong *et al.* 2017; Boubakri *et al.* 2021). I take the total sum of green patents for each firm over the period, which gives a sense of how a company's green innovation activity has changed over time.

I build on prior work by Sautner *et al.* (2023a) that analyses earnings calls to understand firms' exposure to climate change. A firm's exposure to climate change is the conversation share dedicated to climate-related topics, capturing the market perception of a firm's exposure to climate change opportunities, physical threats, and regulations. They address challenges in identifying climate-specific language by using bigrams to measure the frequency of climate discussions in earnings calls. They start with a short list of initial keywords related to climate change, a foundation for the machine learning process. Using a keyword discovery algorithm based on research by King *et al.* (2017), the algorithm goes beyond the initial keywords and learns additional relevant bigrams from various sources. This process creates four distinct sets of climate change bigrams: broad aspects, opportunities, physical threats, and regulatory changes. These bigrams are used to measure the frequency of climate-related discussions in each earnings call transcript. The frequency is scaled by the number of bigrams used in the call.

3.2.2.3 Main Independent Variable

Social networks like the one formed by II consist of investors connected by links, forming the network itself (Bianchi *et al.* 2023). The positioning of investors within the network is not random. II networks are intricate structures where each II holds varying degrees of power based on their position within the network (Bajo *et al.* 2020; Chen *et al.* 2023). Certain characteristics grant greater influence, including extensive connections to other investors, proximity to a large portion of the network, the ability to control information flow by lying on the shortest paths between others, and connections to highly influential investors. This power translates into two key advantages: superior access to information circulating within the network and a potential bargaining edge due to their strategic network position.[36] [37] While these dimensions are distinct, observing power dynamics can shed light on the dominant dimension at play.

I construct the network graph for all II and extend beyond the active-passive classification.[38] Previous research on investor networks has been dominated by investors who are considered active (Bajo *et al.* 2020; Chen *et al.* 2023), overlooking the significant influence of less-studied passive investors (Chinco & Sammon 2024). The combined voting power of major stakeholders on issues concerning corporate behavior could be much greater than their individual influence (Fichtner *et al.* 2017). Coordinated effects within institutional networks can amplify their impact by presenting a collective voice, sharing best practices on sustainable investing strategies, and launching joint initiatives across the market, thus impacting corporate behavior as a whole (Appel *et al.* 2016; Crane *et al.* 2019).

I construct centrality measures that represent the importance of II being in a central position to take advantage of information that can be used for monitoring (Bajo *et al.* 2020; Dissanaike *et al.* 2023). Centrality refers to the position within a network implying the II importance or influence within the network. I construct centrality measures (*II_centrality*) for each institutional investor in the sample, such as degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality index (Hochberg *et al.* 2007; Larcker *et al.* 2013; Ozsoylev *et al.* 2013; El-Khatib *et al.* 2015; Bajo *et al.* 2016; Chuluun *et al.* 2017; Intintoli *et al.* 2018; Maggio *et al.* 2019; Bakke *et al.* 2024).

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[36] the research focuses on the exchange of information in II networks, without considering the impact of network position on bargaining power. To measure bargaining power, I would need more data than just the network structure. Therefore, I concentrate on analyzing the flow of information within the II network.

[37] II often have access to information that is beyond information readily available to the public (Borochin & Yang 2017). II may have direct communication with corporate boards, giving them insights into strategic plans and operational challenges (McCahery *et al.* 2016). II use industry trends, innovations, and non-public financial data to make investment decisions (Bushee & Goodman 2007). Investors geographically closer to firms enjoy higher returns due to their informational advantage (Coval & Moskowitz 1999). II leverage private information to gain an advantage in IPO participation (Chemmanur *et al.* 2010).

[38] Computational limitations restrict the analysis to investors holding at least 0.1% of a company's equity stock, ensuring I focus on those with a vested interest and having the incentive to influence players within the network.

Degree centrality measures how well-connected an institutional investor is based on the number of direct connections. It identifies the popularity or connectivity of an investor within the network. Betweenness centrality measures the extent to which an investor lies on the shortest path between other investors. It identifies the investors that act as critical bridges or intermediaries between other investors. Closeness centrality measures how quickly an investor can communicate with others in the network. It identifies investors with efficient access to the entire network, facilitating swift communication. Eigenvector centrality emphasizes the quality of connections between influential investors, rather than quantity. It captures how well-positioned an investor is in a network by considering both the amount and the delay of the information received through connections. Please see Appendix A for a detailed discussion on the construction of the centrality measures along with the mathematical formulas and a simple example showcasing a network.

3.2.2.4 Control Variables

Following the existing literature, I control for observable firm-level characteristics that could potentially be associated with the firm's carbon emissions and the variations in II centrality measures (Intintoli *et al.* 2018; Azar *et al.* 2021; Bolton & Kacperczyk 2021; Cohen *et al.* 2023; Dissanaike *et al.* 2023).

First, I capture the coordination effects of a group of investors. Higher coordination can lead to more unified investment strategies, enhancing prominence in the network and prioritizing sustainability, ultimately leading to lower carbon emissions. I expect the relationship to be empirical. I follow Dissanaike *et al.* (2023) and control for coordination (*Clique_Own*) in the analysis to empirically entangle both concepts. Clique ownership refers to the total percentage of a firm's ownership held by institutions belonging to highly clustered communities.[39] Clique ownership serves as a coordination proxy (Crane *et al.* 2019), while the centrality measures focus on accessing information like network centrality.

Following the methodology of Crane *et al.* (2019), I define II as connected if they are linked through a web of overlapping ownership positions across different firms. A clique refers to a group of IIs connected to each other through any stock holding. The methodology for constructing the II network incorporates a unique perspective on coordination. Using a matrix *(N×N)* representing investors, Crane *et al.* (2019) focus on large holdings, i.e., the investors are said to be connected (assigned a value of one) if both own at least 5% of the same company. Using Louvain's algorithm, a community detection method to analyze the entire network I consider overlapping ownership positions regardless of the ownership stake, even if none of the investors reach the 5% mark individually.[40] I also broaden the perspective to include ownership positions across various firms globally and extend the analysis to situations where coordination is relevant.

Next, I control the overall scale of a company's operations. Larger companies have higher economic activity and may face public pressure to reduce their environmental impact (Azar *et al.* 2021). Likewise, large firms are more likely to have fewer growth opportunities implying lesser investment demand from II (Bajo *et al.* 2020), thereby decreasing their connectedness. Overall, I conclude and expect a positive relationship between the scale of operations and carbon emissions. To proxy for the scale of operations, I use the natural logarithm of a firm's total assets (*Size*).

Next, I capture the firm's growth potential. Firms with higher growth potential might prioritize expansion and invest in new ventures, potentially increasing emissions through added

[39] Cliques are fully connected subnetworks where each member is connected to every other member (Crane *et al.* 2019).
[40] Consequently, I move away from the conventional definition of block ownership, which relies on a fixed 5% ownership threshold. This shift aligns with Edmans and Holderness (2017) that such thresholds are arbitrary and underscores the value of exploring the impact of smaller ownership stakes in enriching the understanding.

economic activity. It could also be argued that such firms might be concerned about longer-term outlook and reputation, possibly leading to increased investment in sustainable practices reducing their carbon emissions. II, especially those seeking to capitalize on future returns, could drive increased engagement, elevating their centrality in the network. We, therefore, expect a positive relationship between a firm's growth potential and carbon emissions. I proxy growth potential using market capitalization divided by the book value of equity (*MTB*).

Next, I capture a firm's reliance on debt financing. Firms with high leverage may face financial constraints limiting their ability to invest in sustainable investments benefiting the environment (Azar *et al.* 2021). Alternatively, they might be incentivized to adopt sustainable practices to improve creditworthiness or access green financing options. II might be concerned about risk management in these firms, drawing their attention and monitoring, potentially fostering their connectedness. I expect a positive relationship between a firm’s leverage and carbon emissions. I proxy for a firm's indebtedness using leverage, which is calculated as total debt over total assets (*Leverage*).

Next, I capture the firm's efficiency in utilizing its assets to generate profits. Firms with higher profitability might have more financial resources at their disposal to allocate towards sustainability initiatives, leading to lower emissions. More profitable firms represent lower-risk and high-return investment opportunities, enhancing connectedness as II look to maintain or increase their stake in successful firms. I expect a negative relationship between a firm’s profitability and carbon emissions. I proxy for profitability by calculating EBIT over total assets (*ROA*).

Next, I capture a firm's capital investments. Firms that make substantial capital investments have the ability to support increased borrowing, enabling them to further expand their capital investments (Azar *et al.* 2021). However, capital intensive industries often have higher emissions due to the nature of their operations. II, having a long-term view, may be attracted to such firms considering them important for future growth, increasing their connectedness. I expect a positive relationship between a firm's capital investments and carbon emissions. I proxy for capital investments using plant, property, and equipment (PPE), which is calculated as total PPE over total assets (*PPE*).

Next, I capture the company's shareholder reward. High dividend payouts might limit resources available for investments in sustainability initiatives as they prioritize returning profits to shareholders, potentially limiting their ability to reduce emissions. High dividend-paying firms tend to attract dividend-seeking investors, increasing network ties due to their stable and attractive cash-flow distribution. I expect a negative relationship between a firm's dividends payout and carbon emissions. I proxy the company's shareholder reward by calculating dividends paid out over net income (*Dividend*).

Next, I capture an investment's overall profitability. Firms that achieve higher returns might attract more attention from shareholders and the public regarding their environmental performance, leading to lower emissions. It could also be argued that focusing on maximizing shareholder returns could incentivize prioritizing short-term profits over long-term investments in emissions reduction, potentially leading to higher emissions. II benefitting from rising valuation are more likely to increase holdings or new investors might enter the market which can increase the investors engagement boosting the company's connectedness. This relationship is empirical in nature. I proxy for overall holding profitability by using the total holding investment return for the year (*Return*).

Finally, I capture a firm's expansion in sales and economic activity. Firms with higher revenue growth may have higher production and operational demands, leading to higher carbon emissions. However, fast-growing firms may also face greater scrutiny from regulators and consumers, prompting them to adopt greener practices to sustain growth. Firms with strong growth are perceived as high-growth companies attracting more investments from II looking for expansion opportunities and increasing their connectedness. I expect a positive relationship between a firm's sales growth and carbon emissions. I proxy for revenue growth by calculating the percentage increase from the previous to the current year (*Growth*).

I winsorized all continuous variables at the 2nd and 98th percentiles, addressing the issue of outliers. Appendix B notes a brief description of the variables.

3.2.3 Summary Statistics

Table 2.1 reports summary statistics for variables relating to investee firms' sustainability measures, II network, firm characteristics, and instrument characteristics in Panels A—D, respectively.

<Insert Table 2.1>

Panel A shows the mean (median) level of scope 1 emissions is 1.189 (0.031) million metric tonnes while that of scope 2 emissions is 0.199 (0.03) million metric tonnes, respectively. Scope 1 emissions have a higher mean value in comparison to scope 2 emissions, with the distribution spread out indicating greater variability in emissions across firms. On average, Gr_Patents is 10, indicating environmental-related innovations. This is comparable to an average of 16 patents granted per year in the study conducted by Luong *et al.* (2017) and 16.67 patents by Chuluun *et al.* (2017). The data on green patent filings are highly skewed, suggesting that many firms do not file patents related to green technologies, while a few firms account for a large number of patents. CCE_Exp is 1.337, indicating exposure to climate change discussions during earnings calls, comparable to an average CCE_Exp level of 1.01 as reported by Sautner *et al.* (2023a). The share of earnings call discussions climate-related topics suggests varying levels of emphasis on climate issues.

Panel B reports the characteristics of II network (scaled by 10^2). Investor centrality measures reveal differences in the influence of II. II with degree centrality (mean 2.138) indicates that some investors maintain extensive connections, while betweenness centrality (mean 0.019) remains low suggesting that few investors hold pivotal positions in controlling network flows. Closeness centrality (mean 43.184) is tightly distributed showing most investors are relatively well-positioned to access other investors in the network. Eigenvector centrality (mean 0.752) implies that most investors are not connected to highly central investors in the network. Bajo *et al.* (2020) find centrality measures for US institutional block-ownership as follows: degree 0.24, betweenness 0.17 and eigenvector 0.22. Fan *et al.* (2023) find centrality measures for 2,196 Chinese II shown as degree 0.061, betweenness 0.003, closeness 0.095 and eigenvector 0.015. While Chen *et al.* (2023) shows that the betweenness centrality for mutual funds in their sample is 0.0011.

Panel C reports firm characteristics for portfolio companies in the sample. On average, a company has a clique ownership of 28.42%, market capitalization of $5.32 billion, market-to-book ratio of 2.74 times, leverage of 23.66%, ROA of 0.069%, PPE of $2,207.17 million, dividends of $123.79 million, investment return of 12.65%, revenue of $4.66 billion, and revenue growth of 1.9%.

Panel D reports instrument characteristics with respect to the II holding portfolio companies. The average distance between a focal institutional investor and all other II holding equity of a portfolio company is 2,604 miles.

<Insert Table 2.2>

In Table 2.2, Panel A summarizes the II network based on geographical location, while Panel B summarizes based on industry. In the sample, Japan (2,161), China (2,054), and the

USA (1,842) have the highest number of unique investee firms. The highest number of unique investors are from the United States (7,014), the United Kingdom (4,333), and Japan (3,488). Industrials and Consumer Discretion sectors have the highest number of unique investee firms, with 3,004 and 2,483, and unique investors, with 12,907 and 11,013, respectively. Panel C shows how II ownership and interconnectedness have changed over time. From 2004 to 2021, the number of II grew significantly with the average influence (as measured by centrality) declining. This is also observed in Bajo *et al.* (2020). This could be because the market is more fragmented, with new connections forming between a wider range of participants rather than a concentration of power among a few.

4 Chapter 4: Empirical Results and Strategy

In this chapter I employ OLS fixed-effects models to analyse the relationship between the main variables of interest. I account for variations within the dataset and use fixed effects models. I lag all control variables by a year to address multi-collinearity issues. To address potential endogeneity concerns, I conduct a series of robustness tests and find that my results still hold. I also incorporate exogenous shocks by using MSCI-ACWI as an instrumental variable in the first empirical chapter to further validate the findings. Although the literature is silent on using an exogenous shock for institutional investor network, I use distance between II as an instrument and a series of tests to enhance reliability. I delve deeper to explore the heterogeneity among II, examining how their distinct characteristics influence observed outcomes.

In the first empirical chapter, I find that higher IO is associated with lower ESG misbehavior, suggesting that II play a crucial role in influencing portfolio company's sustainability behavior. However, this impact varies by investor characteristics, indicating that not all II exerts the same influence. In the second empirical chapter, I find that well-connected II are associated with reducing carbon emissions among portfolio companies through the channels of promoting green innovation and increased climate change exposure. Overall, my findings contribute to a broader understanding on the responsibilities of II in impacting corporate sustainability.

4.1 Empirical Findings: First Empirical Chapter

4.1.1 Hypothesis 1: ESG-MVR and FL_IO

I estimate different variants of the below-noted baseline general fixed-effect ordinary least squares (OLS) specification to test the hypothesis *(H_1)* linking institutional ownership (*FL_IO)* and the future level of *ESG-MVR*.

$$ESG - MVR_{it+n} = \beta_1(FL\_IO_{it}) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it} \qquad (1)$$

where *i, t,* and *c* are indexed as the investee firm, year, and investee country, respectively. *n* is the lead year and takes the value of one or two, depending on the specification.[41] The variables $ESG - MVR_{it+n}$ is the exogenously media-reported ESG misbehavior and FL_IO_{it} is the investee firm-level institutional ownership of firm *i* for the year *t.* $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$ are vectors of all the time-varying investee firm-level and country-level control variables, respectively. All the variables are described in Section 3 and briefly defined in Appendix B. *FE* denotes country, industry, year, and the interaction of country and industry (country×industry) fixed effects, depending on the specification. ε_{it} is the error term clustered at the country and industry levels. Table 1.3 reports the baseline regression results of four different variants of the general specification (1).

<Insert Table 1.3>

The outcomes of models (1) and (2) are related to the first-year lead and models (3) and (4) for the second-year lead of $ESG - MVR_{it+n}$. In models (2) and (4), I replace country and

[41] I examine the lead values of one and two because companies often take time to implement improvements in response to ESG issues, and RepRisk scores tend to decay over time.

industry fixed effects with the interaction (country×industry) fixed effects. In all models, the coefficients of the primary variable *FL_IO, i.e.,* β_1 are negative and statistically significant at either 1% or 5% level. Consistent with the prediction of hypothesis one, these negative figures suggest that the current level of institutional ownership is negatively related to investee firms' subsequent *ESG-MVR*. Within the scope of the sample, the quantitative interpretation in model 1 implies that a one-standard-deviation increase in *FL_IO* (0.55) is associated with 5.67% decline in the following year's *ESG-MVR*.[42] Such quantitative interpretations are similar for models 2, 3, and 4. For example, in terms of model (3) a one-standard-deviation increase in *FL_IO* (0.521) is associated with a 4.99% decline in the *ESG-MVR* in the following two years.[43]

To summarize, the negative signs of all the four coefficients of β_1, which are statistically significant and quantitatively material, offer strong clues that higher levels of institutional ownership seem to exert a positive influence in abating, to a certain extent, the possibility of future *ESG-MVR*.

4.1.2 Addressing Endogeneity Concerns

Although time-invariant factors are controlled in a fixed-effects model, time-varying factors that influence both *FL_IO* and *ESG-MVR* could introduce bias. It is plausible that firms with stronger governance structures might attract more II due to better risk management and transparency (Kim *et al.* 2020; Ge *et al.* 2022). These practices could lower ESG misbehavior as effective governance helps mitigate ESG risks (Colak *et al.* 2024). It is also plausible that higher ESG performance could attract both investors seeking sustainable investments (Kim *et al.* 2019; Bolton & Kacperczyk 2021) and lead to lower ESG misbehavior (Li & Wu 2020), as

[42] The calculation is as follows: coefficient of -0.019 and one standard deviation increase in *FL_IO* (28.940), the effect on *ESG-MVR* is -0.55 (-0.019 x 28.940) points, which translates to a -5.43% (-0.55/10.134 x 100) decline in mean *ESG-MVR* (10.134).

[43] The calculation is as follows: coefficient of -0.018 and one standard deviation increase in *FL_IO* (28.940), the effect on *ESG-MVR* is -0.521 (-0.018 x 28.940) points, which translates to a -4.99% (-0.521/10.441 x 100) decline in mean *ESG-MVR* (10.441).

firms with stronger ESG policies are less likely to have significant violations in the future. Enhanced disclosure of non-financial information could improve a firm's transparency and attract II focused on ESG criteria (Bond & Zeng 2022; Ilhan *et al.* 2023), in turn lowering ESG misbehavior by increasing accountability and aligning corporate strategies with ESG goals (Wang & Li 2019). The potential for reverse causality exists if lower ESG misbehavior attracts IO. For example, II, with a focus on sustainable or responsible investing, may prefer firms with lower ESG risks, resulting in a higher concentration of IO in companies with better ESG-MVR scores. This concern is supported by evidence in prior studies like Dyck *et al.* (2019), which shows that II significantly influences corporate ESG practices and is drawn to firms with strong ESG credentials. Further, literature on ESG misbehavior has demonstrated that these risks influence investor decision-making. For instance, E&S incidents can deter investors from firms with high levels of such incidents, showing a direct impact on IO patterns (Gantchev *et al.* 2022).

Focusing on good governance can lead to portfolios with lower ESG-MVR. This is not necessarily mitigation, but investors trying to avoid risky companies and not actively changing their behavior. For instance, governance on its own has limited scope and does not represent a full spectrum of ESG issues. The pressure for short-term gains comes with a trade-off to overlook long-term ESG risks. While some investors tolerate some ESG-MVR if it does not impact the bottom line. Even for all well-governed firms, engagement is crucial to strengthen ESG integration.

To mitigate these endogeneity concerns, I conduct further analysis. I employ the traditional two-stage least square (2SLS) IV regressions by exploiting the firm's addition to the MSCI-ACWI index as an instrument reflecting potential shock to *FL_IO*.

4.1.2.1 Instrumental Variable Approach

Instrumental variables help mitigate concerns about reverse causality, measurement errors, and time-variant omitted variables (Angrist & Krueger 2001). IV methods address the challenge of endogeneity, that is when the explanatory variable in a regression model is correlated with the error term, which can lead to biased and inconsistent estimates. IV methods allow isolating the variation in the endogenous variable (*FL_IO*) solely attributable to exogenous shocks (*MSCI*). This isolation is crucial to establish causal relationships, as OLS could be confounded by factors that simultaneously affect both independent and dependent variables. MSCI index holds a role as a benchmark for II reflecting a country's financial market accessibility, transparency, and integration into global capital markets.

In the first test, I use the inclusion of the investee firm's stock in the MSCI-ACWI as an instrument within the empirical framework of 2SLS estimation (Aggarwal *et al.* 2011; Bena *et al.* 2017). I exploit the exogenous variation in *FL_IO* when added to the MSCI-ACWI. Following the theoretical arguments offered by the existing studies that employ this instrument, a firm's exogenous inclusion to the MSCI-ACWI should be associated with an increase in the firm's IO (Aggarwal *et al.* 2011; Bena *et al.* 2017). In line with the International Capital Asset Pricing Model's (ICAPM) prediction, investors should benchmark a globally diversified portfolio proxy index for optimal allocations (Solnik 1974).

Literature notes that investors generally employ the MSCI-ACWI index as the proxy benchmark for globally well-diversified optimal portfolio allocation (Bena *et al.* 2017). When the criteria for inclusion in the index are met, the firm is added to the coveted MSCI-ACWI index.[44] The variation in ESG-MVR is plausibly exogenous, as the mechanical rule based on free-float market capitalization determines the firm's inclusion to the index. The exogenous

[44] MSCI inclusion is determined by covering approximately 85% of the free float-adjusted market capitalization within each country (MSCI 2015). Stocks are selected in descending order of their free-float adjusted market capitalization until the cumulative total of firms reaches 85% of the free float-adjusted market capitalization in that country.

addition should then prompt investors to rebalance their portfolios. In light of the information that the newly added firm is now part of the benchmarked MSCI-ACWI, investors should boost its holdings in their portfolio. This suggests that I should expect an exogenous increase in the firm's II holdings after its inclusion in the MSCI-ACWI.[45]

To test the above-stated conjecture of ICAPM, Figure 1.1 shows the evolution of the average *FL_IO* of investee firms up to three years before and after inclusion in MSCI-ACWI. The index inclusion occurs between year -1 and year 0. Compared to the pre-inclusion period (-3 to -1), I observe statistically significant and economically material jumps in the post-inclusion period (+1 to +3), which persists even up to three years. Such observation is consistent with the expectation of the ICAPM theory.

<Insert Figure 1.1>

The exogenous variations induced in *FL_IO,* promoted by the firm's inclusion in MSCI-ACWI, offer us near-random segregation of firms into those affected and unaffected by the inclusion. These additions do not inherently affect a firm's *ESG-MVR* directly aligning with the exclusion criteria. In intuitive terms, the addition merely increases the pool of investors but does not directly affect the *ESG-MVR* of the portfolio firm. While many companies that are added to the MSCI-ACWI index could alter ESG policies in response to heightened visibility, these shifts are unlikely to immediately impact *ESG-MVR* as reputational metrics (as captured by RepRisk, see section 3.2.1) reflect a firm's established behaviors and incidents over time. Many studies use index inclusions as instruments for IO, expecting no direct effects on their

[45] In a more intuitive sense, the first stage of IV regression identifies the effect of MSCI inclusion on IO, isolating the impact on firms that experience changes in ownership due to their MSCI status.

outcome variables (See Bena *et al.* (2017) and Cohen *et al.* (2023)). For estimating the causal effect of FL_IO, I use the following first and second-stage regression models:

First stage: $$FL\_IO_{it} = \alpha_0 + \gamma_1(D\_MSCI_i) + \boldsymbol{\gamma_2 X_{it}} + \boldsymbol{\gamma_3 K_{ct}} + FE + \varepsilon_{it} \quad (2)$$

Second stage: $$ESG - MVR_{it+n} = \alpha_1 + \beta_1.\widehat{FL\_IO}_{it} + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it} \quad (3)$$

where D_MSCI_i takes the value of one for firms added to the MSCI-ACWI (starting from the year of a firm's inclusion in the MSCI-ACWI and continuing for up to three years following the addition) and zero otherwise. If a firm is deleted from the MSCI-ACWI within three years, it takes the value of zero. $\widehat{FL\_IO}_{it}$ is the fitted variable of the FL_IO_{it} from the first-stage regression estimation. All other variables are as defined in equation (1). I present the results of the first and second-stage estimations in Table 1.4.

<Insert Table 1.4>

The first-stage regressions outputs in column (1) suggest a strong relation between the *D_MSCI* and the *FL_IO*, which is positive and statistically significant at a 1% level. The *F*-test statistics is 42.98 and is significant at a 1% significance level. The potential for weak instrument bias appears to be low, given that an F-statistic above 10 is generally considered indicative of a strong instrument (Stock *et al.* 2002). The positive and significant correlations and *F*-statistics suggest that the instrument strongly correlates with the endogenous variable (*FL_IO*), satisfying the relevance condition.

The negative signs and the statistical significance of the estimated coefficients in the second-stage regression results, which are statistically significant at the 1% level except for model (4) at the 5% level (reported in columns (2 to 5)), confirm the baseline regression estimates, thus supporting the validity of H1.

In terms of the instrument's validity, the Cragg Donald Wald F-statistics ranges from 14.590 to 22.087 (columns 2-5). Across the three specifications (columns 2-4), the F-statistics are higher than the 10% maximal value with the standard critical value of 16.38 (Stock & Yogo 2002), thus, rejecting the null for the instrument's weakness. However, model (5) with an F-statistic of 14.590 falls short of the 10% critical value and appears moderately strong. Similarly, all four models have Kleibergen-Paap Wald F statistics ranging from 14.545 to 21.807 (columns 2-5) are above/ close to the critical value of 16.38, indicating that the MSCI-ACWI inclusion as an instrument is not weak. The instrument's strength seems to vary because of the modeling, so the coefficients must be interpreted carefully but are not invalid.

The significant difference between the OLS and IV estimates for the impact of IO on *ESG-MVR* warrants a detailed discussion. For instance, in model (2), the IV estimate is -0.433 while the corresponding OLS estimate from Table 1.3 is -0.019. The IV to OLS estimates ratio is 22.8 (-0.433/-0.019).[46] The IV approach addresses endogeneity concerns by providing a more rigorous estimate. Yet the substantial magnitude of IV estimates suggests potential bias beyond confounding factors that cause the OLS estimates to be biased by unobserved factors, leading to a smaller estimate. Several factors may contribute to this disparity. First, MSCI inclusion serves as an exogenous shock to IO but does not guarantee a completely random assignment of treatment across firms. MSCI inclusion might drastically change IO probabilities without achieving uniform treatment. This could lead to a situation where the IV estimates reflect the impact on firms that are particularly responsive to MSCI inclusion having different characteristics than firms that are less responsive. For instance, addition to the index would bring visibility from large, ESG-conscious II who may exert more pressure on firms to manage *ESG-MVR* actively. This suggests that MSCI-driven ownership might be particularly potent in

[46] This is notably higher than the ratio found in a survey of 255 papers from the top three finance journals, where the IV estimates, after winsorizing the extremes at 1%, were on average 9.2 times larger than OLS estimates (18.8 times without winsorization) (Jiang 2017).

influencing ESG risk management behaviors whereas OLS captures average ownership impacts which could be diluted by firms with less active institutional oversight. Hence, this selection bias could lead to IV estimates that deviate more from the average treatment effect than the OLS estimates.

4.1.3 Further Robustness Tests

4.1.3.1 Individual E, S, and G Misbehavior

In this section, I examine the impact of *FL_IO* on the separate components of *ESG-MVR*. Examining the individual components of ESG misbehavior can help identify the drivers and implications for investor decisions. For instance, the RRI score developed by Reprisk is based on the frequency of negative news related to these dimensions, but without distinguishing the component driving the risks, insights may be lost. Asante-Appiah and Lambert (2022) found that firms with environmental and governance issues dominating their ESG-MVR score tend to purchase more non-audit related services from their external auditors, but the relationship does not hold when social issues dominate the risk. Wang and Li (2019) show that MNCs enhance information control and ownership control in their foreign subsidiaries in response to individual aspects of *ESG-MVR*. Hence, it is essential to understand the impact of the components individually to examine how investors manage *ESG-MVR*. RepRisk reports the proportion of RRI that can be attributed to each element of ESG. I multiply the proportion with the subsequent *ESG-MVR* to measure the three components separately. I re-run equation (1) but replace the dependent variable with the index of each component of ESG. The results are presented in Table 1.5.

<Insert Table 1.5>

The direction of the individual components is consistent, but the magnitude varies. II seems to care differently for each element of *ESG-MVR*. I find II significantly reduces the environmental ($p < 0.05$) and governance components ($p < 0.01$) of *ESG-MVR,* but the impact on firms' social component is insignificant next year and marginally significant in the two-year lead ($p < 0.10$). A one-standard-deviation increase in *FL_IO* is associated with a 7.91% decline in Env-ESG-MVR, a 5.08% decline in *Soc-ESG-MVR*, and a 7.26% decline in *Gov-ESG-MVR* in the subsequent year.[47] [48] [49]Again, the results are consistent with the two-year lead. Based on the analysis above, a pattern emerges. IO tends to care more about environmental and governance aspects of ESG misbehavior, but early evidence supports the inference that the impact is insignificant on social aspects of ESG misbehavior.

