Technological Green Innovation and Financial Markets

PhD Thesis

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Thesis Submitted in Fulfilment of the Requirement for the Degree of Doctor of Philosophy

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July, 2024

Declaration of Authenticity and Author's Rights

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

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Date: 31 July 2024

Abstract

This PhD thesis comprises three empirical chapters investigating the impact of technological green innovation (TGI) on equity markets. The first empirical chapter examines whether institutional investors (IIs) invest more in firms with higher levels of TGI intensity and whether such investments depend on the characteristics of IIs. I answer these questions by employing a time-varying investor-level dataset of IIs' equity ownership of their investee firms across 50 countries and exploiting the 1st Kyoto Protocol commitment as an exogenous variation to TGI. The results indicate that firms with higher TGI (TGI firms) draw higher equity ownership from IIs. Further, the attractiveness of TGI depends on the heterogeneous characteristics of IIs. Specifically, I find that IIs that are independent and have longer-term investment horizons invest more in TGI firms.

In the second empirical chapter, I examine the effects of TGI intensity on financial analysts' perspectives of TGI firms. In particular, I investigate if firms engaged in TGI development can attract more active involvement of analysts (i.e., the number of analysts following the firm, revisions of recommendations, and the quality of earnings forecast). We apply the same setup employed in the first empirical study. The results suggest that financial analysts have a negative view of TGI firms, evidenced by reduced analyst coverage and the downgrading of their recommendations. TGI intensity also adversely affects the analysts' forecast accuracy and consistency in earnings forecasts.

The third empirical chapter focuses on the short-term relationship between TGI information and investors' perceptions. I employ non-technological green innovation (non-TGI) to investigate the market reaction to TGI and non-TGI information. Using the Japanese stock exchange, which dominates the largest innovative patents of globally listed

firms, discovers the negative response of investors to both TGI and non-TGI information, and there is no difference in the market reaction among them. However, including the 1st Kyoto Protocol commitment as a regulation indicator demonstrates that the regulation has a negative impact on the market reaction to non-TGI information, while it does not influence the market reaction to TGI information. In addition, the evidence suggests that the value of analysts' recommendations is associated with the TGI information.

My empirical evidence suggests that market participants (i.e. investors and financial analysts) have different perspectives on TGI activities regarding the implications on firms' environmental and financial performance. Short-term operating uncertainty rising along TGI activities can impede investors and financial analysts from incorporating the value of TGI benefits, reducing the value of TGI firms. On the other hand, firms engaged in TGI activities promote long-term maximisation through operating performance and sustainability, which can support stakeholders' long-term benefits.

Acknowledgements

First of all, I would like to convey my deep appreciation to my supervisors, Professor Krishna Paudyal and Professor Chandra Thapa, for their exceptional assistance, recommendations, and, above all, encouragement throughout the PhD journey.

I am grateful for the valuable experience and opportunity to undertake my PhD research on Technological Green Innovation and Capital Markets at the University of Strathclyde.

Special thanks to the Department of Accounting and Finance for providing world class facilities, and especially to the professors for their wealth of knowledge and to guide me in my research, and all staffs for their encouragement.

I would also like to express my deepest gratitude to my parents for their unwavering support throughout my academic journey. Their encouragement, patience and belief in me have been the foundation upon which built my success.

I am especially grateful to my loving wife, Anyaphat Chetteeraphat, for her unwavering assistance and motivation. The progression would not have yielded such abundant results devoid of her unconditional care and support.

I am thankful to Chiang Mai University and the faculty of Business Administration for the full scholarship, which allowed me to receive valuable experience.

Finally, my special acknowledgements go to my colleagues at Chiang Mai University, especially Dr. Chanon Chingchayanurak and Dr. Anin Rupp, for their advice in developing the PhD research. Thank you all for all the encouragement!

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List of Abbreviations

Abbreviation	Full term
BM	Book-to-Market
CAR	Cumulative Abnormal Return
CO2	Carbon Dioxide
CPC	Cooperative Patent Classification
CSR	Corporate Social Responsibility
DiD	Difference-in-Differences
DIIs	Domestic Institutional Investors
DIO	Domestic Institutional Ownership
EMS	Environmental Management System
EPO	European Patent Office
EPS	Earnings-per-Share
ESG	Environmental, Social, and Governance Performance
ETS	Emissions Trading Scheme
EU	European Union
FDI	Foreign Direct Investment
FIIs	Foreign Institutional Investors
FIO	Foreign Institutional Ownership
GHG	Greenhouse Gas
HML	High Minus Low
IIs	Institutional Investors
IMF	The International Monetary Fund
IO	Institutional Ownership
IPC	International Patent Classification
ISIN	International Securities Identification Number
ISO	International Organization for Standardization
ITC	International Trade Centre
JPO	Japan Patent Office
MSCI-ACWI	Morgan Stanley Capital International's All-Country World Index

Abbreviation	Full term
NRBV	The Natural-Resource-Based View Theory
OECD	The Organisation for Economic Cooperation and Development
PATSTAT	The World Patent Statistical Database
PSM	Propensity Score Matching
R&D	Research & Development
ROA	Return on Assets
ROE	Return on Equity
SB	Standardized Bias
SMB	Small Minus Big
TGI	Technological Green Innovation
TISE	The International Stock Exchange
TOPIX	Tokyo Stock Price Index
UK	United Kingdom
UNCTAD	United Nations Conference on Trade and Development
UNFCCC	The United Nations Framework Convention on Climate Change
USTPO	The United States Patent and Trademark Office
WIPO	The World Intellectual Property Organization
WMO	The World Meteorological Organization

1. INTRODUCTION

1.1 Overview and Motivation for the Study

In recent decades, the information pertaining to climate change have stimulated social actions to prevent future climate catastrophes. According to the World Meteorological Organization (WMO) report, global surface temperature reached 1.15 Celsius above the pre-industrial era (1850 – 1900), and there is much concern over what is considered the major contributing factor: greenhouse gas emissions (GHGs). The report state that GHGs are increasing by roughly 1% in 2022 relative to 2021[1]. The report raises a question about the potential of environmental policy enforcement mechanisms aimed at mitigating climate change[2]. In fact, this evidence emphasises the crucial role of global participation and requests a solid commitment to climate risk prevention.

Although international cooperation committed to preventing climate change widely motivates social perceptions of the importance of sustainable development, the engagement of governments, policymakers, private sectors, and academics is crucial in driving environmental practices to reduce climate issues. In particular, the shifting views of financial market participants towards sustainability enhance the economic benefits of the global green transition. A large body of studies highlights the growing impact of sustainability on business performance (Ambec and Lanoie, 2008, Guenster et al., 2011

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[1] United in Science 2023, Sustainable development edition
https://library.wmo.int/records/item/68235-united-in-science-2023

[2] For instance, United Nations Framework Convention on Climate Change (UNFCCC) has launched the Kyoto Protocol in December 1997 to decrease GHG emissions by 5.2% on average compared to the GHG emission level in the base year 1990 (UNFCCC, 2007). The European Union has initiated the Emission Trading System in 2005 to enforce polluters pay for their GHG and pressure them to limit their GHG emissions. The Paris Agreement is a legally binding international treaty on climate change which is adopted by 196 parties to limit the temperature increase to 1.5°C by the end of this century (UNFCCC, 2015).

and Lanoie et al., 2011) and promotes the implications through market value and investment opportunities (Dyck et al., 2019, Azar et al., 2021 and Marshall et al., 2022).

However, recent studies disclose nonparallel actions of investors' decision-making on responsible investing preferences. Transition and pollution risks still push higher stock returns in high-polluting industries (Görgen et al., 2020, Bolton and Kacperczyk, 2021a, 2022a and Hsu et al., 2023). Bolton and Kacperczyk (2021a) suggest a hypothesis that investors cannot efficiently identify carbon risk, leading to the underpricing of risks linked to carbon emissions. Starks (2023) addresses the idea of *value versus values-based* preferences in financial market participants' decision-making, representing pecuniary and nonpecuniary expectations in sustainable investment. Market participants, such as investors and managers, may prioritise investment strategies based on their pecuniary and nonpecuniary motives. Understanding climate-friendly investing behaviour requires more theoretical frameworks to identify *value versus values-based* preferences. Moreover, the more controversial perspectives bring my inquisitiveness to the implications of climate-friendly development strategies on financial markets. To this end, this thesis investigates whether a firm's engagement in technological green innovation (TGI) affects the financial market participants' views towards the firm.

Focusing on the responses of financial market participants in climate-friendly activities helps us better identify their views regarding the commitment to sustainable practices. This is because evidence from business studies reveals the diverse effects of sustainable strategies on firms' performance and the levels of uncertainty. Darnell and Edwards (2006) documents that the higher operating costs are related to adopting climate-friendly strategies. Some corporate decisions related to environmental development do not lead to firms' future growth and profitability (Klassen and McLaughlin, 1996, Ghisetti and Rennings, 2014 and Rexhäuser and Rammer, 2014). Furthermore, it is possible that managers tend to manipulate sustainability measurements instead of improving them. Bose et al. (2021) report that firms may acquire an offshore firm located in a country with weak environmental policies to avoid environmental risk disclosure. Existing evidence indicates the importance of exploring the nexus between firms' climate-friendly strategies and markets' perceptions. In particular, firms engaged in TGI activities represent a commitment to environmental practices.

To our knowledge, the initiation of innovative advantages on economic value has been addressed by Schumpeter (1942). The level of technological knowledge significantly boosts marginal productivity and supports productivity optimisation in aggregate production functions (Segerstrom et al., 1990, Aghion and Howitt, 1992 and Boutellier, 2014). The impact of technological knowledge spillover motivates inventors to seek better long-term productivity functions. The demand for new technologies leads academic fields to promote environmentally friendly innovation that supports sustainability improvement along with economic benefit enhancement, e.g. operating performance, cost and resource reduction, industrial competitiveness, and managerial cost reduction on pollution (Shrivastava, 1995, Ambec and Lanoie, 2008 and Lanoie et al., 2011). Moreover, the implications of TGI activities could promote firms' potential ability to mitigate climate regulation risks.

Increasing climate risk awareness encourages firms' stakeholders to look for corporate actions and appeals the managers to make strategic decisions to maintain the maximisation of their benefits. Investing in TGI can be a primary solution for the firms to satisfy stakeholders' expectations and reduce social pressure. Firms allocating more resources to TGI activities also reflect management's perspective regarding a degree of environmental commitment, which can attract investors' investment and increase firm value under environmental regulation uncertainty. However, the paucity of literature on the association between managers' TGI decisions and the responses of market participants motivates me to investigate this issue.

Shrivastava (1995) defines TGI as technologies involving productivity functions such as production equipment, methods and procedures, product designs, and product delivery mechanisms which consider energy and natural resources conservation, minimising the environmental damage caused by human activities, and maintaining the environment. In this thesis, I identify TGI following Haščič and Migotto (2015) working paper published by the Organisation for Economic Cooperation and Development (OECD). They describe TGI identification by selecting a technological patent related to four primary environmental policy targets, i.e., environmental health impacts, water scarcity, ecosystem health and biodiversity treatments (e.g., water and wastewater treatment) and climate change mitigation. Based on these policy objectives, they identify TGI classifications into seven categories:

- Environmental management
- Water-related adaptation technologies
- Biodiversity protection and ecosystem health
- Climate change mitigation technologies related to energy generation, transmission or distribution
- Capture, storage, sequestration or disposal of greenhouse gases

- Climate change mitigation technologies related to transportation
- Climate change mitigation technologies related to building

For decades, strategic management literature has identified the necessity of developing innovation related to environmental prevention in supporting economic growth through the aspect of the Natural-Resource-Based View theory (NRBV). Hart (1995) documents that NRBV highlights the concept of the relationships among firm resources, capabilities, and sources of competitive advantage. Business strategies connected to pollution prevention, product stewardship, and sustainable development create more opportunities for firms to gain competitive industrial advantages. Firms investing in TGI development can effectively utilise internal and external resources, affecting competitive advantage capability. For example, the transition to using TGI can increase manufacturing efficiency, create a barrier to imitating external competitors, and reduce the costs of input raw materials and waste in the production process. TGI activities also support product stewardship by improving the value chain of businesses, e.g., by minimising the life-cycle environmental costs of their product systems.

Furthermore, Porter and Van Der Linde (1995) indicate that the arrival of a new environmental policy changes the paradigm of business strategic competitions, e.g. accessing the cheapest raw materials or dominating the largest productivity functions, into environment-related technology competition, which focuses on productivity efficiency. They argue that TGI activities reduce the operating costs of arriving environmental regulations, fully offset the costs of complying with said regulations, and offer more advantages over industry peers. One possibility is that innovation in response to environmental regulation can reduce the amount of pollution and/or harmful material generated, leading to the cost reduction of compliance with pollution control. Moreover, the value of TGI can exceed compliance costs depending on the TGI types, i.e., product and process innovations. TGI leads to higher-quality, environmentally friendly products, and lower product costs. Meanwhile, TGI-related production processes generate productive efficiency by controlling pollution emissions and energy consumption. Shrivastava (1995) and Lanoie et al. (2011) suggest that the implications of the TGI transition will maximise benefits under stringent environmental regulations.

Existing business literature provides empirical evidence of TGI enhancing business sustainability. With regards to environmental development, Dangelico and Pujari (2010) survey the impact of TGI on firms committed to environmental sustainability, specifically green product innovation. They explain that a product claimed as being environmentally friendly will have less environmental impact throughout its life cycle, which includes disposing of packaging and consuming energy from transportation. By comparing the life cycle of conventional products, TGI products improve firms' environmental performance by enhancing pollution abatement. They also indicate that reducing the material used in packaging and adopting recycled or biodegradable materials will become the primary strategy in developing TGI to reduce the additional costs from regulation enforcement. Chen and Chang (2013) survey that firms with environmental capabilities, e.g. green knowledge and technologies, are confident about developing environmentally friendly production through TGI transformation. Kraus et al. (2020) and Rehman et al. (2021) discover that increasing TGI activities enhance firms' environmental performance. Yusliza et al. (2020) suggest that cleaner production development in the manufacturing industry is related to the growth of green intellectual capital. Moreover, Wurlod and Noailly (2018) explore climate-friendly development through energy consumption in 14 industries, finding that TGI development can decrease energy consumption intensity in production processes.

On the other hand, some studies that debate the impact of TGI on environmental development. Lanoie et al. (2011) uncover that TGI may not affect environmental performance if firms tend to invest more in product-related TGI. Cohen et al. (2020) find that TGI benefits disconnect from environmental performance because most TGI patents are owned by energy industry firms, which do not aim to improve environmental performance but to dominate the competition for innovative technologies. However, they find that products related to TGI, including products from energy industries, positively impact pollution abatement.

In terms of financial performance contributions, Shrivastava (1995) and Ambec and Lanoie (2008) identify that firms promoting TGI activities support sustainable growth through revenue enhancement that could be achieved through improved social image and reputation, ability to enter new markets with differentiating products, selling TGI, as well as cost reductions (e.g. by waste management costs, raw material costs and cost of capital). Lanoie et al. (2011) and Cheng et al. (2014) indicate that firms engaged in TGI under stringent environmental regulation can support their operating profitability. Meanwhile, studies suggest that typologies of TGI matter to firms' future profitability. For example, Ghisetti and Rennings (2014) provide evidence that innovation that improves material and energy consumption efficiency is more profitable than innovation that reduces pollution emissions. Similarly, Rexhäuser and Rammer (2014) find that operating profitability is associated with TGI related to environmental regulations and production efficiency, but profitability is not related to TGI typologies reducing pollution emissions. Furthermore, Dechezleprêtre et al. (2020) show the different effects of firms with clean and dirty innovations on stock market value. They indicate that potential clean innovation can increase stock values due to the ability to reduce costs and mitigate regulatory risk.

These studies show that TGI implications significantly impact nonpecuniary and pecuniary dimensions. These implications can motivate market participants to support shifting investment strategies toward climate-friendly engagement. However, the existing literature lacks empirical evidence on the effect of TGI activities on market participants. The lack of such evidence potentially affects the investment decisions of corporate managers regarding TGI development and environmentally friendly strategies, which also impacts the maximisation of the benefits of stakeholders. Therefore, this thesis aims to identify the responses of financial market participants (investors and financial analysts) to the firms engaged in TGI development. I focus on whether (and how) the market participants, such as institutional investors and financial analysts, respond to the firms that are engaged in TGI activities. This study provides evidence on the long-term and short-term implications of firms' engagement in TGI from the perspectives of institutional investors and financial analysts. This thesis addresses three key questions pertinent to the implications of TGI on market participants' views with respect to firms' involvement in TGI activities. Each of the three key issues is addressed in an empirical chapter. The first empirical chapter (Chapter 2) examines the association between firms promoting TGI activities and institutional investors. The second empirical chapter (Chapter 3) investigates the levels of TGI intensity and financial analysts' forecasts. The third empirical chapter (Chapter 4) identifies investors' short-term responses to the news of firms' TGI activities.

The evidence reported in these chapters helps me identify the implications of environmental strategies-related decisions of corporate managers to investors and analysts.

1.2 Does Technological Green Innovation Attract Institutional Investors?

1.2.1 Motivation

The first empirical chapter investigates whether a firm's engagement in TGI affects the investment of institutional investors (IIs) in that firm. My study documents the long-term view of institutional investors' investment in firms promoting TGI activities. I also indicate the possibility of the bond between firms engaged in TGI and institutional investors being stronger under regulation uncertainty.

A growing body of literature proposes a paradigm shift into sustainable investment in financial markets (Dyck et al., 2019, Azar et al., 2021 and Starks, 2023). Bolton and Kacperczyk (2021a) suggest that the preference of sustainable investors to hold their investment in low-polluting firms impacts asset pricing and excess returns of the stocks. They also find IIs' divestment in industries with disproportionate carbon emissions. Marshall et al. (2022) reveal that firms committed to sustainable development attract more investment from foreign institutional investors. Rising climate risk awareness also generates higher stock liquidity in sustainable firms (Krueger et al., 2023).

Existing studies expose convincing arguments behind ESG issues related to investors' investment. Krueger et al. (2020) suggest that the rising concerns about environmental regulations push investors to invest more in firms improving sustainability. Pástor et al. (2020) indicate that investors holding sustainable assets receive greater benefits than those holding assets ignoring sustainability, such as mitigation of unexpected risks in customers' demand shifts and lower costs of investment capital. Studies also suggest that investors' climate concerns and mounting social pressure motivate investors to modify their investment strategies into firms committed to sustainability (Dyck et al., 2019 and Starks, 2023). These convincing arguments emphasise opportunities for investors to gain more investment benefits along with participation in environmental practice. These studies also indicate the possibility for firms investing in TGI to attract more investment from IIs.

As discussed in Section 1.1, the NRBV theoretical frameworks argue that firms engaged in TGI gain significant business advantages over their industry peers, e.g., reductions in operational, resource, and capital costs (Shrivastava, 1995 and Ambec and Lanoie, 2008). Moreover, firms investing in TGI can gain long-term premium profits using the end-of-pipe approach or developing new manufacturing functions complying with environmental policies (Russo and Fouts, 1997). These benefits of TGI engagement can enhance firms' future value and attract IIs. Thus, I examine the nature of, if any, association between a firm's engagement in TGI activities and the investments of IIs.

In addition, my study investigates the heterogeneity of IIs to understand conditional preference based on IIs' characteristics, i.e., independent versus grey IIs, and long-term versus short-term IIs. For independent versus grey, I consider that IIs' investment decisions depend on professional money managers' potential to monitor firms' operations (Ferreira and Matos, 2008). The higher business monitoring concerns of independent IIs over grey IIs will incentivise them to consider firms engaged in TGI to maintain portfolio performance as well as a reputation for being socially and environmentally conscious. Furthermore, I suggest IIs with different investment strategies (long-term and short-term) will express different perspectives on investing in TGI firms. For example, short-term IIs tend to force corporate managers to increase short-term performance but pressure them to reduce long-term value-enhancing investments. Meanwhile, long-term IIs diversify portfolios into green and environment-friendly assets to manage climate risks (Krueger et al., 2023) and support innovative development (Luong et al., 2017). These different investment perspectives inspire me to identify the relationship between firms engaged in TGI and the heterogeneous characteristics of IIs.

1.2.2 Findings and Discussions

The first empirical chapter addresses the impact of firms engaged in TGI on IIs' investment by investigating domestic institutional investors (DIIs) and foreign institutional investors (FIIs) separately. I set up an identification strategy through the triple difference model (DiDiD) using the 1^{st} Kyoto Protocol commitment as an exogenous shock indicator. My main evidence indicates that the stock ownerships of both DIIs and FIIs are positively related to levels of TGI intensity. This finding implies that firms investing in TGI can attract DII and FII investment portfolios. The evidence is robust to placebo experimentation when I provide a false exogenous shock period.

Regarding Dyck et al. (2019) and Azar et al. (2021), suggest that IIs tend to participate more in firms' environmental practices to reduce social pressures. It is possible that firms engaged in TGI increase the attention of DIIs and FIIs as the TGI intensity shows an intentional signal of environmental commitment, which supports IIs' image and reputation. This is because investing in TGI requires management's effort to provide technical experts, knowledge, and large financial capital (see Holmstrom, 1989, Ayyagari et al., 2011 and Brown et al., 2012). A successful TGI implies a firm's intensive effort in response to the expectations of customers, regulators and stakeholders.

Moreover, it is possible that firms engaged in TGI activities can support the investment of IIs who are concerned about the impact of regulation risk (Krueger et al., 2020). The identification under the environmental regulation setup points out investors' positive view on TGI implications to firms' financial performance. Following the NRBV, TGI adoption leads to improved production and manufacturing processes which make more efficient use of internal and external resources (Hart, 1995 and Shrivastava, 1995). The green transition by a TGI mechanism reduces external costs of regulation compliance (Porter and Van Der Linde, 1995). These TGI implications enhance firms' competitive advantages and sustainable growth, which induces the investment of IIs under compliance with environmental regulation.

Next, my findings show that firms with higher TGI intensity attract the investment of independent IIs more than grey IIs. The finding supports my prediction of the characteristics and behaviours of professional money managers and their potential to monitor managers' decisions actively. Ferreira and Matos (2008) suggest that independent IIs (mutual funds and independent investment advisors) are active investors in the role of monitoring, and grey IIs (banks, insurance companies, and other institutions) are passive investors. Independent IIs are intensively involved in shareholder wealth, corporate governance, and social responsibility. They are keen to build a greater reputation among associated firms (Ferreira and Matos, 2008 and Dyck et al., 2019). Holding ownership in a firm promoting TGI activities elevates independent IIs' reputation and reduces their monitoring costs. In contrast, grey investors, who monitor business operations far less and tend to tie business relationships with investee firms, will support managerial myopia rather than long-term innovative development.

Finally, with regard to styles of investment strategies, I find that long-term IIs invest in firms engaged in TGI more than short-term IIs. Bushee (1998) and Chen et al. (2007) documents that investors committed to short-term strategies can actively pressure the management of firms to make decisions that favour said strategies. Investors with long-term strategies neither need nor promote such myopic outlooks among management. Furthermore, Luong et al. (2017) indicate that long-term IIs (passive investors) holding long-term capital have more potential to contribute to firm innovation compared to short-term IIs. Therefore, firms promoting TGI activities attract long-term IIs but they may not be attractive to IIs with short-term aims. This is because the potential benefits of TGI activities, such as increasing firms' competitiveness, production efficiency and profitability, are likely to be achieved only in the long-term.

1.2.3 Contributions

The findings of the first empirical chapter contribute to the literature pertinent to the determinants of IIs' preferences (Ferreira and Matos, 2008). The existing literature addresses non-pecuniary factors affecting IIs' investment decisions, such as corporate governance quality and mechanisms (Leuz et al., 2009, Chung and Zhang, 2011 and McCahery et al., 2016) and climate regulations in explaining the variations in IIs' allocations (Krueger et al., 2020, Marshall et al., 2022 and Ilhan et al., 2023). Studies also explore the connection between environmental strategies' outputs and IIs' investment, such as ESG disclosure (Krueger et al., 2023) and pollution emissions (Bolton and Kacperczyk, 2021a, 2022a). To this body of literature, my study adds evidence on the investors' responses to climate risk. My evidence indicates that firms engaged in TGI, which implies a credible commitment to firms' non-pecuniary and pecuniary development, attract more IIs' investment.

My findings contribute to the literature on firms' innovative activities and investors' perspectives (Daniel and Titman, 2006, Pastor and Veronesi, 2009 and Hirshleifer et al., 2013). Existing studies mainly investigate how investors respond to innovative firms through stock price variations (Chan et al., 2001, Eberhart et al., 2004 and Gu, 2005). Although the literature suggests that divestment of investors presses the equity price of innovative firms due to uncertain risks, the evidence still has been debated. Moreover, studies note that FIIs tend to attend more innovative activities compared to DIIs (Ayyagari et al., 2011, Guadalupe et al., 2012 and Bena et al., 2017). I add to this strand of literature by suggesting that DIIs and FIIs are attracted more to firms engaged in promoting TGI.

Finally, I add to the literature on the heterogeneity of IIs' preferences. Literature shows that larger size IIs have more potential to reduce the firms' carbon emissions (Azar et al., 2021). Bolton and Kacperczyk (2021b) find that insurance companies, investment advisers, or pension funds are more likely to face investor pressure to mitigate climate regulatory risks, leading them to avoid high-emission companies. Marshall et al. (2022) document that FII types, i.e., independent, long-term, and originating from civil law jurisdictions, are highly concerned about sustainable practice. My evidence points out that types of IIs reflect different perspectives on climate-friendly engagement. My findings identify that firms engaged in TGI gain more independent IIs' investment than grey IIs, and attract more long-term IIs than short-term IIs.

1.2.4 The Implications

Evidence in the first empirical chapter reveals the relationship between firms promoting TGI and institutional investors' ownership. Rising concerns about climate risks and social pressure draw IIs to focus more on investment in firms engaged in sustainability. However, it is essential for IIs to consider sustainable corporate strategies that are able to develop their reputation and portfolio profitability. Firms promoting TGI activities offer the reliability of environmental and financial development. Investors who hold TGI firms not only benefit from building their image related to environmental commitment but potentially gain investment returns from firms' competitive advantage in external cost mitigation of climate regulation risks. On the other hand, IIs are a crucial element in enhancing TGI investment in the financial markets. Developing a technological innovation requires large resources, e.g. knowledge and financial capital. Encouragement from all IIs, including funding from grey and short-term investors, is needed in the technological development process.

The evidence also suggests that the strategic decisions relating to green transition that are made by firm managers impact stakeholders' perspectives and the value of firms. Managers should be aware of valuable investment opportunities from each option, including the potential risk of investment communicated to their stakeholders. Likewise, investing in a technological innovation related to environmental engagement requires managers' ability to communicate among firms and investors. Managers who can transfer information on TGIs' potential benefits to investors, e.g. long-term growth opportunities, competitive advantages and climate risk mitigation, can attract more investment from investors.

1.3 Financial Analysts and Technological Green Innovation Firms

1.3.1 Motivation

The evidence in the first empirical chapter reveals the causal relationship between levels of TGI intensity and institutional investors, the findings prompted me to investigate and understand other stakeholders' perceptions regarding firms promoting TGI activities. Therefore, the second empirical chapter aims to investigate the view of financial analysts as influential participants in driving financial market investment. This chapter constructs an argument following the career concern hypothesis trading off the TGI implications between the compensation following the market expectation versus reputational risk (McNichols and O'Brien, 1997 and Harford et al., 2019).

Prevailing information asymmetry in imperfect financial markets raises the crucial level of the financial analyst's role as an intermediary in increasing the efficiency of information dissemination. Studies note that financial analysts can be influential players in controlling markets' responses to firms' specific information. Womack (1996) argues that analysts' recommendations embody valuable information to investors. The study shows that the stock price impact of analysts' recommendations is not mean-reverting but significant and is in the direction forecasted by the analysts. Existing literature indicates that the impact of analysts' informativeness on stock price movement is also conveyed via other activities, e.g. earnings forecasts (Piotroski and Roulstone, 2004), adding(dropping) firms in analysts' coverage portfolios (Chan and Hameed, 2006), and characteristics and reputation of analysts (Loh and Stulz, 2011).

On the other hand, the informativeness of analysts' recommendations and earnings forecasts can be influenced by investors' preferences. Harford et al. (2019) suggest that analysts tend to put more effort into firms that are attractive to investors, e.g., large market capitalisation, trading volume, and size of institutional ownership. They argue that the pressure from brokerage houses and competition in the analysts' labour market affect analysts' concerns regarding their careers, which causes them to consider covering the firm that can promote their reputations. Jackson (2005) notes that analysts' commissions based on covered firms' trading value may lead analysts to upwardly bias their forecasts and recommendations, depending on levels of market preferences in the firms. These arguments raise questions about analysts' behaviours alter due to increased sustainable investments in the capital market, particularly in firms supporting TGI.

Regarding the adverse effects of TGI intensity on firms' short-term financial performance and information environment, analysts who are conservative and prefer managerial myopia may believe that TGI intensity can damage their reputation. Studies document that analysts focusing on financial profitability induce managers to manipulate short-term profitability by reducing long-term investment projects (He and Tian, 2013 and Guo et al., 2019) This is because firms engaged in TGI intensity tend to increase profitability uncertainty, which impacts earnings forecasts (Kothari et al., 2002). Levels of TGI intensity also increase the firm's information asymmetry and complexity, causing the reduction of analysts' forecast ability (Bhattacharya and Ritter, 1983).

To investigate the stand of financial analysts in response to firms promoting TGI activities, I therefore suggest the argument of the career concern hypothesis to identify analysts have favourable/unfavourable biases about TGI intensity. I examine analysts' behaviours on firms engaged in TGI through their activities, i.e., covering the TGI firms, issuing recommendations, and forecasting future earnings.

1.3.2 Findings and Discussions

In this study, I identify the implications of firms promoting TGI development on financial analysts' activities, i.e. (a) changes in the number of analysts following the TGI firms, (b) changes in analysts' recommendations, and (c) the earnings forecast abilities. My main evidence suggests that analysts' career security and reputation concerns induce analysts' pessimism about firms promoting TGI activities.

First, higher TGI intensity decreases the number of analysts covering the firms. This evidence is consistent with the McNichols and O'Brien (1997) argument that analysts are favourably biased to cover a predictable firm with better operating performance. I posit that firms engaged in TGI transition decrease short-term profitability and increase cashflow uncertainty, which adversely affects analysts' earning predictions and reduces their favourable bias toward the firms. The short-term uncertainty of firms investing in TGI also dilutes stocks' attraction to investors, which adversely impacts the stock trading value relating to analysts' trading commissions. In addition, a firm with high TGI intensity reflects more information complexity, which causes analysts covering the firm to consider the potential benefit of covering industry peers by comparing resources used, costs of monitoring, and trading commissions (see discussion in Griffin et al., 2020).

Second, the finding suggests analysts are pessimistic about firms promoting TGI; and this is reflected in the downgrading of their recommendations. He and Tian (2013) and Lin (2018) argue that analysts are conservative and averse to uncertainty. Lin (2018) proposes that analysts are highly responsive to firms' uncertainty, leading them to overestimate new uncertain risks and offer unfavourable recommendations. Therefore, it is possible that TGI intensity increases the uncertainty regarding the prospects of firms' operating performance, causing analysts to overestimate uncertainty in fundamental changes and downgrade their recommendations.

Lastly, I find that TGI intensity is associated with the underperforming of analysts' forecast ability. The findings point out that firms engaged in TGI increase analysts' forecast errors and inconsistency of earnings forecasts. Hope (2003) notes that the conditions of firms' information environment connect to the informativeness of analysts. Firms with high information asymmetry and complexity potentially impede analysts' forecast ability. My evidence is consistent with this argument by indicating that TGI intensity raises short-term cash flow uncertainty and information complexity, adversely affecting analysts' ability to forecast the value of the firms.

1.3.3 Contributions

This empirical chapter contributes three strands of literature. First, I add literature pertinent to the implications of analysts' career concerns. Existing studies identify that analysts' career concern impacts their decisions in considering a firm they cover (Harford et al., 2019). McNichols and O'Brien (1997) note that analysts are induced to cover firms with high potential performance. Hong and Kubik (2003) find that analysts who provide optimistic forecasts will benefit more from their brokerage house. Frankel et al. (2006) document that firms with larger trading values and institutional ownership motivate analysts to produce reports frequently to generate more commission fee revenue for brokerage houses. My research adds to this strand of literature by demonstrating that the TGI implications on the firms' operating performance and information environment cause analysts to be pessimistic and tend to avoid firms engaged in TGI.

Second, I expand the literature on non-financial information connected to financial analysts' informativeness. Existing literature reveals non-financial factors affecting analysts' forecast ability. For instance, Dhaliwal et al. (2012) present that firms disclosing corporate social responsibility (CSR) reduce firms' information asymmetry and increase analysts' forecast ability. On the other hand, Ioannou and Serafeim (2015) argue that the relationship between analysts' recommendations and firms' CSR ratings is inverse because firms with higher CSR show greater agency costs and conflict of interest among managers and stockholders. literature also suggests that firms with greater environmental information disclosure increase analysts' information processing costs, which causes analysts to cover fewer firms and provide fewer forecast reports (Griffin et al., 2020). My study adds a new line of argument on the effect of environmental information on analysts' behaviours. I propose that a TGI activity increases information complexity, affecting analysts' forecast ability. Financial analysts are conservative and sensitive to firms' fundamental transformation through the TGI mechanism, reflecting the view on short-run operational costs and the cashflow volatility of TGI firms.

Finally, I contribute literature on environmental technologies and capital markets. Many studies promote environmental technologies in capital markets via long-term TGI contributions, e.g. sustainable performance (Shrivastava, 1995 and Ambec and Lanoie, 2008) and climate risk mitigation (Porter and Van Der Linde, 1995 and Rexhäuser and Rammer, 2014). However, the existing literature lacks systematic evidence that connects the short-term impact of firms engaged in technological activities. To the best of my knowledge, I propose a new systematic framework to understand these short-term TGI implications and capital markets through the view of financial analysts.

1.3.4 The Implications

My evidence highlights the consequences that arise from analysts' career concerns and their subsequent selection biases. Analysts' pessimistic bias towards firms promoting TGI activities can both enhance and damage their reputations. Analysts lacking technological knowledge and experience can avoid covering TGI firms, which creates high information complexity and uncertainty of future cash flow performance to maintain their forecast ability. However, heightened awareness toward climate risks and growing sustainable investment of investors can reward analysts covering TGI firms by offering greater trading commissions. These implications point out the necessity of analysts' knowledge and ability to assess the intrinsic value of technological investment, including the value associated with climate regulation management. Analysts who have better technological knowledge can build on their reputation and gain more trading commissions. Moreover, this ability can enhance their relationships with firm managers who aim to promote TGI activity information to the public.

On the other hand, in terms of corporate managers, they need to consider possible outcomes of TGI information disclosure; essentially, the trade-off between information leakage and stock value promotion. Offering more information regarding TGI activities to financial analysts can reduce firms’ information asymmetry and support analysts’ earnings forecasts, promoting firms' stock value, reducing pressure from stakeholders, and protecting against a hostile takeover.

1.4 Market Reactions and Analysts’ Recommendation Revisions on Technological Green Innovation

1.4.1 Motivation

In the third empirical chapter, I investigate the markets’ response to TGI information disclosure. According to the key findings in the first and second empirical chapters, the divergent TGI implications between institutional investors and financial analysts represent long-term and short-term views towards TGI value. In the meantime, the conflict between the TGI benefits and short-run uncertainty raises my question about the markets’ short-run perception of TGI information. To this end, I examine if TGI information impacts the investors’ reactions. Moreover, I indicate the consequences of analysts’ informativeness related to TGI information on the stock price impact.

Studies offer different arguments regarding investors’ reactions to the arrival of new information related to innovative activities. Studies indicate that firms announcing R&D investments motivate investors’ perception of firms’ future profitability and induce them to hold more stocks (Chan et al., 1990 and Szewczyk et al., 1996). On the other hand, Cohen et al. (2013) argue that investors overestimate innovation value from R&D

expenditures but cannot identify the value benefit of successful innovation. Eberhart et al. (2004) and Gu (2005) offer an inefficient market argument that investors delay incorporating corporate event information and underreact to the beneficial investment of innovation.

As reported by these existing studies, investors remain largely inconsistent in their response to innovative information. Debating investors' perceptions of the short-term value of innovation raises a question: Can firms promoting TGI activities that signify the reliability of future environmental development attract short-term investment from investors who are concerned about climate risks? To address this question, I provide multiple analyses to investigate the market reaction to TGI information.

First, I employ non-technological green innovation (non-TGI) to compare the market reaction to TGI and non-TGI information. As mentioned in Section 1.1, compared to non-TGI activities, generating maximum value of TGI activities requires better exogenous conditions related to environmental regulation (see Shrivastava, 1995, Ambec and Lanoie, 2008 and Lanoie et al., 2011). The uncertainty of TGI benefits to environmental and financial contributions can causes investors to underestimate the intrinsic value of TGI activities (Ghisetti and Rennings, 2014, Rexhäuser and Rammer, 2014 and Cohen et al., 2020). The lower reliability of TGI benefits can lead investors to neglect the information contained and underreact to TGI information compared to non-TGI information. The argument for investors' limited attention suggests that investors are more inclined to incorporate salient information into stock prices than less salient information (Hirshleifer and Teoh, 2003 and Hirshleifer et al., 2009).

Second, I offer the impact of the 1st Kyoto Protocol commitment to investigate investors' behaviour shift toward TGI information disclosure. Mainstream sustainable finance literature proposes that climate risks impact the investment decisions of investors, especially risks related to environmental regulations (Balachandran and Nguyen, 2018, Krueger et al., 2020 and Ilhan et al., 2023). However, studies discover that firms with higher levels of carbon emissions are associated with larger stock returns, which is the offer of transition risk premiums to investors (Bolton and Kacperczyk, 2021a, 2022a). Hsu et al. (2023) suggest that the stock profitability of firms with high pollution emissions is related to environmental policy uncertainty. The different evidence of these studies raises a question regarding the impact of environmental regulation in financial markets. Motivated by this gap in the literature, my study connects climate regulations and investors' shifts in behaviour by investigating the effect of environmental regulation enforcement on investors' perceptions of TGI and non-TGI information. Moreover, the adverse impact of environmental regulation on the high-pollution industry can encourage investors to monitor firms' environmental engagement activities more closely in this industry than in others. Hence, I also provide an empirical framework to examine the market reaction of TGI information across industries between high- and low-polluting industries.

Finally, I examine the value of analysts' recommendation revisions relevant to TGI information. Growing firms' information asymmetry following innovation intensity pushes investors to consider more public information available (Bhattacharya and Ritter, 1983 and Aboody and Lev, 2000). Studies suggest that the stock price impact of analysts' reports, i.e., earnings forecasts and recommendations, is associated with the public information disclosed of the firm (Frankel et al., 2006 and Altınkılıç and Hansen, 2009). Markets' misinterpretation of TGI information can benefit analysts who monitor firms engaged in TGI and revise their reports in response to TGI news. Therefore, to identify some nexus between TGI information and the value of analysts' recommendation revisions, I investigate the stock price impact of analysts' recommendations relevant to TGI information disclosure.

1.4.2 Findings and Discussions

This empirical chapter develops model assumptions and predictions to investigate the short-term market reaction to TGI and non-TGI information. I summarise the predictions in three primary topics.

I first measure the market reaction using the cumulative abnormal returns related to the TGI and non-TGI patent application filing dates. I find that TGI and non-TGI information create negative stock returns before and after the day the firm files patent applications. This finding is consistent with existing studies suggesting that investors mis-react to innovative information because an innovative transition reflects short-run variation arising in operations and productions, adversely affecting investors' valuation of firms with innovation (Eberhart et al., 2004, Gu, 2005 and Cohen et al., 2013). Then, I examine the limit attention argument by comparing the market reactions between TGI and non-TGI information. The result suggests that there is no difference between TGI and non-TGI information regarding market price movement. According to Bhattacharya and Ritter (1983) indicate that firms allocating resources to innovation development tend to limit information flow regarding innovation projects. The information restriction can cause investors to misinterpret TGI and/or non-TGI information and react inaccurately to innovation benefits due to the increase of firms' information asymmetry (Eberhart et al., 2004 and Gu, 2005). On the other hand, Daniel and Titman (2006) state that investors focus more on tangible assets than intangible assets, leading to a lack of effort in incorporating innovation-related information and potentially misinterpreting the value of TGI and non-TGI information.

Next, I investigate the impact of the 1st Kyoto Protocol commitment on the market reaction to TGI and non-TGI information. The finding reveals during the period of the 1st Kyoto Protocol commitment, the market responded more favourably to TGI information compared to non-TGI information. I also find that the 1st Kyoto Protocol commitment significantly decreases the stock price impact of non-TGI information but insignificantly affects investors in response to TGI information. One possibility is related to Krueger et al. (2020), indicating that enforcing environmental regulations raises investors' concerns and leads them to consider investments that mitigate the impact of regulatory risks. Shane and Spicer (1983) also suggest that the market reaction to firms' specific information is related to investors' perceptions about firms involved in the regulation practices. Therefore, it is possible that the regulation can boost investors' anticipation of firms' environmental engagement e.g., allocating more resources to TGI activities that are able to minimise the regulatory risks. In contrast, the regulation can cause investors to reduce investments in firms promoting non-TGI activities, which are not able to mitigate regulatory risks.

I also find that during the 1st Kyoto Protocol commitment period, there was no difference in the stock price impact of TGI information between the high- and low-polluting industries. This can be interpreted as the result of the market having expectations of the firms engaged in TGI activities and already incorporated the value of these investments (see Shane and Spicer, 1983).

Lastly, this study investigates the value of analysts' recommendations in response to TGI information. I present an empirical framework by comparing the stock price impacts of analysts' recommendation revisions relevant to TGI information disclosed (TGI-relevant revisions), and analysts' recommendation revisions irrelevant to TGI information disclosed (TGI-irrelevant revisions). I also divide the empirical findings of analysts' recommendations between upgrading and downgrading revisions. The findings indicate that TGI-relevant upgrading revisions affect higher stock prices than TGI-irrelevant upgrading revisions, but there is no differential impact on stock prices of downgrading revisions. These findings are consistent with the argument of Bradley et al. (2014), suggesting that analysts' contrarian revisions to markets' expectations demonstrate the comparison between private information they acquired and public information available. Consequently, the contrarian revisions will adjust investors' perceptions and impact stock prices more than analysts' recommendations that correspond to the market's expectations.

In addition, I find that the 1st Kyoto Protocol commitment dilutes the stock price impact of TGI-relevant upgrading (downgrading) revisions. Regarding Krueger et al. (2023), suggest that environmental regulation encourages firms to disclose information on sustainable activities, reducing information asymmetry. This impact can reduce investors' misinterpretation of TGI activities, which decreases the market's response to analysts' recommendations on TGI information. My finding aligns with Loh and Stulz (2018) and Bradley et al. (2014), who find that stock price movement of analysts' recommendation revisions is connected to information asymmetry levels.

1.4.3 Contributions

This empirical chapter adds literature pertinent to innovation in capital markets. Existing studies address the implications of innovative information on financial markets by observing through several channels. Chan et al. (1990) and Szewcyk et al. (1996) explore the stock price impact in response to corporate events related to R&D announcements. Eberhart et al. (2004) and Daniel and Titman (2006) expose investors' underreaction to and misvaluation of innovative information based on accounting financial information. Cohen et al. (2013) and Hirshleifer et al. (2013) consider the efficiency of innovative investment affecting future profitability and stock value. My study offers novel evidence to the literature by presenting investors' perceptions of firms disclosing new innovative information using the patent application filling dates. I also address the fact that investors are pessimistic about innovation in the short run.

Furthermore, this study builds on growing literature that investigates the policy implications of environmental regulations on capital markets. Previous literature suggests that environmental regulation concerns motivate investors to consider external costs related to regulation compliance and respond to firms' public environmental information (Shane and Spicer, 1983). Krueger et al. (2020) document that environmental regulations influence investors' portfolio allocation to concentrate more on firms engaged in environmental development, which mitigates regulatory risk. The argument is consistent with the evidence given by Marshall et al. (2022) and Krueger et al. (2023) that mandatory environmental disclosure increases investors' investment in firms committed to ESG disclosure. On the other hand, recent studies indicate that levels of environmental regulation mandates impact investors' demand for compensation for holding exposure stocks to carbon emission risk

(Bolton and Kacperczyk, 2021a, 2022a and Ilhan et al., 2023). My study adds to this strand of literature by demonstrating that the implications of environmental regulation drive the market's expectations of firms' green transition commitment. Firms promoting TGI activities, which reflect the reliability of green transition take the regulations' advantage. In contrast, firms' investment information regarding activities unrelated to environmental engagement, i.e., non-TGI activities, increases investors' concern about performance uncertainty and adversely impacts their stock value.

In addition, my empirical evidence builds on literature exploring the determinants of analysts' informative values (Lang and Lundholm, 1996). Existing studies identify that the stock price impact of analysts' reports is associated with firm and analyst characteristics such as trading volatility and intensity of institutional ownership (Frankel et al., 2006), information environment and individual analyst reputation (Loh and Stulz, 2011), economic uncertainty (Loh and Stulz, 2018), firms' publicly available information (Conrad et al., 2006 and Altınkılıç and Hansen, 2009), and the ability to access superior information (Green et al., 2014). I provide novel evidence that the stock price impact of analysts' recommendations is related to investors' perceptions in response to TGI information.

1.4.4 The Implications

Findings in this empirical chapter suggest that information asymmetry is a key determinant of investors' pessimism about TGI information. Disclosing information by managers about TGI potential is an important signal which generates the reliability of green transition using a TGI activity. In the meantime, underreaction of TGI information indicates that investors lack technological knowledge and awareness, which causes investors to mis-react to firms promoting TGI activities in the short run. My evidence suggests that it is important to investors' investment decisions to consider and incorporate TGI benefits in their stock valuations comprehensively.

In addition, this study points out that mandatory environmental regulation is a key determinant of driving investors' perceptions of TGI information. My study encourages regulators and policymakers to develop efficient environmental policy mechanisms which promote climate risk awareness. These mechanisms not only drive environmental engagement in financial markets but also increase investment in environmentally technological activities impacting economic development.

1.5 Thesis Contributions

This thesis contributes by examining the short-term and long-term views of the key stakeholders in financial markets (individual investors, institutional investors, and financial analysts) concerning TGI information. The findings indicate that in the short term, the investors incorporate the possible implications of the uncertainty of TGI outcomes in their investment decisions. Such effects cause a delay in investors' responses to TGI information with an unfavourable reaction to TGI information. Similarly, financial analysts monitoring the TGI firms hold a pessimistic bias in the short-term financial performance of such firms. Although the firms' TGI activities raise long-term growth opportunities and competitive advantage within the industry, the increased uncertainty in profitability and information asymmetry adversely affect the analysts' ability to forecast.

On the other hand, the enforcement of environmental regulations can lead investors to respond more accurately to TGI information in the short term. The empirical findings also indicate that in the long run, the benefits of TGI activities related to sustainable growth opportunities and climate risk mitigation attract more investment from institutional investors who are highly concerned about social pressure and regulatory risks. The evidence indicates the systematic perception of investors' climate risk concerns, which motivates them to consider more firms' management decisions regarding climate-friendly strategies e.g. TGI activities.

1.6 Structure of the Thesis

The thesis is structured by way of empirical chapters. The outline of each empirical chapter develops from the introduction, literature review and hypothesis development, data collection and identification strategies, empirical results and conclusions. A brief synopsis of the remaining four chapters of the thesis is as follows.

Chapter Two explores the relationship between firms promoting TGI activities and the ownership of institutional investors. Chapter Three features an empirical study investigating the relationship between TGI intensity and financial analysts. In Chapter Four, I consider the short-term impact of TGI activities on the capital market by investigating the market reaction to TGI information. Chapter Five summarises the findings and implications of the thesis, provides some closing remarks, and indicates potential directions for future research.

2. DOES TECHNOLOGICAL GREEN INNOVATION ATTRACT INSTITUTIONAL INVESTORS?

2.1 Introduction

"The pace of change [transition to net zero] *will be very different in developing and developed countries. But all markets will require unprecedented investment in decarbonization technology. We need transformative discoveries on a level with the electric light bulb, and we need to foster investment in them so that they are scalable and affordable."* [3]

Larry Finak, CEO, BlackRock

The ever-increasing values-based voices of institutional investors (IIs) are signalling investee firms to incorporate practices to improve their climate and environmental performance.[4] If the climate-conscious rhetoric of IIs holds substance, then they should invest more in firms with higher levels of technological green innovation (hereafter, TGI firms).[5] Furthermore, it is also possible that the strength of the relationship between firms' technological innovation and IIs' investments depends on the differing characteristics of IIs, such as independent versus grey IIs (Ferreira and Matos, 2008, Luong et al., 2017 and

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[3] https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter.

[4] Larry Fink, CEO of BlackRock, notes that, "In a few short years, we have all watched innovators reimagine the auto industry. And today, every car manufacturer is racing toward an electric future. The auto industry, however, is merely on the leading edge – every sector will be transformed by new, sustainable technology. Engineers and scientists are working around the clock on how to decarbonize cement, steel, and plastics; shipping, trucking, and aviation; agriculture, energy, and construction. I believe the decarbonizing of the global economy is going to create the greatest investment opportunity of our lifetime. It will also leave behind the companies that don't adapt, regardless of what industry they are in… [..]" (https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter.)

[5] Following OECD, we define TGI as innovations for designing climate and environmentally-friendly technologies. The specific technology classes include four environmental policy goals, including human health impacts of environmental pollution, water scarcity, ecosystem health and climate change mitigation (Haščič and Migotto, 2015, page 20, for the detailed fields).

Kacperczyk et al., 2021) and short-versus long-term IIs (Tian and Wang, 2014). This study investigates two related issues. First, I test whether firms with higher TGI levels attract more equity capital from IIs. Second, I examine whether the strength of the association between IIs' investments and firms' TGI levels depends on the characteristics of the IIs.

A growing body of finance and accounting literature proposes that successful green innovations improve a company's environmental performance and boost the operating and financial performances by promoting the reputational brand and value of social capital (Hart, 1995, Porter and Van Der Linde, 1995, Ambec and Lanoie, 2008 and Salvadó et al., 2012). A sizeable body of recent literature also argues that TGI firms can better mitigate and manage their climate change-related risks, which is a significant concern for IIs (Krueger et al., 2020, Ilhan et al., 2021 and Bolton and Kacperczyk, 2021a). Regarding financial implications, these findings suggest that firms with a greater level of TGI experience lower costs of capital and better capital market-based valuations than firms with lower TGI levels. Consequently, firms promoting higher levels of TGI should attract more equity investments from IIs.

The literature on the natural resource-based view (NRBV) suggests that TGI improves a firm’s environmental and operating performance by creating economic value, reducing operational costs, boosting the export of green technologies, and advancing market competitiveness (Costantini and Crespi, 2008 and Costantini and Mazzanti, 2012). Drawing on the accounting/finance and NRBV theories of the positive outcomes of TGI and the greater demand for green assets by IIs, I hypothesise that firms exhibiting a greater degree of TGI should attract higher equity investments from IIs.

Although economic views suggest that a higher TGI level should, on average, attract more investments from environmentally conscious IIs, theoretical arguments predict that boosting TGI should differentially induce IIs, conditional on their differing characteristics. For example, compared to grey IIs, independent IIs, who play more active monitoring roles and are more conscious of investee firms' reputations, are likely to invest more in TGI firms (Ferreira and Matos, 2008, Luong et al., 2017, Kacperczyk et al., 2021 and Marshall et al., 2022). Similarly, because TGI is a long-term sustainable investment strategy, long-term investors, such as pension funds, should be more attracted to TGI firms than short-term investors, such as hedge funds (Luong et al., 2017).

In this study, I test the above hypotheses using investor-level data of IIs' investment in firms across 50 countries, including all constituent nations of Morgan Stanley Capital International's All-Country World Index (MSCI-ACWI).[6] I also use investee firm-level green patents and citation data from MSCI-ACWI constituent firms. For empirical identification, I employ the propensity score matching (PSM) technique in a quasi-natural experiment by exploiting the 1st Kyoto Protocol commitment as an exogenous variation in TGI. Initially ratified in 1997, the Kyoto Protocol was the first official commitment to reduce carbon emissions between 2008 and 2012. In my sample of firms from 50 countries, 24 countries (developed and developing) signed this treaty. Empirical evidence documents that firms domiciled in countries that signed the 1st Kyoto Protocol commitment (treatment group/firms) invested more in TGI in the post-commitment period of 2008-2012 compared to firms from 26 non-signed countries (control group/ firms). Earlier studies also

[6] https://www.msci.com/our-solutions/indexes/acwi.

demonstrate that the demand for environment- and carbon-friendly technological products in signed countries increased after adopting the Kyoto Protocol (Tran, 2021). Thus, I exploit these exogenous differential changes in firm-level TGI to investigate their impact on the IIs' investments. I take 2004-2007 as the pre-commitment period.

My analysis reveals several interesting findings. First, firms that sign the Kyoto Protocol (the treatment group) attracted higher IIs' investments (domestic and foreign) in the post-commitment period (2008-2012) than their counterparts from the countries that did not sign the commitment. Furthermore, within the treated group and post-commitment period, firms with a higher degree of TGI drawn in more investments from IIs (domestic and foreign) than control group firms. Quantitatively, a one standard deviation increase in the proportion of green patent counts (approximately 5.669%) by a typical firm in the treated firms, compared to the controlled firms, attracted higher investments of around US$ 0.345 million to US$ 0.529 million from regular domestic and foreign IIs, respectively.

Second, my results also indicate that the strength of the association between TGI levels and IIs' equity investments depends on the types of IIs. Specifically, I find that relative to grey IIs, independent IIs who play a more active monitoring role in managing their investee firms invested more in the treated firms in the post-commitment period of 2008-2012. Meanwhile, compared to short-term IIs, long-term IIs also exhibit higher investments in the treated firms with higher levels of TGI. Thus, the results suggest that IIs' monitoring roles and investment horizons are important in defining the strength of the association between TGI levels and IIs' equity ownership.

My findings make the following contributions. First, they add to the literature on the determinants of IIs' ownership. Prior studies in this area identify several factors driving

IIs’ preferences, such as financial performance characteristics (Ferreira and Matos, 2008), corporate governance quality and mechanisms (Leuz et al., 2009, Chung and Zhang, 2011 and McCahery et al., 2016), and macroeconomic and geographic factors (Chan et al., 2005, Schumacher, 2018 and Karolyi et al., 2020). The recent but growing literature highlights the role of firm-level environment and social performance and associated macro-level regulatory factors in explaining the variations in IIs’ allocations (Krueger et al., 2020, Pástor et al., 2020, Pedersen et al., 2020, Bolton and Kacperczyk, 2021a and Ilhan et al., 2023). To the best of my knowledge, this is the first study to offer credible and systematic scientific evidence of the role of TGI in attracting IIs’ equity investments.

Second, this study expands the literature linking the implication of innovation and investors’ perceptions (Eberhart et al., 2004, Daniel and Titman, 2006, Pastor and Veronesi, 2009, Ayyagari et al., 2011 and Hirshleifer et al., 2013). Previous evidence suggests that, in the short term, investors generally react by divesting in response to firms' research and development (R&D) activities (Chan et al., 2001 and Pastor and Veronesi, 2009)[7]. However, evidence also indicates that IIs, particularly foreign IIs (FIIs), promote long-term innovative corporate investments through their monitoring roles (Ayyagari et al., 2011, Guadalupe et al., 2012 and Luong et al., 2017). I add to this strand of literature by demonstrating that firms engaged in TGI are rewarded with higher investments from domestic and foreign IIs. This implies that IIs view TGI as a means of sustainable competitive advantage.

[7] Evidence also documents that compared to others, firms that invest more in R&D experience a loss of financial value in the short-term but relatively do much better in the long run (see Bhojraj et al., 2009).

Finally, I contribute to the growing body of literature on the role of investor heterogeneity. Studies note that not all types of IIs are equally responsive to firms' ESG engagements and performance. For example, Azar et al. (2021) show that the bigger the size of the IIs, the more effective they are in driving down the carbon footprint of the investee firms. Studies also note that compared to other investors, pension funds focus more on a firm's social reputation (Hong and Kacperczyk, 2009). Marshall et al. (2022) document that IIs classified as independent, long-term, and originating from civil law jurisdictions have a more pronounced effect on the positive link between CSR performance and FIIs' ownership. My research adds to this strand of literature by demonstrating how unusual characteristics of IIs matter in channelling their funds toward TGI firms.

The remainder of this study is organised as follows. Section 2.2 discusses how the experimental setup of the 1st Kyoto Protocol acts as an exogenous variation to TGI. This is followed by the formulation of testable hypotheses in Section 2.3. Section 2.4 reports data used and data sources in my empirical study. Section 2.5 provides an empirical identification strategy using Propensity Score Matched (PSM) Randomization. Section 2.6 presents and interprets the empirical results, and Section 2.7 concludes the paper.

2.2 Experimental Setup: First Kyoto Protocol

I use the signing of the 1st Kyoto Protocol as a source of exogenous variation in TGI. The 1st Kyoto Protocol was adopted in Kyoto, Japan, in December 1997 and ratified by 192 country members. It was introduced under the United Nations Framework Convention on Climate Change (UNFCCC), which aims to limit and reduce greenhouse gas (GHG) emissions to agreed-upon individual targets. It was implemented between 2008–2012 (hereafter, the post-commitment period) and covered 37 industrialized countries, including European Union member states, the United Kingdom, Canada, Japan, Australia, Russia, Norway, and others.[8] The agreed-upon target of the first Kyoto Protocol was to reduce GHG emissions in industrialized countries by 5.2% (on average) from the level in the 1990s. The scheme established different mechanisms to support environmental improvements across countries and accomplish the target. One such initiative was establishing an international emissions-trading mechanism that provided economic incentives for reducing GHG emissions and investing in TGI.[9]

For the post-commitment period of 2008–2012, the literature offers convincing empirical evidence on environment-related corporate performance/consequences and the subsequent boost in the ecological/greener innovations of firms domiciled in countries that signed the 1st Kyoto Protocol. For example, Nguyen (2018) indicates that firms in highly polluting industries experienced a reduction in investments from IIs in the post-commitment period. Studies also report that firms with high carbon emissions suffer from high capital costs, driven by the stringency of environmental policies in the post-commitment period (Nguyen et al., 2020). Evidence also suggests that the Protocol reduces the dividend payouts of highly polluting firms because of the increased environmental costs and taxes (Balachandran and Nguyen, 2018). Connected to TGI activities, firms located in the committed countries were motivated to allocate more resources to climate-friendly strategies, e.g., TGI development, because of the increase in environmental management

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[8] UNFCCC. (2005). *Kyoto Protocol Reference Manual on Accounting of Emissions and Assigned Amount*; The UNFCCC website: https://unfccc.int/kyoto_protocol. See Appendix A2.2 for the list of committed and non-committed countries.
[9] UNFCCC. (2007), *Investment and Financial Flows to Address Climate Changes.*

costs (Balachandran and Nguyen, 2018 and Nguyen et al., 2020) and the pressure of their stakeholders (Nguyen and Phan, 2020). The crucial evidence for my research purpose is that studies note that in the face of financial incentives and the need to manage regulatory risks, countries committed to stringent environmental regulations, including the 1st Kyoto Protocol, experience higher TGI exports related to pollution management, cleaner environments, and resource management (Costantini and Crespi, 2008, Costantini and Mazzanti, 2012 and Tran, 2021).

Considering the discussion above, empirical evidence corroborates that the post-commitment period (2008-2012) is associated with an exogenously greater boost in cleaner/greener technological exports from firms domiciled in committed countries than from non-committed countries. These changes in TGI impart an ideal quasi-natural experimental setup to test whether firms engaged in a higher level of TGI attract relatively more IIs' investments in the post-commitment period (2008-2012) as compared to the pre-commitment period (2004-2007)[10].

2.3 Related Literature and Hypotheses Development

2.3.1 Green Innovations and Institutional Investments

I establish the economic nexus between TGI and investment of IIs through the simple equilibrium condition of how demand-driven signals by users of capital (i.e., TGI firms) appeal to the climate and environmentally friendly preferences of external suppliers of

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[10] Considering the process of TGI development, inventing a successful TGI requires a long-term process, which is possible that using the later climate regulations after the Kyoto Protocol as the exogenous variation of TGI may cause estimation bias in identifying the magnitude of TGI activities among firms in committed countries of the Kyoto Protocol and firms in uncommitted countries.

equity capital (i.e., IIs). Recent empirical studies on supply-side economics offer convincing arguments and evidence of IIs' and capital markets' consideration of ESG issues in the investment (or divestment) allocation and valuation strategies.[11] Evidence suggests that with the mounting social and regulatory pressures, investors (*value* and *values-based*) are increasingly seeking to invest in firms engaged in furthering positive environmental and social (ES) changes and managing ES-related risks (see Dyck et al., 2019, Li et al., 2019 and Starks, 2023). These preferences, particularly *values-based*, are stronger for IIs based in jurisdictions with stronger social norms (such as civil law countries) (Krueger et al., 2020).

Recent studies advocate that a value-based investment philosophy (higher financial returns and efficient risk management) generally drives the ESG preference for IIs relative to values-driven environmental and societal benefit orientations. For instance, a growing body of literature implies that firms with good sustainability practices (ESG engagements) are associated with larger financial returns (see Matsumura et al. 2014, Albuquerque et al., 2019, Hartzmark and Sussman, 2019 and Krueger et al., 2023). Similarly, Hoepner et al. (2020) and Pástor et al. (2020) note that investors tend to hold high ESG-rated assets because they mitigate unexpected ESG-related risks, such as a shift in consumer behavior (demanding more ESG-oriented products and services), regulatory risks (greater disclosure

[11] In the 2020 annual letter, BlackRock CEO Larry Fink issued the following message to firms' CEOs, "*Foresighted companies across a wide range of carbon-intensive sectors are transforming their businesses, and their actions are a critical part of decarbonization. We believe the companies leading the transition present a vital investment opportunity for our clients, and driving capital towards these phoenixes will be essential to achieving a net zero world*." (https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter).

of non-financial information, such as CO_2 emissions), social pressure (stakeholder-oriented corporate practices), and changes in the preferences of IIs for more ESG-linked assets.

Specific to environmental and climate issues, investigations note that long-term *values-based* investors (e.g., public pension funds, foundations, and endowments) allocate their portfolios to firms with high environmental performance (Ziegler et al., 2007 and Jagannathan et al., 2017). Similarly, a sizeable body of literature demonstrates that despite the potential costs and questionable effectiveness of the approach[12], these *values-based* investors are excluding/divesting portfolio firms exhibiting high levels of environmentally harmful emissions, such as CO_2 emissions (see Li et al., 2019, Atta-Darkua et al., 2023 and Becht et al., 2023)

Further, a growing thread of empirical evidence champions the conjecture that the systematic perception of climate risk negatively affects the valuation of financial assets exposed to higher climate risk (see Andersson et al., 2016, Engle et al., 2020, Bolton and Kacperczyk, 2021a, 2022a, 2022b and Bolton et al., 2022) Such risks include physical hazards (extreme weather conditions, such as floods, drought, and hurricanes), transitional (regulatory, policy, liability, and technology), and reputational (Derwall et al., 2005, Ziegler et al., 2007 and Krueger et al., 2020). Recent research also hints that higher carbon-intensive firms are more vulnerable to climate change-related downside risks because their future cash flows are systematically related to carbon management regulations and policies (Hoepner et al., 2018 and Ilhan et al., 2021). Such cash flow sensitivity implies that

[12] For potential costs and benefits of divesting/exclusion approach, see Teoh et al. (1999) Statman (2000), Skancke et al. (2014), Bessembinder (2016), Davies and Van Wesep (2018), Li et al. (2019), Berk and Van Binsbergen (2021), Edmans et al. (2022) and Gantchev et al. (2022).

investors are signalling potential divestments or discouraging investments in more carbon-intensive firms unless they offer a countersignal of their intentions to pursue more green business practices. Highlighting the empirical evidence supporting such a hypothesis, Pástor et al. (2020) and Bolton and Kacperczyk (2021a) note that investors are increasingly divesting from firms with high carbon emissions.[13]

A recent study finds that the world's three most prominent IIs (BlackRock, Vanguard, and State Street Global Advisors, also known as the "Big Three") significantly engage with the highly carbon-intensive firms in their portfolio (Azar et al., 2021). Consistent with the *engagement influence* conjecture, Azar et al. (2021) report an economically sizable and time-progressive negative nexus between the "Big Three" equity ownership and subsequent lower carbon emission rate within the MSCI index firms. Regarding clientele preferences, Ceccarelli et al. (2022) illustrate that clients of IIs are increasingly attracted to investing in low-carbon portfolios. Studies also demonstrate that IIs who disclose evidence of environmental governance activism may develop their social capital, disseminating strong positive signals to their environmentally conscious clients and encouraging investee firms to adopt more sustainable business practices (see Riedl and Smeets, 2017). The preceding discussions imply that IIs (*value* and *values-based*) increasingly prefer to invest in firms that demonstrate their efforts and initiative to improve their environmental commitments and performance. Such environmental commitments

[13] It is not only IIs that are concerned. For example, evidence suggests that banks charge lower interest rates on lending for firms more aligned with the EU taxonomy of transitional revenue, aimed at climate risk management and preference for green investments (see Sautner et al., 2022).

should include investee firms’ initiatives and credible evidence of investing in climate and environmental green technologies.

I now offer arguments on the demand-side economic lenses to explain why investee firms with higher TGI levels may attract more IIs' investments. First, the signalling framework of corporate finance theory implies that firms reporting TGI patent registrations offer credible signals to stakeholders, including IIs, regarding their sincere intention to transition toward green and more sustainable business/operational practices (Glazer and Konrad, 1996 and Ariely et al., 2009). These sustainability signals are credible because the TGI R&D process warrants a significant allocation of human and financial capital (Holmstrom, 1989, Ayyagari et al., 2011, Brown et al., 2012 and Hsu et al., 2014). Supporting the signalling framework of TGI firms, Ambec and Lanoie (2008) and Kesidou and Demirel (2012) argue that TGI outputs stem from firms' positive attention/response to their customers, environmental regulations, social responsibility, and other stakeholders.

The second theoretical lens, explaining why firms engaged in TGI are likely to attract more institutional ownership, is drawn from the natural resource-based view (NRBV) theoretical framework. The NRBV argues that firms with higher levels of TGI should develop significant competitive business advantages over their rivals. Hart (1995) documents that NRBV is the conceptual framework of the relationships among firm resources, capabilities, and sources of competitive advantage. Business strategies related to pollution prevention, product stewardship, and sustainable development create more opportunities for firms to gain competitive advantages e.g., firms adopting TGI activities can effectively utilise internal and external resources, affecting competitive advantage capability and generating sustainable growth opportunities. For example, investing in TGI firms can reduce operational costs by controlling waste treatment and efficiently employing raw materials and energy in the production process (Hart, 1995, Porter and Van Der Linde, 1995, Ambec and Lanoie, 2008 and Salvadó et al., 2012). Similarly, Ambec and Lanoie (2008) state that firms committed to environmental performance generate higher revenues by entering new markets, differentiating products, and selling ecological innovations. Studies also argue that firms with higher levels of TGI use the end-of-pipe approach to improve their operating and financial performances[14]. For example, Russo and Fouts (1997) note that firms investing in innovative green practices build up intangible capital, such as a favorable green image and authority, which ultimately adds to positive long-term operating and financial performance (Guenster et al., 2011). Beyond financial advantages, the benefits of TGI regarding creating production efficiency and controlling pollution emissions can reduce the climate regulation risk which is the major concerns of IIs (Krueger et al., 2020)

Consistent with the aforementioned discussion on efficiency improvement and reputational capital-building, which further enhance competitive advantage and boost long-term operational and financial performance, I argue that firms with higher TGI levels cater to the environmental preferences of outside investors, as discussed before, and hence should attract higher investments from IIs. These suppositions within my experimental setup, as noted in Section 2.2, suggest that regulators and investors in countries committed to the 1st Kyoto Protocol provisions should pressure their firms to reduce their carbon

[14] The end-of-pipe approach is a pollution management technology that focuses on treating effluents or filtering them before they are released into the environment (Hart, 1995 and Russo and Fouts, 1997). TGI related to the end-of-pipe approach benefits firms by reducing the external cost of regulation compliance

intensity to meet the country's targets. Such pressure may encourage TGI among firms based in countries that have signed the Kyoto Protocol. Studies (e.g., Costantini and Crespi, 2008 and Tran, 2021) demonstrate that countries committed to the 1st Kyoto Protocol export more environmental goods and technologies to address pollution management, improve cleaner environments, and resource management. This evidence provides an ideal quasi-natural experimental setup to test whether firms engaging in a higher degree of TGI attract more investments from IIs. Thus, if firms committed to green practices draw higher investments from IIs, I test the following hypothesis (H1) within my quasi-natural setup of the 1st Kyoto Protocol commitment:

H1: In the post-commitment period of the 1st Kyoto Protocol, firms with higher levels of TGI attracted more IIs' equity ownership.

The hypothesis above implies that relative to the pre-commitment period (2004-2007), firms with a higher level of TGI in the post-commitment period (2008-2012) and based in countries that signed the 1st Kyoto Protocol attract more equity investments from IIs, compared to firms from countries that did not sign the 1st Kyoto Protocol.

2.3.2 Types of Institutional Investors and Green Innovations

Studies report that firms require long-term investments and positive shareholder engagement to pursue innovation strategies (Eccles and Serafeim, 2013). However, not all IIs are likely to have long-term investment preferences and/or the ability to engage closely with firms' activities; therefore, they are unlikely to be identically attracted to firms with high TGI. Thus, I argue that IIs, depending on their investment styles and horizons, exhibit heterogeneous responses to investee firms' TGI outputs.

2.3.2.1 Independent vs. Grey Institutional Investors

I hypothesise that the investment decisions of IIs depend on professional money managers' potential to monitor firms' strategic choices and business practices. Following Ferreira and Matos (2008), I test this proposition by classifying IIs into two groups based on their intensity of monitoring roles. The first group is grey IIs, such as banks, insurance companies, and other institutions closely linked with firm management and, thus, are passive monitors. These are also called "pressure-sensitive" investors because they tend to be more loyal in supporting and rubber-stamping investee firms' strategic decisions and business practices. Literature indicates that grey IIs might want to protect existing or potential business relationships with firms, and therefore, they often vote to align with firm management's decisions (Ferreira and Matos, 2008). For example, they may endorse managers' choices in opposing takeover amendments (Brickley et al., 1988), or not support executive compensation policies that are contingent on performance, as this may result in increased monitoring costs for them (Almazan et al., 2005). The second group comprises independent IIs, such as mutual funds. They actively and critically monitor investee firms' activities, strategic choices, and business practices, thus maintaining arm's length relations with their investee firms' management. These investors are called "pressure-resistant" because they actively and critically monitor firms' activities and voice their concerns.

Connected to ESG issues, studies indicate that independent IIs monitor their investee firms' corporate governance and social responsibility practices more intensely and critically than their grey counterparts. This could be because independent IIs compete for higher client inflows through better financial performance and a better reputation as socially and environmentally conscious IIs (Ferreira and Matos, 2008 and Dyck et al., 2019). Given the evidence that firms engaged in higher levels of TGI improve their environmental performance, foster sustainable growth, generate competitive advantage and build social capital/reputation (Ambec and Lanoie, 2008, Carrión-Flores and Innes, 2010 and Rehman et al., 2021), independent IIs should enhance their reputations and reduce monitoring costs by holding a portfolio of firms that invest more in TGI.

Studies also note that independent IIs are more tolerant of firms' innovative development, whereas grey investors are less patient (Luong et al., 2017). Thus, grey investors, who are relatively passive monitors and tend to have amicable business relationships with investee firms, should prefer managerial myopia more than firms investing in long-term innovative development. Thus, I hypothesise that independent IIs invest more in firms with higher TGI levels. The following hypothesis (*H2a*) is proposed and tested within the empirical setup of the 1st Kyoto Protocol commitment:

H2a: In the post-commitment period of the 1st Kyoto Protocol, firms with higher TGI attracted more equity investments from independent IIs than grey IIs.

2.3.2.2 Long-term vs Short-term Institutional Investors

TGI firms may not be attractive to IIs with short-term investment preferences as they require long-term funding commitments. Thus, I evaluate the effects of II's preferred investment horizons (long vs. short term) on investee firms' TGI practices. Studies suggest that short-term institutional investors, such as hedge funds, exhibit a significantly higher degree of managerial myopia than long-term investors, such as pension funds (Bushee, 1998). Considering regulatory conditions and funding management costs, e.g., the transaction cost, even though hedge funds' lock-up periods (30 – 90 days) can extend the period of their holding ownership, hedge funds are more flexible than other IIs in managing their portfolios with trading strategies (Ackermann et al., 1999). Research also indicates that long-term IIs that follow more passive trading strategies encourage more investee firm-level innovations than short-term investors (Luong et al., 2017).

Moreover, research shows that long-term investors benefit from the information generated by their active monitoring role, whereas short-term investors employ active trading strategies instead of event-specific knowledge (Chen et al., 2007). Literature suggests that short-term IIs e.g., hedge funds, have reduced motivations to allocate resources towards monitoring, as they are less inclined to persist as stakeholders of the organization for an extended period to gain the associated advantages (Gaspar et al., 2005). For instance, Gaspar et al. (2005) and Chen et al. (2007) find that short-term IIs are associated with poor bidding acquisitions. In contrast, they indicate that long-term institutions are related to better mergers and post-merger performance. This is because as active trading investors with superior private information, short-term IIs adopt frequent trading to receive shorter profit horizons (Yan and Zhang, 2009). This benefit, along with the lower transaction cost compared to monitoring costs, may lead them to disregard their monitoring function and resort to trading strategies as a reaction to unfavourable decisions made by the firm's management (Chen et al., 2007).

Furthermore, the literature also documents that short-term investors encourage short-term financial performance by pressuring investee firms to curtail long-term value-enhancing investments (Alvarez et al., 2018).

For environmental and climate risk management, Dyck et al. (2019) note that long-term fund managers engage more with investee firms and support their environmental investments. Conversely, hedge fund managers tend to discourage investments in environmental management. Studies further indicate that relative to short-term, long-term IIs manage climate risks by diversifying portfolios into green and environment-friendly assets (Krueger et al., 2020). Furthermore, Dimson et al. (2015) note that pension funds, considered long-term IIs, are more attracted to firms with higher environmental performance.

Studies also document several reasons for the differences in the long- and short-term IIs' preferences for investing in TGI firms. First, many studies note that green innovation supports long-term growth opportunities by reducing the costs of production processes and increasing firm competitiveness (Porter and Van Der Linde, 1995, Shrivastava, 1995 and Ambec and Lanoie, 2008). This perspective should attract long-term investors. Second, evidence indicates that financial markets underestimate innovative firms' growth potential, depressing short-run returns (Lev and Sougiannis, 1996). For example, Chan et al. (2001) and Eberhart et al. (2004) demonstrate that markets misprice firms that increase their R&D capital and underreact when incorporating long-term value-enhancing information related to investment in innovative projects. Gu (2005) also corroborates that market participants, including investors and analysts, fail to account for innovation capabilities for future earnings in stock prices. Such underestimations of growth potential should attract more long-term investors than short-term investors.

Finally, long-term investors (such as pension funds) are more conscious of their social responsibilities than short-term investors (such as hedge funds), as the latter holds greater regulatory leeway to avoid investment disclosure. Thus, the zeal to build a social reputation also motivates long-term investors to invest more in firms promoting green assets. These preferences of long-term investors contribute to their social image of actively reducing climate change and other environmental concerns.

Given the above-noted differences in preferences, I argue that IIs, with their long-term investment horizons, should be more attracted to climate- and environment-friendly innovative firms. To examine this proposition, I test the following hypothesis:

H2b: In the post-commitment period of the first Kyoto Protocol, firms with higher levels of TGI attracted more equity investments from long-term IIs than short-term IIs.

2.4 Data

This study uses institutional investors, investee firms, countries, and bilateral country pair-level data. The sample ranges from 2004 to 2012, covering the pre-commitment (2004-2008) and post-commitment (2008-2012) periods of the 1st Kyoto Protocol commitment, with the latter being my exogenous shock to TGI. As discussed below, I obtain sample datasets from different sources.

2.4.1 Institutional Ownership

I obtain the outcome variable, i.e., each IIs' percentage of equity holdings of their investee firms from S&P Capital IQ (CIQ). I denote this as $IO_{i,j,t}$, defined as the percentage of shares held by institutional investor *j* in investee firm *i* at the end of year *t*. These bilateral investor-investee level ownership data cover investors and investee firms across 50 countries, primarily comprising Morgan Stanley Capital International's All-Country World Index (MSCI-ACWI).[15]

2.4.2 Measures of Green Innovations

I acquire my key independent variable of interest, i.e., investee firm-level green innovation data from the World Patent Statistical Database (PATSTAT), compiled by the European Patent Office (EPO). The existing literature employs patent data as a proxy for technological innovations, reflecting the firm-level output of ingenious initiatives (Griliches, 1998). Haščič and Migotto (2015) note that patent data offers essential information, such as the nature of the invention and the applicant's name. I employ patent data as a proxy for innovation because evidence suggests that most economically significant inventions are patented (Dernis and Guellec, 2001). Relevant to my study, Haščič and Migotto (2015) stress that patent data is ideal for identifying environmental or green innovations from all other classes of innovations. The primary reason for this identification is that patent classification systems are technological by nature, allowing extensive characterisation of pertinent technologies that explicitly describe the finer details of their engineering features and specific applications. Evidence implies that the International Patent Classification (IPC) and Cooperative Patent Classification (CPC)

[15] https://www.msci.com/our-solutions/indexes/acwi

system hold over 70,000 and 200,000 distinct technological classes, respectively (Haščič and Migotto, 2015).[16]

These advantages corroborate the view that technology-based patent data allow the specific identification of environmental or green technologies. For example, using the technology-based patent classification, it is possible to identify innovative devices that differentiate the management of the precise source of pollution emissions (e.g., Nox, SO_2, CO_2, etc.). As such, it is possible to categorise the applications of each patent into multiple technological classes (see Haščič and Migotto, 2015). For this study, I identify green patents from all other types by following the OECD's definition and classification, as demonstrated in Haščič and Migotto (2015).[17] This classification draws on the most commonly applied approach of searches based on patent classification (IPC, CPC, etc.), relying on the detailed knowledge of patent examiners.

The search strategies represent technology classes directed at the following four environmental policy goals: human health impacts of environmental pollution, addressing water scarcity, ecosystem health, and climate change mitigation. The specific search strategies used are directed at the traditional dimensions of environmental administration (such as air and water pollution and waste disposal) and include those related to water scarcity adaptation, addressing biodiversity threats, and mitigating climate change risks. Table A2.4 in the Appendix provides a snapshot of the mapping between environmental policy priorities and patent search strategies. These search strategies cover approximately

[16] For a comprehensive list of IPC and CPC, see https://worldwide.espacenet.com/classification?locale=en_EP.
[17] For definition details, see Haščič, I., & Migotto, M. (2015). Measuring environmental innovation using patent data. *OECD Working paper*, 89. doi: https://doi.org/10.1787/5js009kf48xw-en

80 technological fields. Table A2.5 in the Appendix reports a sample of the technological classes related to environmental and climate change policies (see Haščič and Migotto (2015), page 20, for the detailed fields).

Since 1844, the PATSTAT has maintained its comprehensive patent applications for corporate firms in more than 90 countries. It covers more than 40 global intellectual property authorities, including those from the United States Patent and Trademark Office (USTPO), European Patent Office (EPO), Japan Patent Office (JPO), and the World Intellectual Property Organization (WIPO). The patent information includes the titles of the patent applications, names of the corporate applicants, patent abstracts, applicant identification, names of the inventor, registered date of the patent applications, grant status, forward citations of each patent, and typologies of innovation identified according to the International Patent Classification (IPC) and Cooperative Patent Classification (CPC).

One limitation of the PATSTAT database is that it does not contain relevant firm-level identification codes matching other databases. Thus, I use the fuzzy matching process, a string-searching algorithm, to match firms from the S&P CIQ database with applicant names from PATSTAT. Following existing studies, I undertake rigorous matching by manually assessing each applicant's information using the company's legal name and location from both databases (Luong et al., 2017 and Hsu et al., 2021). Furthermore, I employ the two-letter International Organization for Standardization ISO codes and three-digit IMF country codes to match country and country pair-level datasets. Thus, the reliability of the final matched dataset is validated.

Using PATSTAT data, I construct two green innovation measures. The first represents the relative quantity of investment in firm-level green innovation activities. For each firm *i* and year *t*, I employ the ratio of green patent counts (*GP_count*) to the total counts of patent applications (*AP_count*). I refer to this ratio as *GP_percent*. Previous studies find a truncation bias in patent databases when the backlog of many recent applications is processed. The truncation results from the lag between the year of application and the year the patent is granted (Hall et al., 2001, Hall et al., 2005 and Dass et al., 2017). To address the truncation bias and following earlier studies, I use the date of a patent application submission for all granted applications (see Luong et al., 2017 and Boubakri et al., 2021)[18].

The second measure represents green innovation quality. For each firm *i* and year *t*, I employ the ratio of green patent forward citation counts (*GC_count*) to total forward citation counts (*TC_count*); in my estimation models, I denote this as *GC_percent*. Although the number of forward citations reflects the quality of firm innovations, truncation bias in citations received occurs when patent applications are submitted in different years. Long-generated patents are cited for a longer period than recent patents; hence, the citations received from patents in different periods are not comparable. Following the existing literature, I adjust the citation count of each patent by scaling the number of citations of firm *i* by its relevant industry-average citation count for the same year. I follow the three-digit IPC or CPC industry classifications (Gu, 2005, Hirshleifer et al., 2012, Luong et al., 2017 and Boubakri et al., 2021).

[18] An innovative output implies intensive engagement in the firm management's TGI transition. Inventing a successful TGI requires large financial resources, knowledge, and time, which reflect the firm's commitment to climate-friendly engagement. Furthermore, it is difficult to identify resources used related to TGI activities, e.g., R&D expenditures.

2.4.3 Firm-level Covariates

I use several firm-level covariates for PSM that potentially affect IIs' investment decisions, particularly those of FIIs. Even though using the TGI patent/citation ratio can control for the commitment of investee firms in the TGI development rather than being performing firms, it is possible that firms with better financial performance can associate with TGI activities. This study reduces this bias in the estimation by controlling firm performance variables e.g., *SIZE, ROE* and *BM*. Drawing on existing literature, I use the most prominent covariates documented to influence institutional investors' investment decisions (Lang et al., 2020 and Kacperczyk et al., 2021). Studies note that firm size is positively related to institutional ownership because larger firms are more transparent, exhibit higher capital market-based liquidity, and are better governed (Gompers and Metrick, 2001, Covrig et al., 2006, Ferreira and Matos, 2008 and Marshall et al., 2022). I proxy firm size (*SIZE)* using the natural logarithm of the investee firm's market capitalisation. Similarly, evidence shows that IIs are more attracted to firms with higher profitability in operating performance (Covrig et al., 2006 and Ferreira and Matos, 2008). Accordingly, as a measure of operating performance, I include return on equity (*ROE*), the ratio of net profit after tax to the book value of equity. Investigations also reveal that firms with higher growth potential attract more investments from IIs (see Fama and French, 1992, Falkenstein, 1996, Coval and Moskowitz, 1999 and Ke et al., 2010). Therefore, I include the book-to-market value ratio of equity (*BM)* as a proxy for capital market valuation and growth opportunities.

Studies also conjecture that for outside investors, cash balance is a strong signal of firms' short-run financial stability, that is, operational liquidity (see Covrig et al., 2006, Ferreira and Matos, 2008 and Marshall et al., 2022). I incorporate the cash holding ratio

(CASH), which is the ratio of the sum of year-end cash and short-term securities to the total book value of assets, as a proxy for operational liquidity. Evidence notes that investors tend to avoid firms with higher leverage because it signifies a higher level of financial distress, which affects shareholder value (Acharya et al., 2011). I account for this risk by including leverage *(LEV)*, the book value of the debt-to-equity ratio. I acquire all data for these firm-level factors from the CIQ database.