4.1.3.2 Additional Firm-level Tests

To ensure the reliability and validity of the findings, i.e., the results hold across different dimensions, I also investigate the relationship between *FL_IO* and alternative *ESG-MVR* measures (He *et al.* 2023). First, I investigate the *Peak-ESG-MVR*, taking advantage of severity-based measures. The *Peak-ESG-MVR* is a company's highest level of RRI in the past two years, indicating their maximum exposure to *ESG-MVR* (refer to Appendix B). This analysis provides insight into their critical risks and how the effects of controversies often persist that are not reflected in *ESG-MVR*. The results are presented in models (1) and (2) of

[47] Coefficient of -0.005 and one standard deviation increase in *FL_IO* (28.940), the effect on *Env-ESG-MVR* is -0.145 (-0.005 x 28.940) points, which translates to a -7.91% (-0.145/1.83 x 100) decline in mean *Env-ESG-MVR* (1.83).
[48] Coefficient of -0.006 and one standard deviation increase in *FL_IO* (28.940), the effect on *Soc-ESG-MVR* is -0.174 (-0.006 x 28.940) points, which translates to a -5.08% (-0.174/3.418 x 100) decline in mean *Soc-ESG-MVR* (3.418).
[49] Coefficient of -0.008 and one standard deviation increase in *FL_IO* (28.940), the effect on *Gov-ESG-MVR* is -0.232 (-0.008 x 28.940) points, which translates to a -7.26% (-0.232/3.188 x 100) decline in mean *Gov-ESG-MVR* (3.188).

Table 1.6. The coefficients are negative and significant at a 10% level in lead year 1. However, the results are not significant in lead year 2. The results support the main findings.

<Insert Table 1.6>

Next, I use incident count as an alternative measure (Li & Wu 2020). The actual observable incidents offer the opportunity to observe specific events' timing, frequency, and recurrence over time, helping assess the underlying causes of a firm's *ESG-MVR*. In models (3) – (10) of Table 1.6, the dependent variable is a count-based variable that takes the value of the number of incidents. I take the 1+ natural log of the number of incidents and the number of incidents related to each component of *ESG-MVR* (refer to Appendix B). The coefficients are all negative and significant at 1%, consistent with the baseline results and H1.

4.1.3.3 Pair Investor-Investee Analysis

I shift from firm-level to individual-level IO to gain a more precise and detailed understanding of how different II influence firm behavior. Examining at the pairwise investor-investee level reveals valuable insights into ESG investing and *ESG-MVR*. Investigating investor-level ownership allows us to control for investor-level differences. I rerun a variant of equation (1), as shown below in equation (4), to test whether the baseline results hold at investor-level IO.

$$ESG - MVR_{it+n} = \beta_1 Inv\_IO_{jit} + \boldsymbol{\beta_2 X}_{it} + \boldsymbol{\beta_3 K}_{ct} + FE + \varepsilon_{it} \tag{4}$$

where, Inv_IO_{jit} is the *IO* of investor *j* in firm *i* in year *t.* In addition to the usual *FE* discussed in equation (1), I also add investor fixed effects as an additional fixed effect to control for any investor-level differences. All other variables are as previously defined.

I show that the baseline results also hold at the investor level (*Inv_IO*). Table 1.7 shows the regression results using a variant of equation (4). In models (1) and (3), I use country, industry, year, and investor fixed effects. I replace investor, country, and industry fixed effects with investor × country × industry fixed effects in models (2) and (4).

<Insert Table 1.7>

In models (1) to (4), I consistently find that *Inv_IO* has a negative coefficient, which is statistically significant at a 1% level and economically material. A one-standard-deviation increase in *Inv_IO* (-0.242) is associated with a 2.39% decline in mean *ESG-MVR*.[50] The negative impact observed persists in the model (2) with a one-year lead, even after interacting with investor, country, and industry fixed effect. This negative effect carries over to models (3) and (4) for the lead second year. Overall, the result supports the baseline result and H1.

4.1.3.4 Additional Investor-Level Cross-sectional Tests

I re-run the tests from sections 4.3.1 and 4.3.2. I examine the impact of *Inv_IO* on the three individual components of *ESG-MVR* and find the results consistent with the main results. In Additional Analysis section 1A.1, I observe that the impact of *Inv_IO* is negative and significant for *Env-ESG-MVR* ($p < 0.01$; $p < 0.05$) and *Gov-ESG-MVR* ($p < 0.01$), and negative and significant for *Soc-ESG-MVR* in the lead one year ($p < 0.05$). However, in the lead year two, the results for *Soc-ESG-MVR* are negative but statistically insignificant. Second, I use *Peak-ESG-MVR* and the natural logarithm of the count of ESG incidents as the primary

[50] The calculation is as follows: coefficient of -0.152 and one standard deviation increase in *Inv_IO* (1.592), the effect on *ESG-MVR* is -0.242 (-0.152 x 1.592) points, which translates to a -2.39% (-0.242/10.134 x 100) decline in mean *ESG-MVR* (10.134).

dependent.[51] The results are presented in Additional Analysis 1A.2 and 1A.3. the results remain consistent and highly significant with the dependent variables *Peak-ESG-MVR* and the count of ESG violations.

4.1.4 Hypothesis 2: Values-based vs. Value II

4.1.4.1 Commitment to Responsible Investment: PRI vs. Non-PRI Signatories

In this section, I focus on the relationship between II commitment to responsible investments and *ESG-MVR* to test H2a. I follow Vasudeva (2013) and Brandon *et al.* (2022) to classify II based on their PRI signatory status. I use the fuzzy matching technique to match investee firms from the PRI signatory database to the II in the sample. During the sample period, there are 5,287 PRI signatories. I manually match II from the S&P Capital IQ database for 4,306 signatories, using the signatory name and headquartered country. I identify 687 potential II matches.[52] I denote *Inv_PRI_IO* if they are a PRI signatory in a given year and *Inv_Non_PRI_IO* to those other than a PRI signatory. As summarized in Table 1.1, in the sample, the average *IO* of a PRI signatory (*Inv_PRI_IO*) is 0.765%, while that of a non-PRI signatory (*Inv_Non_PRI_IO)* is 0.402%.

I analyze the differential impact of PRI signatories on *ESG-MVR* using a variant of equation (4), where I interact *Inv_IO* with *D(PRI)* and include the dummy as an additional FE in the model. *D(PRI)* is a dummy variable that takes the value of one if II is PRI signatory and zero otherwise. The results are presented in models (1) and (2) of Table 1.8. In both models, *Inv_IO* × *D(PRI)* is negative and statistically significant at 1% levels, indicating that *Inv_PRI_IO* reduces *ESG-MVR* of a firm more than *Inv_Non_PRI_IO* consistent with H2a. The

[51] In unreported analysis, I investigate on the individual E, S, G violations and find they are negative and highly significant.
[52] Similarly, Liang *et al.* (2022) identified 307 matches among hedge funds that are PRI signatories.

evidence highlights the positive impact of II identifying as PRI signatories and prioritizing sustainable investing practices to reduce *ESG-MVR*. The results are consistent with the view that PRI signatories assume social responsibility and uphold responsible investment practices (Dyck *et al.* 2019; Brandon *et al.* 2022).

<Insert Table 1.8>

I also investigate whether investors who "walk the talk" address *ESG-MVR* more than others. In order to identify these investors, I follow Liang *et al.* (2022). First, I calculate the portfolio-weighted average ESG scores of all firms in a portfolio of each II each year. Then, I identify "walk the talk" II as those who are PRI signatories and whose portfolio weighted-average ESG score falls in the top tercile.[53] In line with Liang *et al.* (2022), these II can be considered not just "talking the talk" by being PRI signatories but "walking the talk" by being actively involved in considering responsible investments. I denote their ownership as *Inv_PRI_High_ESG_IO*, and in the sample, these investors hold around 0.863% of the shares outstanding of their portfolio firms (*Inv_PRI_Low_ESG_IO* 0.668%).

I analyze the differential impact of *Inv_PRI_High_ESG_IO* using a variant of equation (4), where I interact *Inv_IO* with *D(PRI_ESG)* and include the dummy as an additional FE in the model. *D(PRI_ESG)* is a dummy variable that takes the value of one if the portfolio-weighted average ESG score of a PRI investor is in the top tercile and zero if it is in the bottom tercile.[54] The results in models (3) and (4) of Table 1.8 are consistent with H2a. In both models, *Inv_IO* × *D(PRI_ESG)* is negative and significant at 1% levels, which shows that responsible II who walk the talk reduce *ESG-MVR* more than their counterparts.

[53] the results remain negative and highly significant if I use LSEG E&S scores alternatively.
[54] Alternatively, I also use median value and quintiles as a cutoff to place them into top and bottom-performing groups. the findings remain consistent.

4.1.4.2 Legal Systems: Civil vs. Common

This section investigates H2b examining the differential impact of legal systems in which II operates. Following Porta *et al.* (1998), I classify countries according to four legal origins: English, French, German, and Scandinavian. Civil law is associated with French, German, and Scandinavian legal origins, while common law is associated with English legal origins. Accordingly, *Inv_Civil_IO* and *Inv_Common_IO* refer to *IO* of II domiciled in civil law and common law countries, respectively. In the sample, the average *Inv_Civil_IO* and average *Inv_Common_IO* is 0.419% and 0.471%, respectively.

<Insert Table 1.9>

I analyze the differential impact of *Inv_Civil_IO* on *ESG-MVR* using a variant of equation (4), where I interact *Inv_IO* with *D(Civil)* and include the dummy as an additional FE in the model. *D(Civil)* takes a value of one if the investor is from a civil law country, while zero if the investor is from a common law country. The results are presented in models (1) and (2) of Table 1.9, and the findings support H2b. In both models, *Inv_IO* × *D(Civil)* is negative and significant at 1% and 5% levels for lead one and two years, respectively. This shows that *Inv_Civil_IO* reduces *ESG-MVR* more than *Inv_Common_IO*. The evidence shows that II's approach to ESG considerations and their ability to reduce *ESG-MVR* can be influenced by their social norms inclination and the legal system in which they operate.

4.1.4.3 Independent vs. Grey II

In this section, I investigate H2c, examining the differential impact of II's investment style on firm *ESG-MVR*. Following existing literature, I classify II as Independent and Grey II depending on the type of institution (Chen *et al.* 2007; Ferreira & Matos 2008). In the sample, the average *IO* of independent II (*Inv_Independent_IO)* is around 0.438%, while of grey II (*Inv_Grey_IO*) is 0.687% (see Table 1.1).

I analyze the differential impact of *Inv_Independent_IO* on *ESG-MVR* using a variant of equation (4), where I interact *Inv_IO* with *D(Independent)* and include the dummy variable as an additional FE in the model. *D(Independent)* takes a value of one if the II are classified as independent and zero if classified as grey. The results are presented in models (3) and (4) of Table 1.9 and are consistent with the expectations of H2c.

In both models, *Inv_IO* × *D(Independent)* is negative and statistically significant at the 1% levels, revealing that the differential impact of *Inv_Independent_IO* on *ESG-MVR* is more significantly negative than *Inv_Grey_IO*. The evidence suggests that Independent II, who are active monitors, prioritize ESG considerations and exert positive influence or monitor the ESG performance of the companies they invest in. The findings add to the existing literature by showing that Independent II exhibits better monitoring capabilities than Grey II (Chen *et al.* 2007; Ferreira & Matos 2008), demonstrating a better effect at reducing firm *ESG-MVR*.

4.1.4.4 Long vs. Short-Term

In this section, I examine H2d, investigating the differential impact of II investment horizon and objectives on investee *ESG-MVR*. Consistent with existing literature, I consider pension funds as long-term II and hedge funds as short-term (Marshall *et al.* 2022). In the sample, *IO* of long-term II (*Inv_LT_IO*) and short-term II (*Inv_ST_IO*) is around 0.401% and 0.474%, respectively (see Table 1.1).

I analyze the differential impact of *Inv_LT_IO* on *ESG-MVR* using a variant of equation (4), where I interact *Inv_IO* with *D(LT)* and include the dummy as an additional FE in the model. *D(LT)* takes a value of one if the II is a pension fund and zero if they are hedge funds. The results are presented in models (5) and (6) of Table 1.9, aligning with the predictions of

H2d. In both models, *Inv_IO × D(LT)* is negative and statistically significant at 1% levels, which shows that *Inv_LT_IO* reduces *ESG-MVR* of their portfolio firm more than *Inv_ST_IO*. This finding contributes to the current body of literature by showing that long-term funds not only excel in monitoring capabilities compared to short-term funds (Chen *et al.* 2007; Marshall *et al.* 2022) but also have a greater impact in mitigating a company's *ESG-MVR*.

4.1.5 Large II

Azar *et al.* (2021), Lewellen and Lewellen (2022), and Gormley *et al.* (2023) show that large II, such as the big three investors or block holders, have greater influence and possess better capabilities to engage with the board as larger II have greater financial might, better investment strategies, and extensive resources than small II (Schnatterly *et al.* 2008; Ben-David *et al.* 2021). With a significant stake, IO is incentivized to coordinate and form a collaborative network to achieve collective impact (Huang & Kang 2017; Crane *et al.* 2019; Brav *et al.* 2022). Given this evidence, I argue that the impact of large II is greater than smaller II in addressing *ESG-MVR*, as larger II have more significant influence and incentives to monitor, allowing them to engage more actively (Burkart *et al.* 1997; Konijn *et al.* 2011).

<Insert Table 1A.4>

I analyze the varying effects of II size on *ESG-MVR* using a variant of equation (7) of the main text, where interact *Inv_IO* with *D(Large)* and include the dummy as an additional FE in the model. *D(Large)* is a dummy variable that takes the value of one if the IO of an investor in a firm is higher than the median value of the average *Inv_IO* and zero else.[55] The

[55] Alternatively, I use top and bottom tercile and quintile groups to segregate large and small IO; my findings remain the same.

results are presented in models (1) - (4) of Table 1A.4. I find that *Inv_IO* × *D(Large)* is consistently negative and statistically significant at the 1% level of significance. This indicates that investors with large IO reducing *ESG-MVR* more than those with smaller IO, which is consistent with my expectations.

4.1.6 Foreign vs. Domestic II

FII promotes good corporate governance practices worldwide (Ferreira & Matos 2008; Aggarwal *et al.* 2011). By being acknowledged as active monitors, having higher risk tolerance, and facilitating knowledge transfer, Luong *et al.* (2017) find that FII encourage technological innovations. I expect FII to have a more significant effect than domestic II (DII) as they are likely to enhance governance and knowledge transfer (Aggarwal *et al.* 2011; Luong *et al.* 2017), less likely to have business relationships with investee firms enabling them to pressure the management (Tsang *et al.* 2019), transplant their social norms when operating in a different country because of cultural familiarity (Bena *et al.* 2017; Dyck *et al.* 2019).

<Insert Table 1A.5>

I classify II based on their country of domicile (Aggarwal *et al.* 2011). I analyze the differential impact of foreign II on *ESG-MVR* using a variant of equation (7) of the main text, where I interact *Inv_IO* with *D(Foreign)* and include it as an additional FE in the model. *D(Foreign)* is a binary variable that takes a value of one if the II is domiciled from a different country than the investee firm and zero otherwise. The results are presented in Table 1A.5. In models (1) and (2), the interaction term *Inv_IO* × *D(Foreign)* is negative and significant at a 1% significance level. The results show that FII significantly reduces *ESG-MVR* more than DII. The findings are consistent with the view that FII have more substantial commitments to sustainable practices and robust monitoring capabilities, bringing broader perspective and knowledge transfer from engagements with companies worldwide.

4.2 Empirical Findings: Second Empirical Chapter

4.2.1 Baseline Results

I commence the estimation by employing the following fixed-effect OLS regression specification to test the hypotheses linking II network and the future level of carbon emissions.

$$Ln\_GHG\_Abs\_Scp1_{it+n} = \beta_1(II\_centrality_{jt}) + \beta_2 \boldsymbol{X}_{it-} + FE + \varepsilon_{it} \quad (1)$$

$$Ln\_GHG\_Abs\_Scp2_{it+n} = \beta_1(II\_centrality_{jt}) + \beta_2 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it} \quad (2)$$

where *i* refers to firm, *j* refers to institutional investor and *t* refers to year, respectively. *n* takes the value of one or two. *Ln_GHG_Abs_Scp1, Ln_GHG_Abs_Scp2,* and *II_centrality* measures are defined previously. ***X*** is a vector of time-varying control variables discussed in Section 3 and defined in Appendix B. *FE* denotes fixed effects. I include firm and year fixed effects.[56] ε_{it} is the error term clustered at the company and year levels. The empirical model is in line with Chuluun *et al.* (2017) and Cohen *et al.* (2023).

<Insert Table 2.3>

Table 2.3 shows baseline regressions for scope 1 emissions using equation (1). Panel A shows the OLS regression results for the impact of *II_centrality* on *Ln_GHG_Abs_Scp1* in the following year. Panel B shows the results on scope 1 emissions lead by two years. I find the coefficients to be negative and remain highly significant at 1% for specifications of II centrality. The impact is economically material as well. A one standard deviation increase in *Degree_centrality* is associated with 0.094% reduction in *Ln_GHG_Abs_Scp1* in the following

[56] Including investor fixed effects could lead to over-specification, particularly if the network of investors is correlated with the characteristics of the investee company. That is, a large number of investors hold equity relative to investees as we investigate publicly listed companies. I assume variations in carbon emissions are primarily driven by investee-specific and temporal factors rather than the persistent differences across investors. This is consistent with prior literature (Bajo *et al.* 2020; Chen *et al.* 2023; Dissanaike *et al.* 2023).

year.[57] Although the annual reduction of 0.094% in scope 1 carbon emissions may appear marginal, its compounded effect over a decade results in a 0.94% decrease. Large firms with significant emissions can have substantial cost savings and regulatory advantages over time.

<Insert Table 2. 4>

Table 2.4 shows baseline regressions for scope 2 emissions using equation (2). In Panel A, I find negative coefficients with high significance for all *II_centrality* measures except for *Eigenvector_centrality* in model (4). In Panel B, I find negative coefficients with mixed significance and no significance for *Eigenvector_centrality* in model (4). These results are economically meaningful as well. A one standard deviation increase in *Degree_centrality* is associated with 0.078% reduction in *Ln_GHG_Abs_Scp2* in the following year.[58] Overall, the results support H1.

4.2.2 Sharpening Identification and Robustness Checks

One of the concerns about the tests is that firms could reduce carbon emissions for reasons that may correlate with the IIs network. I conduct several tests to sharpen the identification and also conduct robustness checks.

4.2.2.1 Fixed Effect Models

In the main tests, I control for firm and year fixed effects to mitigate firm-level and year-level omitted variable biases.

[57] The calculation is as follows: coefficient of -0.023 and one standard deviation increase in *Degree_centrality* (0.04089), the effect on *Ln_GHG_Abs_Scp1* is -0.00094 (-0.023 x 0.04089) points, which translates to a -0.094% ($1 - e^{-0.00094047}$) decline in mean *Ln_GHG_Abs_Scp1* (10.652).

[58] The calculation is as follows: coefficient of -0.019 and one standard deviation increase in *Degree_centrality* (0.04089), the effect on *Ln_GHG_Abs_Scp2* is -0.00078 (-0.019 x 0.04089) points, which translates to a -0.078% ($1 - e^{-0.00077691}$) decline in mean *Ln_GHG_Abs_Scp1* (10.355).

<Insert Table 2.5>

Our results are robust to different fixed-effect models. I rerun OLS regressions using equation (1) on scope 1 emissions. I report results for scope 1 emissions the following year in Table 2.5. In models (1) – (4), I use country, and year fixed effects and errors clustered at country and year levels. In models (5) – (8), I use the country, industry, and year fixed effect and errors clustered at industry and year levels. I find the coefficients of network centrality measures are consistently negative and significant except for *Eigenvector_centrality* in models (4) and (8).

4.2.2.2 Exclusion of Crisis Period

First, I estimate the impact of the II network, excluding the period of the financial crisis (2007 to 2009) and COVID-19 crisis (2019 to 2020). As noted in Bolton and Kacperczyk (2021), during the period of the financial crisis the level of emissions is artificially low. I therefore expect these crisis periods to have distorted emissions due to lower economic activity and reduced investor engagement. I find and report in Table 2A.1 of the Additional Analysis section, that excluding the crisis period does not affect the results in a major way. All the network centrality measures in all specifications are negative and significant at the 1% levels.

4.2.2.3 Alternative Dependent Variables

To further mitigate endogeneity concerns, I replace the dependent variables with an alternative database. I use carbon emissions provided by LSEG and rerun the baseline specifications.[59]

[59] LSEG is a reliable and comprehensive source for reported GHG emissions due to its robust data collection, quality control, and long-standing methodology. It gathers data directly from publicly available documents such as annual and sustainability reports, company filings, and websites. The data undergoes a stringent quality check process to ensure the validity and accuracy of emissions figures. In addition to company reported emissions, LSEG also incorporates third-party data like CDP. They use a proprietary algorithm to select the most reliable data point when multiple data sources are available for a single company.

The correlation between scope 1 carbon emissions reported by Trucost and LSEG is 0.5345, while 0.0431 for scope 2 emissions.[60] I run the regressions on scope 1 emissions lead by one year in Table 2.6 Panel A and by two years in Panel B, while scope 2 emissions lead by one year in Panel C and by two years in Panel D. The results are presented in Table 2.6 across Panels A - D.

<Insert Table 2.6>

The results show that all models in Panel A-D are negative and significant except for *Eigenvector_centrality* in model (4) across all panels. I find the corresponding coefficients from Table 2.3 and 2.4 to be similar. The consistency of the findings reinforces the robustness of the conclusions regarding the relationship between II network and carbon emissions.

4.2.2.4 Alternate Measures of Investor Connectedness

In the baseline models, I use four standard centrality metrics to represent connectedness. I run the analyses using each measure separately to capture different aspects of network influence. All measures exhibit similar predictive power in the regressions, which is expected due to the high correlations across each measure (see Panel A of Table 2A.2).

To enhance robustness, I explore alternative connectedness measures (Larcker *et al.* 2013; El-Khatib *et al.* 2015; Intintoli *et al.* 2018). An aggregate composite measure simplifies complex information combining multiple related variables into a single value. First, I follow Intintoli *et al.* (2018) to use factor analysis to extract the common latent factor that explains the variations across these measures. Factor analysis reveals the underlying patterns among the different measures to understand their relation and how they can be fit into one simple measure.

[60] I manually check for differences in the emissions recorded by both the data aggregators and correspond it back to the annual reports. For instance, Alphabet Inc's reported carbon emissions (metric tonnes of carbon dioxide equivalent) are scope 1: 45,073 and scope 2: 6,576,239. Trucost reports Scope 1 as 113,704.902 and Scope 2 as 6,576,239, while LSEG reports 45,100 and 6,576,200. PVR Inox Limited, an entertainment company, has reported carbon emissions in the annual report as Scope 1: 492 and scope 2: 23,721. Trucost reports Scope 1 as 252.684 and Scope 2 as 1,173.389, while LSEG records the annual figures as reported.

I perform factor analysis on these centrality measures and retain number of factors based on eigenvalues greater than one, leading us to retain one factor. The first factor (3.1897) explained 93.42% of the variance in the centrality measures (See Panel B Table 2A.2). The factor scores represent the overall connectedness of each II based on the centrality measures. I run OLS regressions replacing centrality measures with the weighted measure and the results are presented in model (1) of Panel A in Table 2.7. The results for *II_centrality_Factor* are negative and highly significant.

<Insert Table 2.7>

Next, I include a composite measure using principal component analysis (PCA) technique and orthogonalization (Larcker *et al.* 2013; Intintoli *et al.* 2018). PCA transforms the original centrality measures into new variables that are uncorrelated capturing the most variance, thereby retaining essential information. Orthogonalization helps isolate the unique impact of centrality measures from factors that naturally increase over time making them truly independent of each other. Results for *II_centrality_PCA* and *II_centrality_Ortho* remain consistently negative and statistically significant as shown in models (2) – (3) of Panel A in Table 2.7.

Next, I compute a composite measure of connectedness proposed by Larcker et al. (2013), which is referred to as the N-score, by averaging the quintile ranks of the four centrality measures for each investor. The N-score approach identifies underlying factors driving variations in centrality measures to effectively summarize complex data. This N-score serves as a benchmark for overall connectedness.

$$N - Score \;=\; Quint\left(\frac{1}{4}\begin{Bmatrix} Quint(Degree)+Quint(Betweenness)+ \\ Quint(Closeness)+Quint(Eigenvector) \end{Bmatrix}\right) \tag{3}$$

The N-Score divides the centrality measures into quintiles (low to high) using equation (3). I then compare this N-score with the factor score derived from factor analysis (see section 3.2.4.1), and the correlation between them is 0.88. I run separate regressions for each N-score quintile, exploring how the impact of *II_centrality* on *Ln_GHG_Abs_Scp1* differs across II with varying levels of centrality. I present the coefficient table showing sub-sample analysis based on the N-score I created across models (1) – (5) (Low-High) of Panel B in Table 2.7.

The results reveal a distinct pattern in the influence of II centrality on carbon emissions based on N-Score. For lower centrality investors (N=1), the coefficients for *Degree_centrality* and *Closeness_centrality* show positive and significant effects. However, as I move between quintiles, the effects are weaker. For high centrality investors (N=5), *Degree_centrality, Betweenness_centrality, Closeness_centrality, and Eigenvector_centrality* have negative coefficients with high significance ($p<0.01$) leads a significant reduction in *Ln_GHG_Abs_Scp1* suggesting that more central investors encourage firms to lower carbon emissions.

4.2.3 Addressing Endogeneity Concerns

Similar to other research available on networks, a key challenge is untangling cause and effect (Bianchi *et al.* 2023). When analyzing the relationship between II networks and carbon emissions, it can be challenging to separate the influence of the network itself (learning from peers) from the inherent characteristics of the investors (knowledge and expertise). Investors with a strong focus on environmental issues might be more likely to join networks with similar values thus having more connections. On the other hand, it is also possible that being a part of a network influences investor behavior towards being mindful of carbon emissions.

Existing statistical methods used in finance to address these types of issues (where the independent variable, network centrality, might not be randomly assigned) have limitations in the context of network studies (Bianchi *et al.* 2023). I acknowledge that the tests have limitations and caution the readers for interpretation. I also do not know the determinants of II network connections and structure making it difficult to implement a strong instrumental variable (IV) approach (Bianchi *et al.* 2023). Therefore, I advise the readers to interpret the results with caution. Instrumental variables help mitigate omitted variable bias, reverse causality, and measurement errors.

4.2.3.1 Instrumental Variables: Distance

The centrality measures could be endogenous due to reverse causality or omitted variable bias. Firms with high emissions could influence investors' choice to invest, thereby affecting their connectedness. I use the average distance between investors as an instrument, mitigating these endogeneity concerns.

The average distance between investors holding a portfolio firm captures the spatial diversity in investor behavior (Huang & Kang 2017), which can affect a firm's network centrality.[61] Geographic concentration of large institutions forms an implicit coordinated network of shareholders for corporate monitoring, increasing their incentive for active monitoring by reducing communication and transportation costs (Huang & Kang 2017). Geographic proximity may reflect behavioural biases and local preferences influencing firm valuation (Hong *et al.* 2005; Pool *et al.* 2015). Funding constraints faced by firms are reduced when II that are geographically closer, as their investments become less dependent on internal cash flows (Kim *et al.* 2022). Investors closer to a firm have better access to information about firm specific information, improving monitoring and investment decisions (Coval & Moskowitz 1999). Despite its informational benefits, local investing might lead to liquidity

[61] The reason for using local investment as a proxy for informed holdings is that being geographically close reduces the cost of understanding a firm's technical operations, evaluating intangible factors such as management quality, and provides easier access to the firm's facilities and employees to gather informal information, as well as allowing for social interaction with top management (Gaspar & Massa 2007).

problems (Gaspar & Massa 2007). Albuquerque *et al.* (2009) propose that foreign investors, particularly sophisticated US investors possess valuable information that gives them an advantage in multiple countries challenging the idea that local investors always have superior information. Distant investors might compensate for their lack of local knowledge with broader access to global information and more diverse portfolios. Pool *et al.* (2015) using a survey report frequent interactions between fund managers with investor conferences being a popular choice. This suggests physical distance does not serve as a hindrance to the exchange of valuable ideas. I calculate the distance between investors using their addresses provided by S&P Capital IQ, which I geocode to GPS coordinates via a google application.[62]

Defending distance as an exogenous variable is challenging. Gaspar and Massa (2007) argue that the place of the investor's location as a determinant of proximity is reasonably exogenous. The instrument is relevant if it is strongly correlated with the endogenous variable (*II_centrality*). The instrument must affect carbon emissions only through its impact on the centrality measures. Geographic distance is a predetermined immutable factor unlikely to be correlated with unobserved factors influencing II network. Average distance between investors can influence the centrality of the investors but does not directly impact a firms carbon emissions. In other words, the geographical proximity of investors does not inherently cause firms to pollute more or less, but their proximity to each other can affect their connectedness.

First stage: $$II\_centrality_{jt} = \alpha_0 + \gamma_1(Ln\_Distance_{ijt}) + \boldsymbol{\gamma_2 X_{it}} + FE + \varepsilon_{it} \quad (4)$$

Second stage: $$Ln\_GHG\_Abs\_Scp1_{it+1} = \alpha_1 + \beta_1\, \widehat{II\_centrality}_{jt} + \boldsymbol{\beta_2 X_{it}} + FE + \varepsilon_{it} \quad (5)$$

Where *i* refers to firm, *j* refers to institutional investor and *t* refers to year, respectively. *Ln_GHG_Abs_Scp1* and *II_centrality* measures are defined previously. ***X*** is a vector of time-

[62] Geocoding is the process of converting addresses into geographic coordinates (longitude and latitude). These coordinates are used to accurately map and analyze locations on Earth. I apply geodesic methods like haversine formula and vincenty's formulae to compute distances between two points. Geodesic methods are techniques used to calculate the shortest path between two points on the surface of a sphere such as the Earth.

varying control variables discussed in Section 3 and defined in Appendix B. *FE* denotes fixed effects. I include country, industry, and year fixed effects to isolate the effect of industry, geographic concentration, and temporal trends.. Country-specific factors like regulations, governance, industry-specific factors having sectoral differences, different levels of emissions, investment structures, and centrality dynamics and yearly movements of emissions and centrality need to be accounted. ε_{it} is the error term clustered at the company and year levels.

<Insert Table 2.8>

The first stage results using equation (4) are presented in Models (1) – (4) in Panel A of Table 2.8. Across all models the F-statistics are greater than ten (110.03, 71.35, 99.99, 19.49), with the potential for weak instrument bias appearing low, as an F-statistic above ten is generally considered indicative of a strong instrument (Stock *et al.* 2002). I find all the models to be positive and highly significant. The positive and significant correlations and *F*-statistics suggest that the instrument strongly correlates with the endogenous variable (*II_centrality*), satisfying the relevance condition. In a more intuitive sense, the first stage of IV regression identifies the effect of distance between investors on investor connectedness, isolating the impact on II that experience changes in connectedness owing to the distance between them when holding portfolio firms.