2.4.4 Country-level and Bilateral Country-Pair Control Variables

La Porta et al. (1997) argue that increased stock market development is associated with greater industrial diversification, higher capital market liquidity (lower transaction costs), better protection for minority shareholders, and higher institutional quality. Studies (e.g., Chan et al., 2005) note that foreign investors invest more in developed stock markets. I use country-level stock market capitalisation to gross domestic production (*MC_GDP*) as a proxy for stock market development (Chan et al., 2005 and Karolyi et al., 2020). I obtained this factor from the World Bank and the International Stock Exchange (TISE)[19].

Finally, to capture the familiarity bias in the case of foreign investments, I use three different investor-investee country pair variables. First, country pairs generating greater bilateral FDI flows exhibit a more substantial economic relationship and a greater level of information exchange, which should encourage higher portfolio investments across country pairs (Schumacher, 2018 and Karolyi et al., 2020). The variable *FDI_flows* is the ratio of the total FDI inflow between investor and investee countries to the total global FDI

[19] The International Stock Exchange: https://tisegroup.com/market/

flow received by the investee country. In other words, *FDI_flows* = (inflows from investor country into investee country + inflows from investee country into investor country)/(total inflows into investee country from all reported countries). I acquire FDI data from the OECD, United Nations Conference on Trade and Development (UNCTAD), and International Trade Center databases (ITC)[20].

Second, studies suggest that FII tends to allocate more funds to nearby countries because closer proximity between countries encourages information accessibility and breeds greater familiarity (Chan et al., 2005, Fedenia et al., 2013, Thapa et al., 2013, Giofré, 2014, Schumacher, 2018 and Karolyi et al., 2020). I measure familiarity using the natural logarithm of geographical distance (in kilometers) between the capital cities of investor and investee countries (*Distance)*. Finally, I also include the common language dummy (*Com_dum*) as a proxy of information asymmetry that takes the value of one if the investor and investee pair countries share the same common official language and zero otherwise. I obtained these variables from the website of Andrew Rose, University of California[21]. I briefly describe all the variables in Table A2.1 of the Appendix.

2.5 Empirical Identification Strategy: Propensity Score Matched Randomization

My empirical identification strategy employs the difference-in-differences (DiD) approach to estimate the effect of TGI on IIs' ownership. I exploit the 1st Kyoto Protocol commitment as an exogenous shock to TGI. I use investee firms in 50 countries based on MSCI ACWI

[20] International Trade Centre database: https://www.trademap.org/Index.aspx
[21] http://faculty.haas.berkeley.edu/arose/RecRes.htm#Software, accessed November 11, 2022, 16.35 GMT

because the literature indicates that foreign institutional investors have a significant interest in opportunity sets (firms and countries) in the MSCI index (Ferreira and Matos, 2008). Then, I construct a treatment group for firms in the countries that committed to the 1st Kyoto Protocol commitment following Annex I in the Kyoto Protocol Reference Manual[22] and a control group for firms in the countries that have not committed to the 1st Kyoto Protocol. However, for obvious reasons, I expect the baseline descriptive characteristics of the treated and control group firms to be statistically different at the beginning of the commitment period shock. For confirmation, I examine the mean (median) differences in the five key covariates over the pre-commitment period of 2004-2007. Drawing on the existing literature and as discussed in Section 2.4.3, I use the following five most common covariates to explain the variations in IIs' ownership: *SIZE*, *ROE*, *LEV*, *CASH*, and *BM*, also defined in Appendix Table A2.1. I report the mean (median) differences in Table 2.1.

As expected, the results in Panel A of Table 2.1 show that the treated and control groups statistically differ in all baseline characteristics. I employ PSM to generate statistically similar treated and control group firms before the 1st Kyoto Protocol commitment in 2008 to ensure an average statistical balance between the treated and control group firms. I match firm pairs between the treated and control groups using the above-noted five firm-level baseline characteristic covariates.

Following the standard PSM approach, as specified in Equation (1), I first run a probit regression model with the dependent being a dummy variable ($Treat_i$) that takes the value of one for the treated group firms and zero otherwise.

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[22] UNFCCC. (2005). *Kyoto Protocol Reference Manual on Accounting of Emissions and Assigned Amount*; The UNFCCC website: https://unfccc.int/kyoto_protocol.

$$Treat_i = \alpha + \boldsymbol{X}_{i,t}\beta' + \gamma_k + \mathcal{E}_{i,t} \tag{1}$$

My independent variables ($\boldsymbol{X}_{i,t}$) comprise the aforementioned firm baseline characteristics (i.e., *SIZE, ROE, LEV, CASH,* and *BM*). γ_k denotes industry fixed effects using the Standard Industrial Classification (SIC) two-digit codes. I apply the nearest-neighbor caliper algorithm (<0.0001) with replacement to identify a matching set of highly comparable treatment and control firms before the first Kyoto Protocol commitment. Panel B of Table 2.1 reports the outcome of the probit regression estimation.

Column (1) in Panel B of Table 2.1 shows that the differences in characteristics between treated and control firms before the PSM are statistically significant. However, post-PSM, Column (2) figures document statistically insignificant differences between the matched firms. I also confirm the difference and similarity between treated and control groups in the pre-and post-matching regime by graphing the standard diagnostic measures of the *z-scores* and *standardized bias* measures. Figure 2.1 illustrates the *z-score* statics used for testing the difference in the five baseline characteristics. Compared to the unmatched group, the *z-scores* for the matched groups' covariates, denoted by the diamond-shaped figures, are very close to the line representing a *z-score* of zero, which indicates statistically no differences in the average values of covariates.

Figure 2.2 shows the standardized bias (SB) diagnostic measures (Rosenbaum and Rubin, 1985). The SB measure is an alternative indicator for assessing differences in unmatched and matched statistical characteristics by evaluating the range of the marginal distribution of the covariates in the pre-and post-matched samples, as shown in Equations (2) and (3).

$$SB_{pre} = 100 \times \frac{(\bar{X}_1 - \bar{X}_0)}{\sqrt{0.5 \times [V_1(X) + V_0(X)]}} \tag{2}$$

$$SB_{post} = 100 \times \frac{(\bar{X}_{1M} - \bar{X}_{0M})}{\sqrt{0.5 \times [V_{1M}(X) + V_{0M}(X)]}} \tag{3}$$

where $\bar{X}_1$, $\bar{X}_0$ and $V_1(X)$, $V_0(X)$ denote the average and variance statistics of the covariates for the treated and control groups before the matching, respectively. $\bar{X}_{1M}$, $\bar{X}_{0M}$, V_{1M}, V_{0M} are the corresponding values of the covariates after matching. SB values closer to zero indicate statistically insignificant differences between the treated and control firms. As symbolized by the diamond-shaped figures, the SB values of all covariates of the matched sample are close to zero compared to those of the unmatched sample, as represented by the triangular-shaped figures.

All diagnostic tests confirm that the PSM approach generates statistically balanced treated and control group firms before applying the shock of the 1st Kyoto Protocol commitment in 2008. In Figure 2.3, I report the plausibility of the parallel trend assumption by plotting the yearly average institutional ownership (in %) of investor *j* holding the stocks of investee firm *i* for year *t* ($IO_{i,j,t}$) for the PSM matched treated and control firms.

As shown in Figure 2.3, although drifting steadily, the yearly averages of *IO* are relatively similar for the treated and control group firms during 2004-2007. However, from the beginning of 2008, I see a substantial divergence between treated and control firms over the post-commitment period of the 1st Kyoto Protocol (2008-2012). Since then, IIs seems to have significantly increased its equity investments in treated firms compared to control group firms. In the subsequent section, I empirically examine whether a greater boost in TGI by treated group firms, relative to those by control group firms, is a critical driver of the observed changes in the divergence of *IO*.

2.6 Empirical Results

2.6.1 Evidence of TGI During the 1st Kyoto Protocol Commitment Period

I begin my empirical investigation by analysing the descriptive figures of TGI development during the pre- (2004-2007) and post-commitment (2008-2012) periods for the 1st Kyoto Protocol. The results are presented in Table 2.2.

In Table 2.2, I provide the univariate analysis of TGI comparing between pre- and post-commitment periods. The variables of firms promoting TGI activities are composed of *GP_percent* (%) as referred to the intensity of quantitative TGI, *GC_percent* (%) as referred to the intensity of qualitative TGI, and *GP* (*Count*) as referred to the numbers of TGI. Panel A reports the case of full samples (investee-firm-year observations) over 2004 – 2012. I find that the mean differences of TGI variables between pre- and post-commitment periods significantly increased. For instance, during the post-commitment period, *GP_percent* and *GC_percent* increased (by 0.103% and 0.158%, respectively,) compared to before the 1st Kyoto Protocol commitment (see Column (9)).

Panel B and C report univariate analyses of TGI in the treated and the control groups, respectively. All figures discover that TGI variables of the treated and control firms significantly increased during the post-commitment period, relative to the pre-commitment period. However, I find that the intensive level of *GP_percent* (*GC_percent*) in the treated firms increases larger than the *GP_percent* (*GC_percent*) of the control firms. During the post-commitment period, *GP_percent* (*GC_percent*) of the treated firms increased by 0.184%(0.240%) compared to the pre-commitment period, while *GP_percent* (*GC_percent*) of the control firms rose by 0.062%(0.117%) (see Column (9)). Similarly, the difference in *GP* (*Count*) between the pre- and post-commitment periods in the treated firms was larger than in the control firms. I find that *GP* (*Count*) of the treated firms increased by 0.623, whereas *GP* (*Count*) of the control firms only increased by 0.098 (Column (9)).

According to these results, the figures suggest that the 1st Kyoto Protocol commitment can boost TGI activities of the firms in the committed countries. Considering the discussion in section 2.2, the evidence supports my argument that the 1st Kyoto Protocol commitment (2008-2012) is an exogenous factor fostering a greater boost in TGI activities in firms domiciled in committed countries than those in non-committed countries. The impact of the 1st Kyoto Protocol commitment on TGI activities impart an ideal quasi-natural experimental setup to test whether firms engaged in a higher level of TGI activities attract relatively more IIs' investments in the post-commitment period (2008-2012) as compared to the pre-commitment period (2004-2007).

2.6.2 Summary Statistics and Univariate DiD

I summarise the descriptive figures of investee firms' equity ownership for all IIs ($AIO_{i,j,t}$), domestic IIs ($DIO_{i,j,t}$), and foreign IIs ($FIO_{i,j,t}$) during the pre- (2004-2007) and post-commitment (2008-2012) periods for the 1st Kyoto Protocol. After excluding all investee firms with non-institutional ownership, I ended up with 11,751 domestic IIs and 6,237 foreign IIs. Table 2.3 reports the summary statistics of the PSM samples.

Panel A shows that, for the entire sample, the average *IO* increased from 0.126% in the pre-commitment period (Column (7)) to 0.170% in the post- commitment period (Column 8). Therefore, I witness a 35% (1 – 0.170/0.126) increment in the investment by a typical II in an average investee firm. Second, in the case of the treated group, the mean value of *IO* reached 0.229% in the post- commitment period (Column 8) from 0.144% in the pre- commitment period (Column (7)). This reflects an increase of 59% (1 – 0.229/0.144) in the investment of a typical II for an average investee firm. The corresponding changes in the control group firms show an increase of only 16.67% (from 0.114 to 0.133). Regarding the differential change, compared to the control group and the pre-commitment period, a typical II increased their *IO* in an average treated investee firm by 0.067% (Column (9)) in the post-commitment period.

In monetary terms, compared to the control group and in the pre-commitment period, in the post-commitment period, a typical II increased their investments in a firm by US$ 0.83 million (0.067%* US$1,236 million).[23] All the differences above are statistically significant. Although the figure of US$ 0.83 million may seem small, I must recognise that, in my sample, it implies an increase by one typical II (*j*) for an average treated investee firm (*j*) for year *t*. Considering that, during the pre-commitment period, an average of 48 IIs invested in a typical investee firm, the total additional investments received by typical firm *i* in period *t* is approximately US$ 39.75 million (US$ 0.83 million*48).

Panel B of Table 2.3 provides the summary statistics of *GP_percent* and *GC_percent*. The first and fourth rows of Panel B (Column (3)) show that the PSM sample period average of *GP_percent* is 0.99%, and that of *GC_percent* is 1.03%. Among all the types of patents, the relatively low proportion of green patents is consistent with those reported in the literature (see Haščič and Migotto, 2015). Column 7 of Panel B shows that the average of *GP_percent* and *GC_percent* are 0.89% and 0.95%, respectively, in the pre-

[23] The average market capitalization (*SIZE*) of a typical investee firm in our sample is approximately US$ 1,236 million in the pre-Kyoto Protocol period (see Table 2.3, Panel C, first row and Column (7)).

commitment period of the 1st Kyoto Protocol; however, these averages significantly increased to 1.05% and 1.08%, respectively, in the post-commitment period (Column 8).

Table 2.3 compares the green innovations of treated and control group firms. The average *GP_percent* in the treated and control groups is 1.32% and 0.63%, respectively. This indicates a material difference of 0.69% between the two groups. A similar positive difference of 0.77% (1.40 vs. 0.63) is seen in *GC_percent* between the treated and control groups. This pattern is consistent with the findings of all investee-firm samples in 2.6.1 (before PSM-matched samples). This suggests that countries committed to the protocol exported more environmental technologies in the post-commitment period, implying a higher TGI (i.e., *GP_percent* and *GC_percent*).

2.6.3 TGI and Equity Ownership of Institutional Investors

This section examines the effect of TGI on IIs' ownership following hypothesis H1: "*In the post-commitment period of the 1st Kyoto Protocol, firms with higher levels of TGI attracted more IIs' equity ownership*". Studies note that the investment considerations of FIIs differ from those of domestic IIs (see Ferreira and Matos, 2008, Luong et al., 2017 and Kacperczyk et al., 2021). Accordingly, I separately examine domestic and foreign IIs (hereafter DIIs and FIIs, respectively), as shown in Equation (4).

$$\begin{aligned} DIO_{ijt}(FIO_{ijt}) &= \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times TGI_{t-1}) \\ &\quad + \beta_3\, TGI_{t-1} + \rho_i \boldsymbol{X}_{it-1} + \varphi_i \boldsymbol{D}_{dt-1} + \delta_i \boldsymbol{BI}_{ijt-1} + \gamma_{i,j} + \lambda_d + \tau_t + \varepsilon_{ijt} \end{aligned} \tag{4}$$

In Equation (4), *i, j,* and *t* are indexed as the investee firm, institutional investor, and time (years), respectively. DIO_{ijt} (FIO_{ijt}) reflects the share of equity ownership of DII (FII) *j* in investee firm *i* for year *t*. TGI_{t-1} represents *GP_percent* and *GC_percent* (the two measures of TGI defined in Section 2.4.2). The dummy variable *Treat* equals one for the treated group investee firm (*i*) and zero for the control group investee firm (*i*). The variable *Post* takes the value of one for the period following the 1st Kyoto Protocol commitment (i.e., 2008 – 2012) and zero for the years before. $\boldsymbol{X}_{it-1}$ denotes the *SIZE*, *ROE*, *LEV*, *CASH*, and *BM* covariates. $\boldsymbol{D}_{dt-1}$ is the set of investee-country control variables (*MC_GDP)* and bilateral controls between the investor and investee country pairs ($\boldsymbol{BI}_{ijt-1}$), FDI_flows_{ijt-1}, $Distance_{ij}$ and Com_dum_{ij}. $\gamma_{i,j,}$ λ_d and τ_t denote investor×investee-firm, investee-country and year-fixed effects, respectively. All variables are defined in Appendix Table A2.1.

Regarding Equation (4), I investigate hypothesis H1 through the coefficient of $Treat_i \times Post_t \times TGI_{t-1}$ interaction (β_2). I expect the coefficient β_2 to be positive, indicating that during the post-commitment period, higher levels of TGI in the treated firms increased DIO(FIO) compared to the control firms. Table 2.4 reports the estimates of the four specifications of Equation (4).

The statistically significant positive coefficients of ($Treat_i \times Post_t \times TGI_{t-1}$), my key variables, indicate that treated firms in the post-commitment period and those with higher TGI attract more ownership from domestic and foreign IIs than the control firms. Quantitatively, the results suggest that, in the post-commitment period, a 1% increase in *GP_percent* of treated TGI firms, boosted *DIO* and *FIO* by 0.0024% and 0.0008%, respectively, compared to the control firms. These values signify that one standard deviation (5.669%)[24] increase in *GP_percent* corresponds to an increase of approximately 0.030% in *DIO* [0.0024*(5.669/0.453)] and 0.046% [0.0008*(5.669/0.099)] in *FIO*. The

[24] see Table 2.3, Panel B, first row and the fourth column.

application of these changes (0.030% and 0.046%) to the average market capitalization (US$ 1,151 million, full sample period)[25] of a typical firm implies an increase of approximately US$ 0.345 million (1,151 × 0.030%) and US$ 0.529 million (1,151 × 0.046%) in investments from a typical DII and FII, respectively. My sample also shows that in the pre-commitment period (2004-2007), the average number of DIIs and FIIs investing in a typical investee firm is 32 and 35, respectively. Thus, a typical investee firm in the treatment group, relative to the control group, receives additional capital worth US$ 11.04 million (0.345 × 32) and US$ 18.51 million (0.529 × 35) from DIIs and FIIs, respectively.

Similarly, Columns (2) and (4) of Table 2.4 show the statistically significant and positively differential impact of *GC_percent* on *DIO* and *FIO*, respectively. Quantitatively, by applying the approach above, a one standard deviation increase in *GC_percent* (6.317%)[26] leads to enhancements of approximately 0.028% [0.0020 × (6.317/0.453)] and 0.057% [0.0009 × (6.317/0.099)] in the ownership of the DII and FII, respectively. Applying these figures to the numbers of DIIs and FIIs and the average market capitalization for a typical investee firm (USD 1,151 million), the average firm receives US$ 10.31 million (1,151 ×0.028% × 32) and US$ 22.96 million (1,151 × 0.057% × 35) from DIIs and FIIs, respectively.

These findings support the hypothesis H1 that "*In the post-commitment period of the 1st Kyoto Protocol, firms with higher levels of TGI attracted more IIs' equity ownership*".

[25] see Table 2.3, Panel C, first row and the third column.
[26] See Table 2.3, Panel B, first row and the fourth column.

Krueger et al. (2020) suggest that rising investor concerns about environmental regulation can motivate investors to shift their investments by considering more firms with better environmental commitments to mitigate regulatory risks. Dyck et al. (2019) and Azar et al. (2021) also note that increasing social awareness regarding climate issues motivates investors to engage more in firms promoting environmental practices to reduce social pressures. Therefore, I interpret my findings that during the 1st Kyoto Protocol commitment period, investors tend to allocate their investment into firms engaged in TGI to reduce the impacts regarding regulatory risks and social pressures. According to TGI investment, firms promoting TGI activities demonstrate a significant signal of environmental commitment. This is because investing in TGI requires large resources e.g. knowledge, and funding capital (see Holmstrom, 1989, Ayyagari et al., 2011 and Brown et al., 2012). The success of TGI reflects the management's effort in responsive to the demands of stakeholders regarding environmental engagement. Moreover, firms engaged in TGI can increase firms' competitive advantage under the regulation enforcement which promote operating performance and firms' future value (Porter and Van Der Linde, 1995, Shrivastava, 1995 and Ambec and Lanoie, 2008).

2.6.4 Robustness Check: Placebo Test

The phenomenon observed above could be a recurring theme, or firms could have deliberately boosted TGI in anticipation of the Protocol. To ensure that my results are not confounded, I run a placebo test using the triple difference model (DiDiD) in Equation (4) using the same sample for the period between 2004 and 2008; however, this time, I assumed a false shock event in 2005. Accordingly, I generated a false $Post_t$ binary variable that takes the value of zero for 2004 – 2005 (false pre-period) and one for 2006 – 2007 (false post-period). If the results reported and discussed in Section 2.6.3 capture some recurring themes, I should expect the coefficient of $Treat_i \times Post_t \times TGI_{t-1}$ (β_2) to be positive and significant. Table 2.5 reports the outcomes of the placebo tests.

The coefficient on the interaction term ($Treat_i \times Post_t \times TGI_{t-1}$) is not statistically significant. This finding suggests that no firm-level pre-intervention occurred prior to the 2008 shock. Furthermore, it confirms that my results reported in Section 2.6.3 do not capture any other confounding effects.

2.6.5 IIs' Heterogeneity Hypotheses

In this section, I investigate the effects of TGI on ownership of IIs, depending on their type to answer the question that: Does the heterogeneity of IIs differently affect the investment in firms promoting TGI activities? I exploit two forms of investor heterogeneity. First, based on the intensity of the II's monitoring roles (i.e., engagement levels) of their investee firms, I categorize IIs into independent and grey investors, as defined in Section 2.3.2.1 and Table A2.3. The second heterogeneity exploits the classification of IIs based on their potential investment horizons: long-term (e.g., pension funds) and short-term (e.g., hedge funds), as in Section 2.3.2.2 and Table A2.3. I examine the moderating role of II heterogeneity by running the regression specifications of the quasi-natural experiment (Equation 5):

$$DIO_{ijt}(FIO_{ijt}) = \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times TGI_{t-1} \times Type_j) \quad (5)$$
$$+ \beta_3\, TGI_{t-1} + \rho_i \boldsymbol{X}_{it-1} + \varphi_i \boldsymbol{D}_{dt-1} + \delta_i \boldsymbol{BI}_{ijt-1} \quad \gamma_{i,j} + \lambda_d + \tau_t + \varepsilon_{ijt}$$

where $Type_j$ represents a binary variable for the type of IIs, that is, independent or grey and long-term versus short-term investors, as defined in Table A2.1 of the Appendix. All the other variables in Equation (5) are described in Section 2.6.3. The regression coefficient (β_2) of the quadruple differences variable $(Treat_i \times Post_t \times TGI_{t-1} \times Type_j)$ reflects the heterogeneous effects of TGI on the equity ownership of different types of IIs.

2.6.5.1 Heterogeneous Effects: Independent versus Grey IIs

Here, I examine the heterogeneity test centered on the monitoring roles of IIs following hypothesis H2a that "*In the post-commitment period of the 1st Kyoto Protocol, firms with higher TGI attracted more equity investments from independent IIs than grey IIs*". Accordingly, $Type_j$ in Equation (5) is a binary variable that equals one if investor j is classified as an independent investor and zero otherwise.[27] If my hypothesis H2a holds, I should expect the regression coefficient β_2 to be positively significant. This signifies that, relative to grey IIs, independent IIs in the post-commitment period invested more in treated firms with a higher TGI level than in control firms. The results are reported in Table 2.6.

Columns (1) and (3) of Table 2.6 show that the coefficient of the interaction term $(Treat_i \times Post_t \times TGI_{t-1} \times Type_j)$ is positive and statistically significant, at least the 5% level. The results indicate that compared to the control firms, when a treated firm's *GP_percent* increased in the post-commitment period by one standard deviation, independent DIIs (FIIs), relative to grey DIIs (FIIs), raised their share of ownership in that treated firm by 0.026% (0.046%)[28]. In monetary terms, the increase in investment is approximately US$

[27] See Appendix Table A2.3 for the specific classifications of independent versus grey investors.
[28] [0.0021*(5.669/0.453)] and [0.0008*5.669/0.099)], respectively.

0.299 million (US$ 0.529 million) for the treated firm.[29] Similarly, the estimates reported in Columns (2) and (4) of Table 2.6 indicate that during the post-commitment period, when a treated firm's *GC_percent* increased by one standard deviation, the ownership of the independent DIIs(FIIs), relative to grey DIIs(FIIs), increased by 0.026% (0.057%)[30]; in monetary terms, this value is US$ 0.299 million (US$ 0.656 million)[31]. These results validate H2a and indicate that "*In the post-commitment period of the 1st Kyoto Protocol, firms with higher TGI attracted more equity investments from independent IIs than grey IIs*".

These findings support the argument of the attributes and actions of professional fund managers. Regarding Ferreira and Matos (2008), suggest that independent IIs play an active role in monitoring and being deeply engaged in enhancing shareholder wealth, corporate governance, and social responsibility. These investors demonstrate a strong desire to enhance their reputation within the network of affiliated firms. (Ferreira and Matos, 2008 and Dyck et al., 2019). Therefore, it is plausible that firms promoting TGI activities can attract independent IIs than gray IIs who are less monitoring business operations and tend to tie business relationships with investee firms. This is because firms engaged in TGI activities reflecting intensive environmental commitment which can encourage the reputation of independent IIs regarding environmental engagement. TGI activities also increase production and operation efficiency, leading to the monitoring cost

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[29] (USD 1,151 million*0.026% = USD 0.299 million) and (USD 1,151 million*0.046% = USD 0.529 million), respectively.
[30] [0.0019*(6.317/0.453)] and [0.0009*(6.317/0.099)], respectively.
[31] (USD 1,151 million*0.026% = USD 0.299 million) and (USD 1,151 million*0.057% = USD 0.656 million), respectively.

reduction of independent IIs, who are more actively engaged in monitoring firms' operations and managers' decisions than grey IIs.

2.6.5.2 Heterogeneous Effects: Long-term vs. Short-term IIs

This section, I investigate hypothesis H2b: "*In the post-commitment period of the first Kyoto Protocol, firms with higher levels of TGI attracted more equity investments from long-term IIs than short-term IIs*". To examine heterogeneity based on the investment horizons of IIs, I modify Equation (5) with the indicator variable $Type_j$ as a dummy variable representing long- and short-term IIs. The variable $Type_j$ takes the value of one for investor *j* if it is classified as a long-term II and zero for short-term II; this is defined in Table A2.1, and the classifications are described in Table A2.3 (Appendix). The results are summarised in Table 2.7.

Similar to the results reported in Table 2.7, the positive and statistically significant coefficient of the interaction terms $(Treat_i \times Post_t \times TGI_{t-1} \times Type_j)$ indicates that during the post-commitment period, long-term IIs, relative to short-term IIs, invested more in the treated firms with higher levels of TGI than the control firms. Quantitatively, the outcomes reported in Columns (1) and (3) of Table 2.7 indicate that, in the post-commitment period, an increase of one standard deviation in *GP_percent* of the treated firms increased the ownership of the long-term DIIs (FIIs) by 0.274% (0.120%)[32] compared to short-term DIIs (FIIs). In monetary terms, these incremental investments amount to approximately US$

[32] [0.0219*(5.669/0.453)] and [0.0021*5.669/0.099)], respectively.

3.153 million (US$ 1.381 million) for an average treated investee.[33] Likewise, the estimates in Columns (2) and (4) of Table 2.7 confirm that during the post-commitment period, one standard deviation increase in the treated firms' *GC_percent* increased the ownership share of the long-term DIIs (FII) by 0.278% (0.127%) compared to the short-term DIIs (FIIs).[34] Monetarily, these changes translate to approximately US$ 3.199 million (US$ 1.461 million).[35] These findings support hypothesis H2b that "*In the post-commitment period of the first Kyoto Protocol, firms with higher levels of TGI attracted more equity investments from long-term IIs than short-term IIs*".

These results are consistent with my argument regarding different styes of investment strategies. Bushee (1998) suggests that short-term IIs influence managers' decisions, which support short-term operating performance, whereas long-term IIs tend to reduce managers' shortsighted behaviour. Considering profitable portfolio investment, Chen et al. (2007) note that long-term IIs who rely on long-term performance are engaged in manager' strategic decisions to reduce their monitoring costs. In contrast, short-term IIs who are less patient in monitoring will use short-term trading to manage their profits. The different investment strategies can lead long-term IIs to invest more in firms promoting TGI activities compared to short-term IIs as due to the benefits related to TGI implications e.g. increasing firms' competitiveness and operting performance, which supports long-term value rather than short-term value.

[33] (USD 1,151 million*0.274% = USD 3.153 million) and (USD 1,151 million*0.120% = USD 1.381 million), respectively.
[34] [0.0200*(6.317/0.453)] and [0.0020*(6.317/0.099)], respectively.
[35] (USD 1,151 million*0.278% = USD 3.199 million) and (USD 1,151 million*0.127% = USD 1.461 million), respectively.

Furthermore, my findings are related to the evidence of Luong et al. (2017), which shows that long-term IIs encourage firms' investments in innovation activities compared to short-term IIs. They suggest that long-term IIs holding long-term capital have more potential to contribute innovation than short-term IIs who have higher capital restrictions.

2.7 Conclusions

Considering the recent lofty rhetoric of IIs being environmentally conscious, I expect a positive association between investee firms' proven efforts to become environmentally friendly and IIs equity ownership. Furthermore, the mounting evidence that investors incorporate environmental criteria into their investment decisions should offer a strong signal for businesses to improve their environmental performance. In this study, I ask: Do firms that boost TGI attract more investment from IIs? I also examine whether the heterogeneity of IIs could explain the strength of the association between TGI and IIs' ownership.

The theoretical lens of finance and business literature implies that firms engaged in more successful green innovations are associated with improved environmental performance, lower operational costs, more exports of green technologies, and superior market competitiveness. Similarly, innovative green firms exhibit higher reputational brand value, lower cost of capital, and higher operating and financial performance. Furthermore, TGI-oriented firms can better mitigate and manage their climate risks, a key concern for IIs. These positive outcomes of advancing green innovations should attract outside investors, including IIs. Integrating the favorable market and efficiency outcomes of TGI with the view of greater demand for green assets by IIs, I hypothesise that firms demonstrating a superior degree of TGI should draw more investments from the IIs.

This study employs the PSM-DiD procedure for empirical identification in a quasi-natural experiment by exploiting the 1st Kyoto Protocol commitment (2008) as an exogenous variation in TGI. Using investor-investee level data from 50 countries, I find that compared to the pre-commitment period and relative to the control group (investee firms domiciled in countries that have not signed the Protocol), firms from the treatment group (investee firms domiciled in countries that have signed the Protocol) attract higher IIs' investments (domestic and foreign) in the post-commitment period (2008-2012). I also show that the heterogeneity of IIs explains the strength of the association between TGI and ownership. I find that in the post-commitment period (2008-2012), independent IIs (e.g., mutual funds), which play a more significant monitoring role in managing the investee firms, compared to grey IIs (e.g., insurance firms), invest more in treatment group firms with higher TGI. Furthermore, in the same post-commitment period, long-term IIs (e.g., pension funds) invest more in treatment firms with a higher TGI than short-term IIs do (e.g., hedge funds). Both heterogeneity outcomes imply that IIs' monitoring roles and investment horizons guide the intensity of the nexus between TGI and IIs' ownership.

To the extent that boosting TGI is imperative to address the sustainability challenges rooted in the raging climate crisis and environmental degradation, firms promoting TGI may have idiosyncratic advantages to attract lucrative outside investors, particularly independent and long-term IIs.

Table 2.1 Propensity Score Matching (PSM) Results

Panel A provides the univariate analysis of treatment and control groups between the pre and post-period of the 1st Kyoto Protocol commitment by reporting the t-test and z-score of mean and median differences, respectively. Panel B reports a probit analysis of samples between pre and post-matching.

$$Treat_i = \alpha + \boldsymbol{X}_{i,t}\beta' + \gamma_k + \mathcal{E}_{i,t}$$

Treat is a dummy variable equal to one if the firm is in the country committing to the 1st Kyoto Protocol treaty and zero otherwise. $X_{i,t}$ is the vector of covariates comprising *SIZE*, *ROE*, *CASH*, *LEV*, and *BM*. I define all these covariates in Table A2.1 of the appendix. γ_k is the industry fixed effects using the two-digit Standard Industrial Classification (SIC). I present the z-score in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Panel A: Mean and median comparisons in covariates between treatment and control groups in 2004 – 2007

	Treatment group			Control group			Differences	
Variable	**Obs.**	**Mean**	**Median**	**Obs.**	**Mean**	**Median**	**Mean**	**Median**
SIZE	22,988	18.663	18.544	37,177	18.263	18.181	0.400***	0.363***
ROE	22,988	-1.885	6.093	37,177	3.283	8.796	-5.169***	-2.703***
CASH	22,988	17.234	10.580	37,177	11.951	6.991	5.283***	3.589***
LEV	22,988	57.723	23.873	37,177	64.959	34.780	-7.236***	-10.907***
BM	22,988	0.715	0.542	37,177	0.845	0.574	-1.303***	-0.032***

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

	The binary variable equals one if the country of the investee firm *i* is associated with the Kyoto Protocol and zero otherwise.	
Variable	**Pre-match (1)**	**Post-match (2)**
SIZE	0.0984***	0.0095
	(18.13)	(0.98)
ROE	-0.0011***	-0.0005
	(-5.17)	(-1.37)
CASH	0.0585***	-0.0851
	(13.48)	(-0.07)
LEV	-0.0003**	0.0001
	(3.78)	(0.42)
BM	0.0529***	-0.0354
	(4.65)	(-1.61)
Constant	-1.2157***	0.4765
	(-7.83)	(1.20)
Industry FE	Yes	Yes
Pseudo R^2	0.144	0.001
P-value of χ^2	0.000	0.743
Firms	18,117	4,756
Firm-year Observations	60,165	16,156

Table 2.2 Univariates of Technological Green Innovation Between Pre- and Post-Periods of the 1st Kyoto Protocol Commitment

This table reports the univariate analysis of green innovations of global listed firms between pre-period (2004-2007) and post-period (2008-2012) of the 1st Kyoto Protocol commitment. Panel A presents all firm-year observations covering MSCI_ACWI countries. Panel B presents the treatment group referring to firm-year observations in the countries committed to the 1st Kyoto Protocol commitment. Panel C presents the control group referring to firm-year observations in the uncommitted countries of the 1st Kyoto Protocol commitment. The numbers in parenthesis present firm-year observations of the pre and post periods. *GP_percent* is the percentage of firm green patents divided by firm total patents. *GC_percent* is the percentage of adjusted green citations of the firms divided by total adjusted citations of the firms. *GP (count)* is the number of green patents. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Variable (1)	Observations (2)	Mean (3)	Std. (4)	Minimum (5)	Maximum (6)	Before (7)	After (8)	Diff (9)	t-stat (10)	p-value (11)
Panel A: Full sample										
GP_percent(%)	228,053	0.718	6.384	0	100	0.660	0.763	0.103***	3.84	0.00
						(101,556)	(126,486)			
GC_percent(%)	228,053	0.786	7.117	0	100	0.698	0.856	0.158***	5.28	0.00
						(101,556)	(126,486)			
GP (count)	228,053	0.629	20.301	0	3,461	0.476	0.752	0.276***	3.22	0.00
						(101,556)	(126,486)			
Panel B: Treatment group										
GP_percent(%)	77,184	1.182	8.172	0	100	1.080	1.264	0.184***	3.10	0.00
						(34,384)	(42,800)			
GC_percent(%)	77,184	1.287	8.970	0	100	1.154	1.394	0.240***	3.69	0.00
						(34,384)	(42,800)			
GP (count)	77,184	1.440	33.305	0	3,461	1.094	1.717	0.623***	2.58	0.00
						(34,384)	(42,800)			
Panel C: Control group										
GP_percent(%)	150,869	0.480	5.222	0	100	0.445	0.508	0.062**	2.31	0.02
						(67,172)	(83,697)			
GC_percent(%)	150,869	0.529	5.934	0	100	0.464	0.581	0.117***	3.80	0.00
						(67,172)	(83,697)			
GP (count)	150,869	0.214	7.415	0	1,103	0.160	0.258	0.098**	2.54	0.01
						(67,172)	(83,697)			

Table 2.3 Summary Statistics and Univariate Difference in Differences

This table reports the univariate summary statistics of all time-varying variables for the entire PSM-matched sample and by treated and control group investee firms. The statistics reported for the entire sample period of 2004-2012 (columns 2-6) are the total number of observations (*Observations*), the mean value (*Mean*), the standard deviation (*Std*.), the minimum value (*Minimum*), and the maximum value (*Maximum*). Columns 7 and 8 report the average values for the pre-period of 2004-2007 (*Before*) and the post-period of 2008-2012 (*After*) of the 1st Kyoto Protocol commitment, respectively. The figures in columns 7 and 8 parentheses are firm-year observations for the *Before* and *After* periods. Column 9 reports the difference between the *After* and *Before* mean values, with columns 10 and 11 reporting their associated t-stats and p-values.

Panel A reports statistics on all institutional ownership ($IO_{i,j,t}$), domestic institutional ownership ($DIO_{i,j,t}$), and foreign institutional ownership ($FIO_{i,j,t}$). I index *j* as an institutional investor, *i* as the investee firm, and *t* as the year. Panel B reports statistics of green innovation variables. *GP_percent* and *GC_percent*. Panel C reports statistics of investee firm-specific covariates (*SIZE*, *ROE*, *LEV*, *CASH*, and *BM*) and other country-level and bilateral-level time-varying variables (*MC_GDP* and *FDI_flows*, respectively). I define all these variables in Table A2.1 of the appendix. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Panel A: Institutional Ownership

Variable (1)	**Observations** (2)	**Mean** (3)	**Std.** (4)	**Minimum** (5)	**Maximum** (6)	**Before** (7)	**After** (8)	**Diff** (9)	**t-stat** (10)	**p-value** (11)
All institutional ownership ($IO_{i,j,t}$, %)										
Full sample	4,354,961	0.151	0.879	0	30.00	0.126	0.170	0.044***	51.99	0.00
						(1,852,053)	(2,502,908)			
Treated group	1,670,052	0.193	1.033	0	30.00	0.144	0.229	0.085***	52.40	0.00
						(704,145)	(965,907)			
Control group	2,684,909	0.125	0.766	0	30.00	0. 114	0.133	0.018***	19.62	0.00
						(1,147,908)	(1,537,001)			
Differential ownership (treated – control)						0.029	0.095	0.067***	4.59	0.00
Domestic institutional ownership ($DIO_{i,j,t}$, %)										
Full sample	2,257,759	0.205	1.043	0	30	0.166	0.234	0.068***	48.40	0.00
						(960,133)	(1,297,626)			
Treated group	440,134	0.453	1.622	0	29.984	0.316	0.547	0.231***	46.59	0.00
						(180,478)	(259,656)			
Control group	1,817,625	0.145	0.834	0	30	0.131	0.156	0.024***	19.44	0.00
						(779,655)	(1,037,970)			

Table 2.3 continued

Variable (1)	Observations (2)	Mean (3)	Std. (4)	Minimum (5)	Maximum (6)	Before (7)	After (8)	Diff (9)	t-stat (10)	p-value (11)
Foreign institutional ownership ($FIO_{i,j,t}$, %)										
Full sample	2,129,438	0.092	0.653	0	30	0.081 (905,835)	0.100 (1,223,603)	0.019^{***}	21.12	0.00
Treated group	1,251,922	0.099	0.689	0	30	0.083 (533,160)	0.110 (718,762)	0.027^{***}	21.98	0.00
Control group	877,516	0.082	0.598	0	29.765	0.078 (372,675)	0.085 (504,841)	0.007^{***}	5.71	0.00
Panel B: Green Innovation Variables (Investee Firm Level)										
GP_percent(%)										
Full sample	34,845	0.991	5.669	0	100	0.898 (13,597)	1.050 (21,248)	0.152^{**}	2.43	0.01
Treated group	18,061	1.320	6.408	0	100	1.216 (7,059)	1.387 (11,002)	0.171^{*}	1.75	0.07
Control group	16,784	0.636	4.721	0	100	0. 556 (6,538)	0.688 (10,746)	0.132^{*}	1.77	0.07
GC_percent(%)										
Full sample	34,845	1.032	6.317	0	100	0.957 (13,597)	1.081 (21,248)	0.124^{*}	1.79	0.07
Treated group	18,061	1.406	7.345	0	100	1.325 (7,059)	1.457 (11,002)	0.132	1.18	0.23
Control group	16,784	0.631	4.947	0	100	0.559 (6,538)	0.677 (10,746)	0.117	1.50	0.13
Panel C: Investee firm-level covariates, country-level, and bilateral country-level variables										
Investee Firm Level										
SIZE (million dollars)	34,845	1,151.605	3,612.491	10.312	26,956.19	1,236.584 (13,597)	1,097.225 (21,248)	-139.359^{***}	-3.51	0.00
ROE (%)	34,845	2.941	26.860	-121.930	58.158	5.294 (13,597)	1.432 (21,248)	-3.861^{***}	-13.11	0.00
LEV (%)	34,845	63.734	91.246	0	550.265	62.756 (13,597)	64.363 (21,248)	-1.607	-1.60	0.10

Table 2.3 continued

Variable (1)	Observations (2)	Mean (3)	Std. (4)	Minimum (5)	Maximum (6)	Before (7)	After (8)	Diff (9)	t-stat (10)	p-value (11)
CASH (%)	34,845	12.857	12.931	0.127	60.602	12.270 (13,597)	13.236 (21,248)	0.966***	6.78	0.00
BM	34,845	0.981	0.772	0.032	2.926	0.763 (13,597)	1.121 (21,248)	0.358***	43.23	0.00
Investee Country Level										
MC_GDP (%)	429	90.982	189.976	4.845	2,195.627	94.342 (189)	88.336 (240)	-6.006	-0.32	0.74
Investor-investee Country Level										
FDI_flows (%)	11,279	3.993	8.819	0	55.170	3.458 (4,930)	4.407 (6,349)	0.948***	5.67	0.00

Table 2.4 Institutional Ownership and Technological Green Innovation

The table below reports the results of a quasi-natural experiment model by following the equation (4):

$$DIO_{ijt}\ (FIO_{ijt}) = \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times TGI_{t-1}) + \beta_3\, TGI_{t-1} + \rho_i \boldsymbol{X}_{it-1} + \varphi_i \boldsymbol{D}_{dt-1} + \delta_i \boldsymbol{BI}_{ijt-1}\ \ \gamma_{i,j} + \lambda_d + \tau_t + \varepsilon_{ijt}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Table A2.1 of the appendix. The interaction term [$Treat_i \times Post_t$] is the DiD variable, and [$Treat_i \times Post_t \times TGI_{it-1}$] is my key triple interaction DiDiD variable of interest. TGI_{t-1} represents the two measures of technological green innovations, i.e., *GC_percent* and *GP_percent*, defined in Table A2.1 of the appendix. Other interactions are included in the model. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged investee firm-level covariates (*SIZE, ROE, LEV, CASH,* and *BM*). $\boldsymbol{D}_{dt-1}$ is an investee-country control variable (*MC_GDP* is in natural logarithm). $\boldsymbol{BI}_{ijt}$ is a set of bilateral investor-investee level control variables (FDI_flows_{ijt-1}, $Distance_{ij}$ and Com_dum_{ij}). γ_{ij} is the bilateral pair observations of investor (j) investing in investee firm (i) fixed effect, λ_d, and τ_t are the investee country and year fixed effects. $\varepsilon_{i,j,t}$ is the bilateral pair (ij) error term for year t. All covariates and country control variables are winsorized at 1% and 99%. Standard errors are clustered at the bilateral investor-investee level ($_{ij}$), and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	DIO_{ijt}		FIO_{ijt}	
	(1)	**(2)**	**(3)**	**(4)**
$Treat_i \times Post_t$	0.1925***	0.1928***	0.0289***	0.0277***
	(32.90)	(32.97)	(12.21)	(12.18)
$Treat_i \times Post_t \times GP\_percent_{it-1}$	**0.0024*** **		**0.0008*** **	
	(2.75)		**(2.93)**	
$Treat_i \times Post_t \times GC\_percent_{it-1}$		**0.0020** **		**0.0009*** **
		(2.42)		**(3.71)**
$GP\_percent_{it-1}$	0.0007***		0.0002	
	(2.64)		(0.91)	
$GC\_percent_{it-1}$		0.0007***		0.0002
		(3.02)		(1.13)
$SIZE_{it-1}$	0.0210***	0.0211***	0.0115***	0.0115***
	(9.64)	(9.66)	(6.68)	(6.69)
ROE_{it-1}	0.0001	0.0001	0.0002***	0.0002***
	(1.10)	(1.07)	(4.60)	(4.62)
LEV_{it-1}	-0.0001	-0.0001	-0.0001**	-0.0001**
	(-1.22)	(-1.22)	(-2.51)	(-2.50)
$CASH_{it-1}$	0.0001	0.0001	0.0002	0.0002
	(1.38)	(1.40)	(1.56)	(1.55)
BM_{it-1}	0.0123***	0.0124***	-0.0041	-0.0041
	(3.08)	(3.09)	(-1.53)	(-1.53)
MC_GDP_{it-1}			0.0562***	0.0563***
			(16.77)	(16.79)
FDI_flows_{ijt-1}			0.0010***	0.0010***
			(13.92)	(13.92)
$Distance_{ij}$			-0.3697***	-0.3697***
			(-8.62)	(-8.62)
Com_dum_{ij}			0.1904**	0.1908**
			(2.12)	(2.12)
Investor-investee FE	Yes	Yes	Yes	Yes
Investee country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
adjust-R^2	0.573	0.573	0.506	0.506
Number of investee firms	4,231	4,231	3,735	3,735
Number of investors	11,751	11,751	6,237	6,237
Observations	2,257,643	2,257,643	2,129,438	2,129,438

Table 2.5 Placebo Test
Using 2004-2005 for the Pre-false Period and 2006-2007 for the Post-false Period

This table reports the results of a quasi-natural experiment model by following the equation (4):

$$DIO_{ijt}\ (FIO_{ijt}) = \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times TGI_{t-1}) + \beta_3\, TGI_{t-1} + \rho_i \boldsymbol{X}_{it-1} + \varphi_i \boldsymbol{D}_{dt-1} + \delta_i \boldsymbol{BI}_{ijt-1}\ \ \gamma_{i,j} + \lambda_d + \tau_t + \varepsilon_{ijt}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Table A2.1 of the appendix. The interaction term [$Treat_i \times Post_t$] is the DiD variable, and [$Treat_i \times Post_t \times TGI_{it-1}$] is my key triple interaction DiDiD variable of interest. TGI_{t-1} represents the two measures of technological green innovations, i.e., *GC_percent* and *GP_percent*, defined in Table A2.1 of the appendix. Other interactions are included in the model. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged investee firm-level covariates (*SIZE, ROE, LEV, CASH,* and *BM*). $\boldsymbol{D}_{dt-1}$ is an investee-country control variable (*MC_GDP* is in natural logarithm). $\boldsymbol{BI}_{ijt}$ is a set of bilateral investor-investee level control variables (FDI_flows_{ijt-1}, $Distance_{ij}$, and Com_dum_{ij}). γ_{ij} is the bilateral pair observations of investor (j) investing in investee firm (i) fixed effect, λ_d, and τ_t are the investee country and year fixed effects. $\varepsilon_{i,j,t}$ is the bilateral pair (ij) error term for year t. All covariates and country control variables are winsorized at 1% and 99%. Standard errors are clustered at the bilateral investor-investee level ($_{ij}$), and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	DIO_{ijt}		FIO_{ijt}	
	(1)	**(2)**	**(3)**	**(4)**
$Treat_i \times Post_t$	0.1028***	0.1028***	0.0102***	0.0102***
	(19.79)	(19.79)	(3.43)	(3.43)
$Treat_i \times Post_t \times GP\_percent_{it-1}$	**0.0003**		**0.0003**	
	(0.28)		**(1.01)**	
$Treat_i \times Post_t \times GC\_percent_{it-1}$		**0.0005**		**0.0003**
		(0.48)		**(1.09)**
$GP\_percent_{it-1}$	0.0003		0.0001	
	(0.28)		(0.12)	
$GC\_percent_{it-1}$		0.0005		0.0001
		(0.48)		(0.39)
$SIZE_{it-1}$	0.0271***	0.0271***	0.0051*	0.0051*
	(7.34)	(7.35)	(1.95)	(1.94)
ROE_{it-1}	-0.0001	-0.0001	0.0002***	0.0002***
	(-1.01)	(-1.00)	(4.35)	(4.35)
LEV_{it-1}	-0.0001	-0.0001	0.0001	0.0001
	(-0.76)	(-0.77)	(0.55)	(0.53)
$CASH_{it-1}$	-0.0001	-0.0001	-0.0004**	-0.0004**
	(-0.54)	(-0.56)	(-2.45)	(-2.46)
BM_{it-1}	0.0213**	0.0213**	-0.0181***	-0.0182***
	(2.45)	(2.45)	(-3.31)	(-3.33)
MC_GDP_{it-1}			0.0399***	0.0402***
			(6.88)	(6.92)
FDI_flows_{ijt-1}			0.0005***	0.0005***
			(5.17)	(5.15)
$Distance_{ij}$			-0.3339***	-0.3339***
			(-6.45)	(-6.45)
Com_dum_{ij}			0.1323	0.1323
			(0.92)	(0.92)
Investor-investee FE	Yes	Yes	Yes	Yes
Investee country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
adjust-R^2	0.646	0.646	0.593	0.593
Number of investee firms	3,806	3,806	3,397	3,397
Number of investors	11,044	11,044	6,104	6,104
Observations	951,382	951,382	905,835	905,835

Table 2.6 Independent Versus Grey Institutional Investors and Technological Green Innovation

The table reports the results of a quasi-natural experiment model by following the equation (5):

$$DIO_{ijt}\ (FIO_{ijt}) = \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times TGI_{t-1} \times Type_j) + \beta_3\ TGI_{t-1} + \rho_i \boldsymbol{X}_{it-1} + \varphi_i \boldsymbol{D}_{dt-1} + \delta_i \boldsymbol{BI}_{ijt-1}\ \ \gamma_{i,j} + \lambda_d + \tau_t + \varepsilon_{ijt}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Table A2.1 of the appendix. The interaction term [$Treat_i \times Post_t$] is the DiD variable, and [$Treat_i \times Post_t \times TGI_{t-1} \times Type_j$] is my key interaction variable of interest. TGI_{t-1} represents the two measures of technological green innovations, i.e., *GC_percent* and *GP_percent,* defined in Table A2.1 of the appendix. Other interactions are included in the model. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged investee firm-level covariates (*SIZE, ROE, LEV, CASH,* and *BM).* $\boldsymbol{D}_{dt-1}$ is an investee-country control variable (*MC_GDP* is in natural logarithm). (FDI_flows_{ijt-1}, $Distance_{ij}$ and Com_dum_{ij}). $\boldsymbol{BI}_{ijt}$ is a set of bilateral investor-investee level control variables (FDI_flows_{ijt-1}, $Distance_{ij}$, and Com_dum_{ij}). γ_{ij} is the bilateral pair observations of investor (j) investing in investee firm (i) fixed effect, λ_d, and τ_t are the investee country and year fixed effects. $\varepsilon_{i,j,t}$ is the bilateral pair (*ij*) error term for year *t*. All covariates and country control variables are winsorized at 1% and 99%. Standard errors are clustered at the bilateral investor-investee level ($_{ij}$), and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Independent Institutional Investor			
	DIO_{ijt}		FIO_{ijt}	
	(1)	**(2)**	**(3)**	**(4)**
$Treat_i \times Post_t$	0.5204***	0.5203***	0. 0276***	0.0275***
	(21.40)	(21.39)	(12.14)	(12.12)
$Treat_i \times Post_t \times GP\_percent_{it-1} \times Type_j$	**0.0021****		**0.0008*****	
	(2.51)		**(3.04)**	
$Treat_i \times Post_t \times GC\_percent_{it-1} \times Type_j$		**0.0019****		**0.0009*****
		(2.36)		**(3.69)**
$GP\_percent_{it-1}$	0.0005*		0.0001	
	(1.77)		(0.26)	
$GC\_percent_{it-1}$		0.0006**		0.0001
		(2.38)		(0.26)
$SIZE_{it-1}$	0.0221***	0.0222***	0.0117***	0.0117***
	(10.14)	(10.17)	(6.82)	(6.83)
ROE_{it-1}	0.0001	0.0001	0.0002***	0.0002***
	(0.78)	(0.75)	(4.58)	(4.59)
LEV_{it-1}	-0.0001	-0.0001	-0.0001	-0.0001
	(-1.25)	(-1.23)	(-2.48)	(-2.46)
$CASH_{it-1}$	0.0002*	0.0002*	0.0002	0.0002
	(1.66)	(1.68)	(1.56)	(1.56)
BM_{it-1}	0.0106***	0.0108***	-0.0040	-0.0040
	(2.66)	(2.68)	(-1.50)	(-1.50)
MC_GDP_{it-1}			0.0561***	0.0562***
			(16.75)	(16.77)
FDI_flows_{ijt-1}			0.0009***	0.0010***
			(13.92)	(13.92)
$Distance_{ij}$			-0.3784***	-0. 3784***
			(-8.84)	(-8.84)
Com_dum_{ij}			0.1587**	0.1587**
			(1.99)	(1.99)
Investor-investee FE	Yes	Yes	Yes	Yes
Investee country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
adjust-R^2	0.573	0.574	0.506	0.506
Number of investee firms	4,231	4,231	3,735	3,735
Number of investors	11,751	11,751	6,237	6,237
Observations	2,257,643	2,257,643	2,129,438	2,129,438

Table 2.7 Long-term Versus Short-term Institutional Investors and Technological Green Innovation

This table reports the results of a quasi-natural experiment model by following the equation (5):

$$DIO_{ijt}\ (FIO_{ijt}) = \alpha + \beta_1(Treat_i \times Post_t) + \beta_2(Treat_i \times Post_t \times TGI_{t-1} \times Type_j) + \beta_3\ TGI_{t-1} + \rho_i \boldsymbol{X}_{it-1} + \varphi_i \boldsymbol{D}_{dt-1} + \delta_i \boldsymbol{BI}_{ijt-1}\ \ \gamma_{i,j} + \lambda_d + \tau_t + \varepsilon_{ijt}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Table A2.1 of the appendix. The interaction term [$Treat_i \times Post_t$] is the DiD variable, and [$Treat_i \times Post_t \times TGI_{t-1} \times Type_j$] is my key interaction variable of interest. TGI_{t-1} represents the two measures of technological green innovations, i.e., *GC_percent* and *GP_percent,* defined in Table A2.1 of the appendix. Other interactions are included in the model. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged investee firm-level covariates (*SIZE, ROE, LEV, CASH,* and *BM). $\boldsymbol{D}_{dt-1}$* is an investee-country control variable (*MC_GDP* is in natural logarithm). (FDI_flows_{ijt-1}, $Distance_{ij}$ and Com_dum_{ij}). $\boldsymbol{BI}_{ijt}$ is a set of bilateral investor-investee level control variables (FDI_flows_{ijt-1}, $Distance_{ij,}$ and Com_dum_{ij}). γ_{ij} is the bilateral pair observations of investor (j) investing in investee firm (i) fixed effect, $\lambda_{d,}$ and τ_t are the investee country and year fixed effects. $\varepsilon_{i,j,t}$ is the bilateral pair (*ij*) error term for year *t*. All covariates and country control variables are winsorized at 1% and 99%. Standard errors are clustered at the bilateral investor-investee level ($_{ij}$), and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Long-term Institutional Investor			
	DIO_{ijt}		*FIO_{ijt}*	
	(1)	**(2)**	**(3)**	**(4)**
$Treat_i \times Post_t$	0.6259***	0.6250***	0.0381***	0.0381***
	(19.04)	(19.00)	(3.90)	(3.90)
$Treat_i \times Post_t \times GP\_percent_{it-1} \times Type_j$	**0.0219*** **		**0.0021** **	
	(2.63)		**(2.53)**	
$Treat_i \times Post_t \times GC\_percent_{it-1} \times Type_j$		**0.0200** **		**0.0020*** **
		(2.45)		**(2.68)**
$GP\_percent_{it-1}$	0.0012*		0.0004	
	(1.77)		(0.86)	
$GC\_percent_{it-1}$		0.0008		0.0004
		(1.58)		(0.91)
$SIZE_{it-1}$	-0.0034	-0.0035	-0.0073	-0.0074
	(-0.63)	(-0.65)	(-1.05)	(-1.08)
ROE_{it-1}	0.0001	0.0001	0.0001	0.0001
	(0.77)	(0.76)	(0.22)	(0.24)
LEV_{it-1}	-0.0007	-0.0006	-0.0003	-0.0003
	(-1.48)	(-1.35)	(-1.04)	(-1.05)
$CASH_{it-1}$	0.0002	0.0002	0.0005	0.0005
	(0.94)	(0.94)	(0.99)	(0.99)
BM_{it-1}	0.0003	0.0003	-0.0148	-0.0150
	(0.21)	(0.21)	(-1.30)	(-1.31)
MC_GDP_{it-1}			0.0986***	0.0987***
			(5.50)	(5.51)
FDI_flows_{ijt-1}			0.0017***	0.0017***
			(4.04)	(4.04)
$Distance_{ij}$			-3.2382	-3.2382
			(-1.60)	(-1.60)
Com_dum_{ij}			0.1145**	0.1142**
			(1.97)	(1.98)
Investor-investee FE	Yes	Yes	Yes	Yes
Investee country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
adjust-R^2	0.523	0.523	0.452	0.452
Number of investee firms	2,178	2,178	2,477	2,477
Number of investors	2,818	2,818	1,248	1,248
Observations	331,592	331,592	197,429	197,429

Figure 2.1 Pre-and Post-matched Firms' Mean Differences in Covariates

Figure 2.1 shows the test statistics (z-score) of the X set of covariates (*SIZE*, *ROE*, *CASH*, *LEV*, and *BM*) of the treated and control group firms before and after applying the propensity score matching of the following equation:

$$Treat_i = \alpha + \boldsymbol{X}_{i,t}\beta' + \gamma_k + \mathcal{E}_{i,t}$$

I define all the variables of ***X*** in Table A2.1 of the appendix. The sample period of the PSM approach is from 2004 to 2007, covering the period before the beginning of the 1st Kyoto Protocol commitment.

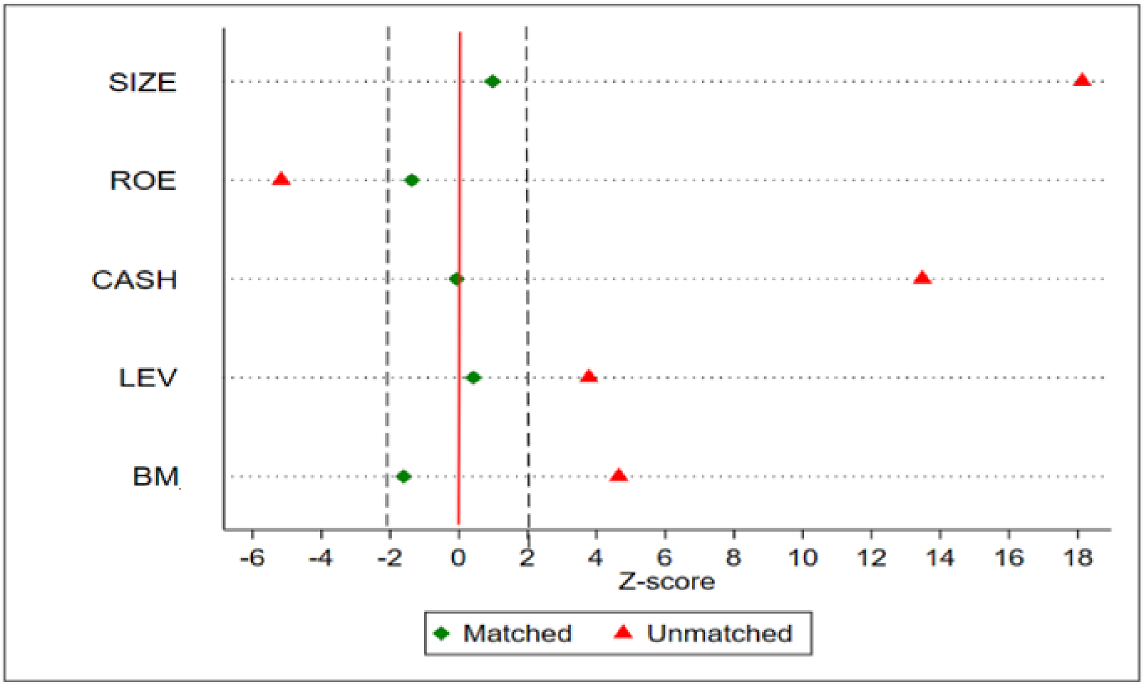


Figure 2.2 Pre-and Post-matched Firms' Mean Differences in Covariates

Figure 2.2 compares the pre-and post-PSM matched standardized percentage bias of the covariates *SIZE*, *ROE*, *CASH*, *LEV*, and *BM* of the treatment and control group. The green diamond figures are for the matched, and the red triangles are for the unmatched samples.

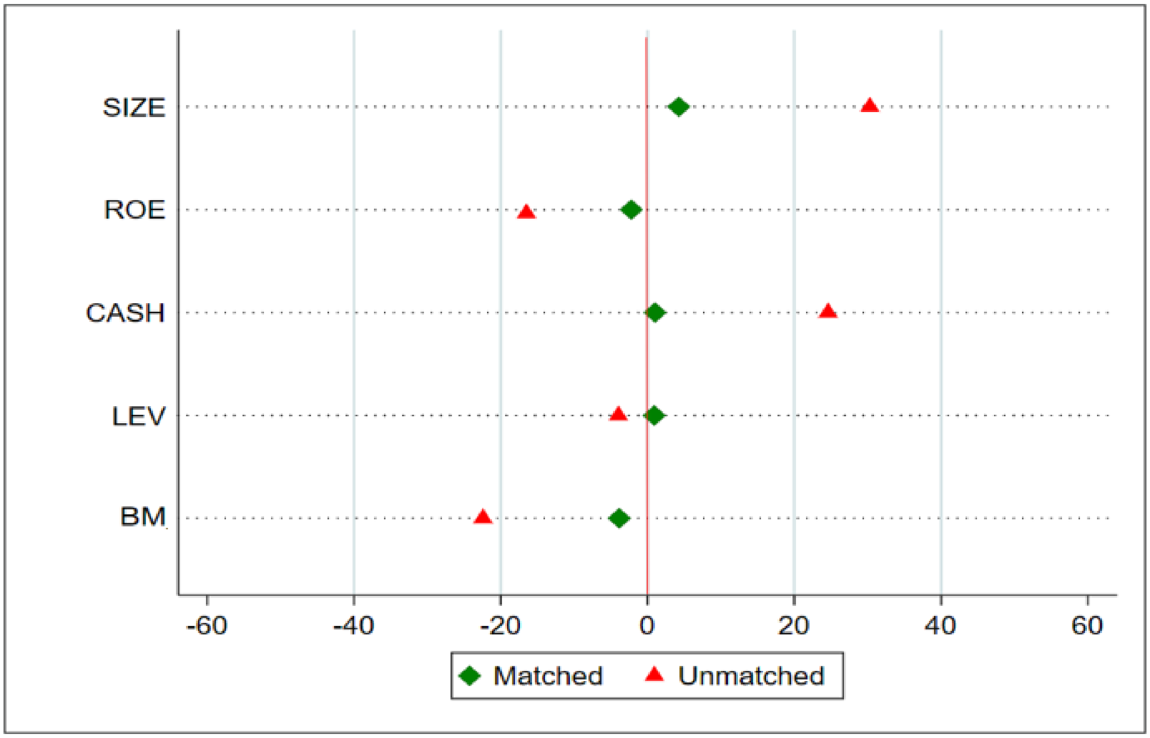
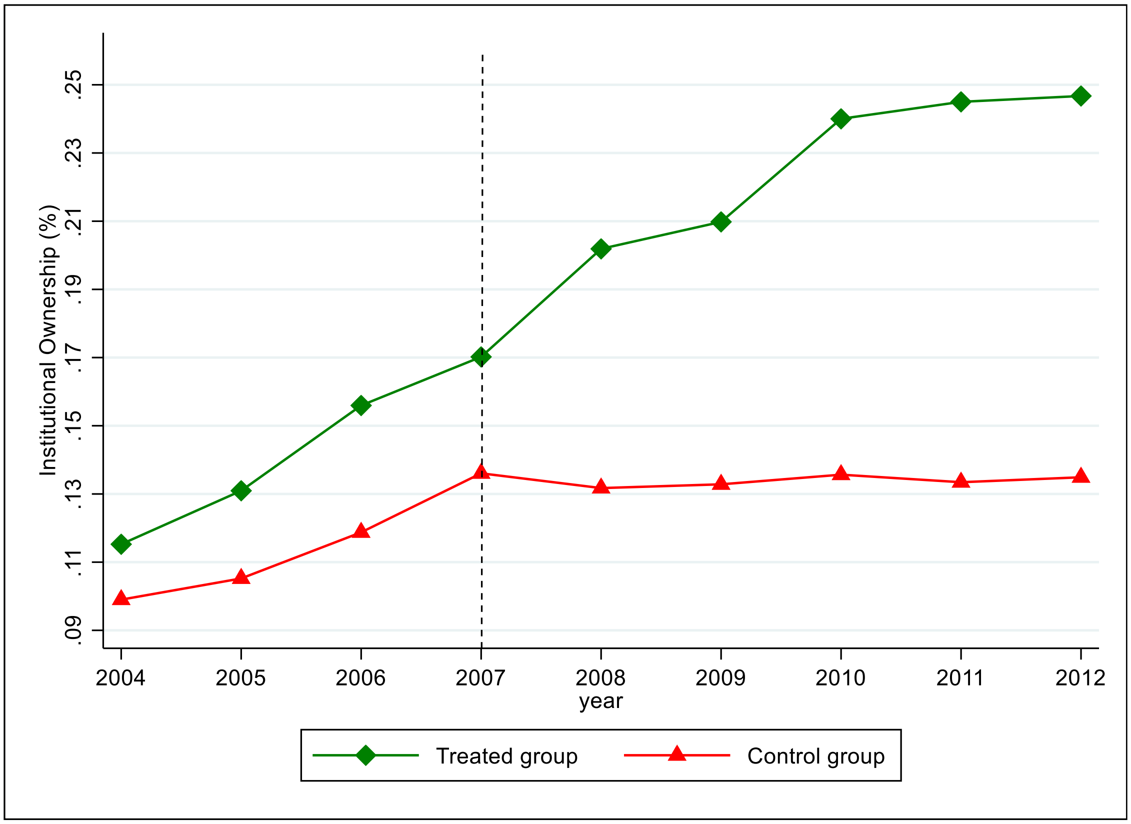


Figure 2.3 Treatment and Control Firms' Annual Mean Values of Institutional Ownership

Figure 2.3 shows the trend of the average ownership percentage of institutional investors based on matched samples after the PSM approach. The green line and red line, respectively, represent the treatment and control groups. The figure covers pre and post-periods of the 1st Kyoto Protocol commitment (2004 – 2012).



Appendix

Table A2.1: Variable Description

Name	Description	Source
Dependent variables		
DIO_{ijt}	Domestic institutional investor (*j*) 's percentage ownership of the total outstanding shares of investee firm (*i)* at the end of year *t*.	S&P Capital IQ
FIO_{ijt}	Foreign institutional investor (*j*) 's percentage ownership of the total outstanding shares of investee firm (*i)* at *)* at the end of year *t*.	S&P Capital IQ
Independent variables		
GP_percent	Percentage of granted green patents to the total patents of the firm *i*.	PATSTAT and Authors' construction.
GC_percent	Percentage of adjusted green citations to total adjusted citations of the firm *i*.	PATSTAT and Authors' construction.
$Post_t$	A binary variable equals one for the year range 2008-2012 and zeroes for 2004-2007.	
$Treat_i$	A binary variable equals one if the investee firm country is committed to the 1st Kyoto Protocol treaty and zero otherwise.	
$Type(D\_Independent_j)$	A binary variable equals one if an institutional investor *j* is defined as independent and zero otherwise.	S&P Capital IQ and Authors' Construction.
$Type(D\_Long_j)$	A binary variable equals one if an institutional investor *j* is classified as a long-term investor and zero for a short-term investor.	S&P Capital IQ and Authors' Construction.
Firm-level covariates		
SIZE	The natural logarithm of equity market value of investee firm *i*.	S&P Capital IQ
ROE	The ratio of net profits after tax to the equity book value of investee firm *i*.	S&P Capital IQ

Table A2.1: Variable Description (cont')

Name	Description	Source
CASH	The ratio of the sum of year-end cash and short-term securities divided by total assets of investee firm *i*.	S&P Capital IQ
LEV	The ratio of debt to equity book value of investee firm *i*.	S&P Capital IQ
BM	Book value scaled by the year-end market value per share of investee firm *i*.	S&P Capital IQ
Country-level variables		
MC_GDP	The ratio of the investee country's total equity market capitalization to gross domestic product.	The World Bank and The International Stock Exchange (TISE)
FDI_flows	*FDI_flows* is the ratio of the total foreign direct investments (FDI) inflows between the investor and the investee countries to the entire global FDI flows received by the investee country. *FDI_flows* = (Inflows from investor country into investee country + inflows from investee country into investor country)/Total inflows into investee country from all reported countries.	Organization for Economic Co-operation and Development (OECD), the United Nations Conference on Trade and Development (UNCTAD), and the International Trade Centre database (ITC).
Distance	The natural logarithm of kilometers between the capital cities of investor and investee countries.	Andrew Rose, University of California, Berkeley
Com_dum	A binary variable that equals one if the investor and investee countries share a common official language and zero otherwise.	Andrew Rose, University of California, Berkeley

Table A2.2 Country Lists of the 1st Kyoto Protocol Commitment

MSCI ACWI			
Committed countries		Non-committed countries	
Developed markets	Emerging market	Developed markets	Emerging market
Australia	Czech Republic	Hong Kong	Argentina
Austria	Greece	Israel	Brazil
Belgium	Hungary	Singapore	Chile
Canada	Poland	United States	China
Denmark	Russia		Colombia
Finland			Egypt
France			India
Germany			Indonesia
Ireland			Kuwait
Italy			Malaysia
Japan			Mexico
Netherlands			Pakistan
New Zealand			Peru
Norway			Philippines
Portugal			Qatar
Spain			Saudi Arabia
Sweden			South Africa
Switzerland			South Korea
United Kingdom			Taiwan
			Thailand
			Turkey
			United Arab Emirates

Table A2.3 Investor Classifications Based on S&P Capital IQ definitions

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

Table A2.4 Approximate Mapping Between Environmental Policy Priorities and Patent Search Strategies

Environmental policy objective	**Patent search strategy**
Environmental health (human health impacts)	1. Environmental management technologies
	2. Water-related adaptation technologies
Water scarcity	3. Biodiversity protection technologies
	4. Climate change mitigation– Energy
Ecosystem health and biodiversity	5. Climate change mitigation – Greenhouse gases
	6. Climate change mitigation – Transport
Climate change	7. Climate change mitigation – Building

Source: Haščič and Migotto (2015, page 20)

Table A2.5 Environment-related Technology

Class	Environmental Technology Identification	IP or CP Classification
1. Environmental Management		
1.1.	**Air pollution abatement**	
1.1.1	Emissions abatement from stationary sources (e.g., SOx, NOx, PM emissions from combustion plants)	B01D53/34-72, F23G7/06, F23J15, F27B1/18, C21B7/22, C21C5/38, F23B80, F23C9, F23C10
1.1.2	Emissions abatement from mobile sources (e.g. NOx, CO, HC, PM emissions from motor vehicles)	B01D53/92, B01D53/94, B01D53/96, B01J23/38-46, F01M13/02-04, F02B47/08-10, F02D21/06-10, F02M25/07, G01M15/10, F02B47/06, F02D41, F02D43, F02D45, F02M3/02-055, F02M23, F02M25, F02M27, F02M31/02-18, F02M39-71, F02P5
1.1.3	Not elsewhere classified	B01D46, B01D47, B01D49, B01D50, B01D51, B03C3, F01N3, F01N5, F01N7, F01N13, F01N9, F01N11, C10L10/02, C10L10/06
1.2	**Water pollution abatement**	
1.2.1	Water and wastewater treatment	B63J4, C02F, C09K3/32, E03C1/12, E03F
1.2.2	Fertilizers from wastewater	C05F7
1.2.3	Oil spill cleanup	E02B15/04-10, B63B35/32, C09K 3/32
1.3	**Waste management**	
1.3.1	Solid waste collection	E01H15, B65F
1.3.2	Material recovery, recycling, and re-use	A23K1/06-10, A43B1/12, A43B21/14, B03B9/06, B22F8, B29B7/66, B29B17, B30B9/32, B62D67, B65H73, B65D65/46, C03B1/02, C03C6/02, C03C6/08, C04B7/24-30, C04B11/26, C04B18/04-10, C04B33/132, C08J11, C09K11/01, C10M175, C22B7, C22B19/28-30, C22B25/06, D01G11, D21B1/08-10, D21B1/32, D21C5/02, D21H17/01, H01B15/00, H01J9/52, H01M6/52, H01M10/54
1.3.3	Fertilizers from waste	C05F1, C05F5, C05F7, C05F9, C05F17
1.3.4	Incineration and energy recovery	C10L5/46-48, F23G5, F23G7
1.3.5	Landfilling	N/A
1.3.6	Waste management – Not elsewhere classified	B09B, C10G1/10, A61L11
1.4	**Soil remediation**	**B09C**
1.5	**Environmental monitoring**	**F01N11, G08B21/12-14**

Table A2.5 Environment-related technology (cont')

Class	Environmental Technology Identification	IP or CP Classification
2. Water-related Adaptation Technologies		
2.1	**Demand-side technologies (water conservation)**	
2.1.1	Indoor water conservation	
	Faucets and showers	F16K21/06-12, F16K21/16-20
	Aeration of water	F16L55/07, E03C1/084
	Sanitation (dual-flush toilets, dry toilets, closed-circuit toilets)	E03D3/12, E03D1/14, A47K11/12, A47K11/02, E03D13/007, E03D5/016
	Greywater	E03B1/041
	Home appliances	Y02B40/46, Y02B40/56
2.1.2	Irrigation water conservation	
	Drip irrigation	A01G25/02, A01G25/06
	Control of watering	A01G25/16
	Drought-resistant crops	C12N15/8273
2.1.3	Water conservation in thermoelectric power production	F01K23/08-10, F01D11
2.1.4	Water distribution	F17D5/02, F16L55/16, G01M 3/08, G01M3/14, G01M3/18, G01M3/22, G01M3/28, E03
2.2	**Supply-side technologies (water availability)**	
2.2.1	Water collection (rain, surface, and groundwater)	
	- Underground water collection	E03B5, E03B3/06-26
	- Surface water collection	E03B9, E033/04, E033/28-38
	- Rainwater water collection	E03B3/02, E03B3/03
	- Not elsewhere classified	E03B3/00, E03B3/40
2.2.2	Water storage	E03B11
2.2.3	Desalination of seawater	
3. Biodiversity Protection and Ecosystem Health	**N/A**	
4. Climate Change Mitigation Technologies Related to Energy Generation, Transmission or Distribution		
4.1	**Renewable energy generation**	**Y02E10**
4.1.1	Wind energy	Y02E10/70
4.1.2	Solar thermal energy	Y02E10/40
4.1.3	Solar photovoltaic (PV) energy	Y02E10/50
4.1.4	Solar thermal-PV hybrids	Y02E10/60
4.1.5	Geothermal energy	Y02E10/10
4.1.6	Marine energy	Y02E10/30
4.1.7	Hydro energy	Y02E10/20

Table A2.5 Environment-related technology (cont')

Class	Environmental Technology Identification	IP or CP Classification
4.2	**Energy generation from fuels of non-fossil origin**	**Y02E50**
4.2.1	Biofuels	Y02E50/10
4.2.2	Fuel from waste	Y02E50/30
4.3	**Combustion technologies with mitigation potential**	**Y02E20**
4.3.1	Technologies for improved output efficiency (Combined heat and power, combined cycles, etc.)	Y02E20/10-185
4.3.2	Technologies for improved input efficiency (Efficient combustion or heat usage)	Y02E20/30-366
4.4	**Nuclear energy**	**Y02E30**
4.4.1	Nuclear fusion reactors	Y02E 30/10-18
4.4.2	Nuclear fission reactors	Y02E 30/30-40
4.5	**Efficiency in electrical power generation, transmission, or distribution**	**Y02E40**
4.5.1	Superconducting electric elements or equipment	Y02E40/60-69
4.5.2	Not elsewhere classified	Y02E40/10-18, Y02E40/20-26, Y02E40/30-34, Y02E40/40, Y02E40/50, Y02E40/70
4.6	**Enabling technologies in the energy sector**	**Y02E60**
4.6.1	Energy storage	Y02E60/10-17
4.6.2	Hydrogen technology	Y02E60/30-368
4.6.3	Fuel cells	Y02E60/50-566
4.6.4	Smart grids in the energy sector	Y02E60/70
4.7	**Other energy conversion or management systems reducing greenhouse gas emissions**	**Y02E70**

5. Capture, Storage, Sequestration or Disposal of Greenhouse Gases

5.1	**CO2 capture or storage**	**Y02C10**
5.2	**Capture or disposal of greenhouse gases other than carbon dioxide (N2O, CH4, PFC, HFC, SF6)**	**Y02C20**

6. Climate Change Mitigation Technologies Related Transportation

6.1	**Road transport**	**Y02T10**
6.1.1	Conventional vehicles (based on internal combustion engine)	Y02T10/10-56
	- Integrated approaches	Y02T10/12-18, Y02T10/40-48, Y02T10/50-56
	- Post-combustion approaches	Y02T10/20-26

Table A2.5 Environment-related technology (cont')

Class	Environmental Technology Identification	IP or CP Classification
	- Fuel substitution	Y02T10/30-38
6.1.2	Hybrid vehicles	Y02T10/62
6.1.3	Electric vehicles	
	Electric machine technologies for applications in electromobility	Y02T10/64-649
	Energy storage for electromobility	Y02T10/70-7094
	Electric energy management in electromobility	Y02T10/72-7291
6.1.4	Fuel efficiency-improving vehicle design (common to all road vehicles)	Y02T10/80-86, Y02T10/90-92
6.2	**Rail transport**	**Y02T30**
6.3	**Air transport**	**Y02T50**
6.4	**Maritime or waterway transport**	**Y02T70**
6.5	**Enabling technologies in transport**	**Y02T90**
6.5.1	Electric vehicle charging	Y02T 90/10-169
6.5.2	Application of fuel cell and hydrogen technology to transportation	Y02T 90/30-38, Y02T 90/40-46
7 Climate Change Mitigation Technologies Related Buildings		
7.1	**Integration of renewable energy sources in buildings**	**Y02B10**
7.2	**Energy efficiency in buildings**	
7.2.1	Lighting	Y02B20
7.2.2	Heating, ventilation, or air conditioning [HVAC]	Y02B30
7.2.3	Home appliances	Y02B40
7.2.4	Elevators, escalators, and moving walkways	Y02B50
7.2.5	Information and communication technologies	Y02B60
7.2.6	End-user side	Y02B70
7.3	**Architectural or constructional elements improving the thermal performance of buildings.**	**Y02B80**
7.4	**Enabling technologies in buildings**	**Y02B90**

Source: Haščič and Migotto (2015, page 46-58)

3. FINANCIAL ANALYSTS AND TECHNOLOGICAL GREEN INNOVATION

3.1 Introduction

> *"Global climate finance almost doubled in the last decade, with a cumulative USD 4.8 trillion in climate finance committed between 2011 - 2020 or USD 480 billion annual average. While climate finance increased at a cumulative average annual growth rate (CAGR) of 7%, the current levels of increase are not on track to meet a 1.5C global warming scenario. We need at least USD 4.3 trillion in annual finance flows by 2030 (CAGR 21%) to avoid the worst impacts of climate change" (Climate Policy Initiative, 2022)*[36].

The Climate Policy Initiative report also reveals that climate investment growth is, surprisingly, covered by all investment players in the financial markets[37]. Starks (2023) identifies that investors' motivations for increasing sustainable investment depend on nonpecuniary and pecuniary preferences (*values versus value-based*). In the meantime, shifting into sustainable investment stimulates my curiosity to explore the impact of firms' sustainable strategies used in the financial markets, specifically adopting technological green innovation (TGI). Moreover, even though existing studies reveal sustainable impacts on investment in financial markets, there is little (or no) evidence of the implications of sustainable practice on participants in financial markets[38]. In particular, this study focuses

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[36] Global Landscape of Climate Finance: A Decade of Data: https://www.climatepolicyinitiative.org/publication/global-landscape-of-climate-finance-a-decade-of-data/

[37] The growth rate of private climate finance e.g. non-financial corporations, commercial banks, households, institutional investors, and private equity funds was 4.8%, whereas the public sector e.g. governments, state-owned entitles (SOEs), financial institutions, climate funds, and development finance institutions (DFIs) increased 9.1% and must increase rapidly at scale. (Global Landscape of Climate Finance: A Decade of Data: https://www.climatepolicyinitiative.org/publication/global-landscape-of-climate-finance-a-decade-of-data/)

[38] Literature document some connection between environmental performance and financial markets' stakeholders e.g. banks and lenders (Chiaramonte et al., 2022, Houston and Shan, 2022 and Wang, 2023),

on the responses of analysts to sustainability-related information of the firms promoting TGI activities. I examine this by investigating three aspects of analysts' responses to the intensity level of TGI. They are: (a) changes in the number of analysts following the TGI firms, (b) changes in analysts' recommendations, and (c) the accuracy of earnings forecasts.

In less than perfect capital markets and where information asymmetry is prevalent, financial analysts play a crucial role as an intermediary in increasing the efficiency of information dissemination. Analysts' reports incorporate superior information, and their forecasts of earnings are highly influential in determining the trading volume of the stocks they covered (Womack, 1996, Piotroski and Roulstone, 2004 and Xu et al., 2013).

On the other hand, the competition in the brokerage industry and compensation related to trading volume motivate analysts to respond to market preferences by providing more analysis reports. (Jackson, 2005 and Conrad et al., 2006). Harford et al. (2019) support the notion that analysts are more inclined to actively participate in firms with higher market capitalisation, trading volume, and size of institutional ownership by frequently providing analysis reports and recommendation revisions. The rising inclination of investors towards making investment choices based on firms' non-financial information motivates analysts to spend more resources incorporating such information to protect their reputations and compensations. Studies suggest that analysts focus and respond more to firms' non-financial information, especially environmental practice disclosure, through

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bondholders (Apergis et al., 2022, Harjoto et al., 2022 and Amiraslani et al., 2023), and analysts (Dhaliwal et al., 2012, Ioannou and Serafeim, 2015 and Adhikari, 2016).

their recommendations and earnings forecasts (Dhaliwal et al., 2012 and Ioannou and Serafeim, 2015).

In contrast, some studies argue that analysts are highly concerned with firms investing in superior environmental development, appearing to generate extreme conflicts of interest (Ioannou and Serafeim, 2015, Adhikari, 2016 and Qian et al., 2019). Moreover, the uncertain benefit of TGI makes the information less salient and lowers the markets' perception (Eberhart et al., 2004 and Daniel and Titman, 2006). The limits of TGI information in the short run might lead analysts to focus more on the value of tangible benefits rather than intangible values[39]. Gu (2005) suggests that investors and analysts underreact to innovative information. Investors' less attention to TGI activities in the short term can cause analysts to overlook or make less effort to incorporate TGI information.

In addition, although the natural resource-based view literature (NRBV) suggests that TGI effectively utilises resources and enhances sustainable profitability (Hart, 1995, Porter and Van Der Linde, 1995 and Ambec and Lanoie, 2008), the corporation must take the higher failure risk in TGI development. Gaddy et al. (2017) uncover that venture capital investors invested $2.5 billion in clean energy technologies during 2006–2011, but over 50% of their investments are identified as failures. They note that innovation failure involves extreme requirements, e.g. capital, long-term development timelines, and significant conditions. Kothari et al. (2002) reveal that innovation intensity increases the uncertainty of a firm's future performance. They document that the benefits of innovative investment are more uncertain than tangible investment benefits. Studies suggest that

[39] See discussion in Hirshleifer and Teoh (2003), Hirshleifer et al. (2009) and Hirshleifer et al. (2011)

analysts seem pessimistic about the performance uncertainty of innovative firms (Amir et al., 2003, He and Tian, 2013 and Guo et al., 2019). Hence, the analysts' perspectives on the consequences of TGI activities pertain to my question of whether TGI information impacts analysts' activities.

Trading off between the benefits and the extraordinary risks of TGI may provoke different responses to TGI firms in equity markets. The informativeness of analysts' reports on TGI information is significant to the market's reaction in identifying and capturing the value of fundamental change in TGI firms. This study addresses a research gap by shedding light on the nexus between firms engaged in TGI and analysts as intermediaries in the financial markets.