Central investors are likely to have broader access to diverse investment opportunities across different regions. Highly central investors may be more strategic in their diversification efforts as they invest alongside investors from different geographic regions to diversify risk or leverage local expertise. The predicted values from this stage replace the original centrality measures in the second stage regression, where I examine the impact of these instrumented connections on firm-level carbon emissions. The results using equation (5) are presented in

Models (1) – (4) of Panel B in Table 2.8.[63] The results are negative and significant at the 1% levels.

In terms of the instrument's validity, the Cragg Donald Wald F-statistics and Kleibergen-Paap Wald F statistics are higher than the 10% maximal value with the standard critical value of 16.38 (Stock & Yogo 2002), thus rejecting the null for the instrument's weakness. This strongly indicates that the *Ln_Distance* as an instrument is not weak. However, it is important to note that these values are large, possibly owing to the large sample, and warrant careful interpretation.

The significant difference between the OLS and IV estimates for the impact of *II_centrality* on *Ln_GHG_Abs_Scp1* warrants a detailed discussion. For instance, in model (1), the IV estimate is -1.377 while the corresponding OLS estimate from model (5) in Table 2.5 is -0.068. The IV to OLS estimates ratio is 20.25 (-1.377/-0.068).[64] The IV approach addresses endogeneity concerns by providing a more rigorous estimate. Yet the substantial magnitude of IV estimates suggests potential bias beyond confounding factors that cause the OLS estimates to be biased by unobserved factors, leading to a smaller estimate. Several factors may contribute to this disparity. First, distance between investors provides meaningful variation in the centrality measures of II but does not serve as a discrete exogenous shock delineating treated and untreated firms. Instead, distances measured evolve based on geographic, strategic, and network factors, exhibiting varying levels of connectedness naturally. Second, distance between investors as an instrument might capture differences in firm characteristics that correlate with investor proximity. Also, firms with closely connected investors could differ systematically from firms with more dispersed investor networks potentially leading to selection bias. Additionally, firms anticipating the influence of high centrality II might adjust

[63] the results are robust to using distance calculated by haversine formula.
[64] This is higher than the ratio found in a survey of 255 papers from the top three finance journals. In that survey, the IV estimates, after adjusting for extreme values at 1%, were on average 9.2 times larger than the OLS estimates (18.8 times larger without the adjustment) (Jiang 2017).

their sustainability behavior in response, further complicating causal interpretations. As a result the IV estimates deviate more from the OLS estimates.

4.2.3.2 Lagged centrality measures and industry average

I use lagged centrality measures and the average centrality measures (except the focal firm) by their respective industry (Bruynseels & Cardinaels 2014; Balsam *et al.* 2017).[65] In the first-stage regressions, I estimate the centrality measures using the above-mentioned instruments. In the second stage, the predicted values from the first stage replace the connected measure. The results from the second stage are presented in Table 2A.3 of the Additional Analysis section. For the lagged measures as an instrument, I find that the models (1) - (4) are negative and statistically significant at 1% levels. For the instrument having the industry average the results are negative and statistically significant at 10% levels except for model (6) and (8) with no statistical significance.

4.2.3.3 Bootstrap Procedure

To ensure the robustness of the results, I follow Pool *et al.* (2015) to implement a bootstrap procedure to address concerns regarding standard errors. Despite clustering standard errors in a two way manner, it is possible that with a large sample size, statistical significance could be overstated. To mitigate these concerns, I perform a bootstrap procedure by rerunning the key regression under the null hypotheses of no effect and randomizing key independent variables. I design placebo-based randomization by creating a baseline scenario where centrality measures are randomized, eliminating any existing systematic relationship. I then compare the actual results with placebo outcomes to observe if the observed relationship is driven by

[65] The industry averages are calculated using a more refined approach by excluding the focal firm from the industry when computing the averages. I use Refinitiv INDM4 series at the sub sector levels for industry classification.

causality or merely by chance. Pool *et al.* (2015) randomize their key variable of interest neighbor status and run multiple regressions to gauge the effect. In the institutional investor context, Chen *et al.* (2023), implement a randomization-based placebo test. First, the authors construct a random network using passive investors, such as index funds and find insignificant results. I chose not to adopt this approach based on findings from Chinco and Sammon (2024) who provide compelling evidence that the share of passive investors in the US markets to be close to 33.5% (double of what everyone knew) including II with internally managed index portfolios and active managers who engage in closet indexing. Given the expanded definition, the passive investor group may include investors exhibiting strategic behavior contrary to the assumption that they are fully detached from decision-making. Consequently, using passive investors as a placebo network could introduce bias as it fails to capture ways in which even passive owners influence carbon emissions.

Secondly, they randomize centrality measures to the large investors. The authors limited their randomization to large investors, only capturing the influence of the most dominant II. I chose to extend the analysis to include all investors irrespective of their size. I randomize the centrality of II by reassigning random investor's centrality measures – degree, betweenness, closeness, and eigenvector to the existing investors. The randomization process preserves the original data structure but reshuffles the centrality measures across II. I repeat this process 5,000 times and record the placebo-generated OLS coefficients comparing it to the actual estimates. I focus on USA-domiciled firms due to computational limitations.

<Insert Figure 2.1>

I plot the distributions of the coefficient estimates for the centrality measures from the placebo regressions, focusing on carbon emissions for USA-domiciled firms. Each histogram in Figure 2.1 represents 5,000 simulations with the actual coefficient marked on the distribution. I present the actual regression coefficients for US-domiciled firms in Table IA.4. The figures (A, B, C, D) show that the actual coefficients are significantly outside the range (to the left) of the entire distribution of placebo-generated coefficients. In the figure, the actual coefficients (Reported in Table IA.4), are significantly to the left (outside the range) of the entire distribution of placebo-generated coefficients. The actual coefficients are several standard deviations away from the mean of the placebo estimates.[66] I conclude that the standard errors on the initial regression estimate are conservative. The results indicate that the relationship between *II_centrality* and *Ln_GHG_Abs_Scp1* is not merely an artifact of randomness or a product of random chance. This reinforces the robustness of the findings.

4.2.4 Heterogeneity of Institutional Investor Network and its impact

Not all II are the same (Zhao *et al.* 2023) and hence it warrants analysing the heterogeneity of well-connected II and their diverse influence on carbon emissions.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{it}) \times D(Het_{ijt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it} \qquad (6)$$

where *i* and *t* refer to firm and year, respectively. *Ln_GHG_Abs_Scp1* and *II_centrality* measures are defined previously. ***X*** is a vector of time-varying control variables discussed in Section 3 and defined in Appendix B. *FE* denotes fixed effects. I include firm and year fixed effects. I also include $D(Het_{ijt})$ as a fixed effect.[67] ε_{it} is the error term clustered at the

[66] *Degree_centrality*: The actual coefficient of -0.049 is 12.25 standard deviations below the mean of placebo estimates (-0.049-0)/0.004 = 12.25. The standard deviation of 0.004 is approximately 52% of the standard error (0.0077). *Betweenness_centrality*: The actual coefficient of -0.330 is 4.58 standard deviations below the mean of placebo estimates (-0.330-0)/0.072 = 12.25. The standard deviation of 0.072 is approximately 125% of the standard error (0.0576). *Closeness_centrality*: The actual coefficient of -0.108 is 10.8 standard deviations below the mean of placebo estimates (-0.108-0)/0.010 = 10.8. The standard deviation of 0.010 is approximately 56% of the standard error (0.0178). *Eigenvector_centrality*: The actual coefficient of -0.258 is 9.56 standard deviations below the mean of placebo estimates (-0.258-0)/0.027 = 9.56. The standard deviation of 0.027 is approximately 54% of the standard error (0.0503). Please see Table 2A.4 for the actual coefficients, and Figure 2.1 for the mean estimates and standard deviation of the placebo estimates. I obtain the standard errors from the regressions.

[67] The effect of centrality on the dependent variable is not assumed to operate directly, rather is contingent on the level of heterogeneity in the group. Centrality is omitted on the right-hand side of the equation to focus on the interaction term. It captures the differential effect of centrality conditioned on heterogeneity which captures the

company and year levels. The empirical model is in line with Chuluun *et al.* (2017) and Cohen *et al.* (2023).

<Insert Table 2.9>

4.2.4.1 Investment Style: Active vs Passive

In this section, I investigate the differential impact of *II_centrality* on *Ln_GHG_Abs_Scp1* based on their investment style. The divergence in strategy employed by active (engage in intensive research, analysis, stock selection) and passive investors (replicating a stock index) could lead to distinct environmental outcomes. II engage directly with companies to influence their environmental practices and integrate climate considerations into their investment decision-making (Cohen *et al.* 2023; He *et al.* 2023).

DesJardine *et al.* (2022) show that IO with a long-term focus, such as investors classified as dedicated and have an active orientation, can benefit from CSR as a tool. Dedicated IO represents a group of committed investors willing to hold on to their investments as they can profit based on their private information, enabling them to retain informational advantage (Boone & White 2015). As they are concentrated in fewer stocks, they can devote more effort to understanding business fundamentals and have incentives to monitor (Zhang & Gimeno 2016; Lai *et al.* 2023). Oehmichen *et al.* (2021) find that Dedicated IO have a superior understanding of the intricate information of target firms focusing on quick gains. Another group of investors with active orientation – Transient investors represent a group of opportunistic traders focusing on quick gains (Oehmichen *et al.* 2021). As they aim for short-term gains, they are susceptible to short-term earnings surprises and have less incentive to

key mechanism driving the key outcome. Intuitively, a variable like position in the hierarchy may only influence carbon performance when interacting with investor heterogeneity dynamics. The inclusion of the interaction term isolates the incremental effect of centrality under varying heterogeneity conditions, making a separate effect unnecessary. Including both centrality and the interaction term could introduce multicollinearity.

monitor (Zhang & Gimeno 2016; Lai *et al.* 2023). While active investment strategy requires time, effort, and expertise, it offers the potential for higher returns compared to passive investing. Active investors are better equipped to assess the financial risks associated with climate change and allocate capital accordingly.

According to Boone and White (2015), quasi-indexers that are considered as having a passive orientation, are strongly incentivized to require more public disclosures because getting private information on their diverse holdings can prove costly. According to Crane *et al.* (2016), incentives for benchmarking can discourage exit, and the IO may be more effective in communicating with and engaging managers.

Therefore, I expect well-connected II, categorized as active, to wield significant influence over corporate decision-making and reduce carbon emissions more than those categorized as passive.

I proxy for active and passive II using S&P Capital IQ definition. S&P Capital IQ conducts manual research on investment firms by scouring public sources for specific keywords related to investment style to determine their investment strategy and approach, whether active or passive.[68]

I analyze the varying effects of II network on *Ln_GHG_Abs_Scp1* using equation (6), where $D\left(Het_{ijt}\right)$ is replaced by $D\left(Active_{ijt}\right)$. $D\left(Active_{ijt}\right)$ is a dummy variable that takes the value of one if the II is categorized as active, and zero for passive investors. The results are presented in Models (1) - (4) of Table 2.9. I find that $II\_centrality_{ijt} \times D\left(Active_{ijt}\right)$ is consistently negative and statistically significant at the 1% level of significance. This indicates

[68] The S&P Capital IQ knowledgebase documents their approach to determining investment style and strategy. They do not rely on automatic methods but instead look at public sources for keywords like outperformance, excess returns, fees based on performance, index, low fees, and replication of the benchmark. Please see https://spglobal.my.site.com/s/article/About-CIQ-Calculated-Investment-Style-and-Investment-Orientation [Accessed 26th April 2024, 09:35 GMT].

that well-connected investors considered active reduce carbon emissions more than those considered passive.

4.2.4.2 Institutional Type: Independent vs Grey

In this section, I explore the differential impact of *II_centrality* on *Ln_GHG_Abs_Scp1* based on the institutional type. Independent investors actively monitor company management and use their autonomy and pressure-resistant reputation to influence management and promote social responsibility (Chen *et al.* 2007; Ferreira & Matos 2008). Independent II is known for being E&S conscious investors and actively promoting firm innovation (Luong *et al.* 2017; Dyck *et al.* 2019).

On the other hand, Grey II's current or potential association with corporate management often leads them to be more sensitive to pressure, thereby prioritizing loyalty to management and enabling corporate actions that may not align with the shareholders' interests (Ferreira & Matos 2008; Aggarwal *et al.* 2011). This could harm their business relationships and affect monitoring costs (Chen *et al.* 2007). Therefore, I conjecture that the well-connected II categorized as independent will significantly reduce carbon emissions more than grey II.

Following existing literature, I classify II as Independent and Grey II depending on the type of institution (Chen *et al.* 2007; Ferreira & Matos 2008). Independent II are mutual funds and independent investment advisors that manage investment portfolios independently of banks, insurance companies, or financial institutions. Hence, they operate more autonomously and prioritize clients' interests and financial performance. Grey II refers to banks, insurance companies, and other institutions that manage investment portfolios as part of their business operations, but their diverse business interests can make monitoring more challenging.

I analyze the varying effects of *II_centrality* on *Ln_GHG_Abs_Scp1* using equation (6), where $D(Het_{ijt})$ is replaced by $D(Independent_{ijt})$. $D(Independent_{ijt})$ is a dummy variable that takes the value of one if the II is categorized as independent and zero if grey. The results are presented in Models (5) - (8) of Table 2.9. I find that $II\_centrality_{ijt} \times D\left(Independent_{ijt}\right)$ is consistently negative and statistically significant at the 1% level of significance. This indicates that well-connected investors who are classified as independent reduce carbon emissions more than those classified as grey.

4.2.4.3 Commitment to Responsible Investment: PRI vs Non-PRI

In this section, I will examine the differential impact of *II_centrality* on *Ln_GHG_Abs_Scp1* based on its commitment to responsible investments. Principles for Responsible Investment (PRI) is a United Nations initiative launched in 2006 to encourage II to incorporate ESG factors into their investment strategies. The main objective is to promote sustainable investments and contribute to the stability of financial markets. To be a signatory, it is required to follow PRI's six principles, which include analyzing and deciding investments based on ESG factors, integrating ESG issues into ownership policies and practices, encouraging the adoption of internationally recognized reporting standards, collaborating to enhance the effectiveness of PRI principles, promoting the principles within the investment industry, and reporting progress on activities.[69] II can join the PRI initiative and become part of the global network of investors, provided they express a commitment to responsible investment, demonstrate their willingness to incorporate the six principles, and commit to reporting on their activities and progress.

Investors who are part of PRI are committed to incorporating ESG factors into their investment strategies, demonstrating their dedication to responsible investment practices (Liang *et al.* 2022). They have a responsibility to actively collaborate with the companies they invest in, advocating for sustainable business practices. Relatedly, Dyck *et al.* (2019) find that

[69] Information of PRI principles available on the website at https://tinyurl.com/UN-PRI. [Accessed on 13th August 2024, 12:07 BST]

the increase in ownership by PRI signatories improves E&S performance. Similarly, Liang *et al.* (2022) find that the signatory's underperformance is driven by lower exposure to responsible firms, attracting large fund inflows. Thapa *et al.* (2024) find that II who are PRI signatories lower ESG misbehavior than non-signatories.

In contrast, Kim and Yoon (2023) and Dikolli *et al.* (2022) find that even after becoming a PRI signatory, mutual funds need to showcase more commitment to social responsibility. Increased PRI signatory involvement is expected to lead to a greater reduction in carbon emissions due to their emphasis on long-term sustainable strategies aligned with PRI principles.

I analyze the varying effects of *II_centrality* on *Ln_GHG_Abs_Scp1* using equation (6), where $D(Het_{ijt})$ is replaced by $D(PRI_{ijt})$. $D(PRI_{ijt})$ is a dummy variable that takes the value of one if the II is a PRI signatory and zero otherwise. The results are presented in Models (9) - (12) of Table 2.9. I find that $II\_centrality_{ijt} \times D\left(PRI_{ijt}\right)$ is consistently negative and statistically significant at the 1% and 5% levels of significance. This indicates that well-connected investors who are PRI signatories reduce carbon emissions more than non-PRI signatories.

When II becomes a PRI signatory, they either avoid firms with low ESG ratings or choose those with high ESG ratings, as expected (Liang *et al.* 2022; Kim & Yoon 2023). ESG funds of PRI signatories tend to support E&S proposals more than non-ESG funds (Dikolli *et al.* 2022). PRI signatories with higher considerations for ESG reduce ESG misbehavior more than their counterparts (Thapa *et al.* 2024). Not all PRI signatories, particularly those from the USA, improve the ESG scores of their portfolio companies, unlike signatories from other countries (Brandon *et al.* 2022).

I also explore whether investors who "walk the talk" are able to reduce carbon emissions more compared to others. In order to identify these investors, I follow Liang *et al.* (2022). I calculate the weighted average ESG scores for each II in a portfolio. "Walk the talk" II are PRI signatories with portfolio ESG scores in the top third tercile.

I analyze the varying effects of *II_centrality* on *Ln_GHG_Abs_Scp1* using equation (6), where $D(Het_{ijt})$ is replaced by $D(PRI - High - ESG_{ijt})$. $D(PRI - High - ESG_{ijt})$ is a dummy variable that takes the value of one if the portfolio-weighted average ESG score of II in the top tercile and zero if the portfolio-weighted average ESG scores are in the bottom tercile. The results are presented in Models (13) - (16) of Table 2.9. I find that $II\_centrality_{ijt} \times D\left(PRI - High - ESG_{ijt}\right)$ is consistently negative and statistically significant at the 1% and 5% levels of significance. This indicates that well-connected investors who are PRI signatories and have higher ESG portfolio scores reduce carbon emissions more than those who are PRI signatories and have lower ESG portfolio scores.

4.2.4.4 Others

4.2.4.4.1 Investor Size: Large vs Small

In this section, I investigate the differential impact of *II_centrality* on *Ln_GHG_Abs_Scp1* based on their size. Large institutional investors, such as the big three investors or blockholders, have greater influence and possess better capabilities to engage with the board compared to smaller institutional investors (Azar *et al.* 2021; Lewellen & Lewellen 2022; Gormley *et al.* 2023). This is due to their greater financial might, better investment strategies, and extensive resources (Schnatterly *et al.* 2008; Ben-David *et al.* 2021). With a significant stake, II have an incentive to coordinate and form a collaborative network to achieve collective impact (Huang & Kang 2017; Crane *et al.* 2019).

II with higher ownership stakes would have a strong incentive to reduce carbon emissions (Azar *et al.* 2021). There might be a reluctance to pursue environmental initiatives to avoid risking short-term profitability (Dharwadkar *et al.* 2008). Given this evidence, I argue that the impact of large, well-connected II is greater than that of smaller II in reducing carbon emissions. In the sample (unreported statistics), Big 3 II exhibit a higher average ownership of 1.629% (median 0.663%), while Non-Big 3 have a lower average ownership of 0.462% (median 0.076%). Large investors have an average ownership of 0.973% (median 0.302%) while small investors have an average of 0.034% (median 0.028%). In the case of Blockholders, the average ownership stake is 8.97% (median 7.16%), while that of Non-Blockholders is 0.339% (median 0.076%). This indicates ownership levels vary among II classified by being a large investor, a part of Big Three, or a Blockholder.

I analyze the varying effects of II network on *Ln_GHG_Abs_Scp1* using equation (6), where $D(Het_{ijt})$ is replaced by $D(Large_{ijt})$. $D(Large_{ijt})$ is a dummy variable that takes the value of one if the IO of an investor in a firm is higher than the median value of the average investor ownership and zero otherwise. The results are presented in Models (1) - (4) of Table 2A.5 in the Additional Analysis section. I find that $II\_centrality_{ijt} \times D\ (Large_{ijt})$ is negative in models (1), (2) and (3), but only models (1) and (2) are statistically significant. I conclude with weak evidence that well-connected investors that are large reduce carbon emissions more than the others.

Additionally, I conduct a subsample analysis to examine the effects of ownership structures on II network and carbon emissions. the analysis in Table 2A. 6 shows Big 3 and large investors exhibit a negative relationship with carbon emissions, with little to no significance. Non-Big 3 and small II have a significant negative relationship with emissions reduction, except for *Eigenvector_centrality* which shows a negative coefficient at 5% and 10% significance levels, respectively. I find that blockholders are associated with a positive impact on carbon emissions, suggesting potential complacency. In contrast, Non-Blockholders demonstrate a negative and highly significant effect at 1% levels. However, the results could be attributed to the large number of transactions. Therefore, I caution the readers while interpreting the results, even though they are in line with expectations.

Well-connected II tend to exert a greater influence in reducing carbon emissions, suggesting that it is not merely the level of ownership that matters, but the nature of II relationships. Therefore, the effectiveness of II in promoting environmental responsibility is more closely linked to their network effects.

4.2.4.4.2 Holding Period: Long-term vs Short-term

In this section, I examine the differential impact of *II_centrality* on *Ln_GHG_Abs_Scp1* based on investment horizon. Several studies show that Pension and Hedge Funds have distinct investment strategies that primarily focus on long-term and short-term goals (Chen *et al.* 2007; Caglayan *et al.* 2018a; Thapa *et al.* 2024).

Pension funds epitomize long-term investment strategies that prioritize stability and sustainability, adhering to stringent standards and exercise careful judgment (Derrien *et al.* 2013). Chen *et al.* (2007) shows that firms with long-term IO experience lower monitoring costs due to their extensive knowledge of the organization and its managers, which allows them to process new information and make informed decisions effectively. Pension funds are essential in corporate governance as they actively monitor and promote changes within targeted companies (Guercio & Hawkins 1999). An increasing number of pension funds are tackling E&S issues (Dimson *et al.* 2015)[70].

Hedge funds are private investment funds managed by professionals who aim to generate superior returns for investors using speculative and riskier approaches, not bound by usual regulations (Caglayan *et al.* 2018a). The basic structure is aligned towards short-term

[70] Pension Funds primarily aim to grow and preserve assets over an extended period to ensure they have sufficient funds to meet future pension obligations, leading to a long-term investment horizon (Woidtke 2002).

profit development by leveraging performance-based fees, which encourages delivering positive returns (French 2008).

Based on the evidence, those involved have a duty to act in their beneficiaries' best interests, incorporating ESG considerations for long-term investment resilience. Long-term II is expected to significantly reduce carbon emissions compared to Short-term II, as it actively engages with its portfolio companies to improve ESG practices.

I analyze the varying effects of *II_centrality* on *Ln_GHG_Abs_Scp1* using equation (6), where $D(Het_{ijt})$ is replaced by $D(Long - Term_{ijt})$. $D(Long - Term_{ijt})$ is a dummy variable that takes the value of one if the II is a pension fund, and zero if II is a hedge fund. The results are presented in Models (5) - (8) of Table 2A.5 in the Additional Analysis section. I find that $II\_centrality_{ijt} \times D\left(Long - Term_{ijt}\right)$ is negative models (5) - (8), and only models (5) and (6) are statistically significant. I conclude with weak evidence that well-connected investors who are long-term holders reduce carbon emissions more than others.

4.2.4.4.3 Investor Nationality: Foreign Vs. Domestic

In this section, I investigate the differential impact of *II_centrality* on *Ln_GHG_Abs_Scp1* based on the investor's country of domicile. Foreign II contribute to promoting good corporate governance practices across the world (Ferreira & Matos 2008; Aggarwal *et al.* 2011). Foreign investors encourage technological innovations through active monitoring, higher risk tolerance, and knowledge transfer (Luong *et al.* 2017). I expect foreign II to have a more significant effect on governance and knowledge transfer than domestic investors due to their lack of business relationships with investee firms. This enables investors to exert pressure on management, and the social norms of investors influence investee companies in different countries (Bena *et al.* 2017).

I analyze the varying effects of *II_centrality* on *Ln_GHG_Abs_Scp1* using equation (5), where $D(Het_{ijt})$ is replaced by $D(Foreign_{ijt})$. $D(Foreign_{ijt})$ is a dummy variable that takes the value of one if the II is domiciled in the same country as that of the portfolio firm, and zero otherwise. The results are presented in Models (9) - (12) of Table 2A.5 in the Additional Analysis section. I find that $II\_centrality_{ijt} \times D\ (Foreign_{ijt})$ is consistently negative and statistically significant at the 1% level of significance. This indicates that well-connected investors who are foreign holders reduce carbon emissions more than their counterparts.

4.2.4.4.4 USA vs Non-USA

In this section, I investigate the differential impact of *II_centrality* on *Ln_GHG_Abs_Scp1* that are based on their country of domicile being from the USA. A larger pool of II from the US can contribute to a more competitive environment, potentially driving better performance.[71] USA is considered a country with a high level of investor protection (Aggarwal *et al.* 2011). Governance influences investment decisions for both US and non-US institutions, with the US market's capital and financial infrastructure amplifying this impact for US-based institutions (Aggarwal *et al.* 2011). Considering these substantiating factors, it is expected that increased involvement by investors from the USA will lead to a greater reduction in carbon emissions compared to non-USA II.

I analyze the varying effects of *II_centrality* on *Ln_GHG_Abs_Scp1* using equation (5), where $D(Het_{ijt})$ is replaced by $D(US_{ijt})$. $D(US_{ijt})$ is a dummy variable that takes the value of one if the II is categorized as being domiciled in the US and zero otherwise. The results are presented in Models (13) - (16) of Table 2A.5 in the Additional Analysis section. I find that $II\_centrality_{ijt} \times D\ (US_{ijt})$ is consistently negative and statistically significant at the 1%

[71] As shown in Panel A of Table 2.2, the sample has 7,014 unique II domiciled in the US.

level of significance. This indicates that well-connected investors who are domiciled in the US reduce carbon emissions more than the others.

4.2.5 Mechanism and Implications

4.2.5.1 Hypotheses 2: Green Innovation

I test the second hypothesis using the following specifications:

$$Ln\_Gr\_Patents_{it+1} = \beta_1(II\_centrality_{it}) + \beta_2 X_{it-1} + FE + \varepsilon_{it} \tag{6}$$

$$Ln\_GHG\_Abs\_Scp1_{it+2} = \beta_1(Ln\_Gr\_Patents)_{it+1} + \beta_2(II\_centrality)_{jt} + \beta_3 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it} \tag{7}$$

Where *i* and *t* refer to firm and year, respectively. *Ln_Gr_Patents*, *II_centrality*, and *Ln_GHG_Abs_Scp1* measures are defined previously. ***X*** is a vector of time-varying control variables discussed in section 3 and defined in Appendix B. *FE* denotes fixed effects. I include industry and year fixed effects for specification (6), while country, industry, and year fixed effects for specification (7). ε_{it} is the error term clustered at the company and year levels. The empirical model is in line with Chuluun *et al.* (2017) and Cohen *et al.* (2023).

To examine the influence of well-connected II on firm-level green innovation, I regress *II_centrality* on *Ln_Gr_Patents* as in equation (6). Innovations are closely tied to broader industry trends such as sector-specific research and development investment or government policies targeting particular industries. I control for industry and year-fixed effects in the regressions, allowing us to control for industry-level variation and yearly changes over time. In equation (7), I investigate whether green innovations contribute to a reduction in carbon emissions. *Ln_Gr_Patents* is the key independent variable, while *II_centrality* measures are added as additional controls. This allows us to test the hypotheses that well-connected II affect emissions indirectly through green innovations, thus capturing the mediating role of green innovation. I control for country, industry, and year fixed effects. Carbon emissions are affected not only by industry-level factors but also by country-specific environmental regulations, policies, and macroeconomic conditions. Hence, I control for unobserved heterogeneity at the country, industry and year levels, isolating the impact of green innovations on emissions while controlling for systematic differences across countries, industries and year.

I add *Cash*, *Research_intensity*, and *HHI* as control variables to the regression models (Chuluun *et al.* 2017). I capture a firm's liquidity, which influences its ability to invest in green innovation. Firms with higher liquidity may be better positioned to allocate resources towards research and development of green patents, enhancing their innovative capacity. This relationship could affect centrality measures as firms with robust financial health might be more attractive for II to invest in. Firms that prioritize investments in sustainability may reduce emissions. Hence, I expect a negative relationship between a firm's liquidity and carbon emissions. I proxy for a firm's liquidity by scaling cash holdings over total assets (*Cash*).

I capture a firm's commitment to innovation. Firms with high commitment to innovations are likely to produce more innovative outputs. High commitments enhances a firm's outlook, attracting investments from II, which could positively impact their centrality. Higher commitment to innovative activity eventually leads to reduced emissions. I expect a negative relationship between a firm's commitment to innovation and carbon emissions. I proxy a firm's commitment to research by scaling research and development expenses to total assets (*Research_intensity*).

I further control for competition faced by a firm. High concentration within industries may limit competition, which could negatively affect the firm's incentives to invest in green innovations. Firms may engage in innovations to differentiate themselves influencing patents, attracting institutional investments, and eventually reducing carbon emissions. I expect a negative relationship between competition and emissions. I proxy for competition using

Herfindahl-Hirschman Index (*HHI*). HHI is a measure of market concentration calculated by summing the squares of the market sales of all firms in a market, providing insights into the level of competition or monopoly within the market. Higher values indicate less competition.

<Insert Table 2.10>

The results for OLS regressions using specification (6) are presented in Panel A of Table 2.10 using equation (6). The results are consistently positive and significant at the 1% levels in models (1) – (4). The results are economically meaningful as well. For instance, a one standard deviation increase in *Closeness_centrality* is associated with a 3.37% increase in *Ln_Gr_Patents* in the following year.[72]

The results for OLS regressions using specification (7) are presented in Panel B of Table 2.10. The coefficient of *Ln_Gr_Patents* is negative and statistically significant at the 10% level. The coefficient for *II_centrality* remains negative with mixed statistical significance across specifications (1) – (3). The coefficients for model (4) is negative but with no statistical significance. This suggests the role of green innovations as a mediator, where well-connected II influences emissions indirectly by promoting green innovation. The results are economically meaningful as well. For instance, a one standard deviation increase in *Closeness_centrality* is associated with a 0.0546% decrease in *Ln_GHG_Abs_Scp1* in the following two years.[73] Overall, the results support H2.

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[72] The calculation is as follows: coefficient of 0.486 and one standard deviation increase in *Closeness_centrality* (0.02732), the effect on *Ln_Gr_Patents* is 0.01329 (0.486 x 0.02732) points, which translates to a 1.34% ($e^{0.01329} - 1$) increase in mean *Ln_Gr_Patents* (0.394).