My study employs firm-level and analyst-level data covering 50 countries included in the All-Country World Index compiled by the Morgan Stanley Capital International (MSCI ACWI). I measure TGI intensity based on green patent applications and green patent citations. I design my empirical framework using the propensity score matching algorithm (PSM) and quasi-natural experiments using the 1st Kyoto Protocol commitment as an exogenous indicator to address the possible endogeneity issue.

My main finding suggests that analysts exhibit pessimism toward TGI firms. I find that the number of analysts following TGI firms decreases significantly, and recommendations are downgraded. Higher TGI intensity generates more information complexity and higher variability in future operating expenses. The concern of job security and competition in the job market pressures analysts to protect their reputations by dropping TGI firms from their coverage portfolios. Moreover, downgrading recommendations implies the adverse views of analysts toward the operational risks and profitability of TGI firms in the short run.

Furthermore, I emphasise that the firms' fundamental changes related to TGI limits the analysts' forecast performance. Firms engaged in TGI contribute more information complexity and fundamental volatility, increasing analysts' forecast errors. Finally, I discover the high variability of individual analysts' forecast earnings toward firms engaged in TGI development. These findings indicate that TGI intensity reduces the analysts' ability to forecast the implications of TGI on the value of the firm.

This study contributes to two distinct bodies of the literature. First, I contribute to the nexus of non-financial information and financial analysts. Existing studies suggest that sustainability disclosure enhances analysts' forecast quality (Dhaliwal et al., 2012). Ioannou and Serafeim (2015) find analysts' pessimism toward firms providing higher sustainability ratings. Meanwhile, Griffin et al. (2020) state that sustainability disclosure reduces the frequency of analyst reports. My study provides a new line of argument on the effect of environmentally friendly strategies on information dissemination and expectations in the financial markets. In particular, I show that the increased information complexity of TGI firms has a negative effect on the analysts' abilities to accurately forecast. Financial analysts are also sensitive to firms' fundamental transformation through TGI, representing the market's concerns on short-run operational costs and the profitable volatility of the TGI firms.

My study also shows an association between environmental technologies and financial markets. Existing literature on environmental technologies attempts to explore the TGI effects on financial markets through several channels e.g. the effects of TGI on environmental performance (Dangelico and Pujari, 2010), operating performance (Shrivastava, 1995, Ambec and Lanoie, 2008, Ambec et al., 2013 and Rexhäuser and Rammer, 2014), and stock values (Dechezleprêtre et al., 2020). To the best of my knowledge, this is the first study to provide a new framework connecting TGI and financial markets through analysts' activities. My evidence also indicates the necessity of TGI information disclosure, supporting the valuation effects of TGI.

My study points out implications related to market participants. The asymmetry of TGI information is the main restriction that impedes market participation and the expansion of TGI investments. I document that firms engaged in TGI generate performance uncertainty and information complexity, which brings about adverse effects on market expectations of the firms' value. Disclosing more TGI details by firm management could gain more investors' attention and the ability to identify TGI benefits. In the meantime, detailed TGI information supports analysts to estimate the intrinsic value of TGI and improve forecast accuracy. In addition, the analysts' ability to access superior information could disseminate TGI information more widely and enhance the value of the firms committed to environmental practice. The combination of detailed TGI information disclosure and superior assessment of the information by analysts will alleviate TGI information asymmetry and market underreaction (or suspicion) to firms promoting TGI activities.

The remainder of this chapter proceeds as follows. Section 3.2 discusses the empirical literature and hypothesis development. This is followed by data and model identification strategies, including evidence of the 1st Kyoto Protocol commitment impact on green innovation in Section 3.3. Section 3.4 presents and interprets the observed results, and Section 3.5 concludes the chapter.

3.2 Related Literature and Hypotheses Development

3.2.1 Financial Analysts and Technological Green Innovation

A growing body of finance literature emphasises the importance of environmental practice on firm value (Russo and Fouts, 1997 and Ziegler et al., 2007) and motivation of investments in sustainability (Dyck et al., 2019, Azar et al., 2021 and Starks, 2023). The increasing paradigm of financial markets to climate risks is the explanation behind this mechanism, particularly the concern over climate regulations affecting firms' operating uncertainty and stocks' profitability (Krueger et al., 2020 and Ilhan et al., 2023). Marshall et al. (2022) and Krueger et al. (2023) uncover that investors are more attracted to firms engaged in environmental disclosures. The higher demand for climate risk information can motivate analysts to identify firms' environmentally relevant information in their reports. In the meantime, analysts who discover better firm-specific information could gain more benefits in their careers. Hence, my study focuses on the causal effects of firms engaged in TGI on analysts' activities.

Existing business studies present the economic value of TGI through the natural resource-based view theory (NRBV; Hart, 1995). Porter and Van Der Linde (1995), Shrivastava (1995) and Lanoie et al. (2011) suggest that firms engaged in TGI gain maximum benefits by creating firms' competitive advantages under environmental regulation stringency. Cheng et al. (2014), Ghisetti and Rennings (2014) and Rexhäuser and Rammer (2014) find that firms committed to TGI increase operating performance. Moreover, TGI intensity attracts more investor investment and increases firm values compared to traditional innovation (Dechezleprêtre et al., 2020). Shrivastava (1995) and Ambec and Lanoie (2008) identify that TGI development can lead to higher sustainable performance through two channels: (a) by revenue enhancement (e.g. gaining social reputation, entering the new market with differentiating products, selling TGI), and (b) from cost reductions (e.g. waste management costs, raw material costs and the cost of capital).

Even though TGI firms seem to attract the informativeness of analysts' reports in identifying and discovering more value-relevant information[40], incorporating TGI firms in their coverage portfolios can put analysts' career security at risk if the implications of TGI impede analysts' forecast ability. Based on the "career concerns" hypothesis, it is argued that financial analysts devote more (less) effort to researching firms that are relatively more (less) important from their career concern perspectives (Cowen et al., 2006, Beyer and Guttman, 2011 and Harford et al., 2019). Literature suggest that analysts' incentives are related to the trading volume of the stocks they cover. The variation in institutional investors' trading behaviours significantly stimulates financial analysts to increase their reports' frequency. (Hong and Kubik, 2003, Jackson, 2005 and Groysberg et al., 2011).

Moreover, analysts' rewards depend on their performance, such as forecasting accuracy and trading value of covered stocks (Stickel, 1992, Mikhail et al., 1999 and Wang et al., 2020). The literature notes that career concerns also push analysts to focus more on investors' preferred stocks. Studies show that analysts prefer firms that are associated with

[40] Literature notes that firms' information environment inversely affects the value of analysts' informativeness such as firms with low informative dissemination functions (Asquith et al., 2005), firms with higher growth and uncertainty (Frankel et al., 2006), and firms posited in highly competitive industries which disclose small public information (Hsu et al., 2023).

higher trading activities (Cowen et al., 2006 and Beyer and Guttman, 2011). Harford et al. (2019) note that analysts' reports and recommendations revision frequency relate to firms' trading values and ownership levels.

However, existing literature documents conflicting evidence of non-financial information such as environmental development and innovation influencing analysts' behaviour. Optimists argue that firms engaged in TGI can lead to higher levels of analysts' coverage. Eccles et al. (2011) document that financial analysts incorporate environmental performance, especially greenhouse gas emissions (GHGs), in their reports. Barth et al. (2001) indicate that analysts put more effort into assessing intangible assets. They suggest that analysts have an extreme preference for firms generating a positive signal to future earnings. Lee and So (2017) show that analysts' coverage bias increases with firms' fundamental performance. In addition, the increasing preference of institutional investors for sustainable investments can motivate analysts to follow TGI firms to cater for the market demand and achieve more on trading commissions (see discussion in Firth et al., 2013 and Wu et al., 2018).

Conversely, the pessimists suggest that levels of TGI intensity can disrupt analysts' forecast accuracy, affecting the reputation of brokerage houses and analysts. McNichols and O'Brien (1997) argue that analysts favour the firms whose future performance can be predicted. Studies find that analysts avoid innovative firms that have high-performance uncertainty (Wang et al., 2020 and Segara et al., 2021). Similarly, He and Tian (2013) and Guo et al. (2019) show that analysts restrict firms' R&D expenditures to maintain short-run revenue. Furthermore, the evidence that the market's under-preference for innovative stocks in the short run can dissuade analysts from following TGI firms (Eberhart et al., 2004, Gu, 2005 and Daniel and Titman, 2006).

Second, superior sustainability investment reflects the extreme agency problem of the firms. Ioannou and Serafeim (2015), Adhikari (2016) and Qian et al. (2019) argue that environmental initiatives are perceived as serving managerial image rather than serving shareholders' wealth. Griffin et al. (2020) show that firms investing in superior sustainability technology increase analysts' monitoring costs and the complexity of estimating the value of the investment.

Although TGI potentially incentivises analysts to monitor the firms because of higher investors' attention, the analysts' career concerns tend to be significantly biased in favour of the short-run perspective rather than the long-term/sustainable benefits of TGI. Firms engaged in TGI generate highly uncertain outcomes in the short run which, in turn, adversely affects the analysts' performance and reputation. Therefore, analysts are likely to refrain from following the firms that are engaged in TGI. This leads to my first hypothesis that:

H1: The intensity of the firms' engagement in TGI and the number of analysts following them are inversely related.

3.2.2 Analysts' Recommendations and Technological Green Innovation

Next, I investigate the effects of the firms' TGI information on the analysts' recommendations. Extant literature documents that analysts incorporate the possible effects of general economic conditions as well as corporate information to arrive at their recommendations, which in turn affects investors' investment decisions (Cornell, 2001, Altınkılıç and Hansen, 2009 and Loh and Stulz, 2011). Thus, the market's interest in specific information also inspires analysts to incorporate the value of such information in their recommendations. In this part, I examine alternative arguments on the impact of a firm's TGI-related information on analysts' recommendations.

First, increasing demand for firms' environmental information can push analysts to incorporate long-term value of TGI information in their predictions. The impacts of climate regulation and investors' trading behaviour generate a better opportunity for TGI stocks to receive positive recommendations due to analysts' selection bias. It is plausible that under climate regulation uncertainty, firms committed to environmental development such as TGI adoption will gain higher operating benefits relative to their industry peers who delay green transition. For instance, Nguyen (2018) finds that the 1st Kyoto Protocol led to lower operating profitability of high-carbon-emitting firms compared to low-carbon-emitting firms. Balachandran and Nguyen (2018) suggest that higher environmental taxes pressure the dividend payout of high-polluting firms than low-polluting firms. McNichols and O'Brien (1997) show that analysts favour stocks with superior future performance and favourable investment value. Firms whose operations are less affected by regulations could motivate optimistic analysts to generate positive recommendations.

Furthermore, McNichols and O'Brien (1997) note that the shifting of favourable recommendations may contribute to their relationships with firms' managers in order to access superior information and gain trading commissions. Firth et al. (2013) support that investors' attention influences the provision of favourable recommendations. One possibility is that highly innovative firms are generally owned by large numbers of institutional investors which are brokerages' clients (Ferreira and Matos, 2008, Guadalupe et al., 2012 and Aghion et al., 2013). Supportive investment recommendations from affiliated stock analysts can generate the value of institutional investors' portfolios. In other words, institutional investors who have large stakes in a firm may pressure analysts to issue favourable recommendations.

Second, although investments in TGI can create long-term value and attract more investors, the transition needs more resources and a longer time to become optimal and achieve sustainable performance (Porter and Van Der Linde, 1995, Shrivastava, 1995 and Ambec and Lanoie, 2008). These conditions conflict with the analysts' view of capturing influential information for short-run performance. Studies show that analyst pressure reduces innovative capital to support short-run profitability (He and Tian, 2013 and Guo et al., 2019). Ramnath (2002) notes that financial analysts always evaluate the financial fundamentals of coverage firms with peers in the same industry. Moreover, TGI intensity increases firms' operational uncertainty and causes disagreement (or diverse opinion) among the analysts on the future performance of the firm and therefore stock returns. Lin (2018) points out that analysts are likely to overweigh uncertain information, leading them issue negative recommendations.

Considering the career concern hypothesis, in the short run, analysts seem to overweigh the uncertainty caused by TGI and undervalue its long-run benefits. This is because firms engaged in TGI face lower short-term operating performance than their peers, and hence, analysts overweigh its impact. This leads to my second hypothesis that:

H2: The intensity of the firms' engagement in TGI and the analysts' recommendations are inversely related.

3.2.3 Analysts' Forecast Errors and Technological Green Innovation

As previously discussed, TGI is likely to promote long-run rather than short-run operating performance of a firm (see sub-section 3.2.1). Shrivastava (1995) and Rexhäuser and Rammer (2014) document that TGI's maximum value depends on the size of operating resources, tangible assets, and types of targeted pollution control. The TGI transition can also create issues of environmental appropriateness of technologies in the production chain and operational risks in the initial stage, increasing short-term cashflow uncertainty. Moreover, Cohen et al. (2013) note that the volatility of R&D ability causes the markets to underreact to innovative stocks. The short-run uncertainty of TGI benefits dilutes investors' attention, adversely affecting analysts' efforts to incorporate TGI information. These short-term implications of TGI raise the question: Does a TGI activity affect analysts' earnings forecast performance?

The literature suggests that the firms committed to sustainable practice improve their financial disclosure which, in turn, enhances the accuracy of analysts' forecasts (Lang and Lundholm, 1996). Dhaliwal et al. (2012) document that environmental information enhances the analysts' forecast accuracy. Similarly, Hope (2003) suggests that when more information is disclosed, the analysts' reports become more accurate. Griffin et al. (2020) discover that analysts put more effort and resources into analysing the firms that are engaged in sustainable development and in revising their earnings forecasts. However, Ioannou and Serafeim (2015) find evidence that the level of non-financial performance disclosure is not associated with the quality of analysts' forecasts.

In contrast, higher innovation intensity pushes firm uncertainty. Kothari et al. (2002) find that intangible investment generates more uncertainty relative to tangible investment. Meanwhile, Bhattacharya and Ritter (1983) suggest that firms investing in more innovative projects are willing to disclose only partial information about the projects to protect against information leakage. The complexity of TGI information also limits estimating the value of TGI, as indicated by the markets' underreaction to innovative information (Eberhart et al., 2004 and Cohen et al., 2013). Amir et al. (2003) and Gu and Wang (2005) show that higher intensity in innovations leads to higher forecast errors of analysts. This indicates that analysts cannot fully incorporate the contributions of the innovations on the firms' future profitability. The literature also suggests that levels of innovative intensity across industries potentially have different impacts on analysts' forecasts. Gu (2005) supports that market participants, including investors and analysts, fail to integrate the potential value of innovation capabilities for future earnings into stock prices and earnings forecasts.

With respect to the career concerns argument, analysts achieving higher forecast accuracy gain a higher reputation. Although the firms engaged in TGI may offer superior investment efficiency and production in the longer run, identifying the contributions of TGI on the operating profitability of such firms requires superior information. Financial analysts can compensate for the intangibles-related information deficiencies of financial reports, but forecasting TGI contributions requires the consideration of short-term operational risks of transforming technology. Short-term uncertainty potentially decreases the analysts' forecast ability which, in turn, increases their forecast errors. Thus, I hypothesise that:

H3a: The intensity of the firms' engagement in TGI and the analysts' forecast errors are *positively related.*

Further, I investigate the effect of TGI firms on analysts' consistency of earnings forecast errors. Hilary and Hsu (2013) suggest that forecast ability should be based on the extent to which an analyst delivers consistent forecast errors, as captured by the volatility of unexpected errors. The high (low) consistency of an individual analyst's earnings forecast errors implies the high (low) efficiency of the analyst's forecast ability and signals more (less) his/her forecast reliability. Hilary and Hsu (2013) indicate that the consistency of individual analysts' earnings forecast errors is associated with investors' decisions, especially institutional investors affecting the larger trading volume and stock price.

However, larger investments in R&D projects lead to higher future performance uncertainty (Kothari et al., 2002). Similarly, innovative processes stimulate greater unsystematic risks and uncertainty of future productivity (Pastor and Veronesi, 2009). Moreover, firms promoting higher TGI activities may implement more stringent measures in order to disclose TGI information during the process of innovative development, with the aim of protecting against information spillover (Bhattacharya and Ritter, 1983). Therefore, TGI activities may not only reduce the accuracy of analysts' forecasts but also restrict analysts' informative ability. To examine this effect, I employ the individual analysts' consistency in earnings forecast errors, referred to as the ability of analysts. Then, I hypothesise that:

H3b: The intensity of the firms' engagement in TGI and the consistency in the analysts' forecast errors are inversely related.

3.3 Data and Identification Strategies

3.3.1 Data

In this study, I obtain information from several sources to construct an empirical analysis. First, sell-side analyst data is acquired from the Institutional Brokers' Estimate System database (I/B/E/S). Second, innovation output data is collected from the World Patent Statistical Database (PATSTAT) compiled by the European Patent Office (EPO). Third, firm financial data and exchange market value are collected from the COMPUSTAT and The International Stock Exchange (TISE), respectively.

My sample covers 50 exchange-market countries based on the All-Country World Index compiled by Morgan Stanley Capital International (MSCI ACWI). The sample includes 23 developed and 27 emerging exchange markets. I investigate the effect of TGI firms and analysts' activities through a regression framework of the triple different-in-difference model (DiDiD, hereafter). I employ the 1st Kyoto Protocol commitment as a source of exogenous variation in TGI. This study covers the period between 2003 and 2012, covering the pre-Kyoto Protocol commitment period (2003-2007) and the post-Kyoto Protocol commitment period (2008-2012). Countries that do not have at least a brokerage house during the sample period are removed.

I employ the ISIN identifier as the primary identification to merge data from different datasets. I use ISO-code with two alphabets created by the International Organization for Standardization (ISO) and the International Monetary Fund's (IMF) three-digit country codes to match country-paired datasets. I randomly check the merged dataset to assess the accuracy of information. Finally, observations that have missing values of control variables are dropped.

3.3.2 Data on Sell-side Analysts

Regarding sell-side analyst data, I conduct my study at firm-level data to examine the effects of TGI firms on analysts' behaviours. I obtained the analysts' reports covering 50 countries provided by the I/B/E/S database. I start with the number of analysts covering the firms and their recommendations as my key dependent variables. The analysts' coverage variable (*Ln_coverage*) is the natural logarithm of one plus the number of analysts that reported earnings-per-share (EPS) forecasts for a firm in a fiscal year. *Ln_coverage* equals zero if no analyst's forecasts are available for a firm for a fiscal year.

Further, I provide an average firm recommendation followed by analyst consensus in my empirical test (hereafter, *Mean_recom*). The historical dataset contains the recommendation consensus with ratings ranging from 1 (strong buy) to 5 (strong sell). To make the interpretation of the results more intuitive, I invert the standard coding recommendations to 1 = Strong Sell, 2 = Sell, 3 = Hold, 4 = Buy, and 5 = Strong Buy. These figures allow for a more natural interpretation that a higher recommendation suggests possible undervaluation and a buy signal for the sample firms. Then, I employ analyst-level data of individual analysts' recommendations (*Recom*) in my empirical model to understand the decisions of individual analysts.

For analysts' forecasts, I use analyst-level data in my analysis. First, I construct an indicator of individual analysts' forecast errors (*Error*, hereafter) using the following measure of forecast error (*FE*):

$$FE_{i,j,t} = \frac{Forecasted\ EPS_{i,j,t} - Actual\ EPS_{i,t}}{Price_{i,t}} \tag{1}$$

In equation (1), i,j,t denote firm, analyst, fiscal year. *Forecasted EPS* is the forecasted EPS of firm i by an individual analyst j at fiscal year t. *Actual EPS* is the actual

EPS of firm *i*, which is reported in fiscal year *t*. *FE* is the value of the difference between forecasted EPS and actual EPS, scaled by the stock price of firm *i* at the beginning of the fiscal year ($Price_{i,t}$). To measure individual analysts' forecast errors (*Error*), I take the absolute value of the *FE* to observe the magnitude of individual analyst forecast errors (Amir et al., 2003, Dhaliwal et al., 2012 and He et al., 2019). The higher value of *Error* means lower accuracy of the individual analyst's forecast.

Further, following Hsu et al. (2017), I calculate the *inconsistency* in analysts' forecast errors by the standard deviation of *FE* over the previous five years, which is the average period of innovative investment (see discussion in Chan et al., 2001 and Hirshleifer et al., 2013)[41]. The large (small) value of *Inconsistency* implies a high (low) variation of individual analyst's forecast errors in the firm's future earnings during the TGI developing period.

3.3.3 Measures of Technological Green Innovation

I create TGI variables from the patent information of the PATSTAT database. The database integrates comprehensive patent applications from over 90 countries with 120 million global patents since 1844. It covers over 40 global intellectual property authorities such as the United States Patent and Trademark Office (USPTO), European Patent Office (EPO), Japan Patent Office (JPO), and World Intellectual Property Organization (WIPO) etc. The patent information includes substantial details, i.e. patent titles, names of applicants, patent abstract, inventor names, application filling dates, grant status, number of the patent's

[41] This approximation is related to Lev and Sougiannis (1996), suggesting the shortest useful life of R&D is 5 years on average.

forward citations, and patent typologies identified by International Patent Classification (IPC) and Cooperative Patent Classification (CPC).

To identify listed firms' patents, I employ the fuzzy matching process, a string-searching algorithm, to match between the company's formal name and the applicant's name based on the S&P Capital IQ and the PATSTAT databases, respectively. I remove all matched data below 90 per cent of the similarity matching score. Next, I manually check each applicant's information using the company's standard name and location.

To categorise between TGI and non-TGI patents, I employ TGI classifications provided by the Organisation for Economic Co-operation and Development (OECD). Haščič and Migotto (2015) identify TGI patents with six categories from IPC and CPC related to OECD environmental policies. This guideline allows me to measure between TGI and non-TGI patents of globally listed firms.

Dernis and Guellec (2001) show that granted patent applications represent firms' successful R&D outputs and economically significant inventions. I capture firms engaged in TGI with two measures. To reduce the firm-size effect, I first calculate the green patent ratio (*GP_percent*, hereafter) measured by green patent counts *(GP_count)* scaled by the total patent counts of the firm. Second, I calculate the green patent citation ratio (*GC_percent*, hereafter), referring to the firm's TGI qualitative intensity by measuring green-patent forward citation counts (*GC_count*) scaled by total forward citation counts.

Furthermore, Hall et al. (2001), Hall et al. (2005) and Dass et al. (2017) show a truncation bias in patent databases. The truncation bias occurs from the delay of the patenting process mechanism, lagging about two years on average between filling application dates and granted dates. Hence, to reduce truncation bias from the green patent variable, I set my data following the patent application filling dates (Luong et al., 2017).

In addition, they also address the issue of inherently truncated citation counts. Although the number of forwarding citations refers to the quality of firm innovations, patents applied in different periods are not comparable. To reduce this issue, I adjust the citation counts of each patent by dividing the average citation count in the same year and patent classification measured at the 3-digit IPC or CPC level (see Hirshleifer et al., 2012).

3.3.4 Covariates and Country Control Variables

I incorporate the numbers of covariates and country control variables affecting analysts' strategic portfolios and informativeness. In terms of covariates, firm size (*Size*) is measured by the natural logarithm of the firm's market value. It controls the firm's size effect on market preferences and analysts' incentives (Barth et al., 2001, Behn et al., 2008 and Hsu et al., 2023). I measure firm profitability by the ratio of net profit after taxes to total assets (*ROA*). Hong and Kacperczyk (2010), Ioannou and Serafeim (2015) and Merkley et al. (2017) show that firms generating higher profitability enhance analysts' recommendations and reduce forecast bias. I employ the standard deviation of *ROA* (*Std_roa*) to measure the earning volatility of the firms, which is potentially related to analysts' efforts and forecasts. Barth et al. (2001), Behn et al. (2008) and Hong and Kacperczyk (2010) indicate that firms with highly volatile earnings require more effort from analysts in forecasting, and this results in increased forecast errors and biases.

I use book-to-market value per share (*BM*) and the ratio of research and development expenditures to total sales (*R&D*) as proxies of firms' information asymmetry. Barth et al. (2001) suggest that firms with higher research and development expenditures increase analysts' efforts, whereas Amir et al. (2003) argue that higher intangible assets reduce analysts' forecast accuracy. He et al. (2019) indicate that larger *R&D* and lower *BM* are associated with high financial opacity and information asymmetry. Loh and Stulz (2011) also suggest that lower *BM*, representing a firm's potential growth, has more influence on analysts' recommendations.

Following Barth et al. (2001), I include the natural logarithm of firm trading volume (*Ln_trading*) to capture possible compensation levels of analysts covering the firm. Moreover, I add a systematic risk of the firm compared to the exchange market (*Beta*) to mitigate firm uncertainty affecting the analysts' behaviour and forecast bias (Bhushan, 1989, Loh and Stulz, 2011 and He et al., 2019).

Based on my empirical analysis covering 50 stock exchanges, I include country control variables in my model. First, the model accounts for the number of brokerage houses in the country (*Broker*), following the career concern hypothesis, indicating that the intensive levels of analyst labour market are positively associated with analysts' efforts and activities (Jackson, 2005). Second, I include the natural logarithm of exchange market capitalisation (*Exchange*) to capture the size of the market. The market size also indicates the level of information efficiency as larger markets are likely to be more efficient than others. A better market efficiency enhances analysts' activities (Hope, 2003). In addition, the larger exchange market value signals an intensive demand for analysts' information, which benefits brokerage houses and analysts' incentives and motivates the analysts to put in additional efforts (see discussion in Merkley et al., 2017). All variables are defined in Appendix Table A3.1.

3.3.5 Experimental Set-up: The 1st Kyoto Protocol Commitment

A larger body of literature emphasises that the maximisation of TGI benefits is significantly related to environmental policies and regulations (Porter and Van Der Linde, 1995, Shrivastava, 1995, Ambec and Lanoie, 2008 and Lanoie et al., 2011). Meanwhile, the econometric concerns of endogeneity question the estimation bias of causal effects. Hence, my study follows the literature to investigate the impact of firms engaged in TGI under the TGI maximise value condition. I construct an empirical framework based on the triple difference-in-differences model (DiDiD) using the 1st Kyoto Protocol commitment period as the exogenous variation boosting TGI activities.

The 1st Kyoto Protocol was initiated in December 1997 under the United Nations Framework Convention on Climate Change (UNFCCC). The protocol aims to control and reduce the greenhouse gas (GHG) emissions of the United Nations members, which initiates with 37 industrialised countries, including the European Union countries, the United Kingdom, Canada, Japan, Australia, Russia, Norway, etc.[42]. The 1st Kyoto Protocol commitment implementation covered the period 2008 – 2012 (the post-commitment period, hereafter), assigning 37 committed countries to reduce and disclose levels of GHG emissions annually during the said period[43]. The protocol created mechanisms to enhance environmental development across countries, particularly establishing an international emissions trading mechanism that creates economic incentives for reducing GHG emissions.[44]

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[42] UNFCCC. (2005). *Kyoto Protocol Reference Manual on accounting of Emissions and Assigned Amount*; The UNFCCC website: https://unfccc.int/kyoto_protocol

[43] The initial target of the 1st Kyoto Protocol commitment was to decrease GHG emissions by 5.2% on average compared to the GHG emission level in the base year 1990.

[44] UNFCCC. (2007). *Investment and Financial Flows to Address climate Changes.*

The literature supports the experimental design with convincing empirical evidence of environmental performance-related firm-level changes in the 1st Kyoto Protocol commitment period (i.e., 2008 – 2012). Nguyen (2018) indicates that the 1st Kyoto Protocol period negatively affects the firm's operating performance in the higher polluting industries. Firms ignoring climate-friendly transition increase firms' climate regulatory risk and cost of capital (Nguyen and Phan, 2020). Similarly, Balachandran and Nguyen (2018) show that increasing environmental costs and taxes cause dividend pay-out reduction of highly polluting firms. Costantini and Crespi (2008), Costantini and Mazzanti (2012) and Tran (2021) support that countries committed to stringent environmental regulations gain higher ecological technologies related to pollution abatement, cleaner environment, and resource management. Kesidou and Demirel (2012) note that the level of strictness of environmental regulations impacts TGI investment, as companies tend to increase their TGI activities to reduce the production costs of complying with environmental regulations.

Thus, from the literature, I can say that the exogenous impact of the 1st Kyoto Protocol commitment increases differential levels of TGI development. Firms in countries committed to the 1st Kyoto Protocol benefit more from TGI optimisation, leading them to encourage more TGI activities compared to those in uncommitted countries. This evidence allows me to contain the 1st Kyoto Protocol commitment as an appropriately exogenous factor in the empirical framework. However, to confirm this ideal quasi-natural experimental setup, I present empirical evidence on the effects of the 1st Kyoto Protocol commitment on driving TGI activities by comparing levels of TGI intensity between firms in countries committed to the 1st Kyoto Protocol (treated group/firms) and firms in uncommitted countries (control group/firms). The results are presented in Table 3.1.

Table 3.1 shows the mean comparison of green patents and green citations received before and after the 1st Kyoto Protocol commitment. Regarding the 1st Kyoto Protocol ratification, the commitment period is from 2008 – 2012. Therefore, I refer to 2003–2007 as the pre-commitment period and 2008–2012 as the post-commitment period. Table 3.1 Panel A reports the cases of the full sample, i.e., treated and control groups, with 210,741 firm-year observations over 2003-2012. The averages of TGI quantitative and qualitative intensity (*GP_percent and GC_percent*) are 0.73% and 0.64%, respectively (Column (1)). The mean comparisons of TGI between the pre- and post-commitment periods show that the intensity of *GP_percent and GC_percent* significantly increased by 0.17% and 0.12%, respectively (see Column (4)).

Panels B and C of Table 3.1 show the TGI comparison of treated and control groups, representing the firms in the committed and uncommitted countries of the 1st Kyoto Protocol ratification, respectively. I discover similar evidence of increasing TGI intensity in both sample groups. However, the deviation level of TGI intensity in the treatment group increases more than in the control group. In particular, during the post-commitment period, the average number of green patents (*GP_count*) of the treated group increased by 0.44 compared to the pre-commitment period, whereas that of the control group rose by 0.12 (see Panels B and C Column (4), respectively).

Further, in Columns (5) – (8), I compare the mean difference in TGI intensity between the pre- and post-commitment period of the innovative firms. I see that during the post-commitment period, the average *GP_percent (GC_percent)* of innovative firms in the treatment group significantly increased by 1.88% (1.50%) compared to the pre-commitment period (see Panel B Column (8). In contrast, I do not find any significant difference in TGI intensity variables between the pre- and post-commitment periods for the innovative firms in the control group (see Panel C Column (8)).

These findings suggest that the 1st Kyoto Protocol commitment significantly enhanced the firms to invest more in TGI activities. The regulation is more effective to firms in the treated groups to engage in TGI activities than the firms in the control groups. Therefore, I can conclude that the more significant benefits of TGI under the 1st Kyoto Protocol commitment draw firms in the committed countries to invest more in TGI development.

3.3.6 Propensity Score Matched (PSM) Randomisation

The economic growth of a nation is also known to be a significant determinant in driving innovations in a country. Countries that encourage financial market liberalisation have large capital markets and opportunities to develop an innovative process through knowledge spillover. Therefore, globally listed firms located in countries with different economic conditions should heterogeneously affect the development of innovative processes and TGI intensity levels. To reduce this effect, I apply a propensity score matching process (PSM) to identify comparable observations. I match firm pairs between groups of treatment and control firms by using firm baseline characteristics, including *SIZE, BM, ROA, Std_roa, and R&D*. I first observe the mean differences in variables between treatment and control groups before the 1st Kyoto Protocol (2003-2007). The figures are reported in Panel A of Table 3.2.

Table 3.2 Panel A presents mean and median differences of variables by t-test and z-statistic measurement, respectively. The results show the statistical significance of different firm characteristics between treatment and control groups. Then, I construct near-randomised treatment and control groups using the PSM approach. In the initial samples, I employ the firms followed by at least one brokerage house and drop all firms that have no analyst coverage. I run a probit regression model by creating a dummy variable to divide treatment and control firms as the endogenous variable. My key covariates relate to firm baseline characteristics. Then, I apply the nearest neighbour caliper algorithm method with replacement to identify a matching set of highly comparable treated and control firms prior to the 1st Kyoto Protocol commitment (2003 – 2007).

$$Treat_i = \alpha + X_{i,t}\beta' + \gamma_k + \varepsilon_{i,t} \tag{2}$$

In equation (2) is the probit regression model investigating the average value of my key covariates before and after remodelling matched samples. $Treat_i$ is equal to one for the firm is located in a country committed to the 1st Kyoto Protocol, and zero for the firm is located in an uncommitted country. I denote $X_{i,t}$ as the vector of firm baseline characteristics, including *SIZE, BM, ROA, Std_roa, and R&D*. γ_k is industry fixed effect using Standard Industrial Classification (SIC) with four digits. The results are presented in Panel B of Table 3.2.

Table 3.2 Panel B shows the estimates of the probit regression analysis (equation (2)). Column (1) shows significant differences in all firm characteristics between treatment and control firms (with significant pseudo-R^2 of 0.10) before the PSM match. Column (2) shows an absence of significant difference between the covariates of treatment and control firms after PSM-matching. It has a relatively lower pseudo-R^2 of 0.079 and a p-value of

0.053. The estimates indicate the similarity of baseline characteristics between treatment and control firms in the post-match diagnostics.

3.4 Empirical Results

3.4.1 Summary Statistics and Univariate Analysis

In this section, I discuss descriptive statistics and univariate analysis of all time-varying variables. The univariate analysis examines the mean difference between, before, and after the 1st Kyoto Protocol commitment (the pre- and post-commitment periods, respectively). The figures are obtained from the PSM-matched samples of treated and control firms, excluding non-analyst coverage samples. The figures are reported in Table 3.3.

Panel A of Table 3.3 present the mean difference of all explanatory variables in the treated and control groups, respectively, between the pre-commitment period (2003–2007) and the post-commitment period (2008–2012). With regard to treatment firms in Panel A, the results show that in the post-commitment period, the number of analysts following the firm ($Analyst\_cov_{i,t}$), recommendation consensus ($Mean\_recom_{i,t}$), and individual analysts' recommendations ($Recom_{i,j,t}$) did not change significantly compared to the pre-commitment period. In contrast, for the control group, the change is significant. During the post-commitment period, $Analyst\_cov_{i,t}$ increased by 1.293 compared to the pre-commitment period. Similarly, $Mean\_recom_{i,t}$ and $Recom_{i,j,t}$ increased significantly by 0.031 and 0.135, respectively (see Panel A, Column 9).

In comparison to the control group, the treatment group exhibits a significant increase in the analysts' forecast error during the post-commitment period, denoted as $Error_{i,j,t}$, and $Inconsistency_{i,j,t}$. The mean differences of $Error_{i,j,t}$ and $Inconsistency_{i,j,t}$ in the treated firms between pre- and post-commitment periods are 0.008 and 0.007, respectively, whereas the mean difference of $Error_{i,j,t}$ and $Inconsistency_{i,j,t}$ in the control firms are 0.003 and 0.003, respectively (see Panel A, Column 9). These findings indicate that analysts' forecast ability, with respect to the treated firms, and compared to the controlled firms, declines after the 1st Kyoto Protocol commitment. Moreover, the findings pertain to the substantiation of the pessimistic bias displayed by analysts. This is because a decline in the performance of analysts' forecasts regarding the implications of the 1st Kyoto Protocol commitment has an impact on their remuneration and reputation. Consequently, treated firms that impede the accuracy and consistency of analysts' forecasts exhibit an inverse relationship with the number of analysts following the firms and their recommendations.

I estimate that the commitment to the 1st Kyoto Protocol impacts the operational costs and profitability of the firms in committed countries. Studies suggest that the regulation enforcement reduces cashflow performance and the levels of dividend pay-out but raises the cost of capital instead (Balachandran and Nguyen, 2018, Nguyen, 2018 and Nguyen and Phan, 2020). The regulation can force the treated firms to take actions engaged in environmental development, such as environmental disclosure, changing operating and management strategies, and improving production processes. These actions cause extra costs of operation, putting pressure on the firms' cash flows. In the meantime, Griffin et al. (2020) suggest that increasing operations and activities of the treated firms to comply with the regulation affects the monitoring costs of analysts. Consequently, treated firms in the countries that are committed to the 1st Kyoto Protocol will generate uncertainty in financial performance which, in turn, adversely affects analysts' expectation and impedes analysts' forecast ability. Conversely, control firms that are not experienced with regulatory risks can maintain short-term profitability and induce analysts to take action, i.e., adding the firms to their coverage portfolios and issuing favourable recommendations.

3.4.2 The Effect of TGI on the Number of Analysts Following the Firms

I use a multivariate analysis to test hypothesis H1, i.e., "*The intensity of the firms' engagement in TGI and the number of analysts following them are inversely related*". I construct a triple difference-in-differences regression model (DiDiD) to assess whether the number of analysts following the treated TGI firms, compared to those of the control TGI firms, has increased or decreased in the post-commitment period. I estimate the following regression model (equation (3)) separately for the intensity ratios of green patent (*GP_percent*) and green adjusted citation (*GC_percent*).

$$Ln\_coverage_{i,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \varphi_i \boldsymbol{D}_{dt-1} + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,t} \quad (3)$$

In equation (3), i and t represent firm and time (year), respectively. $Ln\_coverage_{i,t}$ represents is the natural logarithm of one plus the number of analysts that reported earnings-per-share (EPS) forecasts for firm i in fiscal year t. TGI_{t-1} denotes *GP_percent* and *GC_percent*, the two measures of technological greener innovations, as defined in sub-section 3.3.3. The $Treat_i$ dummy variable equals one for the firm (i) in a committed country of the 1st Kyoto Protocol and zero for the firm (i) in an uncommitted country. $Post_t$ takes the value of one for the 1st Kyoto Protocol commitment period (2008-2012) and zero for all the years before (2003 – 2007). $\boldsymbol{X}_{it-1}$ is a vector of covariates, including *SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, and Beta*. $\boldsymbol{D}_{dt-1}$ is the set of the country control variables: *Broker* and *Exchange*. γ_i, π_k, λ_d and τ_t denote firm-, industry-, country- and year-fixed effects, respectively. All variables are defined in Appendix Table A3.1. I winsorise all time-varying control variables at 1% and 99% levels to reduce the influences of possible spurious outliers. In this empirical analysis, I drop all firm-year observations with zero number of analysts and adjust the results by clustering standard errors with firm, industry, country, and year.

The key estimation is explained through the coefficient (β_1) of different triple interactions $(Treat_i \times Post_t \times TGI_{i,t-1})$. I expect the coefficient β_1 to be negative, implying that during the post-commitment period, the increase in TGI intensity of the treated firms caused a lower number of analysts covering the treated TGI firms than that in the control TGI firms. The results are reported in Table 3.4.

Columns (1) – (4) of Table 3.4 show the estimates from the DiDiD model (equation (3)) based on the PSM-matched samples examining the effect of TGI intensity on the number of analysts following the firms. The results indicate that during the post-commitment period, the number of analysts covering the firms with higher TGI intensity declined significantly in the treated firms compared to the control firms. Considering a firm-fixed effect regression in Column (1), during the post-commitment period, the number of analysts' coverage decreased significantly (by 1.03%) in the treated firms, which exhibited a 1% increase in TGI intensity (i.e. *GP_percent*), in comparison to the control TGI firms. Likewise, the industry-fixed effect results show that during the post-commitment period, a 1% increase of *GP_percent* in the treated firms reduced the number of analysts covering the firms by 1.04% compared to the control firms (Column (3)).

Further, Columns (2) and (4) show the effect of TGI firms following the TGI quality levels (*GC_percent*). The Result reported in Column (2) (the firm-fixed effect result), shows that in the post-commitment period, a 1% increase of *GC_percent* in the treated TGI firms dropped the number of analysts following the firms (relative to controlled TGI firms) by 0.92% (see Column (2)). Similarly, the industry-fixed effect regression results reported in Column (4) suggest that during the post-commitment period, increasing *GC_percent* of the treated firms by 1% declined the number of analysts covering the firms by 0.85% compared to the control firms.

These findings indicate that the number of analysts following the firms with higher levels of TGI intensity drops significantly. Therefore, I support hypothesis H1 that "*The intensity of the firms' engagement in TGI and the number of analysts following them are inversely related*".

My evidence contradicts the finding of Barth et al. (2001) whose evidence finds that the number of analysts increases in firms with higher innovative investments. I argue that innovative intensity, specifically TGI activities, will generate information complexity and short-term operating uncertainty that adversely affects analysts' efforts in acquiring firms' information. Firms that allocate greater resources to TGI activities have higher restrictions on disclosing information on innovative projects; this impedes analysts from incorporating and estimating the intrinsic value of TGI. These implications may prompt analysts to exclude TGI firms from their coverage portfolio to protect the performance of their forecasts. Moreover, considering the incentive benefits, informational complexity corresponding to TGI intensity requires more resources and analysts' efforts in monitoring the TGI firms compared to industry peers (Griffin et al., 2020). This extra monitoring cost can cause analysts to cut off the TGI firms and choose to follow the firms with less innovative activities in the same industry.

On the other hand, the limited attention of investors to TGI benefits in the short run adversely affects analysts' decisions to cover TGI firms. Eberhart et al. (2004), Gu (2005) and Cohen et al. (2013) note that short-term uncertainty of innovation dilutes TGI stocks' attraction and causes market underreaction. Lower markets' attention to TGI information implies lower trading commissions, which leads analysts to put in/make less effort in accessing firms engaged in TGI.

In addition, my findings reflect the negative view of analysts about the uncertainty of firms engaged in TGI. This evidence is consistent with McNichols and O'Brien (1997), who suggest that adding (dropping) firms in individual analysts' coverage portfolios are related to their positive (negative) expectations regarding the future performance of said firms. Rather than issuing negative recommendations, analysts tend to drop firms with expected poor performance to maintain their relationship with firm managers. Thus, based on my results, it is plausible that analysts who are apprehensive about establishing a connection with management may opt to remove the TGI firms they covered rather than provide an unfavourable recommendation.

3.4.3 The Effect of TGI on Analysts' Recommendations

In this part, I investigate hypothesis H2 that "*The intensity of the firms' engagement in TGI and analysts' recommendations are inversely related*". I offer datasets at two levels, namely the firm level and analyst level, in order to assess the consensus and individual recommendations of analysts against the levels of TGI intensity. At the firm-level dataset, I provide a recommendation consensus variable in the quasi-natural experiment using the following regression model (equation (4)):

$$Mean\_recom_{i,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) \quad (4)$$

$$+ \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \varphi_i \boldsymbol{D}_{dt-1} + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,t}$$

In equation (4), *i* and *t* represent firm and time (year), respectively. $Mean\_recom_{i,t}$ represents the average of analysts' recommendations for firm *i* and year *t*. TGI_{t-1} denotes *GP_percent* and *GC_percent*, as described in sub-section 3.3.3. The *Treat* dummy variable equals one for the firms (*i*) located in the countries that are committed to the 1st Kyoto Protocol and zero for those who have not committed. *Post* is equal to one for 2008-2012 and zero is for 2003-2007. $\boldsymbol{X}_{it-1}$ and $\boldsymbol{D}_{dt-1}$ are the set of covariates and country variables, as I mentioned in equation (3). I also include a one-year lag in the number of analysts following the firm *i* as a control variable. γ_i, π_k, λ_d and τ_t denote firm-, industry-, country- and year-fixed effects, respectively. Regarding hypothesis H2, I expect a negative indication of the key interaction coefficient (β_1). This would indicate that during the post-commitment period, the treated firms with higher TGI intensity experienced a reduction in consensus recommendations expressed by the analysts, in comparison to the control firms. The results are reported in Table 3.5.

Columns (1) – (4) of Table 3.5 show the estimates of the equation (4) investigating the impact of TGI intensity on analysts' consensus recommendations. The findings suggest that during the post-commitment period, the analysts' consensus recommendations in the treated firms with higher TGI intensity declined significantly compared to the control TGI firms. Columns (1) and (2), presenting the results of the firm-fixed effect regression, signify that during the post-commitment period, a 1% increase in *GP_percent* and *GC_percent* of treated firms reduced the consensus recommendation levels by 0.013 and 0.011 compared to control TGI firms, respectively. These findings are consistent with the industry-fixed effect results, which show that during the post-commitment period, a 1% increase in *GP_percent (GC_percent)* in the treated firms leads to a 0.015 (0.012) decreased in analysts' consensus recommendations, in comparison to the control firms (see Columns (3) and (4)). These findings support the prediction of H2 and suggest that TGI intensity adversely affects analysts' recommendations.

Further, I examine analysts' recommendations at analyst-level data to better understand the perspective of individual analysts on TGI intensity. At this level, I can control analysts' characteristics affecting their forecast ability. I modify the DiDiD model in equation (4) by employing individual analysts' recommendations as the dependent variable and incorporating analyst control variables in the following model (equation (5)):

$$Recom_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} \qquad (5)$$
$$+ \delta_i \boldsymbol{X}_{i,t-1} + \rho_i \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

In equation (5), *i*, *j* and *t* represent firm, analyst, and time (year), respectively. $Recom_{i,j,t}$ is the recommendation of firm *i* by an individual analyst *j* at fiscal year *t*. I also provide $\boldsymbol{T}_{j,t}$ as a set of analyst control variables, i.e., the number of covered firms in the coverage portfolio of the analyst *j* (*Portfolio*), and the number of analysts employed by the analyst's brokerage house (*Broker_size*). I also contain the analyst-fixed effect (μ_j) to capture omitted influential factors in the regression model. Other variables are described in the equation (3). The findings are demonstrated in Table 3.6.

Columns (1) – (4) of Table 3.6 report the estimates of the equation (5), testing the impact of TGI intensity on individual analysts' recommendations. Empirically, the findings of the firm-fixed effect analysis are similar to the industry-fixed effect results, which indicate that during the post-commitment period, a 1% growth rate of *GP_percent*

(*GC_percent*) in the treated firms reduced the recommendation levels of individual analysts by 0.019 (0.016) compared to the control firms[45]. The results are consistent with the prior evidence of the firm-level regression analysis, suggesting that in the post-commitment period, treated firms with higher TGI intensity reduced analysts' recommendations, in comparison to the control TGI firms.

Regarding the estimates of both regression levels, I find that higher TGI intensity can reduce analysts' recommendations. The findings support my hypothesis H2 that "*The intensity of the firms' engagement in TGI and analysts' recommendations are inversely related*". My evidence is also consistent with prior interpretation in hypothesis H1 that analysts are pessimistic about TGI intensity. These results reinforce the view that TGI intensity increases the uncertainty of firms' operating performance. The higher uncertainty of the short-term profitability of the TGI firms compared to their industry peers causes analysts to overestimate unfavourable conditions about the TGI firms and downgrade their recommendations. My evidence is consistent with Lin (2018), who documents that analysts are sensitive to firm uncertainty, which causes analysts to overestimate new uncertain risks and provide unfavourable recommendations.

On the other hand, it is possible that the downgrading of analysts' recommendations is the analysts' signal to communicate with firm management. He and Tian (2013) suggest that analysts tend to pressure firm managers to cut off innovative investments in order to maintain short-term profitability. The downgrading of analysts' recommendations can

[45] In industry-fixed effect results, we find that during the post-commitment period, a 1% increase in GP_percent (GC_percent) of the treated firms caused lower levels of individual analysts' recommendations by 0.018 (0.016) compared to the control firms.

motivate managers to prioritise enhancing short-term profitability over allocating resources to TGI projects in response to analysts' expectations and maintaining the firms' stock values.

3.4.4 The Effect of TGI on Analysts' Forecast Errors

I continue using analyst-level data to examine hypothesis H3a: "*the intensity of the firms' engagement in TGI and analysts' forecast errors are positively related*". I measure individual analysts' forecast errors (*Error*) by the absolute difference between an individual analyst's forecast EPS (earnings per share) and actual EPS, all of which is scaled by stock price (see sub-section 3.3.2). I modify equation (5) to include *Error* as a dependent variable in the DiDiD model (equation (6)):

$$Error_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} \qquad (6)$$
$$+ \delta_i \boldsymbol{X}_{i,t-1} + \rho_i \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

All explanatory variables, $\boldsymbol{X}_{it-1}$ (a set of covariates, i.e,. *SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, and Beta*) and $\boldsymbol{D}_{dt-1}$ (a set of country variables, i.e., *Broker* and *Exchange*) are mentioned in the equation (3). $\boldsymbol{T}_{j,t}$ is vectors of analyst control variables composed of *Portfolio* and *Broker_size* as in equation (5). In this regression, I also include forecast horizon (*Horizon*), the period (day) between the analyst EPS forecast announcement date and the corresponding actual EPS announcement date as an analyst control variable. The variable captures the bias of the time difference in an analyst's forecast, significantly affecting the forecast errors. I exclude the analysts' forecast data with more than a one-year *Horizon* to reduce the influence of stale forecasts (Behn et al., 2008 and Dhaliwal et al., 2012). For hypothesis H3a to hold, I expect a positive value of the coefficient (*β_1*). This signifies that during the post-commitment period, higher TGI intensity of the treated firms increased analysts' forecast errors compared to those of the control firms. The results are reported in Table 3.7.

Columns (1) – (4) of Table 3.7 show the estimates of equation (6) investigating the impact of the TGI intensity on analysts' forecast errors. The findings reveal that in the post-commitment period, levels of TGI intensity significantly escalated analysts' forecast errors in the treated firms compared to the control firms. The estimates from industry-fixed effect regression suggest that there is a significant impact of TGI intensity on increasing analysts' forecast errors. The estimates indicate that during the post-commitment period, a 1% increase in *GP_percent* (*GC_percent*) of treated firms escalated analysts' forecast errors by 0.11% (0.11%) compared to the control firms (see Columns (3) and (4)). This value signifies that during the post-commitment period, if one standard deviation (9.824% and 6.777%)[46] increases in *GP_percent (GC_percent),* there is a corresponding increase in analysts' earnings forecast errors covering the treated TGI firms of 1.08% (0.74%)[47], in comparison to the control firms.

These results show evidence of higher levels of TGI intensity causing higher errors in analysts' earnings forecasts and support hypothesis H3a that *the intensity of the firms' engagement in TGI and analysts' forecast errors are positively related.* I interpret that firms engaged in more TGI activities increase the degrees of firms' information asymmetry and cash flow uncertainty in the short run. The implications adversely impact analysts' forecast accuracy.

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[46] see Table 3.3 Column (4) Panel B
[47] [0.11×9.824] and [0.11×6.777]

Regarding the career concern hypothesis, the negative impact of TGI on analysts' forecast accuracy raises concerns about analysts' reputations. The evidence supports my prior views documented in the context of hypotheses H1 and H2 that higher TGI activities impede analysts' forecast ability, which leads to them having a pessimistic bias toward firms engaged in TGI.

These findings are consistent with the evidence reported by Amir et al. (2003) that analysts' forecast accuracy is inversely associated with levels of the firms' R&D expenditures. I argue that analysts cannot fully identify the intrinsic value of TGI in the information they convey to investors via earnings forecasts. One possibility is that firms adopting an innovation, including TGI, may experience temporary profitability volatility (Kothari et al., 2002). This short-term implication of TGI adoption can impair analysts' accuracy in forecasting future earnings for the firms they monitor. Regarding this interpretation, I also discover that the coefficient of TGI *(β_3)* is inconsequential to analysts' forecast errors, implying that without the effect of the 1st Kyoto Protocol commitment, the degrees of TGI intensity do not significantly impact analysts' forecast errors. This evidence reinforces that analysts cannot fully identify the future value of TGI benefits corresponding to environmental regulations.

Moreover, Hope (2003) indicates that analysts perform better in the context of firms' environmental conditions when the information asymmetry and complexity are low. However, these conditions are inversely related to firms investing in TGI activities, which are unwilling to expose all innovative project details and disclose only partial information to protect against information leakage to their industry competitors (Bhattacharya and

Ritter, 1983). Consequently, the limitation of information disclosure regarding TGI projects can impede the accuracy of analysts' earnings forecasts.

3.4.5 The Effect of TGI on Analysts' Forecast Consistency

In this section, I investigate the predictions of hypothesis H3b, i.e., "*the intensity of the firms' engagement in TGI and the consistency of analysts' forecast errors* are inversely *related*". I measure the level of inconsistency in individual analysts' forecast errors by the standard deviation of individual analysts' forecast errors over the previous five years (see sub-section 3.3.2). I modify equation (5) to employ *Inconsistency* as the dependent variable as in equation (7).

$$Inconsistency_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \rho_i \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t} \quad (7)$$

In equation (7), high (low) *Inconsistency* implies that individual analysts' forecast abilities are less (more) consistent over the TGI development period. I investigate the implication of TGI impact on analysts' forecast ability via the primary coefficient (β_1). For the hypothesis H3c to hold, the coefficient β_1 should be positive, indicating that during the post-commitment period, higher TGI intensity in the treated firms increased (decreased) the inconsistency (consistency) of individual analysts' earnings forecasts compared to that of the controlled firms. The results are reported in Table 3.8.

Estimates reported in Columns (1) – (4) of Table 3.8 show the impact of TGI intensity on the consistency of individual analysts' earnings forecasts. The results suggest that in the post-commitment period, increasing TGI intensity in the treated firms escalated the inconsistency of analysts' forecast errors compared to that of the control firms.

Columns (3) and (4), showing the results of industry-fixed effect regression, signify that during the post-commitment period, one standard deviation increase of *GP_percent* (*GC_percent*) in the treated TGI firms affected a higher substantial deviation of individual analysts' forecast errors by 0.88% (0.41%)[48] compared to the control firms.[49]

These results show that increasing the level of TGI intensity adversely affects the consistency of analysts' earnings forecasts. Hence, the findings support the prediction of hypothesis H3b that *the intensity of the firms' engagement in TGI and the consistency of analysts' forecast errors are inversely related.*

As discussed in sub-section 3.4.4, Kothari et al. (2002) suggest higher earnings volatility under innovative investment throughout the innovative process. Firms that allocate more resources in TGI activities generate more earnings uncertainty during the TGI developing process which can disturb analysts' forecast consistency about firms' future earnings. Furthermore, firms investing more in TGI increase the stringency of information disclosure regarding TGI activities (Bhattacharya and Ritter, 1983). The low information flow from managers limits the analysts' ability to appropriately assess the value of TGI and incorporate its effect on the firm's future earnings.

With respect to the analysts' career concerns, analysts' performance and reputation are associated with the consistency in their earnings forecasts. The results suggest that analysts hold pessimistic views towards firms that are engaged in TGI activities, reflecting

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[48] [0.09×9.824] and [0.06×6.777]

[49] We find that Columns (1) and (2), employing the results of firm-fixed effect regression, show that during the post-commitment period, higher TGI intensity (i.e. *GP_percent* and *GC_percent*) in the treated firms insignificantly raise (drop) analysts' forecast inconsistency (consistency) compared to the control firms.

the roles of higher information complexity and financial uncertainty. These TGI implications can cause the reduction in the analysts' forecast ability.

3.4.6 Robustness Check

3.4.6.1 Technological Green Innovation and the Number of Analysts' Coverage

In the robustness test, I begin by reexamining hypothesis H1 that *the intensity of the firms' engagement in TGI and the number of analysts following them are inversely related*. I employ sensitivity of analyst coverage numbers by including firms with zero number of analysts' coverage in equation (3). The results are reported in Table 3.9.

Columns (1) – (4) of Table 3.9 show the estimates of TGI intensity impact on the number of analysts. The results confirm that during the post-commitment period, increasing TGI intensity in the treated firms significantly reduced the number of analysts following the firms compared to the control firms. This is consistent with the view that TGI intensity represents higher information complexity and short-term profitability uncertainty. Analysts who are responsible for the coverage of TGI firms may not like to provide reports that conflict with the views of the management and instead avoid covering the firms that could potentially harm their reputation. The findings are consistent with the main results reported in section 3.4.2. Moreover, compared to the primary findings in Table 3.4, I see a greater negative impact of TGI intensity on the number of analysts tracking the TGI firm in this table. The results reemphasise the analysts' perspectives on firms' TGI intensity, which deters them from covering the firms engaged in TGI activities. Hence, these results also support the prediction of hypothesis H1 that "*The intensity of the firms' engagement in TGI and the number of analysts following them are inversely related*".

3.4.6.2 Technological Green Innovation and the Revisions in Analysts' Recommendations

Next, I reexamine the effect of TGI intensity on analysts' recommendations (hypothesis H2) by using analysts' recommendation revisions ($Revision_{i,j,t}$) as the dependent variable in analyst-level examination by modifying equation (5) to equation (8).

$$Revision_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \rho_i \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t} \quad (8)$$

In equation (8), *Revision* is the change of individual analysts' recommendations. The maximum and minimum values of *Revision* are +4 and -4, respectively. The positive (negative) *Revision* represents upgrading (downgrading) recommendations of an individual analyst. A negative coefficient (β_1) would support H2, implying that during the post-commitment period, higher TGI intensity in the treated firms leads to analysts more severely downgrading their recommendations compared to those of the control firms. The results are reported in Table 3.10.

Columns (1) – (4) of Table 3.10 show the estimates of equation (8) examining the impact of TGI intensity on analysts' recommendation revisions. I find the results consistent with the results of the main analysis that during the post-commitment period, increasing TGI intensity in the treated firms led the analysts to downgrade their recommendations compared to the control firms. The firm-fixed effect results in Columns (1) and (2) indicate that during the post-commitment period, a 1% increase of *GP_percent* (*GC_percent*) in the treated firms led to analysts' downgrading recommendation revisions by 0.010 (0.009) compared to that of the control firms. I also find similar results when the industry-fixed effect is controlled.

These findings suggest a systematic change in the downgrading of the individual recommendations of those analysts who follow the TGI firms due to higher levels of concern and pessimism of individual analysts in response to the increase in TGI intensity. The findings reconfirm my main findings reported in section 3.4.3 and support hypothesis H2 that "*The intensity of the firms' engagement in TGI and analysts' recommendations are inversely related*".

3.4.6.3 Technological Green Innovation and Analysts' Earnings Forecasts

As further robustness tests, I use an alternative measurement of the analysts' forecast ability variables to investigate the effects of TGI firms on analysts' forecast errors and consistency. I calculate the alternative forecast error (*FE*) by using the difference between analyst forecast EPS and actual EPS, scaled by the actual EPS of the covered firm.

$$FE_{i,j,t} = \frac{Forecasted\ EPS_{i,j,t} - Actual\ EPS_{i,t}}{Actual\ EPS_{i,t}} \tag{9}$$

Then, I investigate hypothesis H3a by taking the absolute value of *FE* to investigate the magnitude of individual analysts' forecast errors (*Error*) and replace the variable in equation (6). The results are reported in Table 3.11.

Columns (1) – (4) of Table 3.11 demonstrate the estimates of TGI intensity impact on alternative forecast errors of individual analysts. These findings are consistent with the evidence reported in the main discussion that increasing TGI activities creates more information complexity and short-run earnings uncertainty, which adversely affects the analysts' predictions of future earnings. Thus, the findings support the predictions of hypothesis H3a that "*The intensity of the firms' engagement in TGI and analysts' forecast errors are positively related*".

Finally, I use an *Inconsistency* variable by calculating the standard deviation of alternative *FE* (in equation (9)) during the last five years to investigate analysts' forecast consistency and test hypothesis H3b. I contain the alternative *Inconsistency* variable as a dependent variable in equation (7). The estimates are reported in Table 3.12.

Columns (1) – (4) of Table 3.12 provide the estimates of the TGI intensity effect on the inconsistent levels of individual analysts' forecast errors. The results indicate that in the post-commitment period, higher TGI intensity in the treated firms escalated the inconsistency of individual analysts' earnings forecasts than the control firms. The evidence supports hypothesis H3c that "*The intensity of the firms' engagement in TGI and the consistency of analysts' forecast errors are inversely related*". My results suggest that the variation of analysts' forecasts increases following the levels of TGI intensity, representing higher uncertainty of short-term performance and information complexity. These findings emphasise my primary estimation that TGI intensity impedes analysts' performance in following the TGI firms.

3.5 Conclusions

Existing literature promotes value advantages of sustainability mechanisms, e.g., increasing fundamental performance and investors' attention. My study aims to motivate green transition by shedding light on the benefits of firms committed to TGI in financial markets. This chapter analysed the relationship between firms engaged in TGI and the analysts' activities and their forecast performance.

I argue that although TGI firms tend to be more attractive for some stakeholders, e.g., institutional investors and clients (see section 3.1), financial analysts deliver a negative response to firms engaged in TGI activities. My evidence indicates that levels of analyst coverage and their recommendation revisions conversely decline against the higher TGI intensity of the firms. I interpret this evidence as a function of growing information complexity, operating short-term uncertainty, and investors' underreaction within the TGI firms. These situations pressure the analysts to overemphasise unfavourable information and negatively respond to TGI intensity. Moreover, firms allocating more investment towards TGI activities generate more short-run profitable variability, and stringency of information disclosure regarding TGI activities to protect against information leakage. These consequences impede analysts' forecast accuracy and consistency.

My results support the career concern hypothesis, suggesting that financial analysts aim to deliver accurate forecast performance and generate trading volume. Innovative firms tend to be more undervalued in the short term due to unpredictable outcomes, affecting analysts' trading commissions. In addition, higher TGI investment, which causes fluctuations in the short-term performance, requires more considerable analyst efforts and brokerage resources to improve the quality of the forecasts and their reports. The lower forecast performance of analysts due to unfavourable conditions in TGI firms can lead them to take unfavourable actions such as downgrading recommendations or removing such firms from their portfolios in order to protect their reputation.

Table 3.1 Mean Comparison of Technological Green Innovation Between Before and After the 1st Kyoto Protocol Commitment

This table reports the univariate analysis of green innovations of globally listed firms between the pre-commitment period 2003 - 2007 (Before) and the post-commitment periods 2008 – 2012 (After) of the 1st Kyoto Protocol. Panel A presents all firm-year observations covering MSCI_ACWI countries. Panel B presents the treatment group referring to firm-year observations in the countries committed to the 1st Kyoto Protocol. Panel C presents the control group referring to firm-year observations in the uncommitted countries to the 1st Kyoto Protocol. All country samples are identified in Appendix Table A3.2. *GP_percent* is the percentage of green patent application counts divided by total patent counts. *GC_percent* is the percentage of adjusted green citations divided by total adjusted citations (see Appendix Table A3.1). *GP_count* is the number of green patent applications. The numbers in parenthesis present t-statistics of a variable mean comparison between pre- and post-periods of the 1st Kyoto Protocol commitment. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Variable	All observations				Innovative observations			
	Mean (Std.)	Before	After	Diff	Mean (Std.)	Before	After	Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full sample								
GP_percent	0.733(6.426)	0.634	0.806	0.172***	6.494(18.118)	5.986	6.828	0.842***
				(6.06)				(3.51)
GC_percent	0.638(6.015)	0.567	0.691	0.124***	5.653(17.088)	5.350	5.852	0.502**
				(4.68)				(2.22)
GP_count	0.709(21.576)	0.584	0.801	0.217**	6.280(63.933)	5.513	6.785	1.272
				(2.28)				(1.50)
Number of observations	210,741	89,162	121,579		23,800	9,447	23,800	
Panel B: Treatment group								
GP_percent	1.158(7.759)	1.037	1.249	0.212***	7.582(18.585)	6.537	8.417	1.880***
				(3.58)				(5.22)
GC_percent	1.034(7.376)	0.942	1.104	0.162***	6.773(17.814)	5.938	7.440	1.502***
				(2.88)				(4.35)
GP_count	1.618(35.057)	1.367	1.806	0.439*	10.593(89.166)	8.614	12.173	3.559**
				(1.65)				(2.06)
Number of observations	70,580	30,172	40,408		10,782	4,787	5,995	
Panel C: Control group								
GP_percent	0.519(5.625)	0.428	0.585	0.157***	5.592(17.672)	5.420	5.688	0.268
				(5.17)				(0.82)
GC_percent	0.439(5.184)	0.375	0.485	0.110***	4.726(16.405)	4.746	4.714	-0.032
				(3.93)				(-0.10)
GP_count	0.251(8.971)	0.184	0.301	0.117**	2.708(29.326)	2.328	2.921	0.593
				(2.40)				(1.10)
Number of observations	140,161	58,990	81,171		13,018	4,660	8,358	

Table 3.2 Propensity Score Matching (PSM) Results

Panel A provides a comparative analysis of mean and median values of the key variables before the 1st Kyoto Protocol commitment period (2003 – 2007) between treatment groups referring to firm-year observations in the countries committed to the 1st Kyoto Protocol and control groups referring to firm-year observations in the uncommitted countries. T-test and z-test are used to test for the differences between the means and medians of the variables, respectively. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Panel B reports a probit analysis of the samples between pre- and post-1st Kyoto Protocol periods matching the nearest neighbour algorithm.

$$Treat_i = \alpha + X_{i,t}\beta' + \gamma_k + \mathcal{E}_{i,t}$$

Where $Treat_i$ is a dummy variable that takes the value of 1 if the firm is based in the country committed to the 1st Kyoto Protocol and 0 otherwise. $X_{i,t}$ is the vector of covariates composed of *SIZE* is the natural logarithm of the firm's market value, *BM_ratio* is the book value per share scaled by the year-end market value per share, *ROA* is the returns to total assets ratio, *Std_roa* is the standard deviation of *ROA* for 3-year rolling period, *R&D_ratio* is the ratio of research and development expenditures to total sales, and γ_k is the industry fixed effects using four-digit of Standard Industrial Classification. The z-statistics are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Panel A Mean and median comparisons in covariates between treatment and control groups in 2003 – 2007

	Treatment group			Control group			Difference	
Variable	**Observa-tions**	**Mean**	**Median**	**Observa-tions**	**Mean**	**Median**	**Mean**	**Median**
SIZE	12,594	20.209	20.114	16,636	20.077	19.949	0.132***	0.165***
BM_ratio	12,594	0.629	0.499	16,636	0.683	0.468	-0.054***	0.031***
ROA	12,594	3.471	4.014	16,636	5.994	6.286	-2.523***	-2.262***
Std_roa	12,594	3.567	1.594	16,636	4.204	2.222	-0.637***	0.628***
R&D_ratio	12,594	1.803	0.000	16,636	2.422	0.000	-0.619***	0.000***

Panel B Pre-match propensity score regression and post-match diagnostic regression using probit analysis

	The binary variable is equal to 1 if the country of the firm *i* is associated with the 1st Kyoto Protocol, 0 otherwise	
Variable	**Pre-match (1)**	**Post-match (2)**
SIZE	0.0419***	0.0323
	(4.37)	(0.99)
BM_ratio	-0.0579***	-0.0489
	(-2.69)	(-1.07)
ROA	-0.0177***	-0.0036
	(-14.01)	(0.45)
Std_roa	0.0194***	0.0013
	(-8.09)	(-0.30)
R&D_ratio	0.0096***	0.0034
	(-4.25)	(0.84)
Constant	-0.8972***	-0.5696
	(-2.69)	(-0.84)
Industry FE	**Yes**	**Yes**
Pseudo R^2	**0.103**	**0.079**
P-value of χ^2	**0.000**	**0.053**
Firms	**8,671**	**1,940**
Number of observations	**28,898**	**7,188**

Table 3.3 Summary Statistics and Univariate Difference in Differences

This table reports the summary and univariate test statistics of all time-varying variables for the entire PSM-matched sample and by treated and control group investee firms. The statistics reported for the entire sample period of 2003-2012 (columns 2-6) are the total number of observations (*Observations*), the mean value (*Mean*), the standard deviation (*Std.*), the minimum value (*Minimum*), and the maximum value (*Maximum*), respectively. Columns 7 and 8 report the average values for the pre-commitment period 2003-2007 (*Before*) and the post-commitment period of 2008-2012 (*After*) of the 1st Kyoto Protocol commitment, respectively. The figures in parentheses of columns 7 and 8 are firm-year observations for the *Before* and *After* periods. Column 9 reports the difference between the *After* and *Before* mean values, with columns 10 and 11 reporting their associated t-stats and p-values, respectively.

Panel A reports statistics on the number of analysts covering the firm (*Analyst_cov*), mean of analysts' recommendations (*Mean_recom*), an individual analyst's recommendation (*Recom*), analysts' forecast errors (*Error*), and the inconsistency of analysts' forecast errors (*Inconsistency*). Panel B reports statistics of green innovation variables. *GP_percent* and *GC_percent*, statistics of firm-specific covariates (*SIZE, BM, Roa,Std_roa, R&D, Trading, and Beta*), statistics of analyst-level variables (*Broker_size, Portfolio, and Horizon*) and other country-level time-varying variables (*Broker* and *Exchange*, respectively). I define all these variables in Appendix Table A3.1. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Panel A: Sell-side analyst variables

Variable (1)	Observations (2)	Mean (3)	Std. (4)	Minimum (5)	Maximum (6)	Before (7)	After (8)	Diff (9)	t-stat (10)	p-value (11)
Treatment group										
$Analyst\_cov_{i,t,}$	7,529	8.702	8.378	1	53	8.606	8.774	0.168	0.86	0.38
						(3,255)	(4,274)			
$Mean\_recom_{i,t}$	7,322	3.602	0.673	1	5	3.610	3.596	-0.013	-0.84	0.39
						(3,195)	(4,127)			
$Recom_{i,j,t}$	47,922	3.291	1.079	1	5	3.293	3.288	0.005	0.51	0.60
						(21,240)	(26,682)			
$Error_{i,j,t}$	36,980	0.049	0.047	0.001	0.377	0.045	0.053	0.008***	15.26	0.00
						(15,023)	(21,957)			
$Inconsistency_{i,j,t}$	30,422	0.026	0.034	0	0.273	0.022	0.029	0.007***	16.09	0.00
						(11,095)	(19,327)			
Control group										
$Analyst\_cov_{i,,t}$	6,034	8.301	7.815	1	56	7.553	8.846	1.293***	6.36	0.00
						(2,540)	(3,494)			
$Mean\_recom_{i,t}$	5,937	3.710	0.690	1	5	3.692	3.723	0.031*	1.72	0.08
						(2,514)	(3,423)			
$Recom_{i,j,t}$	48,017	3.550	1.090	1	5	3.465	3.601	0.135***	13.26	0.00
						(18,135)	(29,882)			
$Error_{i,j,t}$	32,912	0.057	0.047	0.001	0.376	0.055	0.058	0.003***	6.04	0.00
						(12,695)	(20,217)			
$Inconsistency_{i,j,t}$	25,428	0.024	0.032	0	0.274	0.022	0.025	0.003***	6.53	0.00
						(9,951)	(15,477)			

Panel B: TGI variables, firm-level covariates, analyst-level variables, and country-level variables

Variable (1)	Observations (2)	Mean (3)	Std. (4)	Minimum (5)	Maximum (6)	Before (7)	After (8)	Diff (9)	t-stat (10)	p-value (11)
TGI variables										
GP_percent	13,563	1.884	9.824	0	100	1.780	1.962	0.181	1.06	0.28
						(5,795)	(7,768)			
GC_percent	13,563	1.377	6.777	0	100	1.385	1.372	-0.013	-0.11	0.90
						(5,795)	(7,768)			
Firm-level covariates										
SIZE(billion USD)	13,563	4.909	13.837	0.011	102.180	5.458	4.499	0.958***	-3.99	0.00
						(5,795)	(7,768)			
BM	13,563	0.784	0.758	0.058	4.874	0.583	0.934	0.350***	27.33	0.00
						(5,795)	(7,768)			
ROA	13,563	4.945	10.283	-46.000	34.031	5.526	4.511	-1.015	-5.69	0.00
						(5,795)	(7,768)			
Std_roa	13,563	3.450	4.926	0.062	31.704	3.376	3.506	0.130	1.52	0.13
						(5,795)	(7,768)			
R&D	13,563	3.182	14.493	0	127.412	3.120	3.229	0.109	0.43	0.66
						(5,795)	(7,768)			
Trading (million shares)	13,563	780.542	1,982.891	0.038	13,631.74	734.497	814.893	80.396**	2.33	0.02
						(5,795)	(7,768)			
Beta	13,563	0.720	0.537	-0.267	2.410	0.729	0.714	-0.015	-1.65	0.09
						(5,795)	(7,768)			
Analyst-level variables										
Broker_size	95,939	58.572	71.416	4	410	53.344	62.211	8.866***	18.95	0.00
						(39,375)	(56,564)			
Portfolio	95,939	9.482	8.721	1	58	8.697	10.028	1.330***	23.30	0.00
						(39,375)	(56,564)			
Horizon(day)	71,575	138.059	112.395	5	365	142.086	135.412	-6.673***	-7.77	0.00
						(28,387)	(43,188)			
Country-level variables										
Broker	413	51.920	45.442	14	303	46.629	56.607	9.978**	2.24	0.02
						(194)	(219)			
Exchange (billion USD)	413	1,000.959	2,605.344	42.503	19,922.28	1,018.879	985.084	-33.795	-0.13	0.89
						(194)	(219)			

Table 3.4 The Effect of TGI on the Number of Analysts' Coverage

The table below reports the results of a quasi-natural experiment model as in the following equation (3):

$$Ln\_coverage_{i,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3 TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \varphi_i \boldsymbol{D}_{dt-1} + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,t}$$

All variables noted in the above equation, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Ln\_coverage_{i,t}$ is the natural logarithm of one plus the number of analysts that reported earnings-per-share (EPS) forecasts for firm *i* in fiscal year *t*. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, and Beta). $\boldsymbol{D}_{dt-1}$* is a one-year lagged country control variable vector (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. γ_i is *i* firm fixed effect, π_k is the *k* industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. ε_{it} is the error term for firm *i* year *t*. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Ln_coverage			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent$_{t-1}$	**-0.0101****		**-0.0105*****	
	(-2.85)		**(-3.75)**	
Treat×Post×GC_percent$_{t-1}$		**-0.0092****		**-0.0085****
		(-2.76)		**(-3.08)**
Treat×Post	-0.0252	-0.0266	-0.0346	-0.0367
	(-0.64)	(-0.67)	(-0.73)	(-0.77)
GP_percent$_{t-1}$	-0.0024		-0.0065**	
	(-0.73)		(-2.71)	
GC_percent$_{t-1}$		-0.0043		-0.0062**
		(-1.52)		(-2.68)
SIZE$_{t-1}$	0.1993***	0.1993***	0.2943***	0.2944***
	(7.65)	(7.66)	(26.15)	(26.05)
BM_ratio$_{t-1}$	0.0077	0.0076	0.0439**	0.0439**
	(0.49)	(0.48)	(2.90)	(2.91)
Ln_trading$_{t-1}$	0.0434***	0.0435***	0.0672***	0.0671***
	(3.28)	(3.29)	(7.29)	(7.29)
ROA$_{t-1}$	0.0017**	0.0017**	-0.0001	-0.0001
	(2.45)	(2.45)	(-0.09)	(-0.09)
Std_roa$_{t-1}$	-0.0009	-0.0009	-0.0005	-0.0005
	(-0.98)	(-0.96)	(-0.45)	(-0.46)
R&D_ratio$_{t-1}$	-0.0000	-0.0000	0.0008*	0.0008**
	(-0.01)	(-0.01)	(2.22)	(2.26)
Beta$_{t-1}$	0.0396**	0.0394**	0.0572**	0.0571**
	(2.42)	(2.41)	(3.14)	(3.14)
Broker$_{t-1}$	0.0027***	0.0027***	0.0025**	0.0025**
	(3.69)	(3.70)	(2.74)	(2.75)
Exchange$_{t-1}$	0.1197***	0.1198***	0.0522	0.0517
	(3.77)	(3.77)	(1.40)	(1.39)
Firm-fixed	Yes	Yes	No	No
Industry-fixed	No	No	Yes	Yes
Country-fixed	No	No	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.859	0.859	0.702	0.702
Number of observations	13,456	13,456	13,556	13,556

Table 3.5 The Effect of TGI on Analysts' Consensus Recommendations

The table below reports firm-level results of a quasi-natural experiment model as in the following equation (4):

$$Mean\_recom_{i,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3 TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \varphi_i \boldsymbol{D}_{dt-1} + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,t}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Appendix A3.1. *Mean_recom*$_{i,t}$ is the average of analysts' recommendations for firm *i* at year *t*, The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, Beta, and Analyst_cov*). $\boldsymbol{D}_{dt-1}$ is a vector of one-year lagged country control variables (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. γ_i is the *i* firm fixed effect, π_k is the *k* industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. $\varepsilon_{i,t}$ is the error term for firm *i* year *t*. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Mean_recom			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent$_{t-1}$	**-0.0136*****		**-0.0152*****	
	(-3.30)		**(-5.66)**	
Treat×Post×GC_percent$_{t-1}$		**-0.0112*****		**-0.0121*****
		(-3.46)		**(-5.49)**
Treat×Post	-0.0213	-0.0082	-0.0233	-0.0161
	(-0.71)	(-0.26)	(-0.71)	(-0.47)
GP_percent$_{t-1}$	-0.0040		-0.0050*	
	(-1.74)		(-2.00)	
GC_percent$_{t-1}$		-0.0045*		-0.0048*
		(-2.19)		(-2.00)
SIZE$_{t-1}$	-0.0160	-0.0160	-0.0480***	-0.0481***
	(-0.88)	(-0.88)	(-4.41)	(-4.43)
Bm_ratio$_{t-1}$	-0.0889***	-0.0890***	-0.0834***	-0.0834***
	(-5.39)	(-5.38)	(-4.96)	(-4.96)
Ln_trading$_{t-1}$	-0.0212	-0.0212	0.0127	0.0126
	(-1.44)	(-1.45)	(1.79)	(1.79)
ROA$_{t-1}$	-0.0002	-0.0002	0.0023**	0.0023**
	(-0.23)	(-0.23)	(2.60)	(2.60)
Std_roa$_{t-1}$	0.0020	0.0019	-0.0016	-0.0016
	(0.95)	(0.95)	(-1.17)	(-1.19)
R&D_ratio$_{t-1}$	-0.0018	-0.0018	-0.0001	-0.0001
	(-1.20)	(-1.20)	(-0.02)	(-0.01)
Beta$_{t-1}$	0.0004	0.0002	-0.0150	-0.0151
	(0.02)	(0.01)	(-0.67)	(-0.67)
Analyst_cov$_{t-1}$	-0.0402	-0.0399	-0.0587**	-0.0586**
	(-1.34)	(-1.34)	(-2.33)	(-2.32)
Broker$_{t-1}$	0.0022	0.0022	0.0023	0.0023
	(1.50)	(1.53)	(1.55)	(1.58)
Exchange$_{t-1}$	0.0549	0.0551	0.0670	0.0674
	(1.13)	(1.13)	(1.23)	(1.24)
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.354	0.326	0.146	0.135
Number of observations	13,234	13,234	13,234	13,234

Table 3.6 The Effect of TGI on Individual Analysts' Recommendations

The table below reports analyst-level results of a quasi-natural experiment model as in the following equation (5):

$$Recom_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Recom_{i,j,t}$ is individual analysts' recommendations for firm i by analyst j at year t. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, Beta*, and *Analyst_cov*). $\boldsymbol{T}_{j,t}$ as a set of analyst control variables (*Portfolio* and *Broker_size*). $\boldsymbol{D}_{dt-1}$ is a vector of one-year lagged country control variables (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. μ_j is j analyst fixed effect, γ_i is the i firm fixed effect, π_k is the k industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. $\varepsilon_{i,j,t}$ is the error term for firm i, analyst j, and year t. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at analyst, firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Recom			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent $_{t-1}$	**-0.0190***** **(-4.23)**		**-0.0185**** **(-3.15)**	
Treat×Post×GC_percent $_{t-1}$		**-0.0169***** **(-4.53)**		**-0.0162***** **(-3.57)**
Treat×Post	-0.0019 (-0.03)	-0.0041 (-0.07)	-0.0107 (-0.13)	-0.0125 (-0.15)
GP_percent $_{t-1}$	-0.0037 (-1.10)		-0.0068** (-2.40)	
GC_percent $_{t-1}$		-0.0056* (-2.07)		-0.0070** (-2.96)
SIZE $_{t-1}$	0.0842*** (3.92)	0.0839*** (3.88)	0.0407** (2.34)	0.0407** (2.33)
Bm_ratio $_{t-1}$	-0.0811*** (-3.93)	-0.0812*** (-3.93)	-0.0578** (-2.82)	-0.0579** (-2.82)
Ln_trading $_{t-1}$	-0.0094 (-1.02)	-0.0092 (-1.00)	0.0043 (0.46)	0.0044 (0.47)
ROA $_{t-1}$	-0.0030** (-2.36)	-0.0029** (-2.34)	0.0003 (0.28)	0.0003 (0.30)
Std_roa $_{t-1}$	0.0002 (0.13)	0.0002 (0.13)	-0.0028 (-1.21)	-0.0028 (-1.22)
R&D_ratio $_{t-1}$	0.0036 (1.50)	0.0035 (1.47)	-0.0009 (-0.43)	-0.0009 (-0.44)
Beta $_{t-1}$	-0.0255 (-1.38)	-0.0259 (-1.40)	-0.0331* (-1.95)	-0.0331* (-1.95)
Analyst_cov $_{t-1}$	-0.0085*** (-4.94)	-0.0085*** (-4.93)	-0.0086*** (-4.03)	-0.0086*** (-3.99)
Analyst controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Analyst fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.360	0.360	0.315	0.315
Number of observations	92,714	92,714	92,768	92,768

Table 3.7 The Effect of TGI on Analysts' Forecast Errors

The table below reports the analyst-level results of a quasi-natural experiment model as in the following equation (6):

$$Error_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Error_{i,j,t}$ is the absolute value of the difference between forecast earnings and actual earnings, scaled by stock price for firm i by analyst j at year t. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, Beta*, and *Analyst_cov)*. $\boldsymbol{T}_{j,t}$ as a set of analyst control variables (*Horizon*, *Portfolio* and *Broker_size*). $\boldsymbol{D}_{dt-1}$ is a vector of one-year lagged country control variables (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. μ_j is j analyst fixed effect, γ_i is the i firm fixed effect, π_k is the k industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. $\varepsilon_{i,j,t}$ is the error term for firm i, analyst j, and year t. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at analyst, firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Error			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent $_{t-1}$	**0.0009***		**0.0011*****	
	(1.90)		**(3.44)**	
Treat×Post×GC_percent $_{t-1}$		**0.0008***		**0.0011*****
		(2.18)		**(3.79)**
Treat×Post	0.0007	0.0007	0.0017	0.0017
	(0.29)	(0.33)	(0.32)	(0.32)
GP_percent $_{t-1}$	0.0001		0.0001	
	(0.33)		(0.50)	
GC_percent $_{t-1}$		-0.0001		0.0001
		-(0.18)		(0.56)
SIZE $_{t-1}$	-0.0148***	-0.0148***	-0.0041***	-0.0041***
	(-9.21)	(-9.23)	(-6.70)	(-6.64)
Bm_ratio $_{t-1}$	0.0121***	0.0121***	0.0235***	0.0235***
	(5.34)	(5.35)	(10.68)	(10.72)
Ln_trading $_{t-1}$	-0.0001	-0.0001	0.0012	0.0012
	(-0.18)	(-0.09)	(1.79)	(1.76)
ROA $_{t-1}$	0.0001	0.0001	0.0001	0.0001
	(0.95)	(0.96)	(0.12)	(0.11)
Std_roa $_{t-1}$	-0.0003	-0.0003	0.0002	0.0002
	(-0.77)	(-0.76)	(0.43)	(0.44)
R&D_ratio $_{t-1}$	0.0002	0.0002	0.0001	0.0001
	(0.87)	(0.81)	(0.19)	(0.19)
Beta $_{t-1}$	0.0031**	0.0031**	0.0021	0.0021
	(2.93)	(2.91)	(1.77)	(1.77)
Analyst_cov $_{t-1}$	0.0004*	0.0004**	0.0002**	0.0002**
	(2.26)	(2.29)	(2.52)	(2.59)
Analyst controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Analyst fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.513	0.513	0.392	0.392
Number of observations	66,062	66,062	66,140	66,140