[73] The calculation is as follows: coefficient of -0.020 and one standard deviation increase in *Closeness_centrality* (0.02732), the effect on *Ln_GHG_Abs_Scp1* in the next two years is -0.00054 (-0.020 x 0.02732) points, which translates to a -0.0546% ($1 - e^{0.0005464}$) decline in mean *Ln_GHG_Abs_Scp1* (10.765).

4.2.5.2 Hypotheses 3: Climate Change Exposure

I test the third hypothesis using the following specifications:

$$CCE_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it} \quad (8)$$

$$Ln\_GHG\_Abs\_Scp1_{it+2} = \beta_1 \left(II\_centrality \times D(\Delta CCE > 0)\right)_{it} + \beta_2 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it} \quad (9)$$

Where *i* and *t* refer to firm and year, respectively. *CCE* and *II_centrality* measures are defined previously. ***X*** is a vector of time-varying control variables discussed in section 3 and defined in Appendix B. FE denotes fixed effects. I include firm and year fixed effects. ε_{it} is the error term clustered at the company and year levels. The empirical model is in line with Chuluun *et al.* (2017) and Cohen *et al.* (2023).

Further, I modify equation (8) to test the mechanism through which the II network influences their portfolio companies' carbon emissions. *D(ΔCCE>0)* is a dummy variable that equals one if there is an increase in change in climate change exposure and zero otherwise. The interaction term *II_centrality* × *CCE*, β_1, is of significant interest capturing the effect of centrality on *Ln_GHG_Abs_Scp1,* which differ depending on the increase in climate change exposure. I also include the dummy, *D(ΔCCE>0)* as a fixed effect in addition to the ones specified in equation (8).

<Insert Table 2.11>

The results are presented in panel A of Table 2.11 in models (1) – (4) using equation (8). The results are consistently positive and highly significant at 1% and 5% levels across specifications. A one standard deviation increase in *Eigenvector_centrality* is associated with a 0.28% increase in *CCE* in the following year.[74] Overall, the results support H3. This suggests that II have a stronger influence on their portfolio companies subsequent CCE indicating a proactive role in shaping climate discussions.

The results for mechanism are presented in panel B of Table 2.11 in models (1) – (4) using equation (9). The interaction term *II_centrality* × *D(ΔCCE>0)* is consistently negative and significant at 1% levels. The effect of *II_centrality* on *Ln_GHG_Abs_Scp1* is negative when portfolio companies' climate change exposure increases. Overall, the results support H3.

[74] The calculation is as follows: coefficient of 0.292 and one standard deviation increase in *Eigenvector_centrality* (0.0096), the effect on *CCE* is a 0.002803 (0.292 x 0.0096) points increment, which translates to a 0.28% ($e^{-0.002803} - 1$) increase in mean *CCE* (0.002).

5 Chapter 5: Conclusion

This thesis offers a thorough analysis of the influential role played by II, individually and in a network, in shaping corporate sustainability behavior in relation to ESG misbehavior and carbon emissions. Further, I emphasize the nuanced impact that II, both individually and within their networks, has on corporate sustainability by investigating these two aspects.

In the first empirical chapter, the analysis of IO and ESG misbehavior shows that investor monitoring and engagement are critical in influencing corporate behavior. The findings suggest that ownership by II is associated with lowering ESG misbehavior. Furthermore, I find that values-based II negatively impacts more than value II.

In the second empirical chapter, the focus on II networks and carbon emissions reveals how investor interconnectedness reduces carbon emissions. Well-connected II encourage green innovation, which indirectly impacts the reduction of carbon emissions. Next, I find that well-connected II engage in climate-related discussions, increasing climate change exposure, which contributes to reducing future carbon emissions.

The empirical chapters advance the ongoing debate on the critical role of II and their networks in promoting corporate sustainability. These studies help us to understand the impact of II monitoring, and engagement, and how network dynamics can influence corporate sustainability behavior. This emphasizes the potential for financial stakeholders to play a significant role in driving environmental change.

5.1 Conclusion: First Empirical Chapter

Ample evidence suggests that media-reported *ESG-MVR,* which tarnish the firm's reputation, are associated with adverse stock market reactions, lower future sales revenue, harmful spillover effects to subsidiary firms, lower growth opportunities, higher credit risk, and even dismissals of CEOs. However, recent studies also document that higher ownership of institutional holdings is associated with endogenously determined better ESG-related performance. Whether such II-driven superior ESG performance of investee firms plays any role in determining the future exogenously media-reported *ESG-MVR* is still unknown. In this study, I investigate whether holdings of II could explain media-reported future ESG-related harmful incidents of the investee firms.

To answer my question, I use a firm-level time-varying quantitative measure that reflects a firm-level assessment of the media-reported *ESG-MVR* on a sample of 14,906 II investing in 4,342 firms across 34 countries from 2007 to 2021. Employing several robustness checks, I convincingly document that higher current *IO* is associated with lower future incidents of *ESG-MVR*. Further investigations suggest that compared to *value* investors, which primarily incorporate ESG factors for managing the risk-return profile, *values-based* investors, who also prefer real ESG impact, exhibit a more pronounced mitigating effect on future *ESG-MVR*. Specifically, I document that PRI signatories, investors from civil law countries, those with long-term investment horizons, and those considered pressure-resistant independent investors seem to have greater *ESG-MVR* mitigating effects on their investee firms.

Our study concludes that II's stake not only helps promote positive sustainability practices but also helps manage future exogenously reported adverse ESG incident risks.

5.2 Conclusion: Second Empirical Chapter

There is an ongoing debate about the impact of well-connected II on corporate sustainability. Literature is silent on whether II network drives firms to be more sustainable. I therefore ask the question do II network reduce carbon emissions? I also investigate the possible mechanisms through which II network reduces carbon emissions.

To answer the question, I employ an investor-level time-varying quantitative measure that reflects an investor-level assessment of the II network on a sample of 17,833 II investing in 12,781 firms across 77 countries from 2005 to 2020. I run a battery of robustness checks and convincingly document that well-connected II is associated with reducing carbon emissions. Further investigations suggest that well-connected II categorized as active, independent, and PRI signatories have a greater impact than their counterparts. I also find that well-connected II reduces carbon emissions by investing in companies with higher green patents and by engaging with companies to increase their climate change exposure, eventually reducing carbon emissions.

Our research has implications for II themselves. Companies are under pressure from stakeholders to maintain financial value and outperform the market, while the public expects them to avoid contributing to global harm. This creates a need to act responsibly and manage risks for long-term value preservation. Well-connectedness enables investors to combine their influence, expanding their reach across regions, fostering a ripple effect, and strengthening their impact on sustainable practices.

5.3 Implications

II plays a crucial role in addressing climate change. As they have a significant stake and the influence to direct capital towards firms that are climate conscious. For corporate managers, the implications for the firm must be to demonstrate a commitment to adhere to sustainable practices and engage with investors in order to attract and retain investment. Firms can then position themselves as attractive investment targets.

The findings from my first empirical chapter reveal that II monitor and engage with portfolio companies to mitigate ESG misbehavior. The study also indicates that not all II are the same, and they have a differing impact based on their distinct characteristics. Policymakers should, therefore, consider implementing stronger frameworks for institutional investor accountability, say in stewardship reports. For corporate managers, engagement with II will avoid risking divestment or reputational damage. When portfolio companies enhance their ESG performance, it reduces issues and provides useful information for policymakers.

The findings from my second empirical chapter reveal that well-connected II play a critical role in reducing carbon emissions. Policymakers and regulators should recognize these players can act as catalysts for corporate change and drive climate-related initiatives. Climate-conscious investors, engage with their investee firms to increase their environmental standards and transparency about future climate-related risks (Angelis *et al.* 2023). These investors also internalize the financial cost of climate externalities, which increases the cost of capital for companies that fail to reduce their greenhouse gas emissions (Angelis *et al.* 2023). It is essential for each institutional investor to ascertain the optimal number of investors to engage with in order to fully leverage market opportunities and execute trades effectively, ultimately aiming to outperform the financial markets.

Bushee (2004) finds that by changing disclosure practices, companies can shift their investor base from short-term to long-term focused investors. Corporate managers would be aware that II may exert greater pressure to adopt sustainable practices. Understanding the network dynamics helps managers of portfolio firms to anticipate and respond to investor demands, aligning strategies with regulatory requirements and investor expectations.

5.4 Limitations

I address the limitations of my thesis below.

In my first empirical chapter, my investigation of ESG misbehavior primarily centered on negative news. However, I lacked a mechanism to analyze positive news reported by the media. Access to such a data source would be crucial for determining its impact on media-reported news, whether positive or negative. It would be of interest to analyze the behavior of investors in response to the positive news. Also, although RepRisk score serves as a robust measure, it would be helpful to find if my setting holds with another database that follows the same outside to inside approach. Lack of such a database is a limitation. Nevertheless I ran a battery of tests with other variables from Reprisk which provides some assurance.

In my second empirical chapter, the investigation of II network was based on the assumption that the investors are in a network based on the ownership position held. Understanding the extent of their influence carries inherent benefits, yet there exists no framework for ascertaining the actual interactions among investors. It would be interesting to see how their influence materializes and how those interactions lead to actual engagement or monitoring with portfolio firms, ultimately impacting corporate decision-making.

In both of the empirical chapters, I come across computational limitations that challenge the scope of the analysis. In the first empirical chapter, I limited the dataset to all IIs with at least 0.01% stake under the assumption that Iis with larger stakes are more incentivized to induce changes in portfolio firms. In the second empirical chapter, I narrowed down the dataset to include only those with at least 0.1% due to computational constraints while creating a network graph. In both scenarios, the data sample at my disposal may offer a limited perspective, particularly with respect to smaller investors. Exploring the impact of smaller investors on network structure and information dissemination among institutional investors presents an intriguing avenue for investigation.

5.5 Future Research

Besides these limitations, future research can investigate the following aspects.

Firstly, Increased demand for climate-related information, as indicated by CDP signatory status, raises the likelihood for firms to disclose to the CDP, thereby increasing transparency and reducing future carbon emissions (Cohen *et al.* 2023). ESG-related regulatory changes could alter II influence on corporate misconduct by further aligning and strengthening investor engagement. Future research could explore how regulatory shifts, such as mandatory ESG disclosures or strict enforcement, affect the relationship between II and ESG Misbehavior.

Shi *et al.* (2022) find that II activism negatively affects employee health and safety, particularly when II and the portfolio company's board are non-liberal. While my research considers network centrality, it leaves out the behavioral dynamics of II, such as investment ideologies, culture, and religion, which could impact collaboration and influence firms' incentives to reduce carbon emissions. Future research could examine how these factors interact with II networks in influencing portfolio firms' decisions, helping us to understand the non-financial influence on corporate decision-making.

Lastly, my research does not address the long-term effects of network evolution on carbon emissions. Can well-connected II maintain their influence over time, or can changes in network structures, market shifts, or regulatory changes alter portfolio company's behavior? Future studies could consider the long-term impact of network creation on a firm's ability to make decisions.

Tables and Appendix

Tables: First Empirical Chapter

Table 1. 1: Descriptive Statistics

This table shows the summary statistics of all the variables – ESG misbehavior measures (Panel A), institutional ownership measures (Panel B), firm characteristic measures (Panel C), and country characteristic measures (Panel D). All continuous variables are winsorized at the 1st and 99th percentiles. The sample covers the period spanning from 2007 to 2021. All variables are defined in Appendix B and C.

	Observations	Mean	Std. Dev.	P25	P50	P75
Panel A: Investee firm's ESG misbehavior						
ESG-MVR$_{it+1}$	38,817	10.134	11.460	0.000	6.750	18.333
Peak-ESG-MVR$_{it+1}$	38,817	22.746	17.762	0.000	26.000	34.000
Env-ESG-MVR$_{it+1}$	38,817	1.830	4.126	0.000	0.000	0.108
Soc-ESG-MVR$_{it+1}$	38,817	3.418	6.000	0.000	0.000	5.436
Gov-ESG-MVR$_{it+1}$	38,817	3.188	6.253	0.000	0.000	3.408
Violations$_{it+1}$	38,817	5.716	22.228	0.000	0.000	3.000
Env_Violations$_{it+1}$	38,817	1.807	9.040	0.000	0.000	0.000
Soc_Violations $_{it+1}$	38,817	2.515	10.363	0.000	0.000	1.000
Gov_Violations $_{it+1}$	38,817	1.393	5.357	0.000	0.000	1.000
Panel B: Institutional ownership						
FL_IO$_{it}$	38,817	42.155	28.940	17.514	35.191	66.485
Inv_IO$_{jit}$	2,775,227	0.459	1.592	0.027	0.072	0.259
Inv_PRI_IO$_{jit}$	433,861	0.765	1.780	0.039	0.134	0.600
Inv_Non_PRI_IO$_{jit}$	2,341,366	0.402	1.548	0.025	0.065	0.221
Inv_PRI_High_ESG_IO$_{jit}$	143,182	0.863	1.911	0.050	0.175	0.695
Inv_PRI_Low_ESG_IO$_{jit}$	143,182	0.668	1.656	0.031	0.095	0.537
Inv_Civil_IO$_{jit}$	826,365	0.419	1.624	0.024	0.063	0.230
Inv_Common_IO$_{jit}$	1,927,988	0.471	1.571	0.028	0.075	0.268
Inv_Independent_IO$_{jit}$	2,536,111	0.438	1.327	0.027	0.072	0.261
Inv_Grey_IO$_{jit}$	228,231	0.687	3.316	0.025	0.066	0.226
Inv_LT_IO$_{jit}$	199,949	0.401	1.313	0.029	0.070	0.232
Inv_ST_IO$_{jit}$	121,471	0.474	1.822	0.030	0.083	0.274
Inv_Foreign_IO$_{jit}$	1,447,952	0.329	1.142	0.025	0.060	0.194
Inv_Domestic_IO$_{jit}$	1,327,275	0.601	1.959	0.030	0.089	0.352
Inv_Large_IO$_{jit}$	1,387,355	0.886	2.169	0.128	0.259	0.739
Inv_Small_IO$_{jit}$	1,387,239	0.031	0.017	0.017	0.027	0.043
Panel C: Firm Characteristics						
Revenue ($Bn)	38,817	7.627	15.427	0.725	2.306	6.792
Cash / Total assets (Times)	38,817	0.103	0.105	0.030	0.071	0.140
Leverage (%)	38,817	25.435	18.158	10.918	24.336	37.007
MTB (times)	38,817	3.026	3.823	1.141	1.938	3.504
Revenue_Growth (%)	38,817	0.842	2.637	-0.859	0.747	2.428
Age (years)	38,817	21.054	13.275	10.000	19.000	30.000
Panel D: Country Characteristics						
GDPPC ($ '000)	38,817	39.829	18.398	22.351	42.862	54.954
EPI (0-100)	38,817	65.399	13.766	56.600	67.520	76.120

Table 1. 2: Sample Composition by Country and Industry
This table reports the average total institutional ownership (investee firm and investor levels), number of unique investors, and number of unique investee firms in each country in Panel A and by industry in Panel B. The sample spans a period from 2007 to 2021. *FL_IO* denotes firm-level aggregate ownership of II, and *Inv_IO* denotes ownership of individual II in a firm.

Panel A: Country

Country	*FL_IO*	# of unique investee firms	*Inv_IO*	# of unique institutional investors
Australia	29.43	173	0.74	1,681
Austria	28.01	23	0.48	679
Belgium	24.83	29	0.42	1,013
Brazil	36.82	66	0.49	1,268
Canada	42.43	207	0.57	3,041
Chile	19.38	26	0.55	211
China	16.13	559	0.44	2,181
Denmark	39.10	33	0.56	898
Finland	36.45	47	0.57	1,182
France	34.57	116	0.40	1,992
Germany	32.49	112	0.39	1,949
India	23.94	143	0.55	1,112
Indonesia	12.22	38	0.31	614
Ireland	71.15	25	0.38	1,947
Italy	22.00	56	0.35	1,127
Japan	33.99	335	0.46	1,777
Malaysia	31.34	100	1.09	782
Mexico	18.57	45	0.42	898
Netherlands	48.38	39	0.46	1,679
New Zealand	29.75	27	0.88	388
Norway	40.29	42	0.70	945
Philippines	13.42	25	0.32	482
Poland	34.05	24	0.59	332
Russia	12.44	25	0.26	463
Singapore	27.17	37	0.57	963
South Africa	55.78	64	0.79	1,482
South Korea	27.04	130	0.48	1,218
Spain	28.32	56	0.36	1,379
Sweden	50.38	73	0.81	1,250
Switzerland	32.55	80	0.36	2,430
Thailand	15.10	54	0.41	606
Turkey	13.81	35	0.32	541
United Kingdom	72.73	250	0.51	4,571
United States	75.16	1,248	0.40	7,781

Panel B: Industry

Industry	*FL_IO*	# of unique investee firms	*Inv_IO*	# of unique institutional investors
Basic Materials	37.08	517	0.50	6,689
Consumer Discretion	45.58	880	0.48	8,909
Consumer Staples	36.83	434	0.43	6,588
Energy	38.05	309	0.42	5,625
Health Care	47.44	401	0.43	6,362
Industrials	44.47	975	0.49	8,876
Real Estate	30.26	124	0.54	2,722
Technology	49.63	309	0.43	6,058
Telecommunications	38.25	140	0.39	4,258
Utilities	37.70	253	0.40	4,985
Average (Total)	42.155	4,342	0.459	14,906

Table 1. 3: Firm-level Institutional Ownership and ESG Misbehavior

This table reports the estimates of the following general regression specification covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+n} = \beta_1(FL\_IO_{it}) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

I denotes investee-firm, t year, c investee firm country, and n is the lead number. All the variables ($ESG - MVR_{it+n}$, FL_IO_{it}, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B. FE includes country, industry, country × industry, and year-fixed effects, depending on specification. The standard errors in all regressions are clustered at the country-industry levels. T-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	ESG-MVR it+1		*ESG-MVR* it+2	
	(1)	(2)	(3)	(4)
FL_IO	-0.019***	-0.017**	-0.018***	-0.015**
	(-2.82)	(-2.47)	(-2.62)	(-2.18)
Ln_Firm_Size	3.643***	3.736***	3.743***	3.841***
	(26.87)	(26.94)	(27.50)	(27.79)
Ln_Cash	0.249***	0.228***	0.238***	0.222***
	(3.39)	(3.14)	(3.15)	(2.95)
Leverage	-0.302	0.151	-0.588	-0.194
	(-0.44)	(0.23)	(-0.84)	(-0.29)
MTB	0.047*	0.069**	0.078**	0.106***
	(1.70)	(2.51)	(2.55)	(3.47)
Revenue_Growth	0.024	0.028	0.003	0.006
	(0.98)	(1.22)	(0.11)	(0.24)
Ln_Age	0.379***	0.341**	0.245*	0.196
	(2.77)	(2.43)	(1.74)	(1.35)
Cntry_Ln_GDPPC	-4.130***	-4.333***	-4.198***	-4.375***
	(-4.26)	(-4.30)	(-4.56)	(-4.53)
Cntry_EPI	-0.036**	-0.039**	-0.060***	-0.064***
	(-2.17)	(-2.38)	(-3.70)	(-3.87)
Country FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Country × Industry FE	No	Yes	No	Yes
Observations	38,817	38,817	34,666	34,665
R^2 (within)	0.287	0.290	0.294	0.297

Table 1. 4: Firm-level IO and ESG Misbehavior: Instrumental Variable

This table reports the estimates of the following two-stage least squares (2SLS) regressions using MSCI addition as an instrument covering a sample period from 2007 to 2021.

First stage: $FL\_IO_{it} = \alpha_0 + \gamma_1(D\_MSCI_i) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$

Second stage: $ESG - MVR_{it+n} = \alpha_1 + \beta_1 . \widehat{FL\_IO}_{it} + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$

I denotes investee-firm, *t* year, *c* investee firm country, and *n* is the lead number. All the variables (FL_IO_{it}, D_MSCI_i, $ESG - MVR_{it+n}$, $\widehat{FL\_IO}_{it}$ and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B. I present the first-stage regression coefficients in model (1) and the 2SLS estimates in models (2) – (5). *FE* includes country, industry, country × industry, and year-fixed effects, depending on specification. The standard errors in all regressions are clustered at the country-industry levels. *T*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	First-stage	Second-Stage			
	FL_IO	*ESG-MVR* it+1		*ESG-MVR* it+2	
	(1)	(2)	(3)	(4)	(5)
FL_IO		-0.433***	-0.618***	-0.364**	-0.571***
		(-2.93)	(-3.26)	(-2.28)	(-2.72)
D_(MSCI)	1.822***				
	(3.03)				
Ln_Firm_Size	2.462***	5.106***	5.754***	5.036***	5.744***
	(10.54)	(13.63)	(11.46)	(12.43)	(10.29)
Ln_Cash	0.171	0.281***	0.336***	0.248***	0.307***
	(0.82)	(4.15)	(3.93)	(3.82)	(3.63)
Leverage	-0.081	-0.705	-0.463	-0.960**	-0.733
	(-0.05)	(-1.62)	(-0.89)	(-2.25)	(-1.40)
MTB	0.003***	0.002***	0.002***	0.005**	0.005**
	(9.96)	(3.16)	(3.48)	(2.45)	(1.99)
Revenue_Growth	0.100*	0.124***	0.145***	0.105***	0.124***
	(1.68)	(3.33)	(3.24)	(2.83)	(2.75)
Ln_Age	1.035***	0.777***	1.007***	0.629***	0.903***
	(2.74)	(4.48)	(4.16)	(3.04)	(3.02)
Cntry_Ln_GDPPC	-16.459***	-10.922***	-14.208***	-10.522***	-14.459***
	(-8.64)	(-4.09)	(-4.30)	(-3.43)	(-3.70)
Cntry_EPI	0.033	-0.025	-0.025	-0.060***	-0.063***
	(1.27)	(-1.17)	(-1.09)	(-2.76)	(-2.75)
Country FE	Yes	Yes	No	Yes	No
Industry FE	Yes	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes
Country × Industry FE	No	No	Yes	No	Yes
Observations	38,851	38,851	38,851	34,692	34,691
R^2 (within)	0.050				
Craag-Donald statistics		22.087	19.126	17.056	14.590
Kleibergen-Paap statistics		21.807	19.060	16.886	14.545

Table 1. 5: Firm-level IO and Components of E, S, and G Misbehavior

This table reports the estimates of the following general regression specification of environment, social, and governance components of *ESG-MVR* covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+n} = \beta_1(FL\_IO_{it}) + \boldsymbol{\beta_2 X}_{it} + \boldsymbol{\beta_3 K}_{ct} + FE + \varepsilon_{it}$$

I denotes investee-firm, *t* year, *c* investee firm country, and *n* is the lead number. All the variables ($ESG - MVR_{it+n}$, $Env - MVR_{it+n}$, $Soc - MVR_{it+n}$, $Gov - MVR_{it+n}$, FL_IO_{it}, and set of controls in $\boldsymbol{X}_{it}$ and $\boldsymbol{K}_{ct}$) are defined in Appendix B. I replace *ESG-MVR* with *Env-MVR* in models (1) and (2), *Soc-MVR* in models (3) and (4), and *Gov-MVR* in models (5) and (6). *FE* includes country, industry, and year-fixed effects. The standard errors in all regressions are clustered at the country-industry levels. *T*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Environment		Social		Governance	
	Env-MVR $_{it+1}$	*Env-MVR* $_{it+2}$	*Soc-MVR* $_{it+1}$	*Soc-MVR* $_{it+2}$	*Gov-MVR* $_{it+1}$	*Gov-MVR* $_{it+2}$
	(1)	(2)	(3)	(4)	(5)	(6)
FL_IO	-0.005**	-0.005**	-0.006	-0.007*	-0.008***	-0.009***
	(-2.11)	(-2.16)	(-1.64)	(-1.93)	(-2.69)	(-2.70)
Ln_Firm_Size	0.745***	0.758***	1.403***	1.423***	1.226***	1.273***
	(15.79)	(15.80)	(20.85)	(20.85)	(18.48)	(18.22)
Ln_Cash	-0.024	0.007	0.032	0.057	0.174***	0.181***
	(-0.85)	(0.24)	(0.86)	(1.53)	(4.59)	(4.36)
Leverage	-0.410	-0.347	-0.899***	-0.916***	0.344	0.412
	(-1.52)	(-1.26)	(-2.60)	(-2.65)	(1.05)	(1.17)
MTB	-0.011	-0.008	0.030**	0.042***	0.000	0.017
	(-1.44)	(-0.93)	(2.10)	(2.62)	(0.02)	(1.22)
Revenue_Growth	0.010	-0.007	0.016	0.002	-0.001	0.001
	(1.02)	(-0.69)	(1.09)	(0.14)	(-0.06)	(0.07)
Ln_Age	0.200***	0.174**	0.078	0.027	-0.094	-0.079
	(2.95)	(2.55)	(0.86)	(0.30)	(-1.11)	(-0.86)
Cntry_Ln_GDPPC	-0.498	-1.404***	0.341	-0.875**	0.984*	-0.751
	(-1.64)	(-4.19)	(0.76)	(-2.05)	(1.89)	(-1.45)
Cntry_EPI	0.001	0.002	0.024***	0.023***	0.043***	0.024***
	(0.33)	(0.53)	(4.27)	(3.92)	(6.46)	(3.27)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,817	34,666	38,817	34,666	38,817	34,666
R^2 (within)	0.102	0.103	0.150	0.152	0.106	0.110

Table 1. 6: Robustness Tests: Alternative Definitions of ESG Misbehavior

This table reports the estimates of the following general regression specification on alternative definitions of *ESG-MVR* covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+} = \beta_1(FL\_IO_{it}) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

I denotes investee-firm, t year, c investee firm country, and n is the lead number. All the variables ($ESG - MVR_{it+n}$, $Peak - ESG - MVR_{it+n}$, $Violations_{it+n}$, $Env - Violations_{it+n}$, $Soc - Violations_{it+n}$, $Gov - Violations_{it+n}$, FL_IO_{it}, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B. I replace *ESG_MVR* with *Peak-ESG-MVR* in models (1) and (2), *Violations* in models (3) and (4), *Env_Violations* in models (5) and (6), *Soc_Violations* in models (7) and (8), and *Gov_Violations* in models (9) and (10). *FE* includes country, industry, and year-fixed effects. The standard errors in all regressions are clustered at the country-industry levels. *T*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Peak-ESG-MVR		ESG violations		Env_Violations		Soc_Violations		Gov_Violations	
	Peak-ESG-MVR $_{it+1}$	*Peak-ESG-MVR $_{it+2}$*	*Violations $_{it+1}$*	*Violations $_{it+2}$*	*Env_ Violations $_{it+1}$*	*Env_ Violations $_{it+2}$*	*Soc_ Violations $_{it+1}$*	*Soc_ Violations $_{it+2}$*	*Gov_ Violations $_{it+1}$*	*Gov_ Violations $_{it+2}$*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FL_IO	-0.015*	-0.012	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-1.65)	(-1.40)	(-3.03)	(-2.94)	(-3.23)	(-3.18)	(-3.23)	(-3.19)	(-4.99)	(-4.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,817	34,666	38,817	34,666	38,817	34,666	38,817	34,666	38,817	34,666
R^2 (within)	0.220	0.224	0.268	0.277	0.166	0.171	0.222	0.229	0.225	0.236

Table 1. 7: Individual IO and ESG Misbehavior

This table reports the estimates of the following general regression specification at the investor level, covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+n} = \beta_1(Inv\_IO_{it}) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

I denotes investee-firm, t year, c investee firm country, and n is the lead number. All the variables ($ESG - MVR_{it+n}$, Inv_IO_{it}, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B. FE includes investor, country, industry, investor × country × industry, and year-fixed effects, depending on specification. The standard errors in all regressions are clustered at the country-industry levels. T-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	ESG-MVR it+1		*ESG-MVR* it+2	
	(1)	(2)	(3)	(4)
Inv_IO	-0.152***	-0.155***	-0.155***	-0.150***
	(-5.43)	(-5.23)	(-5.48)	(-4.99)
Ln_Firm_Size	5.381***	5.383***	5.522***	5.499***
	(24.55)	(24.49)	(24.67)	(24.68)
Cash	0.465***	0.462***	0.425***	0.423***
	(3.76)	(3.65)	(3.25)	(3.14)
Leverage	-0.031	0.511	-0.567	-0.131
	(-0.03)	(0.44)	(-0.46)	(-0.11)
MTB	0.040	0.051*	0.074**	0.090***
	(1.37)	(1.82)	(2.32)	(2.90)
Revenue_Growth	0.035	0.031	0.055	0.051
	(1.03)	(0.95)	(1.57)	(1.54)
Ln_Age	0.223	0.019	0.116	-0.100
	(0.88)	(0.07)	(0.42)	(-0.34)
Cntry_Ln_GDPPC	-3.559***	-4.823***	-3.484**	-4.618***
	(-2.60)	(-3.75)	(-2.47)	(-3.44)
Cntry_EPI	-0.040*	-0.048**	-0.062***	-0.073***
	(-1.78)	(-2.22)	(-2.64)	(-3.21)
Investor FE	Yes	No	Yes	No
Country FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Investor × Country × Industry FE	No	Yes	No	Yes
Observations	2,772,575	2,737,295	2,067,993	2,043,534
R^2 (within)	0.385	0.368	0.397	0.377

Table 1. 8: Responsible II and ESG Misbehavior

This table reports the estimates of the following general regression specification at the investor level based on their commitment to responsible investment covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+n} = \beta_1(Inv\_IO_{it}) \times D(X) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