Table 3.8 The Effect of TGI on Analysts' Forecast Consistency

The table below reports analyst-level results of a quasi-natural experiment model as in the following equation (7):

$$Inconsistency_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Inconsistency_{i,j,t}$ is the standard deviation of analyst's forecast errors in a 5-year rolling period for firm *i* by analyst *j* at year *t*. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE*, *BM_ratio*, *Ln_trading*, *ROA*, *Std_roa*, *R&D_ratio*, *Beta*, and *Analyst_cov*). $\boldsymbol{T}_{j,t}$ as a set of analyst control variables (*Portfolio* and *Broker_size*). $\boldsymbol{D}_{dt-1}$ is a vector of one-year lagged country control variables (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. μ_j is *j* analyst fixed effect, γ_i is the *i* firm fixed effect, π_k is the *k* industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. $\varepsilon_{i,j,t}$ is the error term for firm *i*, analyst *j*, and year *t*. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at analyst, firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Inconsistency			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent$_{t-1}$	**0.0007***		**0.0009****	
	(1.95)		**(2.95)**	
Treat×Post×GC_percent$_{t-1}$		**0.0005**		**0.0006****
		(1.66)		**(2.43)**
Treat×Post	0.0017	0.0019	0.0016	0.0017
	(0.79)	(0.85)	(0.68)	(0.74)
GP_percent$_{t-1}$	-0.0002		0.0004**	
	(-0.99)		(2.99)	
GC_percent$_{t-1}$		-0.0002		0.0003***
		(-1.39)		(3.32)
SIZE$_{t-1}$	-0.0053***	-0.0053***	-0.0035***	-0.0035***
	(-4.19)	(-4.19)	(-3.90)	(-3.91)
Bm_ratio$_{t-1}$	0.0066***	0.0066***	0.0131***	0.0131***
	(3.45)	(3.44)	(12.82)	(12.69)
Ln_trading$_{t-1}$	0.0017*	0.0017*	0.0016*	0.0016*
	(2.10)	(2.12)	(2.14)	(2.14)
ROA$_{t-1}$	-0.0001*	-0.0001*	-0.0003***	-0.0003***
	(-2.21)	(-2.20)	(-4.88)	(-4.89)
Std_roa$_{t-1}$	0.0005***	0.0005***	0.0008***	0.0008***
	(3.49)	(3.50)	(4.06)	(4.07)
R&D_ratio$_{t-1}$	0.0001	0.0001	-0.0001	-0.0001
	(0.35)	(0.32)	(-0.43)	(-0.47)
Beta$_{t-1}$	0.0025**	0.0025**	0.0022**	0.0021**
	(3.18)	(3.16)	(2.84)	(2.71)
Analyst_cov$_{t-1}$	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.65)	(-0.64)	(-0.97)	(-0.91)
Analyst controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Analyst fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.620	0.620	0.477	0.477
Number of observations	52,154	52,154	52,278	52,278

Table 3.9 The Effect of TGI on the Number of Analysts' Coverage Including Non-coverage Firms

The table below reports firm-level results of a quasi-natural experiment model as in the following equation (3):

$$Ln\_coverage_{i,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3 TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \varphi_i \boldsymbol{D}_{dt-1} + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,t}$$

All variables noted in the above equation, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Ln\_coverage_{i,t}$ is the natural logarithm of one plus the number of analysts that reported earnings-per-share (EPS) forecasts for firm i in fiscal year t. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, and Beta*). $\boldsymbol{D}_{dt-1}$ is a one-year lagged country control variable vector (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. γ_i is i firm fixed effect, π_k is the k industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. ε_{it} is the error term for firm i year t. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Ln_coverage			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent$_{t-1}$	-0.0102**		-0.0163***	
	(-2.48)		(-4.29)	
Treat×Post×GC_percent$_{t-1}$		-0.0089**		-0.0123***
		(-2.38)		(-3.60)
Treat×Post	0.0166	0.0156	0.0205	0.0172
	(0.52)	(0.49)	(0.46)	(0.39)
GP_percent$_{t-1}$	-0.0009		-0.0011	
	(-0.42)		(-0.29)	
GC_percent$_{t-1}$		-0.0015		-0.0007
		(-0.89)		(-0.22)
SIZE$_{t-1}$	0.1925***	0.1925***	0.3308***	0.3310***
	(6.42)	(6.42)	(22.52)	(22.45)
BM_ratio$_{t-1}$	0.0026	0.0025	0.0245*	0.0245*
	(0.17)	(0.17)	(1.86)	(1.86)
Ln_trading$_{t-1}$	0.0395**	0.0395**	0.0660***	0.0660***
	(2.78)	(2.78)	(6.94)	(6.94)
ROA$_{t-1}$	0.0024**	0.0024***	0.0015	0.0015
	(3.43)	(3.44)	(1.76)	(1.76)
Std_roa$_{t-1}$	-0.0014	-0.0014	-0.0006	-0.0006
	(-1.48)	(-1.47)	(-0.47)	(-0.49)
R&D_ratio$_{t-1}$	0.0003	0.0003	0.0010	0.0011
	(0.41)	(0.41)	(1.54)	(1.58)
Beta$_{t-1}$	0.0388**	0.0386**	0.0782***	0.0781***
	(2.63)	(2.62)	(3.94)	(3.92)
Broker$_{t-1}$	0.0035***	0.0035***	0.0031***	0.0031***
	(5.24)	(5.21)	(4.10)	(4.12)
Exchange$_{t-1}$	0.1521***	0.1519***	0.0973	0.0967
	(3.45)	(3.44)	(1.79)	(1.77)
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.857	0.857	0.647	0.647
Number of observations	19,099	19,099	19,099	19,099

Table 3.10 The Effect of TGI on Analysts' Recommendation Revisions

The table below reports analyst-level results of a quasi-natural experiment model as in the following equation (8):

$$Revision_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3 TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Revision_{i,j,t}$ is the recommendation revision for firm *i* by analyst *j* at year *t*. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key triple interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, Beta*, and *Analyst_cov*). $\boldsymbol{T}_{j,t}$ as a set of analyst control variables (*Portfolio* and *Broker_size*). $\boldsymbol{D}_{dt-1}$ is a vector of one-year lagged country control variables (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. μ_j is *j* analyst fixed effect, γ_i is the *i* firm fixed effect, π_k is the *k* industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. $\varepsilon_{i,j,t}$ is the error term for firm *i*, analyst *j*, and year *t*. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at analyst, firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Revision	*Revision*			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent$_{t-1}$	-0.0107**		-0.0105*	
	(-2.40)		(-2.06)	
Treat×Post×GC_percent$_{t-1}$		-0.0090**		-0.0090*
		(-2.41)		(-2.19)
Treat×Post	0.0524	0.0508	0.0684	0.0670
	(1.33)	(1.30)	(1.21)	(1.18)
GP_percent$_{t-1}$	-0.0022		-0.0014	
	(-0.78)		(-0.42)	
GC_percent$_{t-1}$		-0.0028		-0.0019
		(-1.07)		(-0.67)
SIZE$_{t-1}$	-0.0377**	-0.0382**	-0.0040	-0.0043
	(-2.50)	(-2.53)	(-0.38)	(-0.41)
Bm_ratio$_{t-1}$	-0.0118	-0.0123	-0.0057	-0.0060
	(-0.62)	(-0.64)	(-0.38)	(-0.41)
Ln_trading$_{t-1}$	0.0046	0.0046	0.0093*	0.0094*
	(0.45)	(0.46)	(2.02)	(2.05)
ROA$_{t-1}$	-0.0071***	-0.0071***	-0.0053**	-0.0053**
	(-4.27)	(-4.26)	(-3.02)	(-3.02)
Std_roa$_{t-1}$	0.0017	0.0017	0.0005	0.0005
	(1.01)	(1.03)	(0.34)	(0.34)
R&D_ratio$_{t-1}$	0.0007	0.0007	-0.0005	-0.0005
	(0.26)	(0.26)	(-0.71)	(-0.76)
Beta$_{t-1}$	0.0433	0.0431	0.0431*	0.0430*
	(1.49)	(1.48)	(1.96)	(1.95)
Analyst_cov$_{t-1}$	-0.0004	-0.0004	0.0017	0.0018
	(-0.21)	(-0.20)	(1.02)	(1.08)
Analyst controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Analyst fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.052	0.052	0.043	0.043
Number of observations	62,490	62,490	62,585	62,585

Table 3.11 The Effect of TGI on Analysts' Forecast Errors

The table below reports analyst-level results of a quasi-natural experiment model as in the following equation (6):

$$Error_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_3\, TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Error_{i,j,t}$ is the absolute value of the difference between forecast earnings and actual earnings, scaled by actual earnings for firm *i* by analyst *j* at year *t*. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, Beta*, and *Analyst_cov).* $\boldsymbol{T}_{j,t}$ as a set of analyst control variables (*Horizon*, *Portfolio* and *Broker_size*). $\boldsymbol{D}_{dt-1}$ is a vector of one-year lagged country control variables (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. μ_j is *j* analyst fixed effect, γ_i is the *i* firm fixed effect, π_k is the *k* industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. $\varepsilon_{i,j,t}$ is the error term for firm *i*, analyst *j*, and year *t*. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at analyst, firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Error			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent$_{t-1}$	0.1142**		0.0997**	
	(2.55)		(2.46)	
Treat×Post×GC_percent$_{t-1}$		0.0866*		0.0922*
		(2.12)		(1.96)
Treat×Post	0.0182	0.0365	-0.0389	-0.0336
	(0.04)	(0.08)	(-0.10)	(-0.08)
GP_percent$_{t-1}$	0.0091		0.0336**	
	(0.30)		(2.98)	
GC_percent$_{t-1}$		0.0113		0.0290*
		(0.33)		(2.02)
SIZE$_{t-1}$	0.7656***	0.7693***	0.0938	0.0972
	(4.16)	(4.18)	(0.53)	(0.55)
Bm_ratio$_{t-1}$	0.5375	0.5413	0.0695	0.0718
	(1.33)	(1.34)	(0.23)	(0.24)
Ln_trading$_{t-1}$	0.1224	0.1219	-0.1194	-0.1214
	(1.42)	(1.43)	(-1.45)	(-1.49)
ROA$_{t-1}$	-0.0157	-0.0159	-0.0232*	-0.0230*
	(-1.04)	(-1.04)	(-2.01)	(-2.01)
Std_roa$_{t-1}$	0.0045	0.0048	-0.0030	-0.0032
	(0.21)	(0.22)	(-0.14)	(-0.14)
R&D_ratio$_{t-1}$	-0.0095	-0.0097	-0.0347	-0.0340
	(-0.24)	(-0.25)	(-1.27)	(-1.20)
Beta$_{t-1}$	-0.0473	-0.0477	0.1116	0.1123
	(-0.36)	(-0.36)	(0.77)	(0.74)
Analyst_cov$_{t-1}$	0.0304	0.0310	0.0103	0.0098
	(1.36)	(1.39)	(0.53)	(0.51)
Analyst controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Analyst fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.238	0.239	0.143	0.143
Number of observations	66,282	66,282	66,353	66,353

Table 3.12 The Effect of TGI on Analysts' Forecast Consistency

The table below reports the results of a quasi-natural experiment model by following the equation (7):

$$Inconsistency_{i,j,t} = \alpha + \beta_1(Treat_i \times Post_t \times TGI_{i,t-1}) + \beta_2(Treat_i \times Post_t) + \beta_5 TGI_{i,t-1} + \delta_i \boldsymbol{X}_{i,t-1} + \boldsymbol{T}_{j,t} + \varphi_i \boldsymbol{D}_{dt-1} + \mu_j + \gamma_i + \pi_k + \lambda_d + \tau_t + \varepsilon_{i,j,t}$$

All variables noted in the above equations, except the interaction and fixed effect terms, are defined in Appendix A3.1. $Inconsistency_{i,j,t}$ is the standard deviation of the alternative forecast errors in a 5-year rolling period for firm *i* by analyst *j* at year *t*. The interaction term [$Treat_i \times Post_t \times TGI_{it-1}$] is my key interaction DiDiD variable of interest, and [$Treat_i \times Post_t$] is the DiD variable. TGI_{t-1} represents the two measures of technological green innovations, i.e. *GC_percent* and *GP_percent*, defined in Appendix A3.1. $\boldsymbol{X}_{it-1}$ is a vector of one-year lagged firm-level covariates (*SIZE, BM_ratio, Ln_trading, ROA, Std_roa, R&D_ratio, Beta*, and *Analyst_cov)*. $\boldsymbol{T}_{j,t}$ as a set of analyst control variables (*Portfolio* and *Broker_size*). $\boldsymbol{D}_{dt-1}$ is a vector of one-year lagged country control variables (*Broker* and *Exchange*). All variables are defined in Appendix A3.1. μ_j is *j* analyst fixed effect, γ_i is the *i* firm fixed effect, π_k is the *k* industry fixed effect, λ_d and τ_t are the firm country and year fixed effects, respectively. $\varepsilon_{i,j,t}$ is the error term for firm *i*, analyst *j*, and year *t*. I winsorise all covariates and country control variables at 1% and 99% levels. The standard errors are corrected for clustering at analyst, firm(industry), country levels and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	Inconsistency			
	(1)	(2)	(3)	(4)
Treat×Post×GP_percent$_{t-1}$	0.1331**		0.1609***	
	(2.69)		(5.99)	
Treat×Post×GC_percent$_{t-1}$		0.1075**		0.1462***
		(2.58)		(5.70)
Treat×Post	0.2786	0.2878	0.2813	0.2859
	(0.58)	(0.60)	(0.54)	(0.55)
GP_percent$_{t-1}$	0.0312		0.0279***	
	(1.48)		(3.32)	
GC_percent$_{t-1}$		0.0442**		0.0243**
		(2.31)		(2.58)
SIZE$_{t-1}$	-0.5145**	-0.5148**	-0.1224	-0.1203
	(-2.31)	(-2.31)	(-0.53)	(-0.52)
Bm_ratio$_{t-1}$	0.5590**	0.5582**	0.6868**	0.6912**
	(2.97)	(2.94)	(2.34)	(2.34)
Ln_trading$_{t-1}$	0.3107**	0.3106**	-0.1317	-0.1331
	(2.58)	(2.58)	(-1.07)	(-1.09)
ROA$_{t-1}$	-0.0248**	-0.0251**	-0.0523*	-0.0520*
	(-2.47)	(-2.49)	(-2.17)	(-2.17)
Std_roa$_{t-1}$	0.0322	0.0325	0.0314	0.0311
	(1.37)	(1.38)	(0.97)	(0.96)
R&D_ratio$_{t-1}$	0.0276	0.0275	-0.0333	-0.0323
	(0.67)	(0.67)	(-1.07)	(-1.05)
Beta$_{t-1}$	0.1769	0.1762	0.5342***	0.5365***
	(1.33)	(1.33)	(3.43)	(3.43)
Analyst_cov$_{t-1}$	0.0379*	0.0381*	0.0151	0.0146
	(2.02)	(2.02)	(0.63)	(0.59)
Analyst controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	No	No
Industry fixed	No	No	Yes	Yes
Country fixed	No	No	Yes	Yes
Analyst fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
adjust-R^2	0.627	0.627	0.381	0.381
Number of observations	52,678	52,678	52,797	52,797

Appendix

Table A3.1 variables and description

Name	Description	Source
Dependent variables		
Ln_coverage	The natural logarithm of one plus the number of analysts that reported earnings-per-share (EPS) forecasts for the firm	I/B/E/S
Mean_recom	Average of analysts' recommendations for the coverage firm. The recommendation consensus with ratings ranging from 1 (strong sell) to 5 (strong buy).	I/B/E/S
Recom	Individual analysts' recommendations following the firm. The recommendation ratings are between 1 (strong sell) and 5 (strong buy).	I/B/E/S
Revision	Change of individual analysts' recommendations following the firm. The range of individual analysts' recommendation changes are between +4 and -4.	I/B/E/S and Authors' Construction
Error	The absolute value of the difference between forecasted EPS and actual EPS of the firm, scaled by firm price	I/B/E/S and Authors' Construction
Inconsistency	The standard deviation over the 5 years of individual analysts' forecast errors for the firm by the analyst	I/B/E/S and Authors' Construction
Independent variables		
GP_percent	The ratio of green patent applications, divided by total patent applications	PATSTAT and Authors' construction.
GC_percent	The ratio of green adjusted citation counts, divided by total adjusted citation counts	PATSTAT and Authors' construction.
Treat	The dummy variable equals one if the firm is in the country that committed to the 1st Kyoto Protocol. Zero otherwise	
Post	The dummy variable equals one for the year 2008 – 2012, and zero is for the year 2003 – 2007	
Firm covariates		
Size	Natural logarithm of firm's market value of equity	COMPUSTAT
BM	Book value per share scaled by the year-end market value per share	COMPUSTAT
Ln_trading	Natural logarithm of trading volume for the firm	COMPUSTAT
ROA	Ratio of net profits after tax to total assets of the firm	COMPUSTAT
Std_roa	The standard deviation over the 3 years of ROA	COMPUSTAT
R&D	The ratio of research and development expenditures to the total sales of the firm	COMPUSTAT
Beta	Systematic risk of the firm compared to the exchange market	COMPUSTAT
Analyst-level controls		
Horizon	The period (day) between the analyst EPS forecast announcement date and corresponding actual EPS announcement date	I/B/E/S
Portfolio	Number of firms followed in the analyst portfolio	I/B/E/S
Broker_size	Number of analysts employed by the analyst's brokerage house	I/B/E/S

Table A3.1 variables and description (cont')

Name	Description	Source
Country-level controls		
Broker	The number of brokerage houses in the country of the covered firm	I/B/E/S
Exchange	The natural logarithm of exchange market capitalisation	The International Stock Exchange (TISE)

Table A3.2 Country Lists of the 1st Kyoto Protocol Commitment

MSCI ACWI			
Committed countries		Non-committed countries	
Developed markets	Emerging market	Developed markets	Emerging market
Australia	Czech Republic	Hong Kong	Argentina
Austria	Greece	Israel	Brazil
Belgium	Hungary	Singapore	Chile
Canada	Poland	United States	China
Denmark	Russia		Colombia
Finland			Egypt
France			India
Germany			Indonesia
Ireland			Kuwait
Italy			Malaysia
Japan			Mexico
Netherlands			Pakistan
New Zealand			Peru
Norway			Philippines
Portugal			Qatar
Spain			Saudi Arabia
Sweden			South Africa
Switzerland			South Korea
United Kingdom			Taiwan
			Thailand
			Turkey
			United Arab Emirates

4. MARKET REACTIONS AND ANALYSTS' RECOMMENDATION REVISIONS ON TECHNOLOGICAL GREEN INNOVATION

4.1 Introduction

"The Glasgow Climate Pact, agreed at COP26 in 2021, called upon Parties to accelerate the development, deployment and dissemination of technologies to transition towards low-emission energy systems. The pact also emphasised the importance of cooperative action on technology development and transfer, including accelerating and enabling innovation, and the importance of predictable, sustainable and adequate funding for the Technology Mechanism."[50]

The Conference of the Parties of the United Nations Framework Convention on Climate Change, 24 October 2022 (COP27)

A growing body of literature discusses the economic advantages of firms' sustainability development, especially investors' demand under climate regulation concerns (Krueger et al., 2020, Marshall et al., 2022 and Krueger et al., 2023)[51]. In light of the increasing attention of various stakeholders paid to environmentally sustainable development, this study aims to examine how market participants respond to technological green innovation and non-technological green innovation (hereafter TGI and non-TGI, respectively). My study provides important evidence on stock market participants' perspectives on the short-run value of TGI information. First, I compare investors' reactions to the news of TGI and

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[50] Joint Work Programme of the UNFCCC Technology Mechanism for 2023–2027. (https://unfccc.int/ttclear/support/technology-mechanism.html)

[51] Literature also address the implications of environmental performance to operating performance (Russo and Fouts, 1997 and Guenster et al., 2011), firm value (Matsumura et al. 2014) , and cost of capital (Ng and Rezaee, 2015),

non-TGI on stock prices. Second, I examine the values of analysts' recommendations in response to TGI information.

Rising climate risk awareness and promoting public environmental campaigns should bring more advantages to firms engaged in TGI activities. For example, recent reports show that relative to 2021, the registration of new electric cars rose by 21.6%[52], and solar power energy generation grew by 17.43%[53] in 2022. Similarly, many studies document that firms engaged in TGI gain higher long-term benefits via various channels[54]. Moreover, the benefits of TGI activities on environmental performance also increase investors' attention with regard to value and values-based sustainable decision-making (Starks, 2023)[55]. Dechezleprêtre et al. (2020) note that the value of firms engaged in TGI experiences greater growth compared to the value of firms developing dirty innovation.

However, studies suggest that investors' responses to innovative firms tend to be ambiguous in the short term. For example, Chan et al. (2001) argue that the short-term stock prices of innovative firms are undervalued and have high volatility. Daniel and Titman (2006) suggest that investors' predictions rely on tangible value but fail to incorporate the future value of intangible assets. Eberhart et al. (2004) note that investors mis-react to intangible information, which reflects their perception of long-term future cash

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[52] The European Environmental Agency: https://www.eea.europa.eu/en/analysis/indicators/new-registrations-of-electric-vehicles

[53] The International Energy Agency: https://www.iea.org/energy-system/renewables/solar-pv

[54] For instance, literature finds that firms engaged in TGI increase competitiveness opportunities (Shrivastava, 1995), brand image (Ambec and Lanoie, 2008), and operating performance (Ghisetti and Rennings, 2014 and Rexhäuser and Rammer, 2014).

[55] Starks (2023) suggests that value (or values) is the view of investors on the implications of sustainable investment. However, value or pecuniary preferences are investment decisions that consider how firms with sustainable issues are connected to financial risks and affect firms' value (e.g., regulations and human capital). Values or nonpecuniary preferences consider investments engaged in environmental-friendly development and avoid corporations that affect the environment, society, and their beliefs.

flows related to intangible assets. Furthermore, the literature argues that firms' increasing innovation intensity can also impact higher information asymmetry (Bhattacharya and Ritter, 1983 and Aboody and Lev, 2000) and future earnings volatility (Kothari et al., 2002). These arguments lead to the question: do investors respond positively to TGI information in the short run?

Although there are several studies on the long-term implications of TGI information, its effect on short-term stock prices remains undetermined. Hence, I aim to address this gap in the literature by systematically investigating short-term market reactions to TGI information.

Short-term implications of TGI information (e.g., higher information asymmetry and uncertainty) lead investors to rely more on expert opinion, such as analysts' recommendations. Analysts play a crucial role as information intermediaries to enhance financial markets' information efficiency. Amiram et al. (2016) indicate that analysts' forecasts reduce information asymmetry in the earnings announcement period. Studies also suggest that the informativeness of analysts' forecasts and recommendations is more valuable following levels of market uncertainty (Loh and Stulz, 2018). In the meantime, the literature notes that the value of analysts' recommendations relates to the firm's information disclosure (Frankel et al., 2006 and Altınkılıç and Hansen, 2009). In summary, the implications of TGI information on the market's reaction appear to be implicitly related to the value of analysts' recommendations. However, the informativeness of analysts' recommendations in the context of uncertainty created by TGI information remains to be investigated. Hence, this study investigates the informativeness (value) of analysts' recommendations (and/or their revisions) in response to TGI information.

This study uses the data of the Tokyo Stock Price Index (TOPIX): the biggest centre of listed companies involved in technological innovation. TOPIX covered 1,456 innovative firms between 2003 and 2012, of which approximately 49% were engaged in TGI development. To assess the short-term market reaction to technological innovation, I have analysed the cumulative abnormal returns (CAR, hereafter) shortly before and after the firms filed their patent applications. Empirical evidence indicates that the market reacts pessimistically to both TGI and non-TGI information. The average stock prices of firms (measured by CAR over -5 to +5 days around the news) involved in both TGI and non-TGI declined by -0.16% and -0.21%, respectively. This finding supports the argument that investors underreact to intangible information (Eberhart et al., 2004 and Daniel and Titman, 2006). Moreover, this evidence emphasises that the market not only underreacts but reacts adversely to highly ambiguous information about the value of innovation.

Further, I investigate the effect of the 1st Kyoto Protocol commitment on the market reaction to TGI and non-TGI information. Several interesting results emerge. First, I discover that during the 1st Kyoto Protocol commitment period (2008–2012), investors reacted more favourably to TGI information compared to non-TGI information. I also find that the 1st Kyoto Protocol commitment does not impact the market reaction to TGI information, but it adversely affects the market reaction to non-TGI information. Second, I find no difference in the market reaction to TGI information between high- and low-polluting industries during the period of the 1st Kyoto Protocol commitment.

Furthermore, I extend my empirical study to examine the value of analysts' recommendations relevant to TGI news. The result suggests that the market responds more strongly to the recommendations of TGI-relevant revisions than to TGI-irrelevant ones. I also find that only TGI-relevant upgrading revisions have significant effects, but downgrading revisions have no effect. During the 1st Kyoto Protocol commitment, the market responded less to the TGI-relevant revisions (both upgrading and downgrading recommendations) compared to TGI-irrelevant revisions.

My empirical results contribute to various strands of literature. First, I add new insights into market reactions to innovation. Previous literature exposes the impact of innovative information on stock value in different informative dimensions, i.e., exploring the market reaction in the technological industry after the R&D project announcement (Chan et al., 1990 and Szewczyk et al., 1996), the long-term value effects of innovation based on accounting financial information (Eberhart et al., 2004 and Daniel and Titman, 2006), the innovative value and future performance of the past innovative success (Cohen et al., 2013 and Hirshleifer et al., 2013), and the value impacts of technological classifications (Rexhäuser and Rammer, 2014, Aghion et al., 2016 and Dechezleprêtre et al., 2020). I add a new dimension to the literature by demonstrating the adverse reaction to innovative information on the patent application filing dates. I also suggest that the type of technological innovation is relevant to stock price movements.

Second, I contribute to the literature on environmental regulatory effects on stock markets. Krueger et al. (2020) suggest that the rising concerns about environmental regulations push investors to invest more in firms engaged in sustainability. Marshall et al. (2022) support that foreign institutional ownership increases in firms committed to sustainability disclosure. Recent studies document that levels of regulatory enforcement are related to carbon risk premiums (Bolton and Kacperczyk, 2021a, 2022a). In addition, Krueger et al. (2023) point out that regulatory enforcement reduces information asymmetry and adverse selection, particularly mandatory sustainability disclosure driving the liquidity of sustainable stocks. I provide concrete evidence that the climate regulatory effect dilutes the information asymmetry on the future value of TGI and encourages investors' awareness of TGI information.

Finally, I contribute to the literature on the determinants of analysts' informative values. Frankel et al. (2006), Altınkılıç and Hansen (2009) and Loh and Stulz (2011) document that firm characteristics (e.g., firm information environment, price volatility and firm-specific news) are related to the analysts' recommendations returns. The literature also indicates differential impacts based on analyst report characteristics. Green et al. (2014) support analyst characteristics, e.g., accessing superior information rewards higher analysts' informative values. Furthermore, Altınkılıç and Hansen (2009) and Green et al. (2014) suggest that the timeliness of revision issued matters to stock price movement, whereas the issued period of analysts' reports also heterogeneously affects stock returns (Loh and Stulz, 2018). I contribute to the literature by offering evidence that investors' misreaction to TGI information increases the value of analysts' informativeness.

My findings have several implications for market participants. First, my study shows the importance of identifying and incorporating the appropriate future value of innovation information in stock prices. Second, I indicate that the analysts covering TGI firms can gain more if they put additional efforts into analysing the information pertaining to specific innovations. Finally, this study shows the importance of innovative information mechanisms, particularly disclosing available innovative information held by firm managers. Transparent information on innovations can reduce firms' future uncertainty, information asymmetry and investors' misreactions to the news.

The remainder of this study is organised as follows. Section 4.2 discusses the empirical literature and hypothesis development. This is followed by data and identification strategies used in Section 4.3. Section 4.4 presents and interprets the observed results. Section 4.5 summarises my findings.

4.2 Related Literature and Hypotheses Development

4.2.1 Market reactions to TGI and non-TGI information

In this study, I begin my investigation of the market's short-term reactions to TGI and non-TGI information. A growing body of finance literature documents that ESG-related issues potentially become a primary strategic decision for investors (Jagannathan et al., 2017 and Marshall et al. 2022). Krueger et al. (2020) suggest that enforcing climate regulation potentially increases investors' concerns regarding the regulation's risk impact, which causes them to engage in firms promoting environmental practice. Ziegler et al. (2007) and Pástor et al. (2020) indicate that investors hold more sustainable assets to mitigate unexpected risks such as demand shift behaviour and changes in investors' preferences. The evidence supports a systematic perception of climate risks affecting investors' portfolio profitability.

However, many studies report that the increase in short-term excess returns is related to the carbon risk premium (Bolton and Kacperczyk, 2021a, 2022a and Hsu et al., 2023). With a view to resolving such conflicts, this study investigates the market perceptions concerning TGI activities of the firms by comparing the market participants' reactions to TGI and non-TGI information.

A large number of studies observe the impact of innovation on firms' market value (Griliches, 1981, Lev and Sougiannis, 1996 and Daniel and Titman, 2006). Eberhart et al. (2004) show that higher R&D expenditures drive firms' future operating profitability and long-term stock value. Gu (2005) and Hall et al. (2005) indicate that markets respond positively to patent citations referring to firms' intangible knowledge. Lin (2012) finds that firms with high R&D investment, supporting the marginal benefit of physical capital and decreasing the marginal cost of physical investment, potentially create higher excess returns. Hirshleifer et al. (2013) support that firms creating innovative efficiencies not only enhance operating performance but also generate future stock value.

On the other hand, Eberhart et al. (2004) and Gu (2005) suggest that investors fail to incorporate information about innovation and mis-react to such information when the market is inefficient and firms' information asymmetry arises within R&D projects. Thus, the literature reports mixed results regarding investors' short-term perceptions of innovation. Chan et al. (1990) show that firms' stock returns are negative before but positive after R&D project announcements. They also find only positive stock returns on R&D intensity in industries heavily invested in R&D. Szewczyk et al. (1996) find evidence of positive abnormal returns in industries with high R&D investment after R&D project announcements. Cohen et al. (2013) argue that investors overestimate innovation value from R&D expenditures but fail to identify past R&D abilities.

In contrast, Hall (1993) shows that market value declines in firms with increased R&D expenditures. International evidence also suggests the different impacts of R&D expenditure on short-term excess returns are associated with efficient market conditions

(Bae and Kim, 2003 and Cohen et al, 2013)[56]. These findings support the inefficient market argument that markets with less efficiency can cause investors to slowly incorporate and underreact to information about innovative activities (Eberhart et al., 2004 and Gu, 2005).

Moreover, Pastor and Veronesi (2009) constructed an explanation behind the mispricing of innovative firms, indicating that uncertainty of new technology productivity is accounted for as idiosyncratic risk. Stock prices are pressured by uncertainty via cash flow volatility and higher discount rates on the stock valuation. Kothari et al. (2002) support that higher innovation intensity increases firms' future earnings variability. Cui and Mak (2002) find that R&D intensity decreases firms' operating performance but enhances firms' future value.

While the literature doesn't reach a consensus on the precise value impact of innovative investment, several studies bring TGI into light by showing the economic benefits of TGI activities (Cheng et al., 2014, Ghisetti and Rennings, 2014 and Rexhäuser and Rammer, 2014)[57]. Adopting TGI creates more opportunities to access the new market and firms' competitiveness in the industry (Shrivastava, 1995, Ambec and Lanoie, 2008 and Lanoie et al., 2011). Ambec and Lanoie (2008) also note that firms engaged in TGI activities create higher profitability by enhancing production efficiency, i.e., reducing costs of input raw materials and emission management costs from the production processes. This argument is related to the findings of Cainelli and Mazzanti (2013) and Aghion et al.

[56] Cohen et al. (2013) find positive impact of R&D investment on short-term excess returns in the US, but no such evidence in the UK, Japan, and Germany. The evidence is related to Bae and Kim (2003), which show that R&D investments impact long-term stock returns more in Japan and Germany compared to the US.

[57] Ghisetti and Rennings (2014) and Rexhäuser and Rammer (2014) show that firms using TGI generate better long-run operating performance. Kemp and Pearson (2007) and Costantini and Mazzanti (2012) find that countries encouraging more TGI activities can benefit from higher innovative exports.

(2016), signifying that the implementation of stringent climate regulation, such as the imposition of carbon taxes on fuel prices, serves as a driving force for firms to allocate more resources to TGI activities. This strategic decision is made in order to effectively mitigate the costs associated with energy consumption and emissions management. However, there is little evidence to support that TGI directly affects firms' market value. Dechezleprêtre et al. (2020), for instance, find that TGI generates higher firm value compared to the firms investing in dirty innovation.

Although firms engaged in TGI activities seem to generate larger benefits and value premiums compared to non-TGI, i.e., the increase of firms' value through environmental performance improvements and the subsequent improvement of public image that follows, the uncertainty of TGI implications can cause investors to slowly incorporate TGI information into stock prices. Ghisetti and Rennings (2014) and Rexhäuser and Rammer (2014) found heterogeneous effects of TGI typologies on firm profitability. They argue that the end of pipe innovation focusing on external pollution reduction cannot encourage the firm's competitiveness but increases the operational costs instead. Cohen et al. (2020) discover that firms' environmental performance is not associated with the levels of TGI intensity.

In addition, TGI adoption also requests higher operational conditions in generating TGI maximum benefits. The literature also indicates that the TGI benefits will be maximised under environmental regulation enforcement (see Shrivastava, 1995, Ambec and Lanoie, 2008 and Lanoie et al., 2011). Rexhäuser and Rammer (2014) show that TGI related to environmental regulation standards enhance firms' profitability more than other TGI.

Hirshleifer and Teoh (2003), Hirshleifer et al. (2009) and Hirshleifer et al. (2011) suggest that firm value does not fully incorporate the arrival of relevant public information, especially when such information is less salient or limits investor attention. Accordingly, the uncertainty surrounding the implications of TGI in terms of financial and environmental development, coupled with the comparatively stricter restrictions on TGI adoption compared to non-TGI adoption, can dilute the value of TGI benefits, causing markets to underreact toward TGI information compared to non-TGI information. This leads to my hypothesis that:

H1: Investors react more favourably to non-TGI information than to TGI information.

4.2.2 The 1st Kyoto Protocol Commitment and the Market Reaction to TGI and Non-TGI Information

In the following section, I examine the effect of the 1st Kyoto Protocol commitment on the market reaction to TGI and non-TGI information. The Kyoto Protocol was initiated in December 1997 under the United Nations Framework Convention on Climate Change (UNFCCC). The 1st Kyoto Protocol commitment implementation covered the period 2008–2012, assigning 37 committed countries to reduce and disclose levels of GHG emissions annually during the period[58]. The protocol also initiates mechanisms to enhance environmental development across countries, particularly establishing an international

[58] The initial target of the 1st Kyoto Protocol commitment was to decrease GHG emissions by 5.2% on average compared to the GHG emission level in the base year 1990.

emissions trading mechanism that creates economic incentives for reducing GHG emissions.[59]

In Japan, specifically, the national government conducted The Act of Promotion of Global Warming Counter study in 2007, which focused on the targets and programs prescribed in the Kyoto Protocol Target Achievement Plan. From the collated results of this study, the government published the revised guidelines in March 2008. These guidelines promoted voluntary action plans by businesses and industrial sectors and set targets for them. Each business voluntarily selected any of the four indicators, i.e., energy consumption intensity, energy consumption, carbon dioxide emissions intensity or carbon dioxide emissions. Moreover, this voluntary action allows the government to access firms' information related to greenhouse gas emissions[60].

Several studies indicate that the 1st Kyoto Protocol affects firms' managing strategies, e.g., the cost of capital and dividend plans, due to the higher costs of pollution emissions (Nguyen, 2018 and Nguyen et al., 2020). Higher costs of environmental management can also impede the stock value of firms that ignore sustainability transformation (Dimson et al., 2015). Hence, it is possible that the 1st Kyoto Protocol commitment could address investors' concerns regarding regulation impact and shift the market reactions to TGI and non-TGI information.

In terms of the 1st Kyoto Protocol's impact on innovative firms' cashflow uncertainty, it appears that the environmental regulation has little effect on firms engaged in TGI. In contrast, the regulation could damage the value of the firms that only invest in

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[59] UNFCCC. (2007). *Investment and Financial Flows to Address climate Changes.*
[60] Kyoto Protocol Target Achievement Plan (2008): www.env.go.jp/en/earth/cc/kptap.pdf

non-TGI and/or ignore a transition to TGI. As discussed in subsection 4.2.1, firms engaged in TGI activities potentially drive future sustainable growth through the efficient production mechanism (Ambec and Lanoie, 2008). This new productivity function focuses on the reduction of raw materials in production, which is associated with pollution abatement costs, including external costs from regulation compliance. On the other hand, although non-TGI adoption supports firms' future growth opportunities, productivity functions have no restrictions regarding disproportionately producing additional waste and pollution.

One apparent distinction between TGI and non-TGI is the benefit of firms' environmental development. Haščič and Migotto (2015) indicate that TGI identification requires a connection to environmental policy goals such as domains of environmental management (air and water pollution, waste disposal), adaptation to water scarcity, addressing biodiversity threats (e.g., water and wastewater treatment) and mitigating climate change. The bond between TGI and environmental development supports the reduction of pollution abatement costs. One empirical piece of evidence supported by Aghion et al. (2016) shows that rising fuel prices on carbon taxes pressure firms in the automobile industry to redirect innovation change from dirty, polluting technologies to cleaner technologies. This evidence suggests that environmental regulations could promote TGI benefits about mitigating climate regulation risks in the financial markets and pressure firms not to overlook technological transition.

On the other hand, the 1st Kyoto Protocol commitment can lead investors to consider more information regarding firms' climate-friendly activities, such as TGI. Recent literature reveals concrete evidence that investors require larger sustainable assets to eliminate uncertainty regarding climate risk concerns (Jagannathan et al., 2017 and Pástor et al., 2020). Dimson et al. (2015) and Starks (2023) find that firms promoting environmental engagement attract higher investment from institutional investors. Marshall et al. (2022) indicate that firms following sustainability disclosure mandates increase foreign institutional ownership. Krueger et al. (2020) explain the relevant results by indicating that investors increasingly demand green assets to mitigate uncertainty regarding climate risks, especially regulatory and technological innovations related to climate risks. Based on this argument, TGI information representing firms' commitment to sustainable practices can attract investment from investors who are concerned by regulation risks.

Furthermore, Krueger et al. (2023) find that mandatory ESG disclosure enhances the liquidity of stocks. They note that enforcing environmental regulations can pressure managers to disclose information about environmental activities, which in turn, potentially reduces information asymmetry and dilutes the markets' misinterpretation of TGI information.

In addition, Shane and Spicer (1983) indicate that environmental regulations and their enforcement can result in increased investor interest towards firms which are directly affected by said regulations, and the information they disclose. They propose the disclosure effect argument, i.e., firms' public information related to pollution control activities changes investors' perception in considering cash flow impact probability of expenditure increased to comply with the environmental regulatory standards. Hence, investors may react more favourably to firms' information (such as TGI activities) that represents compliance with the regulation standards compared to information regarding non-TGI activities, which do not promote firms' regulation compliance.

According to these arguments, I predict that the 1st Kyoto Protocol commitment encourages investors to respond to TGI information more favourably than non-TGI information. The 1st Kyoto Protocol commitment potentially increases investors' perception of TGI information. Conversely, firms providing non-TGI activities cannot mitigate the regulation risk, which can cause the market's adverse reaction to non-TGI information. Hence, with this hypothesis, I estimate that:

H2: In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information than to non-TGI information.

4.2.3 The Market Reaction to TGI Information Under Industrial Heterogeneity

Next, I investigate the market reaction to TGI information by comparing firms from high- and low-polluting industries before and after the 1st Kyoto Protocol commitment period. Recent literature has debated the market price impact of green transition in high-polluting industries. Matsumura et al. (2014) discover that the market negatively responds to firms committed to voluntary emission disclosure. Görgen et al. (2020), Bolton and Kacperczyk (2021a) and Hsu et al. (2023) indicate that investors still gain stock price premiums for firms with high carbon emissions. The pollution premium can reflect the markets' preference for stock returns compared to the industry peer and investors' underreaction to emission abatement. Therefore, markets might be unwilling to follow the TGI transition, especially in high-polluting industries, because of profitability uncertainty regarding TGI activities.

On the other hand, Bolton and Kacperczyk (2021a) note that the market is pessimistic about industries that emit disproportionate levels of carbon. Specifically, they find that carbon premiums become more significant and institutional divestment is smaller in other industries when excluding oil and gas, utilities, and transportation industries. Matsumura et al. (2014) also find that higher polluting firms experience a reduction in their value. One possibility is that social awareness regarding climate risks pressures investors who are concerned about their reputation to avoid investing in high-polluting industries. Dyck et al. (2019) and Azar et al. (2021) argue that fund managers are concerned about social image; hence, participating in environmental development could better their image and help them avoid social sanctions. Azar et al. (2021) also suggest that with a rising concern of regulatory risks, fund managers try to avoid financial damages to their portfolio by directly engaging in firms' carbon emission reduction.

In addition, regulatory enforcement can heterogeneously affect the stock value based on the firms' industrial categories. Nguyen and Phan (2020), when testing the market reaction in Australia, found that investors responded more negatively to firms in the high-polluting industry than those in the low-polluting industry after the announcement of the Kyoto Protocol ratification. They argue that the regulation stringency increases carbon risk and the costs of managing carbon emissions, which depresses corporate performance and increases the risk of financial distress more for firms in the high-polluting industry than firms in the low-polluting industry. Balachandran and Nguyen (2018) find that escalating financial uncertainty after the 1st Kyoto Protocol pressured managers to reduce the dividend payout of firms in high-polluting industries. Similarly, Oestreich and Tsiakas (2015), when testing the European Union's Emissions Trading Scheme (EU ETS) and stock price movements, document that high-polluting industries take large cashflow risk and pay higher prices for carbon allowances. The evidence indicates that climate regulation impacts the compliance costs of firms in high-polluting industries more than that of the firms in low-polluting industries. Therefore, it is possible that high-polluting firms which invest in TGI activities reap greater benefits from reducing compliance costs compared to low-polluting firms.