I denotes investee-firm, *t* year, *c* investee firm country, and *n* is the lead number. All the variables ($ESG - MVR_{it+n}$, Inv_IO_{it}, $D(PRI)_{it}$, $D(PRI\_ESG)_{it}$, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B and C. *D(X)* takes the value of *D(PRI)* and *D(PRI_ESG)*. I present the regression coefficients for *Inv_IO × D (PRI)* in models (1) and (2), while *Inv_IO × D (PRI_ESG)* in models (3) and (4). *FE* includes investor, country, industry, *D(PRI)*, *D(PRI_ESG),* and year-fixed effects, depending on specification. The standard errors in all regressions are clustered at the country-industry levels. *T*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	PRI vs. Non_PRI		PRI_High_ESG vs. PRI_Low_ESG	
	ESG-MVR it+1	*ESG-MVR* it+2	*ESG-MVR* it+1	*ESG-MVR* it+2
	(1)	(2)	(3)	(4)
Inv_IO × D (PRI)	-0.114***	-0.090***		
	(-4.08)	(-3.09)		
Inv_IO × D (PRI_ESG)			-0.805***	-0.810***
			(-12.34)	(-11.64)
Ln_Firm_Size	5.390***	5.533***	4.946***	4.984***
	(24.65)	(24.76)	(19.59)	(19.30)
Ln_Cash	0.465***	0.425***	0.474***	0.397***
	(3.76)	(3.24)	(3.53)	(2.78)
Leverage	-0.036	-0.572	0.216	-0.199
	(-0.03)	(-0.46)	(0.17)	(-0.15)
MTB	0.041	0.074**	0.018	0.053
	(1.39)	(2.34)	(0.50)	(1.35)
Revenue_Growth	0.035	0.055	0.017	0.039
	(1.03)	(1.57)	(0.43)	(1.07)
Ln_Age	0.222	0.114	0.210	0.109
	(0.87)	(0.41)	(0.85)	(0.44)
Cntry_Ln_GDPPC	-3.532**	-3.441**	-4.329**	-4.300**
	(-2.58)	(-2.43)	(-2.51)	(-2.29)
Cntry_EPI	-0.040*	-0.062***	-0.047**	-0.073***
	(-1.76)	(-2.62)	(-2.26)	(-3.31)
Investor FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
D (PRI/ PRI_ESG) FE	Yes	Yes	Yes	Yes
Observations	2,772,575	2,067,993	286,284	204,463
R^2 (within)	0.385	0.397	0.301	0.299

Table 1. 9: Other Heterogeneity of II and ESG Misbehavior

This table reports the estimates of the following general regression specification at the investor level based on their legal origins, institution type, and investment horizon, covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+n} = \beta_1(Inv\_IO_{it}) \times D(X) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

I denotes investee-firm, *t* year, *c* investee firm country, and *n* is the lead number. All the variables ($ESG - MVR_{it+n}$, Inv_IO_{it}, $D(Civil)_{it}$, $D(Independent)_{it}$, $D(LT)_{it}$, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B and C. *D(X)* takes the value of *D(Civil), D(Independent)*, and *D(LT)*. I present the regression coefficients for *Inv_IO × D (Civil)* in models (1) and (2), *Inv_IO × D (Independent)* in models (3) and (4), and *Inv_IO × D (LT)* in models (5) and (6). *FE* includes investor, country, industry, *D(Civil)*, *D(Independent)*, *D(LT)*, and year-fixed effects, depending on specification. The standard errors in all regressions are clustered at the country-industry levels. *T*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Civil vs. Common		Independent vs. Grey		LT vs. ST	
	ESG-MVR $_{it+1}$	*ESG-MVR* $_{it+2}$	*ESG-MVR* $_{it+1}$	*ESG-MVR* $_{it+2}$	*ESG-MVR* $_{it+1}$	*ESG-MVR* $_{it+2}$
	(1)	(2)	(3)	(4)	(5)	(6)
Inv_IO × D (Civil)	-0.070***	-0.070**				
	(-2.67)	(-2.48)				
Inv_IO × D (Independent)			-0.162***	-0.165***		
			(-5.57)	(-5.58)		
Inv_IO × D (LT)					-0.349***	-0.345***
					(-4.75)	(-4.50)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
D (Civil/Independent/LT) FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,751,777	2,052,151	2,761,758	2,063,064	320,946	231,954
R^2 (within)	0.379	0.392	0.385	0.397	0.378	0.390

Table 1A. 1: Investor-level IO and E, S, G Components of ESG Misbehavior

This table reports the estimates of the following general regression specification of environment, social, and governance components of *ESG-MVR* at the investor level, covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+n} = \beta_1(Inv\_IO_{it}) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

I denotes investee-firm, *t* year, *c* investee firm country, and *n* is the lead number. All the variables ($ESG - MVR_{it+n}$, $Env - MVR_{it+n}$, $Soc - MVR_{it+n}$, $Gov - MVR_{it+n}$, Inv_IO_{it}, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B. I replace *ESG-MVR* with *Env-MVR* in models (1) and (2), *Soc-MVR* in models (3) and (4), and *Gov-MVR* in models (5) and (6). *FE* includes investor, country, industry, and year-fixed effects. The standard errors in all regressions are clustered at the country-industry levels. *T*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Environment		Social		Governance	
	Env_MVR $_{it+1}$	*Env_MVR* $_{it+2}$	*Soc_MVR* $_{it+1}$	*Soc_MVR* $_{it+2}$	*Gov_MVR* $_{it+1}$	*Gov_MVR* $_{it+2}$
	(1)	(2)	(3)	(4)	(5)	(6)
Inv_IO	-0.078***	-0.067**	-0.088**	-0.049	-0.130***	-0.096***
	(-2.94)	(-2.48)	(-2.52)	(-1.42)	(-3.65)	(-2.62)
Ln_Firm_Size	1.040***	1.050***	2.095***	2.113***	1.771***	1.881***
	(11.23)	(11.00)	(16.88)	(17.09)	(17.16)	(15.75)
Ln_Cash	0.006	0.028	0.037	0.049	0.361***	0.324***
	(0.12)	(0.55)	(0.51)	(0.68)	(5.16)	(4.25)
Leverage	-0.221	-0.240	-0.640	-0.772	0.568	0.385
	(-0.44)	(-0.47)	(-1.10)	(-1.37)	(1.14)	(0.67)
MTB	-0.003	-0.007	0.028*	0.046**	0.006	0.028*
	(-0.39)	(-0.79)	(1.69)	(2.46)	(0.44)	(1.69)
Revenue_Growth	0.007	0.009	-0.008	-0.000	0.040*	0.029
	(0.46)	(0.66)	(-0.40)	(-0.02)	(1.78)	(1.26)
Ln_Age	0.267***	0.262***	-0.022	-0.079	0.028	-0.005
	(2.97)	(2.96)	(-0.16)	(-0.55)	(0.19)	(-0.03)
Cntry_Ln_GDPPC	0.268	-0.061	0.313	0.383	-1.765**	-1.366
	(0.42)	(-0.11)	(0.33)	(0.42)	(-2.04)	(-1.58)
Cntry_EPI	-0.016	-0.027**	-0.012	-0.007	-0.054***	-0.065***
	(-1.54)	(-2.32)	(-0.90)	(-0.52)	(-3.33)	(-3.57)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,772,575	2,067,993	2,772,575	2,067,993	2,772,575	2,067,993
R^2 (within)	0.127	0.129	0.195	0.199	0.153	0.159

Table 1A. 2: Investor-level IO and Peak ESG Misbehavior

This table reports the estimates of the following general regression specification on *Peak-MVR* at the investor level, covering a sample period from 2007 to 2021.

$$Peak - ESG - MVR_{it+1} = \beta_1(Inv\_IO_{it}) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

$$Peak - ESG - MVR_{it+1} = \beta_1(Inv\_IO_{it}) \times D(X)_{it} + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

i denotes investee-firm, *t* year, and *c* investee firm country. All the variables ($Peak - ESG - MVR_{it+n}$, Inv_IO_{it}, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B. I present regression coefficients for all investors in model (1) and replace (Inv_IO_{it}) with (Inv_IO_{it}) $\times D(X)_{it}$ in models (2) – (9). *D(X)* represents large, PRI, PRI_ESG, Foreign, civil, independent, and LT, respectively. *FE* includes investor, country, industry, *D(X)*, and year-fixed effects depending on the specification. The standard errors in all regressions are clustered at the country-industry levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels.

	All	X=Large	X=PRI	X= PRI_ESG	X=Foreign	X=Civil	X=Independent	X=LT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inv_IO	-0.237***							
	(-6.69)							
Inv_IO × D (X)		-0.118***	-0.202**	-0.797***	-0.238***	-0.182***	-0.249***	-0.323***
		(-3.84)	(-2.37)	(-12.00)	(-4.55)	(-2.62)	(-6.76)	(-3.46)
Ln_Firm_Size	6.340***	6.314***	6.355***	5.512***	6.330***	6.087***	6.341***	6.212***
	(31.06)	(30.94)	(31.21)	(24.43)	(30.98)	(33.50)	(31.06)	(24.49)
Ln_Cash	0.716***	0.716***	0.716***	0.632***	0.715***	0.684***	0.717***	0.914***
	(4.74)	(4.74)	(4.73)	(4.35)	(4.73)	(4.63)	(4.74)	(4.70)
Leverage	0.843	0.845	0.836	1.525	0.852	0.952	0.843	0.373
	(0.61)	(0.61)	(0.60)	(1.17)	(0.62)	(0.72)	(0.61)	(0.24)
MTB	0.038	0.037	0.039	-0.012	0.038	0.040	0.038	0.065**
	(1.27)	(1.23)	(1.30)	(-0.36)	(1.25)	(1.37)	(1.27)	(2.01)
Revenue_Growth	0.054	0.054	0.054	0.049	0.054	0.056	0.053	0.054
	(1.06)	(1.06)	(1.06)	(1.04)	(1.06)	(1.13)	(1.05)	(0.91)
Ln_Age	0.477	0.481*	0.475	0.157	0.475	0.481*	0.479	0.030
	(1.63)	(1.65)	(1.63)	(0.56)	(1.63)	(1.75)	(1.64)	(0.09)
Cntry_Ln_GDPPC	-4.493*	-4.637*	-4.435*	-7.353***	-4.379*	-4.280*	-4.454*	-7.497**
	(-1.89)	(-1.95)	(-1.86)	(-2.90)	(-1.84)	(-1.88)	(-1.87)	(-2.25)
Cntry_EPI	-0.072*	-0.073*	-0.072*	-0.083**	-0.073*	-0.067*	-0.072*	-0.100**
	(-1.92)	(-1.93)	(-1.91)	(-2.44)	(-1.93)	(-1.85)	(-1.92)	(-2.09)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
D (X) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,772,575	2,772,575	2,772,575	286,284	2,772,575	2,751,777	2,761,758	320,946
R^2 (within)	0.298	0.293	0.298	0.213	0.294	0.294	0.298	0.288

Table 1A. 3: Investor-level IO and ESG Violations Count

This table reports the estimates of the following general regression specification on *Violations* at the investor level covering a sample period from 2007 to 2021.

$$Violations_{it+1} = \beta_1(Inv\_IO_{it}) + \boldsymbol{\beta_2 X}_{it} + \boldsymbol{\beta_3 K}_{ct} + FE + \varepsilon_{it}$$

i denotes investee-firm, *t* year, and *c* investee firm country. All the variables ($Violations_{it+n}$, Inv_IO_{it}, and set of controls in $\boldsymbol{X}_{it}$ and $\boldsymbol{K}_{ct}$) are defined in Appendix B. I present regression coefficients for all investors in model (1) and replace (Inv_IO_{it}) with $(Inv\_IO_{it}) \times D(X)_{it}$ in models (2) – (9). *D(X)* represents large, PRI, PRI_ESG, Foreign, civil, independent, and LT, respectively. *FE* includes investor, country, industry, *D(X)*, and year-fixed effects depending on the specification. The standard errors in all regressions are clustered at the country-industry levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	All	X=Large	X=PRI	X= PRI_ESG	X=Foreign	X=Civil	X=Independent	X=LT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inv_IO	-0.006***							
	(-3.59)							
Inv_IO × D (X)		-0.001	-0.009***	-0.043***	-0.006**	-0.002	-0.006***	-0.021***
		(-1.08)	(-5.65)	(-10.73)	(-2.10)	(-0.98)	(-3.80)	(-4.74)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
D (X) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,772,575	2,772,575	2,772,575	286,284	2,772,575	2,751,777	2,761,758	320,946
R^2 (within)	0.319	0.314	0.319	0.258	0.315	0.332	0.319	0.314

Table 1A. 4: Investor Size and ESG Misbehavior

This table reports the estimates of the following general regression specification at the investor level based on the investor size covering a sample period from 2007 to 2021.

$$ESG - MVR_{it+} = \beta_1(Inv\_IO_{it}) \times D(Large) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

i denotes investee-firm, t year, c investee firm country, and n is the lead number. All the variables ($ESG - MVR_{it+n}$, Inv_IO_{it}, $D(Large)_{it}$, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B and C. *FE* includes investor, country, industry, investor × country × industry, *D(Large)*, and year-fixed effects, depending on specification. The standard errors in all regressions are clustered at the country-industry levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	ESG-MVR it+1		*ESG-MVR* it+2	
	(1)	(2)	(3)	(4)
Inv_IO × D (Large)	-0.063***	-0.084***	-0.071***	-0.089***
	(-2.68)	(-3.40)	(-2.94)	(-3.48)
Ln_Firm_Size	5.362***	5.374***	5.505***	5.493***
	(24.49)	(24.49)	(24.63)	(24.69)
Cash	0.465***	0.462***	0.425***	0.423***
	(3.76)	(3.65)	(3.25)	(3.14)
Leverage	-0.029	0.507	-0.567	-0.136
	(-0.02)	(0.44)	(-0.46)	(-0.11)
MTB	0.039	0.051*	0.073**	0.089***
	(1.34)	(1.81)	(2.29)	(2.89)
Revenue_Growth	0.036	0.031	0.055	0.051
	(1.04)	(0.95)	(1.58)	(1.55)
Ln_Age	0.226	0.023	0.120	-0.094
	(0.89)	(0.09)	(0.43)	(-0.32)
Cntry_Ln_GDPPC	-3.666***	-4.930***	-3.608**	-4.725***
	(-2.68)	(-3.83)	(-2.55)	(-3.52)
Cntry_EPI	-0.040*	-0.048**	-0.063***	-0.073***
	(-1.79)	(-2.24)	(-2.65)	(-3.24)
Investor FE	Yes	No	Yes	No
Country FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Investor × Country × Industry FE	No	Yes	No	Yes
D (Large) FE	Yes	Yes	Yes	Yes
Observations	2,772,575	2,737,295	2,067,993	2,043,534
R^2 (within)	0.379	0.366	0.392	0.376

Table 1A. 5: Investor Jurisdiction and ESG Misbehavior

This table reports the estimates of the following general regression specification at the investor level based on the investor jurisdiction covering a sample period from 2007 to 2021.

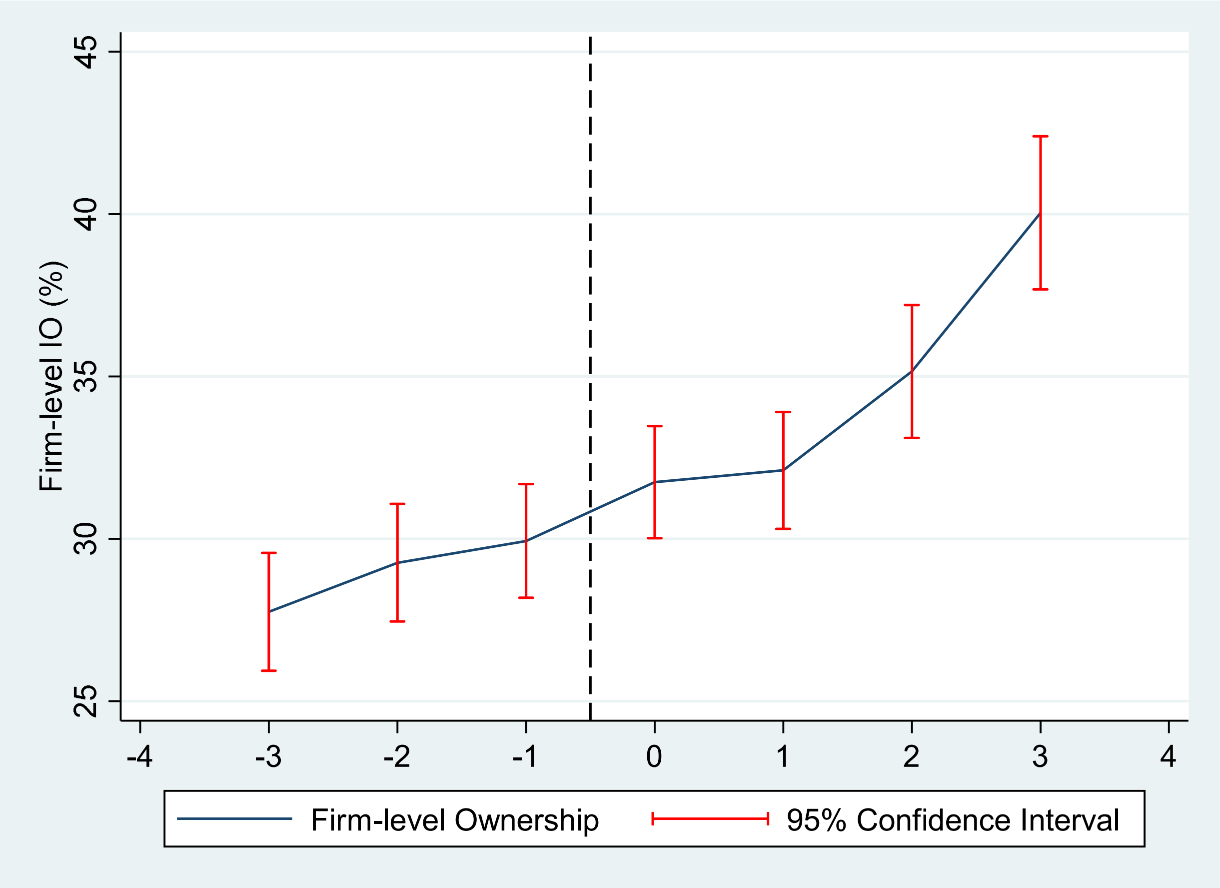
$$ESG-MVR_{it+n} = \beta_1(Inv\_IO_{it}) \times D(Foreign) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 K_{ct}} + FE + \varepsilon_{it}$$

i denotes investee-firm, t year, c investee firm country, and n is the lead number. All the variables ($ESG-MVR_{it+n}$, Inv_IO_{it}, $D(Foreign)_{it}$, and set of controls in $\boldsymbol{X_{it}}$ and $\boldsymbol{K_{ct}}$) are defined in Appendix B and C. *FE* includes investor, country, industry, *D(Foreign)*, and year-fixed effects. The standard errors in all regressions are clustered at the country-industry levels. t-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	ESG-MVR it+1	*ESG-MVR* it+2
	(1)	(2)
Inv_IO × D (Foreign)	-0.333***	-0.331***
	(-3.49)	(-3.47)
Ln_Firm_Size	5.221***	5.221***
	(24.81)	(24.80)
Cash	0.426***	0.427***
	(3.49)	(3.50)
Leverage	0.258	0.260
	(0.22)	(0.22)
MTB	0.012	0.012
	(0.43)	(0.43)
Revenue_Growth	-0.001	-0.001
	(-0.02)	(-0.02)
Ln_Age	0.551**	0.547**
	(2.33)	(2.32)
Cntry_Ln_GDPPC	-3.481**	-3.501**
	(-2.39)	(-2.41)
Cntry_EPI	0.010	0.010
	(0.42)	(0.40)
Investor FE	Yes	Yes
Country FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
D (Foreign) FE	Yes	Yes
Observations	3,407,506	3,407,412
R^2 (within)	0.372	0.372

Figure 1. 1: Firm-level Institutional Ownership around MSCI Addition

The figure below shows the trend of firm-level institutional ownership at a 95% confidence level three years before and after the addition to the MSCI-ACWI index. Firm-level institutional ownership is in percentage spread across time periods in years. All variables are explained in Appendix B.



Appendix: First Empirical Chapter

Appendix A: Examples of ESG Misbehavior

ESG Event	Implications	Source of Information
BP Deepwater Horizon Oil Spill (2010) The oil spill caused by British Petroleum (BP) in the Gulf of Mexico is considered the world's most significant accidental oil leak, with an estimated 3 million barrels of oil being released from the Macondo well and eleven workers losing their lives in the explosion. BP and its contractors failed to design, test, and ensure the integrity of the cement used to seal the Macondo well, thus allowing hydrocarbons to flow into the wellbore, leading to the explosion and subsequent oil spill. BP was held responsible for the spill due to cost-cutting decisions, inadequate risk management practices, and failure to ensure proper safety measures during the drilling.	The Macondo well was declared inactive by the US authorities. The company committed to making a downpayment of $20 billion as compensation. Following the incident, the company had to bear expenses exceeding $65 billion, including cleaning up costs, payments, fines, and legal settlements. Additionally, the CEO was replaced. Investors were surprised as the disaster led to higher compensation settlements, resulting in some payouts being recalibrated upwards. BP faced significant financial challenges as its ongoing financial liabilities weighed heavily.	Financial Times https://tinyurl.com/4zsjnsh2 https://tinyurl.com/mr3wmfk7 https://tinyurl.com/3vjzkbbm
Fukushima Nuclear Disaster (2011) After a significant earthquake and tsunami, the reactors in the facility experienced a nuclear accident due to the loss of power and cooling systems. Tokyo Electric Power Company (TEPCO) allowed pressure in the No.1 reactor to rise far beyond safe levels. A fire broke out in a nuclear power plant that had been rendered inoperable by an earthquake and tsunami, and it subsequently spread to other reactors that were believed to be unaffected. The disaster was not solely an environmental catastrophe but was caused by	As a result, 89,000 individuals were forced to abandon their homes within a 20km radius of the plant and received compensation payments. The company incurred significant expenses for cleaning up and compensation. To prevent bankruptcy, the Japanese government provided financial support amounting to $64 billion. TEPCO faced endless requests for compensation, causing their shares to plummet by almost 90%. Moody’s downgraded its bond rating to junk status, and Standard & Poor followed suit. In 2022, a Tokyo court ordered four former TEPCO executives to pay $95 billion in damages, making them liable for the first time. The court ruled	The Economist https://tinyurl.com/46ee45ju https://tinyurl.com/9wpnwc2e https://tinyurl.com/2t39pdb8 Wall Street Journal https://tinyurl.com/49vfnfme https://tinyurl.com/mr3899hw Reuters https://tinyurl.com/2m8r8vfy

TEPCO's negligence and the lack of accident management plans by the company and regulators.	that the disaster could have been prevented with proper care, contrasting with a 2019 criminal trial that cleared them of negligence, citing the unforeseeable tsunami.	
Volkswagen Diesel Emissions Scandal (2015) The US Environmental Protection Agency confirmed that Volkswagen had installed a defeat device in around 500,000 diesel cars in the US. Vehicles with these devices were found to have released nitrogen oxides up to 40 times higher than the legally permitted standards.	The company had to pay a staggering $33 billion in fines, settlements, vehicle fixes and recalls due to the scandal. The company's stock market value decreased significantly by 37%. The corporation made significant changes to its leadership, replaced six executives, and reassigned the administration of seven of its dozen brands. An agreement was reached to pay a $14.7 billion settlement to resolve accusations of emissions cheating with US regulators and consumers and faced costly settlements with car owners. Motorists could sell back or terminate leases of the affected vehicles or get reimbursed to make them compliant with environmental regulations.	Wall Street Journal https://tinyurl.com/3dtj8cz2 https://tinyurl.com/53u9xw6z https://tinyurl.com/3z4pe36s Reuters https://tinyurl.com/bdenh3pz
Nestle Maggi lead poisoning scandal (2015) Nestles famous instant noodle brand, Maggi, faced a major controversy when the regulatory body conducted tests on samples to find elevated levels of lead and monosodium glutamate exceeding permissible limits. The discovery led to a nationwide recall of Maggi noodles and a ban on their production and sale in several states in India.	Before the scandal, Nestle had a 63% market share in the instant noodle industry in India. Due to the food safety scandal, sales dropped by 17.2%, impacting their earnings. The share price fell by over 12%, raising concerns about the impact of ongoing investigations on the company's sales. In the last quarter of the following year, the company experienced a significant decline in operating performance, with a net loss of 644 million rupees ($10 million approx.) compared to a net profit of 2.88 billion rupees ($35 million approx.) the previous year. The company incurred a write-off of 4.52 billion rupees ($55 million approx.) as it destroyed 350 million noodle packets. The entire industry segment suffered a decrease in size of over 45%.	Wall Street Journal https://tinyurl.com/4df8ks8m https://tinyurl.com/4d26x9pb Economic Times https://tinyurl.com/sc2xkfym Financial Times https://tinyurl.com/4awfvymx https://tinyurl.com/ymenz9pc

Facebook-Cambridge Analytica Data Scandal (2018) A crisis emerged after it was reported that Cambridge Analytica, a data firm linked to Donald Trump's 2016 presidential campaign, had obtained data on millions of Facebook users without authorization. Cambridge Analytica used a personality quiz app to collect data on Facebook users. The app not only gathered information of those who took the quiz but also accessed data on their friends. The harvested data was allegedly used to target voters with personalized political advertisements. According to Facebook, the information of up to 87 million users may have been shared with Cambridge Analytica without proper consent.	During the 2016 election cycle, Cambridge Analytica, with a history of $15 million in US political work, faced allegations of data misuse. This led to the loss of all its clients, eventually resulting in the firing of the CEO and the shutdown of its operations. Facebook received extensive criticism, lawsuits, and regulatory investigations, which negatively impacted the company's reputation and user trust. The UK's privacy watchdog imposed a fine of $645,000 on Facebook, the highest amount allowed under the country's privacy law. This data controversy led to a $670 billion drop in market capitalization for Facebook. Facebook took steps to restrict app developers access to user data, implements new privacy settings and policies to protect user data and issued public apologies acknowledging the company's mistakes.	Wall Street Journal https://tinyurl.com/ymfhe53a https://tinyurl.com/bdz2pc2z https://tinyurl.com/dy47fjsr Reuters https://tinyurl.com/hrphc2nd Forbes https://tinyurl.com/f87zf46f
Boeing 737 Max Crashes (2018) Two crashes of Boeing's 737 Max airliners, a new variant of the popular 737 series, have been linked to a defective flight software system, creating unsafe conditions. The design flaws included the Maneuvering Characteristics Augmentation System- due to the addition of new engines to an older airframe, which shifted the plane's center of gravity and made it prone to stalls. Pilots poorly understood this system as they were transitioning from older 737 models to the 737 Max, not being fully aware of its capabilities, limitations, and potential being activated erroneously.	The initial response from the company was characterized by a lack of transparency and a tendency to blame the pilots. Eventually, the most popular model was banned from flying, and the company chose to ground production until it was authorized to resume operations. The CEO was dismissed, and the company experienced a 19% decline in revenue. Free cash flow turned negative, and the airline division suffered a loss of $4 billion. As a result, the market capitalization decreased by a quarter, equivalent to $65 billion. Boeing suffered significant financial losses due to the crisis, including $21 billion in direct expenses for fines and compensation to airlines for delayed deliveries, as	Economist https://tinyurl.com/u2rhzfay https://tinyurl.com/4xhxrywj Wall Street Journal https://tinyurl.com/yubp8xce

	well as a $2.5 billion settlement with the government that includes payouts to families of the victims.	
Vedanta Group - Sterlite Copper Plant Protests (2018) Violent protests erupted in a southern Indian city due to environmental concerns attributed to the activities of the Sterlite Copper Plant, under the control of Vedanta Limited. The local community accused the plant of causing environmental pollution and posing health hazards. During the parliamentary proceedings, the minister of state for water resources mentioned that the water near the plant had iron levels exceeding acceptable limits, sourcing information from the Central Pollution Control Board. Amid escalating protests, the state police intervened, resulting in 13 deaths and several injuries.	Following public outrage, the largest copper smelter in the country was directed to cease its operations permanently. According to Moody's, a full-year closure is expected to result in a 25% reduction in revenue and a 5% decline in group earnings. The market capitalization of Vedanta Limited experienced a drop of £328 million. After the shooting at protesters, the UK government urged Vedanta group to remove its Indian unit from the London Stock Exchange to avoid any negative impact on the reputation of other companies in the securities exchange.	Financial Times https://tinyurl.com/yrh79hk3 https://tinyurl.com/3dfa9b6s https://tinyurl.com/2n8cusyy Reuters https://tinyurl.com/bf95knn8
Rio Tinto Juukan Gorge Indigenous Heritage Destruction (2020) The world's largest iron ore mining company demolished two sacred rock caves during their mining expansion project, sparking an international outcry. This was mainly because the company failed to abandon demolition when more than 7,000 significant artifacts were discovered during an archaeological dig in 2014. The company gained approval from the government to level the site in 2013 to expand its mine in its main iron ore-producing region. A looming parliamentary inquiry and possible federal intervention have spooked the industry.	The CEO and other senior executives resigned from their positions at Rio Tinto. The CEO and head of corporate relations lost a total of £4 million in bonuses as policies included clawback provisions in cases where actions harm the company's social license to operate. The company has pledged to improve its approach to cultural heritage and community relations to prevent similar incidents in the future. The company faced backlash from shareholders, including entities like Norges Bank and the LAPF. Lawmakers in Western Australia plan to introduce new legislation to improve the relationship between indigenous groups and land users, potentially impacting other mining companies operating in the area.	Financial Times https://tinyurl.com/yr7bw4hx https://tinyurl.com/yurjbna4 Wall Street Journal https://tinyurl.com/4c293ydk https://tinyurl.com/ypcyxp8p Reuters https://tinyurl.com/35r29ft6 https://tinyurl.com/yfdjdzdr

Appendix B: Definition of Variables

This table defines all the variables used in the study. *i* refers to firm, *t* refers to year, and *n* takes a value of one or two.

Variable name	Description
Panel A: ESG misbehavior and alternative variables' definition	
ESG-MVR $_{it+n}$	*ESG-MVR* is a quantitative assessment of a company's ESG misbehavior based on the Reputation Risk Index (RRI). It ranges from 0 to 100. A higher score denotes a higher level of *ESG-MVR*. *n* denotes number of leads. Source: RepRisk.
Peak-ESG-MVR $_{it+n}$	*Peak-ESG-MVR* is the highest level of *ESG-MVR* observed for a company over the last two years. Source: RepRisk
Env-ESG-MVR $_{it+n}$	*Env-ESG-MVR* assesses the level of a company's *ESG-MVR* related to environmental issues. RepRisk reports the proportion of RRI assigned to environmental issues, which I multiply with the *ESG-MVR* score to compute the *Env-ESG-MVR.* Source: RepRisk.
Soc-ESG-MVR $_{it+n}$	*Soc-ESG-MVR* assesses the level of a company's *ESG-MVR* related to social and ethical considerations. RepRisk reports the proportion of RRI assigned to social issues, which I multiply with the *ESG-MVR* score to compute the *Soc-ESG-MVR*. Source: RepRisk.
Gov-ESG-MVR $_{it+n}$	*Gov-ESG-MVR* evaluates the level of a company's ESG misbehavior related to corporate governance. RepRisk reports the proportion of RRI assigned to governance issues, which I multiply with the *ESG-MVR* score to compute the *Gov-ESG-MVR.* Source: RepRisk.
Violations $_{it+n}$	*Violations* are the (natural log of) total count of breaches or non-compliance incidents across twenty-eight specific ESG issues. Source: Reprisk.
Env_Violations $_{it+n}$	*Env_Violations* is the (natural log of) total count of incidents of non-compliance or breaches of environmental concerns' regulations, standards, or ethical practices. Source: RepRisk.
Soc_Violations $_{it+n}$	*Soc_Violations* is the (natural log of) total count of incidents of non-compliance, breaches of regulations, or failure to meet ethical and sustainability standards affecting people, communities, and labor practices. Source: RepRisk
Gov_Violations $_{it+n}$	*Gov_Violations* is the (natural log of) total count of incidents of non-compliance or breaches of corporate governance rules, including ethical and structural governance matters. Source: RepRisk.

Panel B: Institutional Investors

FL_IO_{it}	The total percentage of a company's shares owned by II. Source: S&P Capital IQ.
Inv_IO_{jit}	The percentage of a company's shares owned by an individual institutional investor. Source: S&P Capital IQ.
$D(PRI)_{it}$	A dummy variable that takes the value of one if the investor is a PRI signatory and zero otherwise. See Appendix C for the definition of investor classification. Sources: S&P Capital IQ, PRI signatory database.
$D(PRI\_ESG)_{it}$	A dummy variable that takes the value of one if a PRI investor's weighted average ESG portfolio score is high and zero otherwise. See Appendix C for the definition of investor classification. Sources: S&P Capital IQ, PRI signatory database, LSEG (formerly Refinitiv).
$D(Foreign)_{it}$	A dummy variable that takes the value of one if an investor is domiciled in a country different than that of the investee firm and zero otherwise. See Appendix C for the definition of investor classification. Source: S&P Capital IQ.
$D(Civil)_{it}$	A dummy variable that takes the value of one if an investor is domiciled in a country categorized as civil law and zero if in a country classified as common law. See Appendix C for the definition of investor classification. Source: S&P Capital IQ.
$D(Independent)_{it}$	A dummy variable that takes the value of one if an investor is classified as an "independent" investor and zero if a "grey" investor. See Appendix C for the definition of investor classification. Source: S&P Capital IQ.
$D(LT)_{it}$	A dummy variable that takes the value of one if an investor is a long-term investor and zero if a short-term investor. See Appendix C for the definition of investor classification. Source: S&P Capital IQ.

Panel C: Firm Characteristics

$Ln\_Firm\_Size_{it}$	The natural log of total revenue is deflated by the consumer price index. Sources: LSEG (formerly Refinitiv) and IMF.
Ln_Cash_{it}	Natural log of cash holdings scaled by total assets. Source: LSEG (formerly Refinitiv).
$Leverage_{it}$	Total debt scaled by total assets. Source: LSEG (formerly Refinitiv).
MTB_{it}	Market capitalization scaled by the book value of common shareholders equity. Source: LSEG (formerly Refinitiv).
$Revenue\_Growth_{it}$	Percentage growth in revenue in the current year compared to the previous year. Source: LSEG (formerly Refinitiv).
Ln_Age_{it}	Natural log of the difference between the initial year of stock return and the current year. Source: LSEG (formerly Refinitiv).

Panel D: Country Characteristics for investee firms

$Cntry\_GDPPC_{ct}$	Natural logarithm of a country's gross domestic product per capita. Source: World Bank.
$Cntry\_EPI_{ct}$	Environmental performance index is a scorecard of the state of sustainability. Source: Yale Center for Environmental Law & Policy.

Panel E: Instrument

$D(MSCI)_{it}$	A dummy variable equals one for three years post-addition of the investee firm *i* to MSCI ACWI and zero otherwise. It also takes the zero value if the firm *i* is deleted from MSCI ACWI. Source: MSCI.

Appendix C: Different Types of Institutional Investors

This table defines the various classifications of II. *i* denotes firm, and *t* denotes year.

Investor Classification	**Definition**
$Inv\_PRI\_IO_{jit}$	*Inv_PRI_IO* is the ownership by II that are signatories to the PRI (See Section 4.4.1) (Brandon *et al.* 2022). Sources: PRI signatory database, S&P Capital IQ.
$Inv\_Non\_PRI\_IO_{jit}$	*Inv_Non_PRI_IO* is the ownership by II other than the signatories to the PRI (See Section 4.4.1) (Brandon *et al.* 2022). Sources: PRI signatory database, S&P Capital IQ.
$Inv\_PRI\_High\_ESG\_IO_{jit}$	*Inv_PRI_High_ESG_IO* is the ownership by II that are signatories to PRI and have high (top tercile) ESG weighted portfolio scores (See Section 4.4.1) (Liang *et al.* 2022; Kim & Yoon 2023). Sources: PRI signatory database, S&P Capital IQ, LSEG (formerly Refinitiv).
$Inv\_PRI\_Low\_ESG\_IO_{jit}$	*Inv_PRI_Low_ESG_IO* is the ownership of by that are signatories to PRI and have low (bottom tercile) ESG weighted portfolio scores (See Section 4.4.1) (Liang *et al.* 2022; Kim & Yoon 2023). Sources: PRI signatory database, S&P Capital IQ, LSEG (formerly Refinitiv).
$Inv\_Foreign\_IO_{jit}$	*Inv_Foreign_IO* is the ownership by II that are domiciled in a different country than that of the investee company (Ferreira & Matos 2008). Source: S&P Capital IQ.
$Inv\_Domestic\_IO_{jit}$	*Inv_Domestic_IO* is the ownership by II that are domiciled in the same country to that of the investee company (Ferreira & Matos 2008). Source: S&P Capital IQ.
$Inv\_Civil\_IO_{jit}$	*Inv_Civil_IO* is the ownership by II from a country with a civil law system, i.e., French, German, or Scandinavian origin (Porta *et al.* 1998; Aggarwal *et al.* 2011). Source: S&P Capital IQ.
$Inv\_Common\_IO_{jit}$	*Inv_Common_IO* is the ownership by II from a country with an English origin categorized as a common law system (Porta *et al.* 1998; Aggarwal *et al.* 2011). Source: S&P Capital IQ.
$Inv\_Independent\_IO_{jit}$	*Inv_Independent_IO* is the ownership by II that are categorized as independent. Based on the institutional type, I include "Corporate Pension Plan Sponsor", "REIT/Real Estate Investment Manager", "Structured Finance Pool Manager", "Traditional Investment Manager", "Government Pension Plan Sponsor", "Hedge Fund Manager/CTA", and "Union Pension Plan Sponsor" investors (Ferreira & Matos 2008; Marshall *et al.* 2022). Source: S&P Capital IQ.
$Inv\_Grey\_IO_{jit}$	*Inv_Grey_IO* is the ownership by II categorized as grey. Based on the institutional type, I include "Bank/Investment Bank", "Endowment Fund Sponsor", "Family Office/Family Trust", "Foundation Fund Sponsor", "Insurance Company", "Sovereign Wealth Fund",

	"Unclassified", "VC/PE Firm" investors (Ferreira & Matos 2008; Marshall *et al.* 2022). Source: S&P Capital IQ.
$Inv\_LT\_IO_{jit}$	*Inv_LT_IO* is the ownership by II categorized as long-term. I categorize pension funds as long-term II. Based on the institutional investor type, I include "Corporate Pension Plan Sponsor", "Government Pension Plan Sponsor", and "Union Pension Plan Sponsor" investors (Chen *et al.* 2007; Marshall *et al.* 2022). Source: S&P Capital IQ.
$Inv\_ST\_IO_{jit}$	*Inv_ST_IO* is the ownership by II categorized as short-term. I categorize hedge funds as short-term II. Based on the institutional type, I include "Hedge Fund Manager/ CTA" investors (Chen *et al.* 2007; Marshall *et al.* 2022). Source: S&P Capital IQ.

Appendix D: Measures Reflecting ESG Misbehavior

Here, I describe how the vendor RepRisk constructs the ESG-Misbehavior (*ESG-MVR*) measure by aggregating ESG-related incidents reported in the media. I also illustrate how a company's *ESG-MVR* changes over time using the Boohoo Group case as an example. Furthermore, I demonstrate how the *ESG-MVR* score diminishes in the absence of reported incidents.

ESG-MVR Measure

RepRisk calculates a company's *ESG-MVR* by aggregating and quantifying ESG-related incidents reported in the local and international media. The process begins with a rigorous screening of over 100,000 public media documents daily in 23 languages to identify negative ESG incidents, leveraging machine learning and curated human analysis (see Appendix A for examples). A robust quality assurance process ensures data accuracy and reliability. Subsequently, a team of analysts validates the reported incident's ESG relevance, eliminates duplicates, and categorizes the incidents into twenty-eight predefined ESG categories.[75] These incidents are then assessed for their severity (harshness), reach (influence), and novelty (newness), producing a proprietary quantitative score called the Reputation Risk Index (RRI). The quantitative measure RRI is measured on a scale of zero (lowest) to 100 (highest) risk index, where higher values indicate higher levels of ESG-related reputation risk. The risk exposure levels are categorized from low (0-24) to extremely high (75-100). I use RRI as my proxy of *ESG-MVR*, reflecting a company's severity, reach, and novelty of ESG-related media and stakeholder attention level.

Case Study: Boohoo Group risk profile[76]

Boohoo Group was linked to animal mistreatment, poor employment conditions, and environmental concerns in 2018 and 2020. In July 2020, the company's *ESG-MVR* shifted from medium risk (range of 20-30) to high risk (67), indicating a high level of risk exposure. This change occurred following reports highlighting exploitative labor practices and safety issues within the company's supply chain. In this case, the initial range of 20-30 reflects earlier exposure to allegations viewed as moderate ESG risks. In July 2020, more severe issues surfaced, enhancing their *ESG-MVR* score to 67, indicating a high risk. The increase from the initial range of 20-30 to 67 suggests that Boohoo faced numerous severe or influential ESG incidents, leading to a higher risk score during the period. The detailed mechanics of the scoring system are proprietary to RepRisk.

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[75] RepRisk classifies under Environment, Social, Governance and Cross-cutting issues. See https://www.reprisk.com/approach#why-reprisk [accessed on 14th Jan 2024 17:32 GMT]

[76] See https://www.reprisk.com/news-research/case-studies/boohoo-group [accessed on 29th Sept 2023 11:30 BST]

RRI decay over time

The RRI remains constant for the first fourteen days after a significant risk incident. If no new risk incidents are reported, it decays gradually over two years. RRI values between 25 and 100 decreases by 25 every two months until they reach 25. For RRI values at or below 25, it decays by 25 every 18 months until it reaches zero.

Example: RRI decay from an initial value of 100

Days	**RRI value**	**Decay rate (per day)**	**Notes**
First 0-14 days	100	0	RRI remains constant.
After 60 days	75	25/60 = -0.417	100 - (0.417 x 60)
After 120 days	50	25/60 = -0.417	100 - (0.417 x 120)
After 180 days	25	25/60 = -0.417	100 - (0.417 x 180)
After 240 days	22.2	25/548 = -0.046	25 - (0.046 x (240-180))
After 365 days	8.21	25/548 = -0.046	25 - (0.046 x (365-180))
After 718 days	0.46	25/548 = -0.046	25 - (0.046 x (718-180))

Once RRI decays from 25 to 0.46, it is rounded to 0. Including the initial fourteen days, the RRI decays from 100-0 in about 732 days (approximately two years). Also, Peak_RRI remains at 100 for two years.

Tables: Second Empirical Chapter

Table 2. 1: Descriptive Statistics

This table shows summary statistics of all the variables – Sustainability outcomes (Panel A), institutional investor network (Panel B), firm characteristics (Panel C), and instrument characteristics (Panel D). In Panel B, the centrality measures are multiplied by 10^2 solely for presentation purposes, with their actual values remaining unchanged. All continuous variables are winsorized at the 2nd and 98th percentiles. The sample covers the period spanning from 2005 to 2020. All variables are defined in Appendix B and C.

	Observations	Mean	Std. Dev.	P25	P50	P75
Panel A: Investee firm's Sustainability Measures (Firm – Year)						
GHG_Abs_Scope 1 ('Mn mt)	80,073	1.189	4.023	0.006	0.031	0.216
GHG_Abs_Scope 2 ('Mn mt)	80,073	0.199	0.469	0.007	0.030	0.133
Ln_GHG_Abs_Scope 1	80,073	10.652	2.676	8.752	10.356	12.285
Ln_GHG_Abs_Scope 2	80,073	10.355	2.078	8.865	10.303	11.796
Gr_Patents	67,292	10.541	56.918	0.000	0.000	0.000
CCE_Exp (x 10^3)	26,290	1.337	2.443	0.150	0.427	1.224
Panel B: Institutional Investor Network (Investor – Year)						
Degree_centrality (x 10^2)	103,404	2.138	4.089	0.197	0.727	2.241
Betweenness_centrality (x 10^2)	103,404	0.019	0.162	0.000	0.000	0.002
Closeness_centrality (x 10^2)	103,404	43.184	2.732	41.331	42.735	44.618
Eigenvector_centrality (x 10^2)	103,404	0.752	0.960	0.102	0.378	1.020
Panel C: Investee Firm Characteristics (Firm – Year)						
Clique Ownership (%)	80,072	28.421	24.102	8.153	21.190	44.778
Market Capitalization ($'Bn)	80,072	5.320	10.548	0.434	1.460	4.593
Total Assets ($'Bn)	80,072	0.007	0.014	0.001	0.002	0.006
MTB (times)	80,072	2.737	2.792	1.040	1.806	3.264
Leverage (%)	80,072	23.656	17.602	8.625	22.292	35.525
ROA (%)	80,072	0.069	0.090	0.033	0.067	0.112
PPE ($'Mn)	80,072	2,207.172	4,957.437	90.801	376.949	1,617.818
Dividends ($'Mn)	80,072	123.791	292.084	2.689	20.611	87.333
Return (%)	80,072	12.645	44.159	-15.920	5.960	31.700
Revenue ($'Bn)	80,072	4.662	9.403	0.349	1.150	3.965
Revenue_Growth (%)	80,072	1.897	2.844	0.000	1.635	3.675
Panel D: Instrument (Firm – Investor – Year)						
Distance ('000 Mls)	4,337,995	2.604	1.308	1.721	2.391	3.487

Table 2. 2: Sample Composition by Country and Industry

This table reports the number of unique investors, and number of unique investee firms, in each country in Panel A, by industry in Panel B, and the development of composition of investor influence over time in Panel C. In Panel C, the centrality measures are multiplied by 10^2 solely for presentation purposes. The sample spans a period from 2005 to 2020.

Panel A: Country

Country	# of unique investee firms	# of unique institutional investors
Argentina	7	297
Australia	311	1,774
Austria	31	976
Bahamas	1	21
Bahrain	2	8
Bangladesh	6	60
Belgium	46	1,083
Bermuda	21	1,329
Brazil	115	1,396
British Virgin Islands	1	14
Bulgaria	2	21
Canada	294	2,691
Cayman Islands	22	593
Chile	34	480
China	2,054	3,334
Colombia	10	227
Costa Rica	1	24
Croatia	3	47
Cyprus	2	226
Czech Republic	3	301
Denmark	45	999
Egypt	29	222
Finland	55	1,329
France	245	2,082
Germany	211	1,951
Gibraltar	1	77
Greece	31	686
Guernsey	2	70
Hong Kong	423	1,492
Hungary	5	378
Iceland	1	31
India	553	1,447
Indonesia	129	786
Ireland	38	2,562
Isle of Man	1	150
Israel	98	1,327
Italy	97	1,245
Japan	2,161	3,488
Jersey	7	541
Kuwait	15	62
Luxembourg	22	1,174
Macau	4	216
Malaysia	210	852

Malta	4	81
Mexico	59	1,011
Monaco	4	291
Mongolia	3	52
Netherlands	59	1,896
New Zealand	48	639
Nigeria	12	112
Norway	65	1,177
Pakistan	51	217
Panama	1	332
Papua New Guinea	1	174
Peru	16	150
Philippines	66	687
Poland	58	490
Portugal	16	687
Qatar	19	110
Reunion	1	1
Russia	43	458
Saudi Arabia	88	65
Singapore	105	1,227
South Africa	96	1,484
South Korea	979	1,756
Spain	78	1,365
Sweden	214	1,609
Switzerland	139	2,489
Taiwan	742	1,167
Thailand	173	704
Turkey	79	603
Ukraine	1	149
United Arab Emirates	25	307
United Kingdom	343	4,333
United States	1,842	7,014
Uruguay	1	402
Vietnam	1	16

Panel B: Industry

Industry	# of unique investee firms	# of unique institutional investors
Basic Materials	1,304	7,319
Consumer Discretion	2,483	11,013
Consumer Staples	946	5,638
Energy	540	6,362
Health Care	1,246	6,663
Industrials	3,004	12,907
Real Estate	612	1,633
Technology	1,674	9,145
Telecommunications	425	7,492
Utilities	469	2,816
Average (Total)	12,781	17,833

Panel C: Development of network composition by year

Year	II	*Degree $_j$*	*Betweenness $_j$*	*Closeness $_j$*	*Eigenvector $_j$*
2005	3,171	5.7947	0.0365	46.8439	1.2530
2006	3,713	4.6044	0.0305	46.5321	1.1362
2007	4,333	3.9192	0.0268	46.4845	1.0393
2008	4,489	3.3313	0.0260	45.9664	1.0009
2009	4,734	3.2110	0.0249	45.4902	0.9647
2010	4,927	2.8415	0.0251	44.6273	0.9439
2011	5,193	2.4882	0.0245	43.9300	0.9056
2012	5,380	2.2465	0.0238	42.8934	0.8770
2013	6,165	2.0853	0.0204	43.0055	0.7964
2014	5,962	2.1831	0.0212	43.0786	0.8116
2015	5,752	2.0763	0.0229	43.0198	0.8319
2016	8,868	1.4025	0.0151	42.0544	0.6039
2017	9,658	1.2925	0.0137	41.6371	0.5659
2018	10,033	1.2476	0.0132	41.5367	0.5508
2019	10,435	1.1411	0.0125	41.9235	0.5301
2020	10,591	1.1600	0.0122	41.8804	0.5255
	17,833	2.138	0.019	43.184	0.752

Table 2. 3: Institutional Investor Network and Scope 1 Carbon Emissions

This table reports the estimates of the following OLS regression specification covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+n} = \beta_1(II\_centrality_{jt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, *t* year, and *n* is the lead number. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+n}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. In Panel A, the results are for the main dependent variable, *Ln_GHG_Abs_Scp1* with a one-year lead, while Panel B presents with a two-year lead. *FE* includes firm and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Scope 1 carbon emissions lead by one year				
	All II			
	Ln_GHG_Abs_Scp1 $_{it+1}$			
	(1)	(2)	(3)	(4)
Degree_centrality $_{jt}$	-0.023***			
	(-6.07)			
Betweenness_centrality $_{jt}$		-0.250***		
		(-6.14)		
Closeness_centrality $_{jt}$			-0.050***	
			(-5.35)	
Eigenvector_centrality $_{jt}$				-0.105***
				(-3.31)
Clique_Own $_{it-1}$	-0.002**	-0.002**	-0.002**	-0.002**
	(-2.68)	(-2.68)	(-2.68)	(-2.68)
Size $_{it-1}$	0.367***	0.367***	0.367***	0.367***
	(10.24)	(10.24)	(10.24)	(10.23)
MTB $_{it-1}$	0.004	0.004	0.004	0.004
	(1.03)	(1.03)	(1.03)	(1.03)
Leverage $_{it-1}$	-0.013	-0.013	-0.013	-0.013
	(-0.15)	(-0.15)	(-0.15)	(-0.16)
ROA $_{it-1}$	0.376***	0.376***	0.376***	0.376***
	(3.60)	(3.60)	(3.60)	(3.61)
PPE $_{it-1}$	0.370**	0.370**	0.370**	0.370**
	(2.13)	(2.13)	(2.13)	(2.13)
Dividend $_{it-1}$	-0.006	-0.006	-0.006	-0.006
	(-0.68)	(-0.68)	(-0.68)	(-0.68)
Return $_{it-1}$	0.000***	0.000***	0.000***	0.000***
	(2.98)	(2.98)	(2.98)	(2.98)
Growth $_{it-1}$	0.001	0.001	0.001	0.001
	(0.84)	(0.84)	(0.84)	(0.84)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,340,457	4,340,457	4,340,457	4,340,457
R^2 (within)	0.037	0.037	0.037	0.037

Panel B: Scope 1 carbon emissions lead by two years				
	All II			
	Ln_GHG_Abs_Scp1 $_{it+2}$			
	(1)	(2)	(3)	(4)
Degree_centrality $_{jt}$	-0.024***			
	(-5.77)			
Betweenness_centrality $_{jt}$		-0.235***		
		(-5.71)		
Closeness_centrality $_{jt}$			-0.052***	
			(-4.93)	
Eigenvector_centrality $_{jt}$				-0.127***
				(-3.61)
Clique_Own $_{it-1}$	-0.001*	-0.001*	-0.001*	-0.001*
	(-1.78)	(-1.78)	(-1.78)	(-1.78)
Size $_{it-1}$	0.298***	0.298***	0.298***	0.298***
	(7.76)	(7.76)	(7.76)	(7.75)
MTB $_{it-1}$	0.006	0.006	0.006	0.006
	(1.36)	(1.36)	(1.36)	(1.36)
Leverage $_{it-1}$	-0.043	-0.042	-0.043	-0.043
	(-0.49)	(-0.49)	(-0.49)	(-0.50)
ROA $_{it-1}$	0.232*	0.232*	0.232*	0.232*
	(2.05)	(2.06)	(2.06)	(2.06)
PPE $_{it-1}$	0.326*	0.326*	0.326*	0.326*
	(1.82)	(1.82)	(1.82)	(1.82)
Dividend $_{it-1}$	-0.010	-0.010	-0.010	-0.010
	(-0.85)	(-0.85)	(-0.85)	(-0.85)
Return $_{it-1}$	0.000**	0.000**	0.000**	0.000**
	(2.69)	(2.69)	(2.69)	(2.69)
Growth $_{it-1}$	0.000	0.000	0.000	0.000
	(0.22)	(0.22)	(0.22)	(0.22)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,918,818	3,918,818	3,918,818	3,918,818
R^2 (within)	0.024	0.024	0.024	0.024

Table 2. 4: Institutional Investor Network and Scope 2 Carbon Emissions

This table reports the estimates of the following OLS regression specification covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp2_{it+} = \beta_1(II\_centrality_{jt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, *t* year, and *n* is the lead number. All the variables ($Ln\_GHG\_Abs\_Scp2_{it+n}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. In Panel A, the results are for the main dependent variable, *Ln_GHG_Abs_Scp2* with a one-year lead, while Panel B presents with a two-year lead. *FE* includes firm and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Scope 2 carbon emissions lead by one year				
	All II			
	$Ln\_GHG\_Abs\_Scp2_{it+1}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{jt}$	-0.019***			
	(-3.58)			
$Betweenness\_centrality_{jt}$		-0.184***		
		(-3.76)		
$Closeness\_centrality_{jt}$			-0.039***	
			(-3.13)	
$Eigenvector\_centrality_{jt}$				-0.043
				(-1.04)
$Clique\_Own_{it-1}$	-0.003***	-0.003***	-0.003***	-0.003***
	(-3.75)	(-3.75)	(-3.75)	(-3.75)
$Size_{it-1}$	0.481***	0.481***	0.481***	0.481***
	(14.56)	(14.56)	(14.56)	(14.55)
MTB_{it-1}	0.007**	0.007**	0.007**	0.007**
	(2.54)	(2.53)	(2.54)	(2.54)
$Leverage_{it-1}$	-0.181**	-0.181**	-0.181**	-0.182**
	(-2.25)	(-2.25)	(-2.25)	(-2.25)
ROA_{it-1}	0.533***	0.533***	0.533***	0.533***
	(4.51)	(4.51)	(4.51)	(4.51)
PPE_{it-1}	0.364*	0.364*	0.364*	0.364*
	(2.10)	(2.10)	(2.10)	(2.10)
$Dividend_{it-1}$	-0.007	-0.007	-0.007	-0.007
	(-0.62)	(-0.63)	(-0.63)	(-0.63)
$Return_{it-1}$	0.000***	0.000***	0.000***	0.000***
	(4.35)	(4.35)	(4.35)	(4.35)
$Growth_{it-1}$	-0.000	-0.000	-0.000	-0.000
	(-0.04)	(-0.04)	(-0.04)	(-0.04)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,340,457	4,340,457	4,340,457	4,340,457
R^2 (within)	0.060	0.060	0.060	0.060

Panel B: Scope 2 carbon emissions lead by two years				
	All II			
	$Ln\_GHG\_Abs\_Scp2_{it+2}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{jt}$	-0.017***			
	(-3.83)			
$Betweenness\_centrality_{jt}$		-0.132***		
		(-3.24)		
$Closeness\_centrality_{jt}$			-0.032**	
			(-2.88)	
$Eigenvector\_centrality_{jt}$				-0.047
				(-1.30)
$Clique\_Own_{it-1}$	-0.003***	-0.003***	-0.003***	-0.003***
	(-3.78)	(-3.78)	(-3.78)	(-3.78)
$Size_{it-1}$	0.402***	0.402***	0.402***	0.402***
	(10.33)	(10.33)	(10.33)	(10.33)
MTB_{it-1}	0.005	0.005	0.005	0.005
	(1.59)	(1.59)	(1.59)	(1.59)
$Leverage_{it-1}$	-0.261***	-0.261***	-0.261***	-0.261***
	(-2.97)	(-2.97)	(-2.97)	(-2.97)
ROA_{it-1}	0.468***	0.468***	0.468***	0.469***
	(4.25)	(4.25)	(4.25)	(4.25)
PPE_{it-1}	0.277	0.277	0.277	0.277
	(1.70)	(1.71)	(1.70)	(1.71)
$Dividend_{it-1}$	-0.000	-0.000	-0.000	-0.000
	(-0.02)	(-0.02)	(-0.02)	(-0.02)
$Return_{it-1}$	0.000**	0.000**	0.000**	0.000**
	(2.84)	(2.84)	(2.84)	(2.84)
$Growth_{it-1}$	-0.000	-0.000	-0.000	-0.000
	(-0.21)	(-0.21)	(-0.21)	(-0.21)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,918,818	3,918,818	3,918,818	3,918,818
R^2 (within)	0.043	0.043	0.043	0.043

Table 2. 5: Robustness Tests: Alternative Fixed-effects

This table reports the estimates of the following OLS regression specification with alternative fixed effects models covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+1}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. *FE* includes country, industry and year-fixed effects depending on the specification. The standard errors in the regressions are clustered at the country and year levels in models (1)-(4), while at the industry and year levels in models (5)-(8). *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	All				All			
	$Ln\_GHG\_Abs\_Scp1_{it+1}$				$Ln\_GHG\_Abs\_Scp1_{it+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Degree\_centrality_{jt}$	-0.076*				-0.068***			
	(-1.92)				(-3.09)			
$Betweenness\_centrality_{jt}$		-0.746*				-0.994***		
		(-1.79)				(-5.38)		
$Closeness\_centrality_{jt}$			-0.210**				-0.171***	
			(-2.35)				(-3.14)	
$Eigenvector\_centrality_{jt}$				-0.632				-0.296
				(-1.44)				(-1.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,340,733	4,340,733	4,340,733	4,340,733	4,322,822	4,322,822	4,322,822	4,322,822
R^2 (within)	0.528	0.528	0.528	0.528	0.496	0.496	0.496	0.496

Table 2. 6: Robustness Tests: Alternative Dependent Variables

This table reports the estimates of the following OLS regression specification covering a sample period from 2005 to 2020.

$$Ln\_Ref\_GHG\_Abs\_Scp1_{it+n} = \beta_1(II\_centrality_{jt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

$$Ln\_Ref\_GHG\_Abs\_Scp2_{it+n} = \beta_1(II\_centrality_{jt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, *t* year, and *n* is the lead number. All the variables ($Ln\_Ref\_GHG\_Abs\_Scp1_{it+n}$, $Ln\_Ref\_GHG\_Abs\_Scp2_{it+n}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. In Panel A, the results are for the main dependent variable, *Ln_Ref_GHG_Abs_Scp1* with a one-year lead, while Panel B has a two-year lead. In Panel C, the results are for the main dependent variable, *Ln_GHG_Abs_Scp2* with a one-year lead, while Panel D has a two-year lead. *FE* includes firm and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Scope 1 carbon emissions lead by one year				
	All II			
	$Ln\_Ref\_GHG\_Abs\_Scp1_{it+1}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{jt}$	-0.020***			
	(-3.50)			
$Betweenness\_centrality_{jt}$		-0.254***		
		(-5.71)		
$Closeness\_centrality_{jt}$			-0.046***	
			(-3.14)	
$Eigenvector\_centrality_{jt}$				-0.063
				(-1.41)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,167,312	2,167,312	2,167,312	2,167,312
R^2 (within)	0.042	0.042	0.042	0.042

Panel B: Scope 1 carbon emissions lead by two years				
	$Ln\_Ref\_GHG\_Abs\_Scp1_{it+2}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{jt}$	-0.014**			
	(-2.86)			
$Betweenness\_centrality_{jt}$		-0.193***		
		(-4.34)		
$Closeness\_centrality_{jt}$			-0.033**	
			(-2.61)	
$Eigenvector\_centrality_{jt}$				-0.044
				(-1.20)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,030,922	2,030,922	2,030,922	2,030,922
R^2 (within)	0.034	0.034	0.034	0.034

Panel C: Scope 2 carbon emissions lead by one year				
	All II			
	Ln_Ref_GHG_Abs_Scp2 $_{it+1}$			
	(1)	(2)	(3)	(4)
Degree_centrality $_{jt}$	-0.016***			
	(-3.26)			
Betweenness_centrality $_{jt}$		-0.198***		
		(-4.52)		
Closeness_centrality $_{jt}$			-0.041***	
			(-3.21)	
Eigenvector_centrality $_{jt}$				-0.034
				(-0.93)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,113,434	2,113,434	2,113,434	2,113,434
R^2 (within)	0.040	0.040	0.040	0.040

Panel D: Scope 2 carbon emissions lead by two years				
	All II			
	Ln_Ref_GHG_Abs_Scp2 $_{it+2}$			
	(1)	(2)	(3)	(4)
Degree_centrality $_{jt}$	-0.015***			
	(-3.06)			
Betweenness_centrality $_{jt}$		-0.156***		
		(-3.67)		
Closeness_centrality $_{jt}$			-0.033**	
			(-2.68)	
Eigenvector_centrality $_{jt}$				-0.032
				(-0.88)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,986,970	1,986,970	1,986,970	1,986,970
R^2 (within)	0.034	0.034	0.034	0.034

Table 2. 7: Robustness Tests: Alternative Measures of Connectedness

This table reports the estimates of the following OLS regression specification using different measures of investor connectedness covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+1}$, $II\_centrality_{jt}$, $II\_centrality\_Factor_{jt}$, $II\_centrality\_PCA_{jt}$, $II\_centrality\_Ortho_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, *Eigenvector_centrality, II_centrality_Factor, II_centrality_PCA, and II_centrality_Ortho*. Panel A reports the OLS estimates using the other definitions of *II_centrality*. Panel B presents the coefficient table for the sub-sample analysis for the centrality measures based on the quintile determined by N score. *FE* includes firm and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Other alternative definitions

	All		
	$Ln\_GHG\_Abs\_Scp1_{it+1}$		
	(1)	(2)	(3)
$II\_centrality\_Factor_{jt}$	-0.003***		
	(-6.47)		
$II\_centrality\_PCA_{jt}$		-0.002***	
		(-5.60)	
$II\_centrality\_Ortho_{jt}$			-0.180***
			(-4.39)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,340,457	4,340,457	4,340,457
R^2 (within)	0.037	0.037	0.037

Panel B: Coefficient table showing sub-sample analysis based on N score

	All				
	$Ln\_GHG\_Abs\_Scp1_{it+1}$				
	(1)	(2)	(3)	(4)	(5)
(Low to High) N score =	1	2	3	4	5
$Degree\_centrality_{jt}$	0.277**	0.030	0.013	-0.076**	-0.055***
	(2.46)	(0.42)	(0.33)	(-2.49)	(-6.91)
$Betweenness\_centrality_{jt}$	-19.854	-0.356	-0.303	-0.216	-0.256***
	(-0.79)	(-0.18)	(-0.40)	(-0.94)	(-5.78)
$Closeness\_centrality_{jt}$	0.287**	0.354*	0.210**	-0.124*	-0.131***
	(2.79)	(2.05)	(2.20)	(-2.00)	(-6.77)
$Eigenvector\_centrality_{jt}$	0.380	-0.126	0.049	-0.303	-1.199***
	(1.62)	(-0.41)	(0.28)	(-1.33)	(-5.50)

Table 2. 8: Instrumental Variable

This table reports the estimates of the following 2SLS regression specification using average distance between investors as an instrument covering a sample period from 2005 to 2020.

First stage: $II\_centrality_{it} = \alpha_0 + \gamma_1(Ln\_Distance_{ijt}) + \boldsymbol{\beta_2 X_{it}} + FE + \varepsilon_{it}$

Second stage: $Ln\_GHG\_Abs\_Scp1_{it+1} = \alpha_1 + \beta_1 \widehat{II\_centrality}_{jt} + \boldsymbol{\beta_2 X_{it}} + FE + \varepsilon_{it}$

i denotes investee-firm, j denotes institutional investor, and t year. All the variables ($Ln\_Distance_{ijt}$, $Ln\_GHG\_Abs\_Scp1_{it+1}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X_{it}}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. Panel A presents the results for the first stage regressions while Panel B presents the results for the second stage regressions. *FE* includes country, industry, and year-fixed effects. The standard errors in all regressions are clustered at the industry and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: First stage regressions

	Degree $_{jt}$	Betweenness $_{jt}$	Closeness $_{jt}$	Eigenvector $_{jt}$
	(1)	(2)	(3)	(4)
Ln_Distance $_{ijt}$	0.043***	0.004***	0.019***	0.005***
	(14.24)	(12.60)	(16.49)	(9.40)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,316,773	4,316,773	4,316,773	4,316,773
R^2 (within)	0.024	0.029	0.027	0.013

Panel B: Second stage regressions

	Instrument = Ln_Distance $_{ijt}$			
	Ln_GHG_Abs_Scp1 $_{it+1}$			
	(1)	(2)	(3)	(4)
Degree_centrality $_{jt}$	-1.377***			
	(-7.53)			
Betweenness_centrality $_{jt}$		-14.680***		
		(-7.55)		
Closeness_centrality $_{jt}$			-3.140***	
			(-7.56)	
Eigenvector_centrality $_{jt}$				-12.116***
				(-7.46)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,316,773	4,316,773	4,316,773	4,316,773
R^2 (within)				
Craag-Donald statistics > 16.38	Yes	Yes	Yes	Yes
Kleibergen-Paap statistics > 16.38	Yes	Yes	Yes	Yes

Table 2. 9: Heterogeneity of Institutional Investor Network and Carbon Emissions

This table reports the estimates of the following OLS regression specification on the heterogeneity of II networks covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{jt}) \times D(Het_{jit}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+n}$, $II\_centrality_{jt}$, $D(Het_{jit})$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. The table presents the results for the main dependent variable, *Ln_GHG_Abs_Scp1*. The heterogeneity parameters take the value of *D(Active)*, *D(Independent)*, *D(PRI)*, *D(PRI_ESG)* as indicated. *FE* includes firm, *D(Active)*, *D(Independent)*, *D(PRI)*, *D(PRI_ESG)* and year-fixed effects depending on the specification. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Ln_GHG_Scp1 $_{it+1}$				Ln_GHG_Scp1 $_{it+1}$			
	X = Active				X = Independent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Degree_centrality $_{jt}$ × D (X)	-0.027***				-0.023***			
	(-6.11)				(-6.41)			
Betweenness_centrality $_{jt}$ × D (X)		-0.322***				-0.243***		
		(-7.07)				(-6.28)		
Closeness_centrality $_{jt}$ × D (X)			-0.058***				-0.054***	
			(-5.23)				(-6.12)	
Eigenvector_centrality $_{jt}$ × D (X)				-0.125***				-0.106***
				(-3.51)				(-3.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,119,760	4,119,760	4,119,760	4,119,760	4,312,023	4,312,023	4,312,023	4,312,023
R^2 (within)	0.036	0.036	0.036	0.036	0.037	0.037	0.037	0.037

	X = PRI				X = PRI_High_ESG			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Degree_centrality $_{jt}$ × D (X)	-0.021***				-0.044***			
	(-3.62)				(-3.89)			
Betweenness_centrality $_{jt}$ × D (X)		-0.162***				-0.294***		
		(-3.37)				(-3.82)		
Closeness_centrality $_{jt}$ × D (X)			-0.043**				-0.103***	
			(-2.80)				(-3.52)	
Eigenvector_centrality $_{jt}$ × D (X)				-0.165**				-0.292**
				(-2.66)				(-2.90)

Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,340,457	4,340,457	4,340,457	4,340,457	623,600	623,600	623,600	623,600
R^2 (within)	0.037	0.037	0.037	0.037	0.024	0.024	0.024	0.024

Table 2. 10: Institutional Investor Network and Green Innovation
This table reports the estimates of the following OLS regression specification covering a sample period from 2005 to 2020.

$$Ln\_Gr\_Patents_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2 X_{it-1} + FE + \varepsilon_{it}$$

$$Ln\_GHG\_Abs\_Scp1_{it+2} = \beta_1(Ln\_Gr\_Patents)_{it} + \beta_2(II\_centrality)_{jt} + \beta_4 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_Gr\_Patents_{it+1}$, $Ln\_GHG\_Abs\_Scp1_{it+2}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. Panel A presents the results for the impact of *II_centrality* the main dependent variable, *Ln_Gr_Patents*, with a one-year lead. Panel B presents the results showing the mediating role through which investor centrality impact carbon emissions. *FE* includes country, industry, and year-fixed effects depending on the specification. The standard errors in all regressions are clustered at the industry and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Institutional investor network and green patents

	All			
	$Ln\_Gr\_Patents_{it+1}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{jt}$	0.155***			
	(4.68)			
$Betweenness\_centrality_{jt}$		0.895***		
		(3.71)		
$Closeness\_centrality_{jt}$			0.486***	
			(5.13)	
$Eigenvector\_centrality_{jt}$				1.050***
				(3.73)
$Clique\_Own_{it-1}$	-0.003**	-0.003**	-0.003**	-0.004***
	(-2.95)	(-2.94)	(-2.92)	(-3.01)
$Size_{it-1}$	0.233***	0.233***	0.234***	0.233***
	(7.51)	(7.52)	(7.52)	(7.51)
MTB_{it-1}	-0.012	-0.012	-0.012	-0.012
	(-1.72)	(-1.74)	(-1.72)	(-1.73)
$Leverage_{it-1}$	-0.247	-0.247	-0.247	-0.246
	(-1.64)	(-1.64)	(-1.64)	(-1.63)
ROA_{it-1}	-0.296	-0.299	-0.295	-0.299
	(-1.18)	(-1.19)	(-1.18)	(-1.19)
PPE_{it-1}	0.358**	0.359**	0.358**	0.358**
	(2.17)	(2.17)	(2.17)	(2.17)
$Dividend_{it-1}$	-0.099***	-0.100***	-0.099***	-0.099***
	(-3.66)	(-3.68)	(-3.66)	(-3.65)
$Return_{it-1}$	0.000	0.000	0.000	0.000
	(0.08)	(0.08)	(0.08)	(0.08)
$Growth_{it-1}$	0.001	0.001	0.001	0.001
	(0.34)	(0.35)	(0.33)	(0.34)
$Cash_{it-1}$	0.249	0.251	0.248	0.248
	(1.56)	(1.57)	(1.56)	(1.56)
$Research\_intensity_{it-1}$	6.092***	6.099***	6.095***	6.078***
	(3.26)	(3.27)	(3.26)	(3.25)
HHI_{it-1}	0.849	0.848	0.847	0.847

	(0.50)	(0.50)	(0.50)	(0.50)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,705,199	3,705,199	3,705,199	3,705,199
R^2 (within)	0.080	0.080	0.080	0.080

Panel B: Mediation

	All			
	Ln_GHG_Abs_Scp1 $_{it+2}$			
	(1)	(2)	(3)	(4)
Ln_Gr_Patents $_{it+1}$	-0.020*	-0.021*	-0.020*	-0.020*
	(-1.98)	(-1.99)	(-1.98)	(-1.97)
Degree_centrality $_{jt}$	-0.069**			
	(-2.89)			
Betweenness_centrality $_{jt}$		-1.104***		
		(-5.09)		
Closeness_centrality $_{jt}$			-0.175**	
			(-2.98)	
Eigenvector_centrality $_{jt}$				-0.252
				(-1.33)
Clique_Own $_{it-1}$	-0.000	-0.000	-0.000	-0.000
	(-0.36)	(-0.38)	(-0.36)	(-0.34)
Size $_{it-1}$	0.818***	0.818***	0.818***	0.818***
	(20.80)	(20.81)	(20.80)	(20.83)
MTB $_{it-1}$	0.005	0.005	0.005	0.005
	(0.70)	(0.70)	(0.70)	(0.70)
Leverage $_{it-1}$	0.001	0.002	0.001	0.000
	(0.01)	(0.01)	(0.01)	(0.00)
ROA $_{it-1}$	0.337**	0.336**	0.338**	0.339**
	(2.50)	(2.49)	(2.50)	(2.51)
PPE $_{it-1}$	1.270**	1.270**	1.270**	1.270**
	(3.16)	(3.16)	(3.16)	(3.16)
Dividend $_{it-1}$	-0.033	-0.032	-0.033	-0.033
	(-1.15)	(-1.14)	(-1.15)	(-1.15)
Return $_{it-1}$	0.002***	0.002***	0.002***	0.002***
	(6.28)	(6.28)	(6.28)	(6.28)
Growth $_{it-1}$	0.024***	0.024***	0.024***	0.024***
	(7.45)	(7.46)	(7.45)	(7.45)
Cash $_{it-1}$	-0.278	-0.279	-0.278	-0.278
	(-1.40)	(-1.40)	(-1.40)	(-1.40)
Research_intensity $_{it-1}$	-2.176**	-2.180**	-2.176**	-2.176**
	(-2.69)	(-2.70)	(-2.69)	(-2.69)
HHI $_{it-1}$	-0.049	-0.043	-0.048	-0.050
	(-0.02)	(-0.02)	(-0.02)	(-0.02)
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,705,199	3,705,199	3,705,199	3,705,199
R^2 (within)	0.486	0.486	0.486	0.486

Table 2. 11: Institutional Investor Network and Climate Change Exposure

This table reports the estimates of the following OLS regression specification of II networks on climate change exposure covering a sample period from 2005 to 2020.

$$CCE_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

$$Ln\_GHG\_Abs\_Scp1_{it+2} = \beta_1 (II\_centrality \times D(\Delta CCE > 0))_{it} + \beta_2 \boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, *t* year, and *n* is the lead number. All the variables (CCE_{it+1}, $Ln\_GHG\_Abs\_Scp1_{it+}$, $II\_centrality_{jt}$, $D(\Delta CCE > 0)$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. Panel A presents the results for the main dependent variable, *CCE*, with a one-year lead. Panel B presents the results showing the mechanism through which climate change exposure and investor centrality impact carbon emissions. *FE* includes firm, $D(\Delta CCE > 0)$, and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Institutional investor network and climate change exposure

	All			
	CCE_{it+1}			
	(1)	(2)	(3)	(4)
Degree_centrality $_{jt}$	0.027**			
	(2.42)			
Betweenness_centrality $_{jt}$		0.208**		
		(2.82)		
Closeness_centrality $_{jt}$			0.068**	
			(2.84)	
Eigenvector_centrality $_{jt}$				0.292***
				(3.28)
Clique_Own $_{it-1}$	0.409	0.411	0.409	0.406
	(0.33)	(0.33)	(0.33)	(0.32)
Size $_{it-1}$	-0.146**	-0.146**	-0.146**	-0.146**
	(-2.80)	(-2.80)	(-2.80)	(-2.79)
MTB $_{it-1}$	-0.024***	-0.024***	-0.024***	-0.024***
	(-3.09)	(-3.09)	(-3.09)	(-3.09)
Leverage $_{it-1}$	-0.462**	-0.461**	-0.462**	-0.461**
	(-2.51)	(-2.51)	(-2.51)	(-2.50)
ROA $_{it-1}$	0.064	0.063	0.063	0.064
	(0.30)	(0.30)	(0.30)	(0.30)
PPE $_{it-1}$	0.469	0.469	0.469	0.469
	(1.49)	(1.49)	(1.49)	(1.49)
Dividend $_{it-1}$	0.030	0.030	0.030	0.030
	(0.97)	(0.97)	(0.97)	(0.97)
Return $_{it-1}$	0.246	0.246	0.246	0.246
	(0.72)	(0.72)	(0.72)	(0.72)
Growth $_{it-1}$	1.407	1.408	1.407	1.404
	(0.50)	(0.50)	(0.50)	(0.50)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,702,133	2,702,133	2,702,133	2,702,133
R^2 (within)	0.006	0.006	0.006	0.006

Panel B: Mechanism

	All			
	$Ln\_Abs\_GHG\_Scp1_{it+2}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{it} \times D(\Delta CCE>0)_{jt+1}$	-0.038***			
	(-3.63)			
$Betweenness\_centrality_{it} \times D(\Delta CCE>0)_{jt+1}$		-0.180***		
		(-4.36)		
$Closeness\_centrality_{it} \times D(\Delta CCE>0)_{jt+1}$			-0.100**	
			(-2.64)	
$Eigenvector\_centrality_{it} \times D(\Delta CCE>0)_{jt+1}$				-0.207***
				(-3.19)
$Clique\_Own_{it-1}$	-1.519	-1.520	-1.518	-1.519
	(-1.41)	(-1.41)	(-1.41)	(-1.41)
$Size_{it-1}$	0.258***	0.258***	0.258***	0.258***
	(5.34)	(5.34)	(5.34)	(5.34)
MTB_{it-1}	0.006	0.006	0.006	0.006
	(1.26)	(1.26)	(1.26)	(1.26)
$Leverage_{it-1}$	-0.055	-0.055	-0.055	-0.055
	(-0.46)	(-0.46)	(-0.46)	(-0.47)
ROA_{it-1}	0.233	0.233	0.233	0.233
	(1.57)	(1.57)	(1.57)	(1.57)
PPE_{it-1}	0.046	0.047	0.046	0.046
	(0.23)	(0.23)	(0.23)	(0.23)
$Dividend_{it-1}$	-0.025	-0.025	-0.025	-0.025
	(-1.64)	(-1.64)	(-1.64)	(-1.64)
$Return_{it-1}$	0.338**	0.339**	0.339**	0.339**
	(2.37)	(2.37)	(2.37)	(2.37)
$Growth_{it-1}$	0.301	0.301	0.300	0.300
	(0.19)	(0.19)	(0.19)	(0.19)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
D(ΔCCE>0)	Yes	Yes	Yes	Yes
Observations	2,448,651	2,448,651	2,448,651	2,448,651
R^2 (within)	0.021	0.021	0.021	0.021

Table 2A. 1: Exclusion of Financial Crisis and Covid19 Period

This table reports the estimates of the following OLS regression specification excluding the period of financial crisis (2007-2009) and covid crisis (2019-2020) covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+n}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. The results are for the main dependent variable, *Ln_GHG_Abs_Scp1* with a one-year lead. *FE* includes firm and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Scope 1 carbon emissions lead by one year				
	All II			
	$Ln\_GHG\_Abs\_Scp1_{it+1}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{jt}$	-0.025***			
	(-6.10)			
$Betweenness\_centrality_{jt}$		-0.230***		
		(-4.87)		
$Closeness\_centrality_{jt}$			-0.052***	
			(-5.33)	
$Eigenvector\_centrality_{jt}$				-0.124***
				(-4.23)
$Clique\_Own_{it-1}$	-0.001**	-0.001**	-0.001**	-0.001**
	(-2.26)	(-2.26)	(-2.26)	(-2.26)
$Size_{it-1}$	0.328***	0.328***	0.328***	0.328***
	(6.45)	(6.45)	(6.45)	(6.44)
MTB_{it-1}	0.009	0.009	0.009	0.009
	(1.78)	(1.78)	(1.78)	(1.78)
$Leverage_{it-1}$	-0.006	-0.006	-0.006	-0.006
	(-0.05)	(-0.05)	(-0.05)	(-0.05)
ROA_{it-1}	0.376***	0.376***	0.376***	0.377***
	(3.38)	(3.38)	(3.38)	(3.38)
PPE_{it-1}	0.333	0.333	0.333	0.333
	(1.66)	(1.66)	(1.66)	(1.66)
$Dividend_{it-1}$	0.006	0.006	0.006	0.006
	(0.70)	(0.70)	(0.70)	(0.70)
$Return_{it-1}$	0.000	0.000	0.000	0.000
	(1.51)	(1.51)	(1.51)	(1.51)
$Growth_{it-1}$	0.001	0.001	0.001	0.001
	(0.53)	(0.52)	(0.53)	(0.53)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,914,829	2,914,829	2,914,829	2,914,829
R^2 (within)	0.031	0.031	0.031	0.031

Table 2A. 2: Factor Analysis

This table shows the correlations between centrality measures (Panel A), and the factor analysis (Panel B) used to create a single weighted centrality measure (*II_centrality_Factor*). The sample covers the period spanning from 2005 to 2020. All variables are defined in Appendix B.

Panel A: Correlations between centrality measures

Variable	Degree	Betweenness	Closeness	Eigenvector
Degree	1.000			
Betweenness	0.703	1.000		
Closeness	0.973	0.679	1.000	
Eigenvector	0.892	0.459	0.852	1.000

Panel B: Factor analysis

Variable	Factor 1	Factor 2	Factor 3*	Factor 4*
Degree	0.998	-0.004	-	-
Betweenness	0.692	0.410	-	-
Closeness	0.975	0.006	-	-
Eigenvector	0.874	-0.327	-	-
Eigen value	3.190	0.276	-0.003	-0.047
% variance explained	93.420	8.070	-0.100	-1.390

*Not computed as the eigen values are negative implying the factors are small.

Table 2A. 3: Other Instrumental Variable

This table reports the estimates of the following 2SLS regression specification using lagged centrality measures and the industry average of the centrality measures as an instrument covering a sample period from 2005 to 2020. i denotes investee-firm, j denotes institutional investor, and t year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+1}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. Panel A presents the results for the first stage regressions while Panel B presents the results for the second stage regressions. *FE* includes firm and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Second stage regressions

	Instrument = II_centrality $_{it-1}$				Instrument = Industry_Average $_{it}$			
	Ln_GHG_Abs_Scp1 $_{it+1}$				Ln_GHG_Abs_Scp1 $_{it+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Degree_centrality $_{jt}$	-0.024***				-10.452*			
	(-9.24)				(-1.82)			
Betweenness_centrality $_{jt}$		-0.252***				407.265		
		(-13.54)				(1.20)		
Closeness_centrality $_{jt}$			-0.052***				-41.720*	
			(-8.36)				(-1.73)	
Eigenvector_centrality $_{jt}$				-0.116***				-14.450
				(-5.58)				(-0.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,340,457	4,340,457	4,340,457	4,340,457	3,161,618	3,161,618	3,161,618	3,161,618
R^2 (within)								

Table 2A. 4: US Domiciled Firms

This table reports the estimates of the following OLS regression specification exclusively for US domiciled firms covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+n}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. The results are for the main dependent variable, *Ln_GHG_Abs_Scp1* with a one-year lead. *FE* includes firm and year-fixed effects. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Scope 1 carbon emissions lead by one year				
	All II			
	$Ln\_GHG\_Abs\_Scp1_{it+1}$			
	(1)	(2)	(3)	(4)
$Degree\_centrality_{jt}$	-0.049***			
	(-6.28)			
$Betweenness\_centrality_{jt}$		-0.330***		
		(-5.72)		
$Closeness\_centrality_{jt}$			-0.108***	
			(-6.09)	
$Eigenvector\_centrality_{jt}$				-0.258***
				(-5.12)
$Clique\_Own_{it-1}$	-0.001	-0.001	-0.001	-0.001
	(-0.36)	(-0.36)	(-0.36)	(-0.36)
$Size_{it-1}$	0.325***	0.325***	0.325***	0.325***
	(6.11)	(6.11)	(6.11)	(6.11)
MTB_{it-1}	0.005	0.005	0.005	0.005
	(0.91)	(0.91)	(0.91)	(0.91)
$Leverage_{it-1}$	-0.093	-0.094	-0.093	-0.093
	(-0.61)	(-0.62)	(-0.62)	(-0.62)
ROA_{it-1}	0.361**	0.362**	0.361**	0.361**
	(2.25)	(2.25)	(2.25)	(2.25)
PPE_{it-1}	0.257	0.257	0.257	0.257
	(0.66)	(0.66)	(0.66)	(0.66)
$Dividend_{it-1}$	0.011	0.011	0.011	0.011
	(0.53)	(0.53)	(0.53)	(0.53)
$Return_{it-1}$	0.000	0.000	0.000	0.000
	(1.07)	(1.07)	(1.07)	(1.07)
$Growth_{it-1}$	-0.001	-0.001	-0.001	-0.001
	(-0.27)	(-0.27)	(-0.27)	(-0.27)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,594,017	1,594,017	1,594,017	1,594,017
R^2 (within)	0.035	0.035	0.035	0.035

Table 2A. 5: Additional Tests of II Network Heterogeneity and Carbon Emissions

This table reports the estimates of the following OLS regression specification on the heterogeneity of II networks covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{jt}) \times D(Het_{jit}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+1}$, $II\_centrality_{jt}$, $D(Het_{jit})$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. The table presents the results for the main dependent variable, *Ln_GHG_Abs_Scp1*. The heterogeneity parameters take the value of *D(Large)*, *D(Long-Term)*, *D(Foreign)*, and *D(USA)* as indicated. *FE* includes firm *D(Large)*, *D(Long-Term)*, *D(Foreign)*, *D(USA)* and year-fixed effects depending on the specification. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	$Ln\_GHG\_Scp1_{it+1}$				$Ln\_GHG\_Scp1_{it+1}$			
	X = Large				X = Long-Term			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Degree_centrality $_{jt}$ × D (X)	-0.008*				-0.019*			
	(-1.81)				(-1.93)			
Betweenness_centrality $_{jt}$ × D (X)		-0.116***				-0.246***		
		(-3.08)				(-3.29)		
Closeness_centrality $_{jt}$ × D (X)			-0.017				-0.017	
			(-1.46)				(-0.60)	
Eigenvector_centrality $_{jt}$ × D (X)				0.024				-0.127
				(0.60)				(-1.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,340,457	4,340,457	4,340,457	4,340,457	465,162	465,162	465,162	465,162
R^2 (within)	0.037	0.037	0.037	0.037	0.039	0.039	0.039	0.039

	X = Foreign				X = USA			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Degree_centrality $_{jt}$ × D (X)	-0.028***				-0.038***			
	(-4.65)				(-6.57)			
Betweenness_centrality $_{jt}$ × D (X)		-0.259***				-0.249***		
		(-5.12)				(-5.92)		
Closeness_centrality $_{jt}$ × D (X)			-0.070***				-0.086***	
			(-3.05)				(-4.05)	
Eigenvector_centrality $_{jt}$ × D (X)				-0.136***				-0.223***
				(-3.02)				(-5.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,340,457	4,340,457	4,340,457	4,340,457	4,340,457	4,340,457	4,340,457	4,340,457
R^2 (within)	0.037	0.037	0.037	0.037	0.037	0.037	0.037	0.037

Table 2A. 6: Additional Tests by Ownership on II Network and Carbon Emissions

This table reports the estimates of the following OLS regression specification on the heterogeneity of II networks covering a sample period from 2005 to 2020.

$$Ln\_GHG\_Abs\_Scp1_{it+1} = \beta_1(II\_centrality_{jt}) + \beta_2\boldsymbol{X}_{it-1} + FE + \varepsilon_{it}$$

i denotes investee-firm, *j* denotes institutional investor, and *t* year. All the variables ($Ln\_GHG\_Abs\_Scp1_{it+1}$, $II\_centrality_{jt}$, and set of controls in $\boldsymbol{X}_{it}$) are defined in Appendix B. *II_centrality* takes the value of *Degree_centrality*, *Betweenness_centrality*, *Closeness_centrality*, and *Eigenvector_centrality*. The table presents the results for the main dependent variable, *Ln_GHG_Abs_Scp1*. The categories used to differentiate ownership based on ownership stake are Big Three and Non-Big Three in Panel A, Large and Small in Panel B, and Blockholder and Non-Blockholder in Panel C. *FE* includes firm and year-fixed effects depending on the specification. The standard errors in all regressions are clustered at the firm and year levels. *t*-stats are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Sub sample analysis of Big Three and Non-Big Three

	$Ln\_GHG\_Scp1_{it+1}$				$Ln\_GHG\_Scp1_{it+1}$			
	Big Three				Non-Big Three			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Degree\_centrality_{jt}$	-0.020*				-0.022***			
	(-1.86)				(-5.44)			
$Betweenness\_centrality_{jt}$		-0.085**				-0.296***		
		(-2.28)				(-6.85)		
$Closeness\_centrality_{jt}$			-0.038				-0.046***	
			(-1.64)				(-4.61)	
$Eigenvector\_centrality_{jt}$				-2.348*				-0.088**
				(-1.83)				(-2.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	151,071	151,071	151,071	151,071	4,188,724	4,188,724	4,188,724	4,188,724
R^2 (within)	0.038	0.038	0.038	0.038	0.036	0.036	0.036	0.036

Panel B: Sub sample analysis of Large and Small

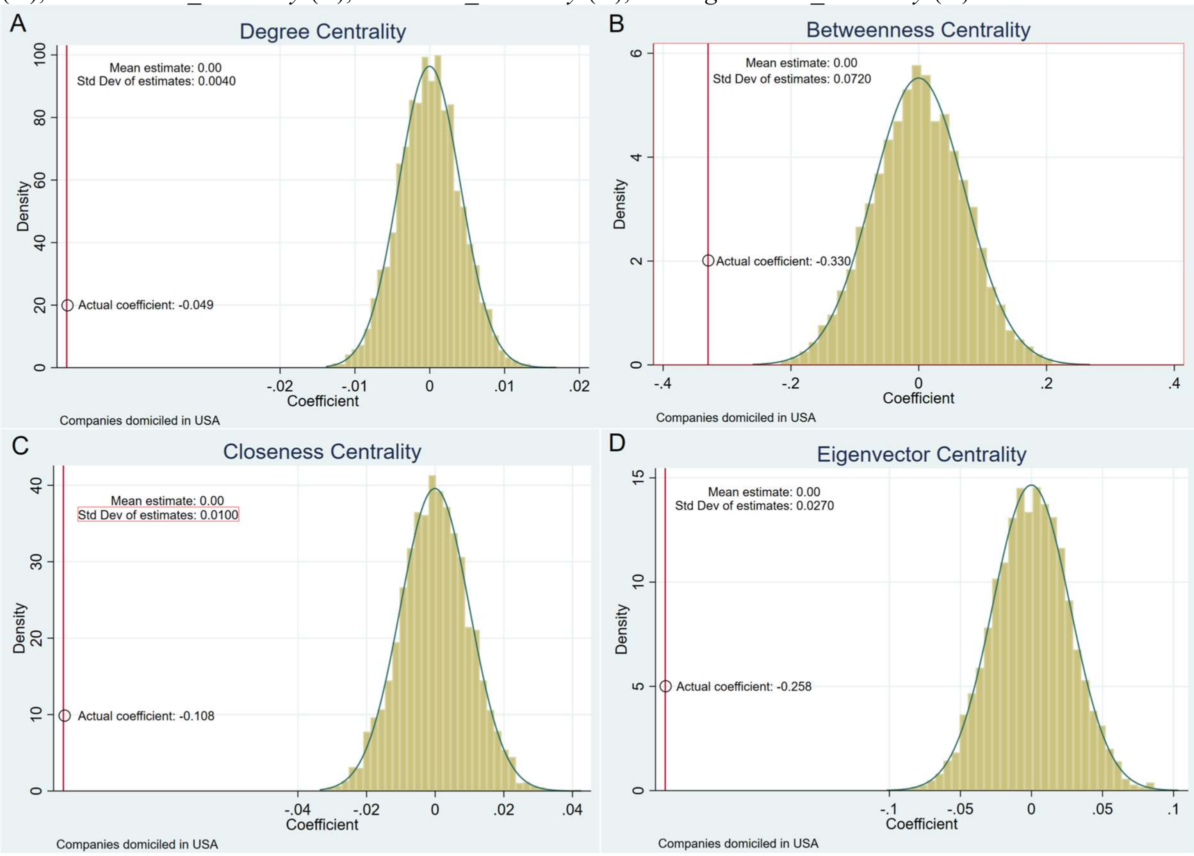
	Large				Small			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Degree_centrality $_{jt}$	-0.007				-0.027***			
	(-1.61)				(-3.71)			
Betweenness_centrality $_{jt}$		-0.119***				-0.434***		
		(-3.20)				(-4.99)		
Closeness_centrality $_{jt}$			-0.011				-0.055***	
			(-1.05)				(-3.35)	
Eigenvector_centrality $_{jt}$				-0.006				-0.085*
				(-0.16)				(-1.87)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,170,041	2,170,041	2,170,041	2,170,041	2,169,805	2,169,805	2,169,805	2,169,805
R^2 (within)	0.042	0.042	0.042	0.042	0.031	0.031	0.031	0.031

Panel C: Sub sample analysis of Block and Non-Block

	Block				Non-Block			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Degree_centrality $_{jt}$	0.045*				-0.024***			
	(1.88)				(-6.06)			
Betweenness_centrality $_{jt}$		0.222				-0.256***		
		(1.29)				(-5.80)		
Closeness_centrality $_{jt}$			0.115*				-0.053***	
			(1.96)				(-5.36)	
Eigenvector_centrality $_{jt}$				0.353				-0.113***
				(1.55)				(-3.53)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,581	81,581	81,581	81,581	4,257,800	4,257,800	4,257,800	4,257,800
R^2 (within)	0.053	0.052	0.053	0.053	0.036	0.036	0.036	0.036

Figure 2. 1: Placebo Tests

Placebo test: Histogram of the estimated coefficients obtained after randomly matching institutional investors with portfolio companies. The centrality measures of those institutional investors are used to examine its impact on *Ln_GHG_Abs_Scp1*, and the coefficients from the fixed-effects models are recorded. I repeat this process 1,000 times. I show the distribution of coefficient estimates when the independent variable is *Degree_centrality* (A), *Betweenness_centrality* (B), *Closeness_centrality* (C), and *Eigenvector_centrality* (D).



Appendix: Second Empirical Chapter

Appendix A: Centrality Measures

Centrality helps us understand which investors hold critical positions in the network of II (Bajo *et al.* 2020; Chen *et al.* 2023). Central positions are equated with opinion leadership (being more likely to influence the opinions and decisions of others) and information hubs (information flow within the network) (Hochberg *et al.* 2007; Ozsoylev *et al.* 2013; Rossi *et al.* 2018). Several centrality measures exist—I use the most common measures: degree, betweenness, closeness, and eigenvector (Freeman 1977; El-Khatib *et al.* 2015).

These centrality measures are all measures of the investors' prominence in a network. While there may be some similarities between these concepts, it's important to note that they are distinct from each other. Investors in the center of a network, with everyone else connected to them, might seem like a powerful position. While they may have many connections, an investor might not have substantial influence. Therefore, understanding how an investor holding strategic positions is connected is important, which allows them to exert influence within the network.

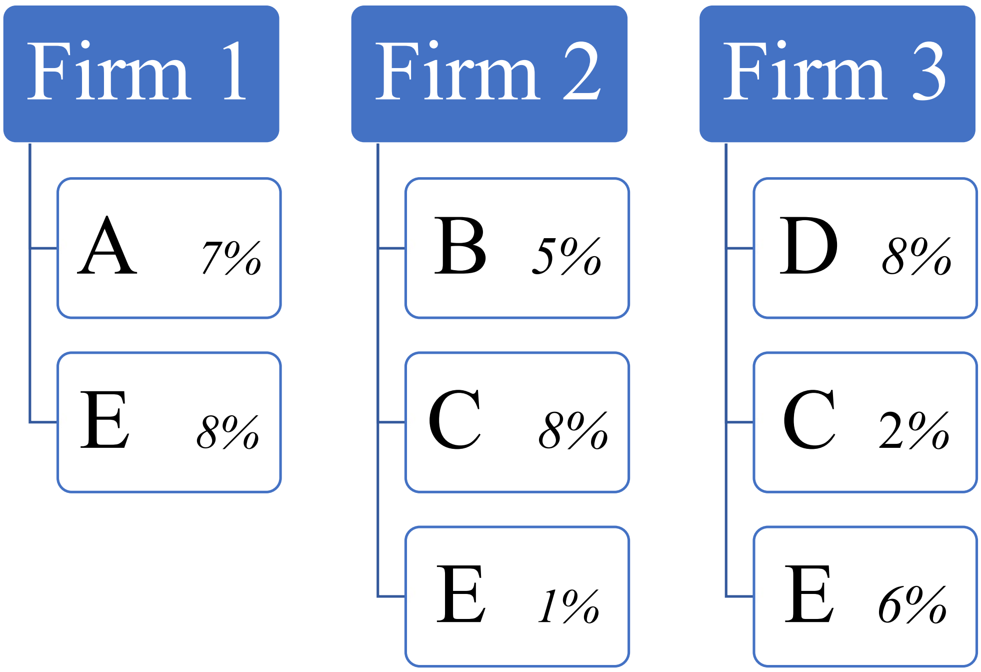


Figure 2. 2: Institutional Investor Ownership at the Firm-level.
The figure shows II that hold common equity shares in a given firm at the end of a given year.

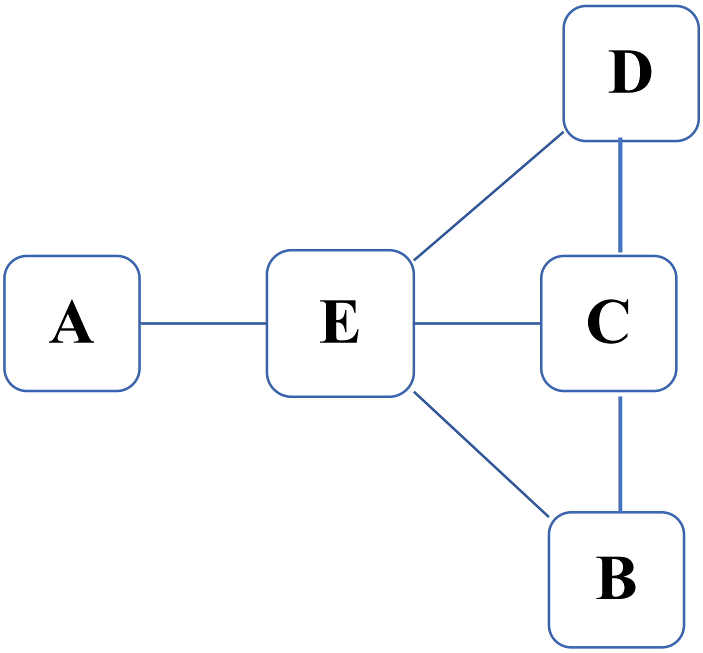


Figure 2. 3: Institutional Investor Ownership Graph
The figure shows the connections of II based on their holdings, as shown in Figure 2.2.

Degree Centrality (How big is your neighborhood)

Degree centrality measures the number of direct connections an institutional investor has within a network (Bajo *et al.* 2020; Dissanaike *et al.* 2023). In simpler terms, it tells us how many other investors a specific investor is directly linked to. It suggests an investor is well-connected within the network, indicating greater access to information, potential influence, and diversification. It helps us find connected or popular investors who can quickly connect with the wider network.

$$Centrality_i^{Degree} = \sum_{j=1}^{n} A_{ij}$$

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix} \text{ x } \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 2 \\ 4 \end{bmatrix}$$

Starting at row j=1 and ending at the last possible row n, I add up all possible values of the cells designated by the row i and column j combination in matrix A.

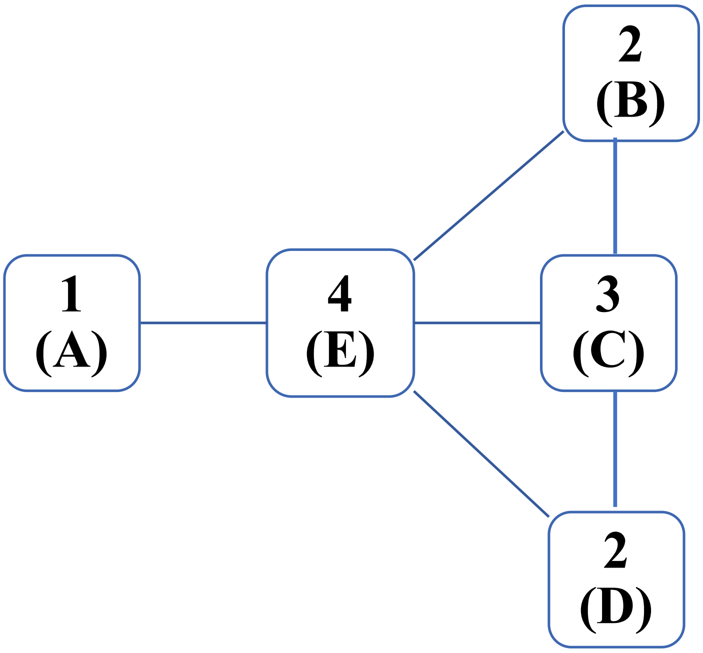


Figure 2. 4: Degree Centrality Measure
The figure shows the non-normalized degree centrality measures, i.e., the number of connections for II as per their holdings in Figure 2.2.

The most central investor in this example is directly connected to four other investors in the network. The least central investors, on the other hand, are only connected to one other investor in the network.

Degree centrality is often normalized by N-1 because I analyze pairs of investors in a network. In a simple undirected network, an investor can have a maximum of N-1 connections, making it easier to compare across networks.

Betweenness Centrality (Role as an intermediary)

This measure reveals how often an investor lies on the shortest paths between other investors in the network (Bajo *et al.* 2020; Dissanaike *et al.* 2023).[77] It essentially identifies investors who act as critical intermediaries or bridges facilitating communication and information flow within the network. By linking investors in the chain of contacts in a network, these investors play a crucial role in information exchange. Their removal from the network can potentially disrupt communications between other investors because they lie on the largest number of paths.

High betweenness centrality scores suggest investors are considered critical intermediaries or gatekeepers of information within the network. The least central investor is not a part of the shortest path between any other investors in the network. If none of the pair combinations pass through an investor, the centrality score is 0.

$$Centrality_v^{Betweenness} = \sum_{s \neq t \neq v} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

$\sigma_{st}(v)$ is the number of those paths that pass-through investor v.

σ_{st} is the total number of shortest paths from the investor s to investor t.

$$\begin{bmatrix} A & None & 0 \\ B & None & 0 \\ C & DCB & 0.5 \\ D & None & 0 \\ E & AED & 1 \\ E & AEC & 1 \\ E & AEB & 1 \\ E & BED & 0.5 \end{bmatrix}$$

77 Paths refers to a sequence of connections between investors within a network, or the route from investor A to investor B.

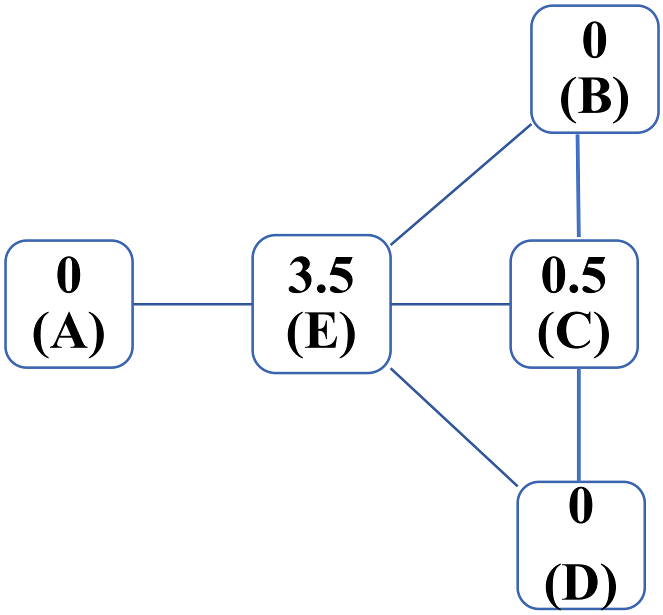


Figure 2. 5: Betweenness Centrality Measure
The figure shows the non-normalized betweenness centrality measure, i.e., the number of connections it played as an intermediary for II as per their holdings in Figure 2.2.

Betweenness centrality is calculated by dividing the number of times the examined investor falls on the shortest path between other investors by the total number of possible shortest paths between other investors in the network.

To make comparisons fair, the measure considers how many possible pairs of investors exist in the network. The combination formula calculates the total number of possible pairs of nodes in the network, excluding the investor being analyzed. In an undirected network, the maximum number of times an investor can appear on the shortest paths between other investors is $\frac{(N-1)(N-2)}{2}$. Normalizing by this maximum value sets the upper limit of betweenness centrality to one, providing a clear upper bound and a more intuitive interpretation of the score.

The key assumption focuses on the shortest paths between investors, not all possible paths. II often operate in a fast-paced environment where timely access to information is crucial for investment decisions, making it strategic and cost-effective. This helps to provide valuable insight into the most efficient and influential information channels within the network.

Closeness Centrality (Ease of reaching other investors)

Closeness centrality scores each investor based on their closeness to all other investors in the network (Bajo *et al.* 2020; Dissanaike *et al.* 2023). In simple words, how easily can an investor reach/be reached by other investors within the network? It considers the shortest paths between each investor and every other investor, assigning a lower score to investors who are closer (having shorter paths) to others. This helps to understand the investors that are best placed to influence the entire network quickly.

$$Centrality_i^{Closeness} = \frac{N-1}{\sum_{i=1}^{N} D(i,j)}$$

I calculate all the shortest paths between entity i and others j and sum the results. I take the inverse so that the smallest number has the highest value, meaning a smaller number signifies a closer and more central position.

$$\begin{bmatrix} AE & AEB & AEC & AED \\ BE & BC & BEA & BED \\ CE & CB & CD & CEA \\ DE & DC & DEB & DEA \\ EA & EB & ED & EC \end{bmatrix}$$

$$\begin{bmatrix} 1+2+2+2 \\ 1+1+2+2 \\ 1+1+1+2 \\ 1+1+2+2 \\ 1+1+1+1 \end{bmatrix}$$

$$\begin{bmatrix} 7 \\ 6 \\ 5 \\ 6 \\ 4 \end{bmatrix}$$

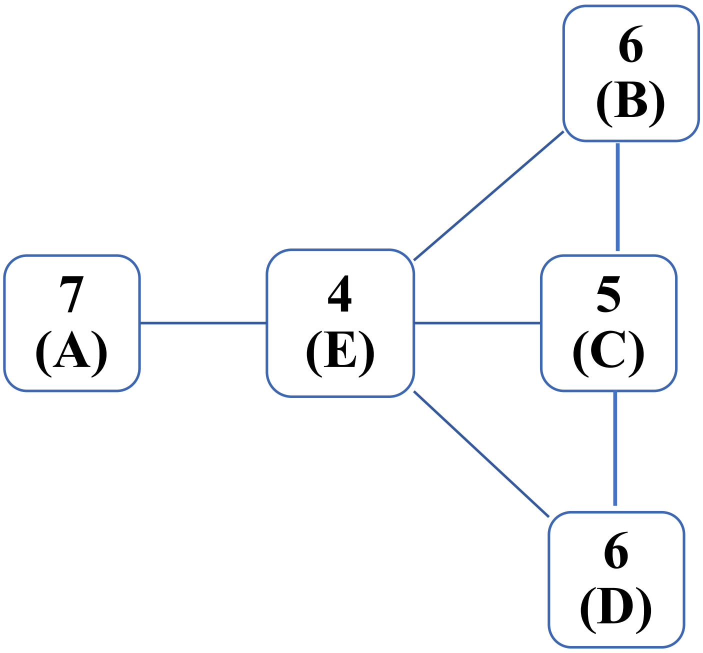


Figure 2. 6: Closeness Centrality Measure
The figure shows the non-normalized closeness centrality measures, i.e., the number of shortest paths for II as per their holdings in Figure 2.2.

Investors with high centrality must travel further along paths to get to other investors in the network. Investors with lower closeness centrality have a shorter average distance to reach others, thus spreading information or influence in the network. The key assumption is that information or influence spreads primarily through the shortest paths which is likely the case considering institutional investors have an incentive to connect with those who can provide valuable information.

Eigenvector Centrality (Not what you know, but whom you know)

This measure goes beyond simply counting an investor's connections by considering their importance (Bajo *et al.* 2020; Dissanaike *et al.* 2023). Connections to highly influential investors carry more weight than connections to less influential ones. It considers the influence of the investors those connections are connected to, creating a kind of chain reaction.

Investors with high eigenvector centrality scores have a broader reach and influence beyond their immediate connections.

$$A\chi = \lambda\chi$$

The adjacency matrix (A) represents the connection between the investors in the network. The eigenvector (χ) is a vector containing scores for each investor, reflecting relative influence. Mathematically, the formula states that the centrality score of an investor ($A\chi$) is proportional to the sum of the centrality scores of their connected investors ($\lambda\chi$).

The magnitude of a vector, denoted by χ, represents its length or distance from the origin. The resulting vector has a magnitude of 1, making it a unit vector.

$$||v|| = \sqrt{(v_1)^2 + (v_2)^2 + \cdots (v_n)^2}$$

$$Normalized\_\chi = \frac{\chi}{||v||}$$

Calculating the eigenvector χ, involves power iteration. By considering how many connections an investor has and how well-connected those connections are, information flow is better reflected considering the delay in information passing through (Ozsoylev *et al.* 2013). This iterative process starts with a normalized value and keeps multiplying it by the adjacency matrix A. With each iteration, the influence of connections and their connections gets factored in, gradually converging on the true eigenvector that reflects the relative influence of each investor within the network.[78] The influence of highly influential investors gradually amplifies, while that of the less influential investors gets diminished as their connections contribute less to the overall score. Investors with connections to highly influential investors (high centrality scores) will themselves have higher centrality scores. Walden (2018) found that eigenvector centrality is a strong indicator of an investor's information advantage in a network compared to other measures like closeness centrality.

[78] Every matrix has associated eigenvalues and eigenvectors. In the context of networks, the largest eigenvalue λ usually corresponds to the dominant eigenvector χ. This captures the most significant information about the network's structure and influence.

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix} \text{ x } \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 2 \\ 4 \end{bmatrix}$$

Normalized score

$$Normalized\_\chi = \sqrt{1^2 + 2^2 + 3^2 + 2^2 + 4^2} = 5.830952$$

First iteration,

$$\begin{bmatrix} 0.171 \\ 0.343 \\ 0.514 \\ 0.343 \\ 0.686 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix} \text{ x } \begin{bmatrix} 0.171 \\ 0.343 \\ 0.514 \\ 0.343 \\ 0.686 \end{bmatrix} = \begin{bmatrix} 0.686 \\ 1.200 \\ 1.372 \\ 1.200 \\ 1.372 \end{bmatrix}$$

Second iteration,

$$Normalized\_\chi = 2.6679$$

$$\begin{bmatrix} 0.257 \\ 0.450 \\ 0.514 \\ 0.450 \\ 0.514 \end{bmatrix}$$

This runs until the normalized scores converge.

$$\begin{bmatrix} 0.217 \\ 0.412 \\ 0.524 \\ 0.412 \\ 0.583 \end{bmatrix}$$

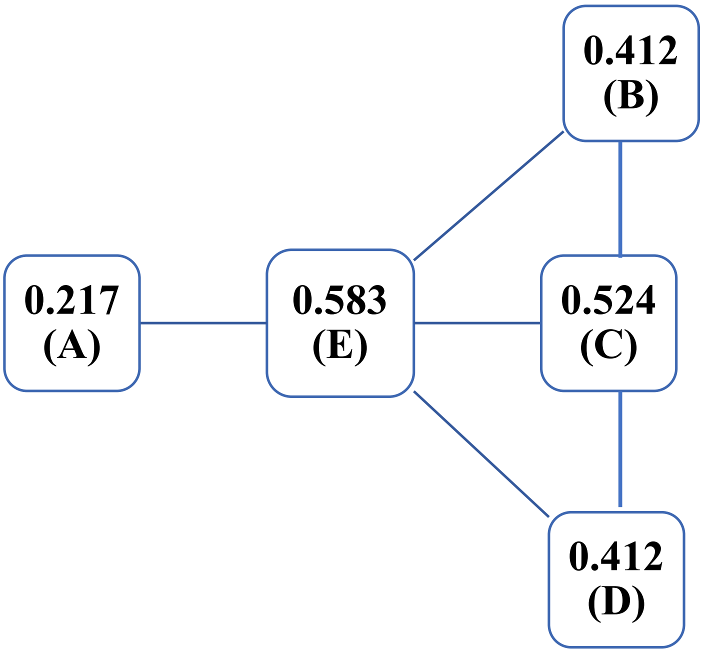


Figure 2. 7: Eigenvector Centrality Measure
The figure shows the eigenvector centrality measures, i.e., the strength of the connection and its connection for II as per their holdings in Figure 2.2.

Difference with Common Ownership

Often measured as the percentage of overlapping ownership between companies or the concentration of ownership held by specific institutions. It identifies the extent to which the same II hold ownership stakes across multiple companies. Common ownership captures the concentration of ownership across multiple entities within an economic system. While centrality measures are the quantified scores representing how well-connected an investor is compared to others in the network. They also signify the relative importance of investors within the network. Therefore, centrality measures capture a different aspect of interconnectedness.

Appendix B: Definition of Variables

Panel A: Sustainability Measures	
Ln_GHG_Abs_Scp1	(Natural logarithm of) Scope 1 emissions are direct greenhouse gas emissions from a company's owned or controlled sources. Source: Trucost.
Ln_GHG_Abs_Scp2	(Natural logarithm of) Scope 2 emissions are indirect greenhouse gas emissions from purchased electricity, heat, or steam used by a company. Source: Trucost.
Ln_GHG_Abs_Dir	(Natural logarithm of) Direct emissions from a company's own operations, typically including company controlled processes. Source Trucost.
Ln_GHG_Abs_Indir	(Natural logarithm of) Indirect emissions resulting from the company's energy consumption or other activities in the value chain such as purchased electricity or outsourced activities. Source Trucost.
Ln_Ref_GHG_Abs_Scp1	(Natural logarithm of) Scope 1 emissions are direct greenhouse gas emissions from a company's owned or controlled sources collected from publicly available sources. Source: LSEG.
Ln_Ref_GHG_Abs_Scp2	(Natural logarithm of) Scope 2 emissions are indirect greenhouse gas emissions from purchased electricity, heat, or steam used by a company collected from publicly available sources. Source: Trucost.
Ln_Gr_Patents	(Natural logarithm of) Environment-related innovations that protect the environment and promote sustainability. Source: Thapa *et al.* (2023).
CCE	A relative measure representing the frequency of bigrams related to climate change representing climate change events or challenges faced by the firm. Source: Sautner *et al.* (2023a).
D(ΔCCE > 0)	A dummy variable that takes the value of one if the change in climate change exposure was positive and zero otherwise. Source: Sautner *et al.* (2023a).

Panel B: Institutional Investors Network (II_centrality)	
$Degree\_centrality_{jt}$	Measures how connected an II is based on the number of direct connections. It identifies an investor's popularity within the financial network. Source: S&P Capital IQ, NetworkX package python.
$Betweenness\_centrality_{jt}$	Measures the extent to which a node lies on the shortest path between other nodes. Identifies investors that act as critical intermediaries between other investors. Source: S&P Capital IQ, NetworkX package python.
$Closeness\_centrality_{jt}$	Measures how quickly an investor can connect with others. It identifies investors with efficient access facilitating swift communication. Source: S&P Capital IQ, NetworkX package python.

Eigenvector_centrality $_{jt}$	Highlights investors connected to other influential investors, emphasizing quality over quantity. It captures the importance of an investor based on the importance of its connections. Source: S&P Capital IQ, NetworkX package python.
II_centrality_Nscore $_{jt}$	I develop a metric derived from II's centrality measures where investors are ranked into quintiles based on their centrality. It captures whether an II is in the most central quintile of the network indicating their potential influence relative to others. Source: S&P Capital IQ, NetworkX package python.
II_centrality_Factor $_{jt}$	Factor Analysis helps identify underlying latent factors that drive relationships between the different centrality measures. It captures common underlying dimensions that explain variations in II influence. Source: S&P Capital IQ, NetworkX package python.
II_centrality_PCA $_{jt}$	Principal Component Analysis (PCA) reduces multiple centrality measures into a variable with uncorrelated components. The dominant features of an investors network are simplified into key independent components. Source: S&P Capital IQ, NetworkX package python.
II_centrality_Ortho $_{jt}$	Orthogonalization helps ensure that different centrality measures for II are uncorrelated, removing shared variance to clarify each measure's unique contribution. It captures the independent aspects of network position for each centrality measure isolating distinct dimensions of investor influence. Source: S&P Capital IQ, NetworkX package python.

Panel C: Heterogeneity of Institutional Investors

D(Active)	A dummy variable that takes the value of one if an investor is classified as "Active" and zero if "Passive". I base it on investor orientation that classifies II as active and passive. Source: S&P Capital IQ.
D(Independent)	A dummy variable that takes the value of one if an investor is classified as an "independent" investor and zero if a "grey" investor. Based on the institutional type, I categorize "Corporate Pension Plan Sponsor", "REIT/Real Estate Investment Manager", "Structured Finance Pool Manager", "Traditional Investment Manager", "Government Pension Plan Sponsor", "Hedge Fund Manager/CTA", and "Union Pension Plan Sponsor" investors as independent investors. I categorize "Bank/Investment Bank", "Endowment Fund Sponsor", "Family Office/Family Trust", "Foundation Fund Sponsor", "Government Pension Plan Sponsor", "Sovereign Wealth Fund", "Unclassified", "VC/PE Firm" investors as grey investors. (Ferreira & Matos 2008; Marshall *et al.* 2022). Source: S&P Capital IQ.
D(PRI)	A dummy variable that takes the value of one if the investor is a PRI signatory and zero otherwise. Sources: S&P Capital IQ, PRI signatory database.

D(PRI_ESG)	A dummy variable that takes the value of one if a PRI investors have high (top tercile) ESG weighted portfolio scores and zero if low (bottom tercile) ESG weighted portfolio scores. Sources: S&P Capital IQ, PRI signatory database, LSEG.
D(Large)	A dummy variable that takes the value of one if an investor is considered a large investor and zero otherwise. I assess the investor's size based on the median ownership threshold, categorizing it as large if above and small otherwise. Source S&P Capital IQ.
D(Long-Term)	A dummy variable that takes the value of one if an investor is a long-term investor and zero if a short-term investor. I categorize pension funds as long-term II. Based on the institutional type, I include "Corporate Pension Plan Sponsor", "Government Pension Plan Sponsor", and "Union Pension Plan Sponsor" investors. I categorize hedge funds as short-term II. Based on the institutional type, I include "Hedge Fund Manager/ CTA" investors (Chen *et al.* 2007; Marshall *et al.* 2022). Source: S&P Capital IQ.
D(Foreign)	A dummy variable that takes the value of one if an investor is domiciled in a country different than that of the investee firm and zero otherwise. Source: S&P Capital IQ.
D(US)	A dummy variable that takes the value of one if an investor is domiciled in “United States of America” and zero otherwise. Source: S&P Capital IQ.
Big Three	A dummy variable that takes the value of one if an investor is BlackRock, Vanguard, or State Street Global Advisor. Source: S&P Capital IQ.
Non-Big Three	A dummy variable that takes the value of zero if an investor is not the Big three. Source: S&P Capital IQ.
Large	A dummy variable that takes the value of one if an investor is considered a large investor based on the median ownership threshold. Source: S&P Capital IQ.
Small	A dummy variable that takes the value of zero if an investor is considered a small investor based on the median ownership threshold. Source: S&P Capital IQ.
Blockholder	A dummy variable that takes the value of one if an investor is considered a blockholder based on the five % ownership threshold. Source: S&P Capital IQ.
Non-Blockholder	A dummy variable that takes the value of zero if an investor is not considered a blockholder based on the five % ownership threshold. Source: S&P Capital IQ.

Panel D: Control variables

Clique_Own	Using Louvain’s algorithm to identify coordination among II.
Size	The natural log of total assets (WC02999). Source: LSEG.

MTB	Market capitalization (WC08001) over common shareholders equity (WC03501). Source: LSEG.
Leverage	Total debt (WC03255) over total assets (WC02999). Source: LSEG.
ROA	Earnings before interest and tax (WC18191) over total assets (WC02999). Source: LSEG.
PPE	Plant, property, and equipment (WC02501) over total assets (WC02999). Source: LSEG.
Dividend	Total dividends paid (WC04551) over net income (WC01751). Source: LSEG.
Return	Total investment return for the year (WC08801). Source: LSEG.
Growth	Percentage growth in revenue (WC01001) in the current year compared to the previous year. Source: LSEG.
Cash	Cash holdings (WC02003) over total assets (WC02999). Source LSEG.
Research_intensity	Research and development expenses (WC01201) over total assets (WC02999). Firms with missing information are given zero. Source LSEG.
HHI	HHI is based on the ICB sub-sector level computed as $\sum_{i=1}^{N} s_i^2$. s represents the proportion of sales for firm i within the firm's sub-sector industry and N is the total number of firms in that industry. Source LSEG.

Panel E: Instrument	
$Ln\_Distance_{ijt}$	The average distance between the focal institutional investor and all other II holding equity in a portfolio company. Source: S&P Capital IQ, Awesome Table by Google.

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