To understand the effect of industrial heterogeneity (i.e., high and low-pollution industries), I investigate the 1st Kyoto Protocol commitment impact on the market reaction to TGI information by comparing the cases of high and low-pollution industries. In the presence of environmental regulation, the high-polluting industry that embraces said regulations (through engaging in TGI activities) can benefit by protecting their reputations, minimising social pressure, and reducing regulatory risks. This leads to my hypothesis that:

H3: In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information of the firms in the high-pollution industry than that of the firms in the low-pollution industry.

4.2.4 Informativeness of Analysts' Recommendations and TGI Stock Returns

Analysts' ability to collect and process firm-specific information, enabling them to evaluate intrinsic value, can identify undervalued or overvalued stocks to support investors' decisions. The literature shows empirical evidence that analysts' activities, e.g., new recommendation announcements, recommendation revisions, and adjusting earnings forecasts, affect investors' investment decisions (Womack, 1996, Barber et al., 2001 and Loh and Mian, 2006). In this part, I aim to examine the consequences of TGI information on the value of analysts' recommendations.

As I discussed in sub-section 4.2.1, although literature enhances future stock values related to innovation, innovative firms are undervalued during innovative developing processes, referring to investors' misinterpretation of the innovation payoff (Eberhart et al., 2004 and Daniel and Titman, 2006). This is because firms promoting innovation activities create higher future profitability volatility (Kothari et al., 2002). According to Kogan and Papanikolaou (2014) and Kung and Schmid (2015), stock risk premia rely on contributing innovative growth opportunities to firm value. The uncertainty of future profitability regarding innovative investment leads investors to delay incorporating innovative information into stock valuation. Another possibility is that firms with higher innovation intensity increase information asymmetry (Bhattacharya and Ritter, 1983 and Aboody and Lev, 2000). Bhattacharya and Ritter, 1983 suggest that firms investing in more innovative projects are willing to disclose only partial information about the projects to protect against information leakage. Higher restrictions on firms' innovative information disclosure can impede investors from identifying the intrinsic value of innovation activities.

Increased TGI information seems advantageous to financial analysts, who can access and identify superior information. Firms engaged in TGI activities create more information complexity and future profitability uncertainty that directly affect the stock valuation of investors. Therefore, information issued by analysts following the TGI firms, i.e., analysts' recommendations, can support investors' investment decisions regarding TGI news. Moreover, increasing sustainable portfolio investment in institutional investors rewards analysts for reporting favourable information (Hong and Kubik, 2003, Groysberg et al., 2011 and Harford et al., 2019). However, little evidence observes the connection between analysts' reports incorporating superior and complex information and stock value (Asquith et al., 2005). Amir et al. (2003) find that analysts' forecasts are more sensitive to investors' trading in firms with higher intangible intensity than firms with lower intangible intensity. Green et al. (2014) note that investor trading is associated with revising the recommendations of analysts who obtain management information.

Furthermore, Altinkiliç et al. (2013) and Yezegel (2015) argue that the value of analysts' forecasts is associated with firms' news and private information regarding firm fundamental changes. Altınkılıç and Hansen (2009) suggest that the stock price impacts of analysts' recommendations rely on timeliness and the information disclosed before issuing analysts' reports. They also show that investors are less responsive to analysts' upgrading (downgrading) recommendations issued after disclosing firms' good (bad) news. Conrad et al. (2006) and Bradley et al. (2014) support the case that analysts' contrarian recommendations in response to public information reflecting their private information could receive higher commission rewards.

According to these studies, it is possible that higher uncertainty and information asymmetry of firms promoting TGI activities can lead investors to follow more analysts' recommendations to avoid the misvaluation of TGI information. Therefore, I expect investors to respond more prominently to analysts' recommendations if the recommendations are issued after disclosing TGI information. To investigate this hypothesis, I compare the stock price impacts of analysts' recommendation revisions which are relevant to the TGI information disclosed (TGI-relevant revisions), and analysts' recommendation revisions which are irrelevant to the TGI information disclosed (TGI-irrelevant revisions).

H4a: The stock price impact of TGI-relevant revisions in analysts' recommendations is greater than the impact of TGI-irrelevant revisions.

Next, I examine the influence of analysts' recommendation revisions through the exogenous variation of enforcing environmental regulation during the 1st Kyoto Protocol commitment period.

As discussed in 4.2.2, risks regarding environmental regulations are primary concerns for investors; hence, firms dealing with the regulation risks effectively can attract more investment (Krueger et al., 2020). However, the rising concern about regulatory climate risk can affect the stock returns of analysts' recommendations in two circumstances. In terms of positive impact, enforcing environmental regulations encourages investors to invest more in firms engaged in environmental development (Derwall et al., 2005, Ziegler et al., 2007 and Pástor et al., 2020). This implication can push investors' demand for firms' sustainability information. Jegadeesh et al. (2004), Asquith et al. (2005) and Green et al. (2014) note that investors are highly responsive to analysts' reports incorporating favourable information.

On the other hand, environmental regulation can reduce the impact of analysts' recommendation revisions corresponding to TGI information. Following Krueger et al. (2023), markets respond faster to firms with environmental engagement under mandatory ESG disclosure. They argue that environmental regulations, specifically mandatory disclosure, can reduce information asymmetry related to sustainable development activities. In addition, Bolton and Kacperczyk (2021a) show that after the Paris Agreement was signed, firms with higher carbon emissions continued to experience higher excess returns, because of taking on more of the carbon risk premium. They argue that the higher risk premium is a reflection of a lower investors' demand of firms with high carbon emissions, contrary to firms with lower carbon emissions that attract investors to hold their investments and reduce mispricing value.

According to these studies, it is possible that climate regulatory concerns push investors to determine the value of TGI information. Moreover, the implication of enforcing climate regulation, i.e., disclosing firms' environmental practices, allows investors to access more firms' information regarding sustainability and reduce information asymmetry. Therefore, if the 1st Kyoto Protocol commitment is assigned, it is possible that the stock price impact of analysts' revisions corresponding to TGI information will be reduced. Therefore, I hypothesise that:

H4b: In the post-Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of the TGI-irrelevant revisions.

4.3 Data and Sample

This study obtains information from several sources. First, patent application data is collected from the World Patent Statistical Database (PATSTAT) compiled by the European Patent Office (EPO). Second, financial analyst data is acquired from the Institutional Brokers' Estimate System database (I/B/E/S). Third, firm-specific data such as stock price, stock returns and financial information, are collected from COMPUSTAT.

Japan produces the largest technological patents of listed companies. Therefore, this chapter analyses the investors' responses to the news of TGI/Non-TGI in the Tokyo Stock Price Index (TOPIX) market covering 2003 to 2012. Regarding the PATSTAT database, Japanese firms dominate about 433,515 granted patents or over 54% compared to globally listed firms in the All-Country World Index compiled by Morgan Stanley Capital International (MSCI ACWI) during 2003-2012. This information is similar to Boubakri et al. (2021), showing granted patents of globally listed companies using the Derwent Innovation database. Their statistics find that Japanese listed firms covered more than 57% of the global listed firms' patents between 1992 and 2016.

To match the datasets, I employ the ISIN identifier as the primary identification to merge across the datasets. I manually random-checked the merged dataset to assess the accuracy of the information and dropped any observations that found missing values for control variables.

4.3.1 TGI and Non-TGI Information

Patent application data is constructed from data compiled by the PATSTAT database. The database collects comprehensive patent applications from more than 90 countries; the information has been compiled since 1844. It covers over 40 global intellectual property authorities such as the United States Patent and Trademark Office (USPTO), European Patent Office (EPO), Japan Patent Office (JPO), and World Intellectual Property Organization (WIPO). The patent information includes the title of a patent application, the company name of the applicant, the patent abstract, the applicant's identification, the name of the inventor, the registered date of a patent application, grant status, forward citation of each patent, the patent's granted date, and typologies of innovation identified by International Patent Classification (IPC) and Cooperative Patent Classification (CPC).

According to patent details, I construct a dataset of firms' innovation using the Fuzzy matching process, a string-searching algorithm, to match the company's name from the S&P Capital IQ database and the applicant's name from PATSTAT. I drop all matched data with a similarity matching score below 90%. Next, I manually assess each applicant's information using the company's standard name and location. Subsequently, by matching the patent information dataset, this study categorises patent applications with green innovation following the Organisation for Economic Co-operation and Development (OECD)[61]. Haščič and Migotto (2015) classify environmental innovation into seven typologies. It identifies the innovative information using IPC and CPC of patent applications except for the class of biodiversity protection and ecosystem health, which cannot be observed. Then, I continue with this approach to divide samples between TGI and non-TGI patent applications.

However, literature reports a truncation bias in patent databases when the backlog of many recent applications is still being processed due to the lag between the year of applying for a patent application and the granted year (see Hall et al., 2001, Hall et al., 2005 and Dass et al., 2017). Hence, this study investigates the market reaction to information disclosure regarding innovation by using the filing date of a patent application instead of the patent's granted date, so as to reduce the bias of information leakage (Brunnermeier, 2005 and Tetlock, 2011). I create a dummy variable that equals one for the day the firm filed a TGI patent application and zero for the day the firm filed a non-TGI patent application, *TGI_patent* hereafter. I exclude samples in which the firm made TGI and non-TGI patent applications on the same day.

[61] Haščič, I., & Migotto, M. (2015). Measuring environmental innovation using patent data. OECD Environment Working Papers, 89. https://doi.org/10.1787/5js009kf48xw-en

4.3.2 Sell-side Analyst Information

4.3.2.1 Analysts' Recommendation Revisions

I obtain analysts' reports from the Institutional Brokers' Estimate System (I/B/E/S) to measure the informativeness of analysts' recommendations. The database reports the daily recommendations of individual analysts with a standard rating between 1 (strong buy) and 5 (strong sell). I found 37 brokerage houses and 3,582 Japanese-listed firms covered by analysts during the sample period. My study provides recommendation revisions of individual analysts following the prior literature, suggesting the informativeness of recommendation revisions is better than the levels of recommendations (Womack, 1996, Jegadeesh et al., 2004 and Green et al., 2014). I remove brokerages and analysts coded as anonymous by the database, as they cannot be traced. Then, I define individual analysts' recommendations revisions from the current rating minus the prior rating by the same analysts. I exclude the analysts' recommendation revisions if the prior rating is over one year old based on the I/B/E/S review date (Loh and Stulz, 2018). I exclude analysts' recommendations covering the three-day window around the quarterly earnings announcement date based on COMPUSTAT or a company earnings guidance date in First Call Guidelines in an effort to reduce the duplicating reactions to the firm's specific news (see discussion in Loh and Stulz, 2011, Green et al., 2014 and Loh and Stulz, 2018). Following Green et al. (2014), I also control for the timing of recommendations revisions, i.e., if they were made two weeks before or two weeks after the day of earnings announcement.

To distinguish the individual analysts' recommendation changes relevant to TGI information (TGI-relevant revisions) from those not relevant to TGI information (TGI-irrelevant revisions), I follow Green et al. (2014). Accordingly, I construct a dummy variable (*TGI_revision*, hereafter) that takes the value of one if the recommendation changes within 21 trading days after the firm filed a TGI patent application, and zero if otherwise. I capture the revisions in 21 trading days to reduce the overlapping issue of filing patent applications. I also consider only the firms engaged in TGI activities to reduce sample characteristics bias.

4.3.2.2 Analysts Related Control Variables

I control for several characteristics of analysts and their reports. Following the literature, I include *Analyst_cov* to represent the natural logarithm of the number of analysts following the firms in the corresponding period. The literature suggests that the number of analysts covering the firm represents levels of the market's attention to the firm. The indicator also represents the volume of public information disclosed (Frankel et al., 2006 and Green et al., 2014). Following Jegadeesh and Kim (2010) and Loh and Stulz (2011), I include a variable *Away_from_concensus.* This is because a recommendation that differs from the consensus is likely to be based on new information and have a higher impact on stock prices than the herding recommendations. *Away_from_concensus* is a dummy variable that takes the value of one if the absolute deviation of the new recommendation is higher than the absolute deviation of the prior recommendation from the consensus, and zero is otherwise. I also set the value as zero if less than two analysts cover the firm.

Ivković and Jegadeesh (2004) suggest that the recommendations issued before (after) an earnings announcement can have a higher (lower) market response. Thus, I include *Pre-earnings* as a dummy variable that takes a value of one if the recommendation revision is issued in the two weeks (10 trading days) prior to a quarterly earnings announcement date, and zero if otherwise. Then, *Post-earnings* as a dummy variable equal one if the recommendation revision is issued in the two weeks (10 trading days) after an earnings announcement date, zero if otherwise (see Green et al., 2014).

I also control for brokerage-analyst characteristics. Ivković and Jegadeesh (2004) suggest that investors react more significantly to the recommendations issued by analysts who cover more extensive portfolios, work for bigger brokerage houses, and have more experience. Clement (1999) and Green et al. (2014) note that the size of brokerage houses implies better internal instruments and resources available to analysts in incorporating and analysing a firm's information. Harford et al. (2019) note that the number of firms analysts cover is related to their forecast ability. Similarly, Mikhail et al. (1997) and Ivković and Jegadeesh (2004) support that analysts' experience implies their prediction skill and ability to access superior information.

Therefore, I account for these variables in my regression framework, i.e., brokerage size (*Broker_size*), the natural logarithm of employed analyst numbers by the brokerage house, analyst's portfolio (*Portfolio*), the number of firms followed by an individual analyst, analyst's experience (*Experience*) is the period (year) the analyst has covered the firm minus the average number of years that all analysts have covered. All variables are defined in Appendix Table A4.1.

4.3.3 Controlling for Firm-Specific Characteristics

My regression framework contains multiple stock characteristic control variables influencing stock returns on corporate announcement events composed of *Size, Bm_ratio, Volatility, Beta, MOM*. I follow Hirshleifer et al. (2009) and measure *Size* as the natural logarithm of the market value of the firm at the end of the year prior to the day *t.* Chambers and Penman (1984) document that the market reaction to earnings announcements of small firms is greater than that of large firms. Similarly, Chae (2005) finds an inverse impact between firm size and trading volatility after earning announcement dates. Atiase (1985) argues that levels of private pre-information disclosure and dissemination are an increasing function of firm size. Based on this notion, information asymmetry should be inverse related to firms' size and leads to different market reactions when new information is exposed.

Furthermore, Fama and French (1992, 1993) identify common risk factors combined to capture the cross-sectional variation in average stock returns, i.e., firm size (small minus big: SMB) and book-to-market (high minus low: HML). SMB captures the historical outperformance of small stocks over large stocks, demonstrating the effect company size has on stock returns. Meanwhile, HML captures the excess return of the value stocks over that of the growth stocks. Stocks with poor past performance suffering high book-to-market ratios could gain higher expected stock returns than low book-to-market stocks as a result of investor overreaction to past performance. *Bm_ratio* is measured as the ratio of book value per share to the market value per share of firms at the end of the year prior to the day *t.*

I then consider price risk factors. Traditional asset pricing theories document that the market incorporates the systematic risk in stock price but diversifies the unsystematic risk (Sharpe, 1964 and Lintner, 1965). Intertemporal asset pricing theories argue that idiosyncratic risk affects stock pricing (Campbell, 1992, 1996). Stock volatility induces the drifting of investment opportunities and expected future stock returns, i.e., a deterioration in pricing profitability or hedging against risky stocks. However, studies find mixed results on the relationship between stock returns and stock volatility. Ang et al. (2006) and Brockman and Yan (2008) find that stock return is inversely proportional to stock volatility. Malkiel and Xu (2002) and Brown and Ferreira (2016) find stock returns are related to stock volatility.

To control for the movements in stock price (i.e., the risk factor), I incorporate *Volatility* (measured by the standard deviation of daily stock returns) of firm *i* in the previous month to day *t* and *Beta* (a measure of the systematic risk) of the firm *i* for one year prior to the day *t*.

Finally, it is possible that the momentum of stocks could reflect a market delay in incorporating firm-specific information. Jegadeesh and Titman (1993) show that the announcement date returns of stocks in past high returns exceed the announcement date returns of stocks in past low returns. Carhart (1997) shows that the past momentum in stock returns can affect future stock returns. Moreover, Hong et al. (2000) identify that momentum reflects market underreaction on firm-specific information diffuses gradually across the investing public. They note that the profitability of the momentum strategy is more robust among stocks with low information diffusions. Therefore, I control for momentum in stock returns (*MOM*) measured as the buy-and-hold return of firm *i* between

-12 and -2 months prior to day *t* (see Green et al., 2014 and Loh and Stulz, 2018). All variables are defined in Appendix Table A4.1.

4.3.4 Cumulative Abnormal Returns

This study investigates the markets' reaction to TGI information by analysing its effect on stock prices. I follow two different approaches. First, I examine the markets' reactions to TGI and non-TGI information. Second, I investigate the reactions to analysts' recommendations in response to TGI information.

I estimate the market reaction to TGI (non-TGI) information by using the cumulative abnormal return (CAR) from the patent application filing date (or the recommendation revision date) to the next trading day, i.e., a two-day event window (0,+1). I also extend the event window period of 11 days, i.e., five days before and after the event date (-5, +5)[62]. As in Green et al. (2014) and Loh and Stulz (2018), I measure CAR from the cumulative raw return on the stock minus the cumulative raw return of a benchmark portfolio. Following Daniel et al. (1997, DGTW), I create a benchmark portfolio based on three firm characteristics, i.e., firm market value, book-to-market ratio, and the prior year's returns (momentum) as in equation (1), hereafter referred to as DGTW CAR:

$$CAR_i = \prod_{t=0}^{1}(1 + R_{it}) - \prod_{t=0}^{1}\left(1 + R_{it}^{DGTW}\right) \qquad (1)$$

Where, R_{it} is the raw return of stock i on day t, and R_{it}^{DGTW} is the raw return based on a benchmark portfolio on day *t*. I compute the benchmark portfolios based on monthly

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[62] Regarding analysts' informativeness, Womack (1996) finds that stock price movement drifts following analysts' recommendation revisions. Green et al. (2014) show the stock price impacts of recommendation changes are highest at two-day event windows. Whereas Altınkılıç and Hansen (2009) document significant abnormal returns over five days before and after the issuing recommendation date.

data of firm market value (*Size*), book-to-market value per share ratio (*Bm_ratio*) and momentum portfolio (*Mom*). All variables are defined in Appendix Table A4.1. Further, I also compute alternative CARs from two different methods: the market-adjusted model (Brown and Warner, 1980), and the value-weight industry-adjusted model (Womack, 1996) from 48 Fama & French industry identifications.

4.4 Empirical Results

The Market Reaction to TGI and Non-TGI Information

4.4.1 Descriptive Statistics

I begin my analysis by summarising descriptive statistics of all control variables included in the regression framework. I also compare the mean difference of these variables between TGI and non-TGI samples. I identify TGI (non-TGI) samples based on TGI (non-TGI) patent application filing dates. I exclude TGI (non-TGI) samples if patent applications are submitted on the same day as non-TGI (TGI) patent applications. The statistics are reported in Table 4.1.

Columns (2) – (4) of Table 4.1 summarise the descriptive statistics of all control variables for total patent, TGI patent, and non-TGI patent samples, respectively. There are 272,823 total patent applications filed by 1,267 firms during the sample period. I discovered that 647 and 1,242 firms applied for TGI and non-TGI patent applications, respectively. This implies that almost all firms engaged in TGI are also engaged in non-TGI patent filing. I also find that the average *Size* of TGI sample firms is larger than that of non-TGI firms, but the opposite is the case for their *Bm_ratio*. It is plausible that firms with larger market capitalisation are motivated by stakeholders and the public to engage in sustainability development (Dyck et al., 2019 and Azar et al., 2021). Moreover, the uncertainty surrounding the potential benefits of TGI activities, compared to that of non-TGI activities, could also cause the stock prices in TGI firms to be more volatile than non-TGI firms (Ghisetti and Rennings, 2014 and Rexhäuser and Rammer, 2014). In the meantime, higher *MOM* of TGI samples than that of non-TGI samples indicates the low perception and slow diffusion of TGI information in the capital market (Hong et al., 2000). It is possible that TGI uncertainty impacts investors' perceptions of future value related to TGI activities, causing investors to delay incorporating TGI information.

4.4.2 Do Investors Respond to TGI and Non-TGI Information Differently?

4.4.2.1 Univariate Analysis

In univariate analysis, I examine the CAR measured using three methods (see sub-section 4.3.4). I investigate hypothesis H1: "*Investors react more favourably to non-TGI information than to TGI information*". In this section, I assess the market reaction between TGI and non-TGI information for the entire sample period (2003–2012). The results are presented in Table 4.2.

Panel A of Table 4.2 shows that during 2003–2012, the CARs of TGI information are negative for all event windows. The DGTW CARs of the two-day and six-day windows are -0.01% and -0.06%, respectively (see Columns (1) and (2))[63]. I also see a negative

[63] For market-adjusted returns measure, the CAR(0,+1) and CAR(0,+5) are -0.02% and -0.10%, respectively (Panel A Columns (5) and (6)). For industry-adjusted returns measure, the CAR(0,+1) and CAR(0,+5) are -0.01% and -0.10%, respectively (Panel A Columns (9) and (10)).

signal to TGI information in the two and five days before and after the day the firms filed TGI patent applications by -0.04% and -0.12%, respectively (see Columns (3) and (4))[64].

Panel B of Table 4.2 reports the CAR of non-TGI information. From 2003 to 2012, I discover negative CARs of non-TGI information for all three CAR measurements. I also find that the negative figures of CARs for non-TGI information are larger than those for TGI information.

Panel C of Table 4.2 reports the differences in the market reaction between TGI and non-TGI information from 2003 to 2012. The results of all event windows indicate that the CARs of TGI information are slightly higher compared to those of non-TGI information. Considering the DGTW CAR, only the average CARs of over five-day and eleven-day windows for TGI information are significantly higher than those of non-TGI information by 0.07% and 0.09%, respectively (see Panel C Columns (3) and (4)). I also find an insignificant difference between the CARs of TGI and non-TGI information in alternative measures (see Columns (5) - (12))[65]. Therefore, my hypothesis H1, "*Investors react more favourably to non-TGI information than to TGI information*" is rejected, indicating that the market does not distinguish between TGI and non-TGI information.

However, it is important to note that the univariate analysis does not account for the effects of other factors that can influence the movements in stock prices. Moreover, I discover that the CAR of non-TGI information is inconsistent for the entire sample period. To address these issues, first, I employ a multivariate regression analysis by including

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[64] We find similar results but greater magnitudes in the CARs of market-adjusted and industry-adjusted returns measures (see Panel Columns (5) – (12)).

[65] Except the (-2,+2) window of industry-adjusted returns measurement, which find the negative CAR of TGI information is larger than non-TGI information at statistical insignificance (see Panel C Column (11)).

control variables to investigate this hypothesis. Second, I further investigate the market reaction to TGI and non-TGI information before (2003 – 2007) and after (2008 – 2012) the 1st Kyoto Protocol commitment.

4.4.2.2 Multivariate Analysis

In this section, I examine hypothesis H1 by using a multivariate analysis to control for the effects of the factors that can influence stock returns. I provide a regression framework following equation (2):

$$CAR_{i,t} = \alpha + \beta_1 TGI\_patent_{i,t} + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{i,t} \quad (2)$$

In equation (2), i and t are indexed as the firm and time (days), respectively. $CAR_{i,t}$ is the DGTW cumulative abnormal return based on the event windows. $TGI\_patent_{i,t}$ is a dummy variable equal to one if a firm filed a TGI patent application on day t, and zero is for a firm filed a non-TGI patent application on day t. I exclude samples where patent applications of both innovations were submitted on the same day. $\boldsymbol{X}_{i,t}$ is a vector of control variables known as influential factors of price movement (i.e., *Size, Bm_ratio, Volatility, MOM, Beta*). γ_i and τ_t are the firm- and year-fixed effects, respectively. ε_{it} is the error term for firm i and day t. I winsorise all control variables at 1% and 99% levels to reduce the influences of possible spurious outliers. All variables are defined in Appendix Table A4.1. For the hypothesis H1 to hold, I expect the coefficient of $TGI\_patent_{i,t}$ (β_1) to be negative, implying that investors respond more negatively to TGI information than non-TGI information. Results are presented in Table 4.3.

Table 4.3 reports the estimates of equation (2), comparing the market reaction impacts between TGI and non-TGI information. The results show an insignificant difference in the CARs between TGI and non-TGI information for all event windows (see Columns (1) – (4)). These findings suggest that there is no significant difference in the market reaction to TGI and non-TGI information. Thus, I reject hypothesis H1, that "*Investors react more favourably to non-TGI information than to TGI information*". One possibility is that investors cannot fully identify the differences in the values of firms' TGI and non-TGI activities. Eberhart et al. (2004) and Gu (2005) suggest that in the short term, higher information asymmetry can lead investors to overlook public information and react inaccurately to the benefits of innovation. This is because firms that allocate more resources to innovation projects tend to disclose only partial information to protect against information leakage to their competitors (Bhattacharya and Ritter, 1983). This practice results in a rise in firms' information asymmetry and can cause investors not to identify the different value benefits between TGI and non-TGI activities. Moreover, Daniel and Titman (2006) indicate that investors tend to put more efforts into incorporating information regarding tangible assets than intangible assets. Therefore, the less effort investors put into assessing information related to innovation, the more likely it is that they fail to identify the difference in the values of TGI and non-TGI activities.

4.4.3 Does the 1st Kyoto Protocol Commitment Impact the Market Reaction to TGI and Non-TGI Information Differently?

4.4.3.1 Univariate Analysis

In this section, I provide the univariate analysis to examine hypothesis H2 that "*In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information than to non-TGI information*". I investigate the 1st Kyoto Protocol commitment impact by dividing the sample period between the pre-commitment period (2003–2007) and the post-commitment period (2008–2012), as demonstrated in Table 4.2.

The results from 2003 – 2007 reported in Panel C of Table 4.2 indicate that during the pre-commitment period, there was no difference in the stock price impact of TGI and non-TGI information. In contrast, the results from 2008 – 2012 in Panel C show a significant difference in the CARs around TGI and non-TGI information. For the two- and six-day windows, results indicate that during the post-commitment period, the CARs of TGI information were higher than those of non-TGI information by 0.04% and 0.10%, respectively (Columns (1) and (2)). Moreover, I find significant differences in the CARs between TGI and non-TGI information: 0.13% and 0.18% for five- and eleven-day windows, respectively (Columns (3) and (4)). The results signify that during the post-commitment period, investors responded more favourably to TGI information compared to non-TGI information[66]. The substantial divergence of CAR between TGI and non-TGI information during the post-commitment period signifies that the 1st Kyoto Protocol commitment has different impacts on stock returns between TGI and non-TGI information. The findings support hypothesis H2 "*In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information than to non-TGI information*".

Krueger et al. (2020) argue that increasing investors' concerns about environmental regulation risks can motivate them to invest in firms that can mitigate the regulation risks. They also suggest that environmental regulations increase investors' awareness of environmental information. My findings that show the significant effect of the 1st Kyoto

[66] We also find significant positive differences in the CAR between TGI and non-TGI information during the post-commitment period in the market-adjusted returns CAR as well as in the industry-adjusted returns CAR.

Protocol commitment support this argument. This is because TGI activities reflect the environmental commitment of the firms, whereas non-TGI activities do not.

From the estimates in Panel A of Table 4.2, I find that there is no difference in impact on the market reaction to TGI information between the pre- and the post-commitment periods for all event windows. The results suggest that the market reaction to TGI information was not affected by the 1st Kyoto Protocol commitment. One possibility is that investors may have already anticipated that firms would comply with the regulation by participating in TGI activities. The evidence provided by Aghion et al. (2016) indicates that enforcing environmental regulation motivates firms to allocate more resources to TGI activities in order to prevent regulation risk and maintain competitiveness. Therefore, a systematic increase in TGI activities under the regulation enforcement, i.e., the 1st Kyoto Protocol commitment, may have influenced investors' expectations and caused them to anticipate the news of firms' engagement on TGI.

On the other hand, estimates reported in Panel B of Table 4.2 (i.e., the comparison of CARs for non-TGI information between the pre- and post-commitment period) show that during the post-commitment period, investors reacted more unfavourably to non-TGI information compared to that in the pre-commitment period. I find that during the post-commitment period, the CARs of non-TGI information were highly negative in all event windows compared to those in the pre-commitment period.

These findings suggest that the 1st Kyoto Protocol commitment adversely affected the stock price impact of non-TGI information. It is possible that, as argued by (Krueger et al., 2020), environmental regulation enforcement raised investors' concerns about regulatory punishment, leading them to decrease their investments in firms that exhibit lower levels of engagement in sustainable development. Therefore, firms disclosing information about non-TGI activities, reflecting a low commitment to regulation compliance and sustainable practices, can cause investors to adopt a pessimistic view and adversely react to non-TGI information. My results are also consistent with the evidence of Shane and Spicer (1983) who find that markets react negatively to firms' information which does not correspond to the environmental regulation standards.

In conclusion, the comparisons of CARs between TGI and non-TGI information during the pre-and the post-commitment periods indicate that the 1st Kyoto Protocol commitment insignificantly affected the market reaction to TGI information but adversely affected the market reaction to non-TGI information. During the post-commitment period, the differential market reaction between TGI and non-TGI information demonstrates that during the 1st Kyoto Protocol commitment period, investors reacted more favourably to firms that were engaged in environment improvements (such as TGI activities) but reacted unfavourably to firms ignoring them. Next, I proceed with my empirical analysis by using a multivariate regression model to assess the conclusions suggested by the univariate analysis.

4.4.3.2 Multivariate Analysis

In this section, I investigate hypothesis H2, i.e., "*In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information than to non-TGI information*". I modify equation (2) by including a dummy variable to represent the post-1st Kyoto Protocol commitment period (2008–2012).

$$CAR_{i,t} = \alpha + \beta_1(TGI\_patent_{i,t} \times Post_t) + \beta_2 TGI\_patent_i + \beta_3 Post_t \qquad (3)$$

$$+ \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{i,t}$$

In equation (3), i and t are indexed as the firm and time (days), respectively. $Post_t$ is a dummy variable equal to one if the firm filed a patent application during 2008-2012, and zero for the firms that applied for a patent during 2003-2007. The rest of the variables are defined in equation (2). In equation (3), the coefficient of interest is β_1, representing the interaction variable, i.e., $TGI\_patent_{i,t} \times Post_t$. A positive value of β_1 will suggest that during the post-commitment period, investors responded more favourably to TGI information compared to non-TGI information. The findings are reported in Table 4.4.

Table 4.4 shows the estimates of equation (3). Columns (1) – (4) report firm-fixed effect regression results, which allow us to investigate the coefficient of the key interaction and the coefficients of two key independent variables. The results indicate that during the post-commitment period, the market reacted more favourably to TGI information than to non-TGI information. Columns (1) and (2) which report the estimates of CARs for the two- and six-day windows suggest that in the post-commitment period, the two- and six-day window CARs of the TGI information were higher than those of the non-TGI information by 0.089% and 0.183%, respectively. I also find similar results in the estimates for five- and eleven-day windows (see Columns (3) and (4)).

Columns (5) – (8) of Table 4.4 demonstrate the estimates of firm-year fixed-effect regressions. I find consistent results that during the post-commitment period, the market responded more favourably to TGI information compared to non-TGI information. Based on these results, I support hypothesis H2 that "*In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information than to non-TGI information*".

Balachandran and Nguyen (2018) and Nguyen and Phan (2020) report that the 1st Kyoto Protocol increased firms' operating and cash flow uncertainty. These implications can adversely impact firms' financial performance and their future value. Therefore, it is possible that such regulations affect investors' perceptions by leading them to favour firms engaged in TGI activities that minimise the regulatory risks (Krueger et al., 2020). Conversely, environmental regulations prompt investors to decrease their investments in firms allocating resources to non-TGI activities and therefore failing to mitigate regulatory risk.

Furthermore, these results are associated with the argument proposed by Shane and Spicer (1983) which argues that the dissemination of firms' new information to investors regarding the activities of the firm's involvement in pollution-control compliance prompts a change in investors' perception of the firms about future cashflow stemming from regulatory compliance. They find that investors react positively (negatively) to firms which are reported as having high (low) compliance with pollution-control standards. My evidence supports this argument by indicating that firms providing TGI information, representing their environmental commitment, can lead to investors responding more favourably compared to non-TGI information, which does not promote firms' environmental engagement.

Additionally, the coefficients of TGI_patent_i (β_2) in Columns (1) – (8) present a significantly negative signal, implying that in general (without the 1st Kyoto Protocol commitment impact), investors react more favourably to non-TGI than to TGI information. This signal can be interpreted as investors underestimating the benefits of TGI activities relative to non-TGI activities due to the higher profitable uncertainty of TGI compared to non-TGI. Rexhäuser and Rammer (2014) find that adopting TGI can increase higher operating costs and adversely affect firms' profitability. Shrivastava (1995) and Lanoie et al. (2011) also suggest that the benefit of TGI regarding competitiveness is related to the level of environmental regulation enforcement. Therefore, the high uncertainty of TGI implications can cause investors to react more unfavourably to TGI information compared to non-TGI information.

I also find the coefficients of $Post_t$ (β_3) in Columns (1) – (4) are negative, which implies a possibility that during the post-commitment period, the market reaction to both innovations were lower than in the pre-commitment period. However, these estimates cannot identify the heterogeneous effect of the 1st Kyoto Protocol commitment on the market reaction between TGI and non-TGI information. Therefore, a subsample analysis is conducted by following equation (4) to investigate the market reaction to TGI and non-TGI information separately.

$$CAR_{i,t} = \alpha + \beta_1 Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{i,t} \quad (4)$$

In equation (4), i and t are indexed as the firm and time (days), respectively. $Post_t$ is a dummy variable equal to one if the firm filed a patent application during 2008-2012, and zero for if the firm applied a patent application during 2003-2007. The remaining variables are defined in equation (2). I start with the samples of TGI information to examine the effect of the1st Kyoto Protocol commitment on the market reaction to TGI information. The results are presented in Table 4.5.

Columns 1–4 of Table 4.5 report the estimates of equation (4) testing the impact of the 1st Kyoto Protocol on the market reaction to TGI information. The results suggest that there is no difference in the market reaction to TGI information between the pre- and post-commitment periods. These findings are consistent with the univariate results showing that the 1st Kyoto Protocol commitment has no significant impact on TGI information with regard to CAR.

The results indicate that the 1st Kyoto Protocol commitment did not impact the market reaction to TGI information. Aghion et al. (2016) show that environmental regulations significantly drive managers to develop more innovations related to green technologies. The expansion of TGI activities as a reaction to environmental regulations might be a situation in which the market preemptively forecasts the investment and strategic choices made by managers in relation to environmental progress in an attempt to mitigate the expenses associated with regulatory compliance (see discussion in Shane and Spicer, 1983). Hence, it is possible that during the 1st Kyoto Protocol commitment period, the market anticipated firms' investments in TGI activities and incorporated the value in stock prices. Hence, disclosing TGI information did not carry any new price-sensitive information.

Next, I employ the samples of non-TGI information in equation (4) to investigate the effect of the 1st Kyoto Protocol commitment on the market reaction to non-TGI information. The results are reported in Table 4.6.

Columns (1) – (4) of Table 4.6 show the estimates of equation (4) testing the impact of the 1st Kyoto Protocol commitment on the market reaction to non-TGI information. The results reveal that the 1st Kyoto Protocol commitment adversely affected the market reaction to non-TGI information. Compared to the pre-commitment period, the CAR of the two-day window decreased by -0.125% during the post-commitment period (Column (1)). I also find consistent results in other event windows, implying that during the post-commitment period, the market responded more unfavourably to non-TGI information compared to the pre-commitment period.

These findings are related to the argument of Krueger et al. (2020), indicating that investors' increasing concerns about regulation may change their investment views and prompt more consideration to climate risk regulations. Therefore, it is possible that any information that is not supportive of mitigating regulation risk (i.e., non-TGI information) can cause the market to respond adversely. My results are also consistent with the evidence of Shane and Spicer (1983), who find that markets exhibit a negative response to information disclosure that does not support the advancement of environmental practices.

Figure 4.1 demonstrates the yearly CAR average over the two-day event window on TGI and non-TGI patent application filling dates. For 2003–2007, I see the CAR was relatively similar for the TGI and non-TGI samples. However, from the beginning of 2008, I see the CAR of non-TGI samples was considerably lower relative to that of the TGI samples for almost the entire 1st Kyoto Protocol commitment period.

Likewise, Figure 4.2 finds that TGI and non-TGI samples show an identical pattern and magnitude of CARs in the event window (-5, +5) during 2003–2007. Then, I discover a substantial deviation of the CAR between TGI and non-TGI samples in the post-commitment period. The evidence from both figures supports my regression results of equation (3), confirming the differential impact of the 1st Kyoto Protocol commitment on the market reaction to TGI and non-TGI information. These figures point out that after the 1st Kyoto Protocol commitment, investors responded more favourably to TGI information than to non-TGI information.

4.4.4 Does Industrial Heterogeneity Impact Investors in Response to TGI Information?

This section investigates the market's reaction to TGI information across high- and low-polluting industries during the 1st Kyoto Protocol commitment period to test hypothesis H3 that "*In the post- Kyoto Protocol commitment period, investors reacted more favourably to TGI information of the firms in the high-pollution industry than that of the firms in the low-pollution industry*". I identify industry categories using the average global carbon emission intensity. I obtain global carbon emission data between 2000 and 2020 from the Trucost database. I employ a dummy variable to represent high and low total carbon emission industries following The Global Industry Classification Standard (GICS 6-digit)[67]. I use TGI information sub-samples to identify the stock price impact of TGI information under industrial heterogeneity.

$$CAR_{i,t} = \alpha + \beta_1(Post_t \times Industry_i) + \beta_2\, Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \varepsilon_I \qquad (5)$$

In equation (5), $Industry_i$ is a dummy variable if firm i is in the top 10 carbon emission industries, and zero if otherwise[68]. $Post_t$ is a dummy variable equal to one if the firm submitted a patent application during 2008-2012, and zero if the firm submitted a patent application during 2003-2007. All other variables are described in equation (2). In this equation, I investigate the market response to TGI information between high- and low-polluting industries during the 1st Kyoto Protocol commitment period through the coefficient of $Post_t \times Industry_i$ interaction (β_1). A positive β_1 would imply that during the post-commitment period, the market reacted more favourably to TGI information in the

[67] See in Appendix Table A4.2
[68] See in Appendix Table A4.2

high-polluting industry compared to that in the low-polluting industry. The results are reported in Table 4.7.

Columns (1) – (4) of Table 4.7 report the estimates of equation (5) testing for the possible differences in the market reaction to TGI information between high- and low-polluting industries during the 1st Kyoto Protocol commitment period. The results in Columns (1) – (3) show that during the post-commitment period, there is no difference in the market reaction to TGI information between high- and low-polluting industries. Only the estimate of the eleven-day window shows that in the post-commitment period, the market reaction to TGI information in high-polluting industries was significantly higher (by 0.278%) compared to that of low-polluting industries (Column (4)). Hence, I reject hypothesis H3 that "*In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information of the firms in the high-pollution industry than that of the firms in the low-pollution industry*".

These findings show no difference in the response of investors to TGI information in the high-polluting industry compared to the low-polluting industry. One possibility is that environmental regulation enforcement can motivate investors to expect and respond to firms' information regarding environmental practices (Shane and Spicer, 1983). This increased expectation leads investors to anticipate firms investing in TGI activities prior to the news of the application and incorporate the value of such investments in advance. Therefore, the findings, that there is no different impact on the market reaction to TGI information between high- and low-polluting industries, can emphasise the increase in investors' perception regarding the value of TGI activities in response to the regulations.

TGI Information and the Value of Analysts' Recommendation Revisions

In this section, I explore whether TGI information affects the informative value of analysts' recommendation revisions. I compare the stock price movements between individual analysts' recommendation revisions that are relevant to and irrelevant to TGI information (TGI-relevant and TGI-irrelevant revisions, respectively). I also divide individual analysts' recommendation revisions (TGI-relevant and TGI-irrelevant revisions) between upgrades and downgrades to investigate the value of analysts' recommendation revisions separately.

Table 4.8 reports the number of individual analysts' recommendation revisions by grouping them into TGI-relevant and TGI-irrelevant revisions. Panels A and B demonstrate analysts' upgrading and downgrading recommendation revisions, respectively.

Based on I/B/E/S, 588 TGI firms were covered by analysts during 2003–2012. For analysts' upgrading recommendation revisions in Panel A of Table 4.8, I find 3,627 upgrading recommendations in 325 TGI firms. 1,776 upgrading recommendations are identified as relevant to 1,630 TGI patent applications. For analysts' downgrading recommendation revisions in Panel B, I find 3,983 downgrading recommendations in 337 TGI firms. 2,047 recommendation revisions are identified as relevant to 1,827 TGI patent applications. I provide the frequency of TGI-relevant revisions (upgrades and downgrades) in Figure 4.3.

Figure 4.3 demonstrates the frequency of analysts' recommendation revisions associated with TGI information (TGI-relevant revisions) based on the issuing day of recommendation revisions. This figure is started from the day the firms filed TGI patent applications (day zero) to 21 days after. The figure shows that analysts significantly issued the recommendation revisions on the same day as the firms made TGI patent applications.

Analysts issued 739 and 862 reports (20.37% and 21.64% of all recommendation revisions) for upgrading and downgrading recommendations on the day of the TGI patent application filling dates, respectively. However, I exclude revisions issued on the same day as the TGI application filling date to avoid information reiteration (see discussion in Loh and Stulz, 2011). Green et al. (2014) note that recommendations issued the same day as corporate events might not incorporate the new information but could have been initiated prior to the event. Finally, I find that the average upgrade and downgrade periods are 6.54 days and 7.08 days after the day of application filing, respectively.

4.4.5 Descriptive statistics

I use univariate and multivariate techniques to investigate whether there is any difference in the informativeness of analysts' TGI-relevant and TGI-irrelevant recommendation revisions. I control for factors that can affect the value of analysts' recommendations in a regression model, i.e., firm, broker and analyst characteristics. I summarise the descriptive statistics of all variables included in my regression framework in Table 4.9.

Table 4.9 summarises descriptive statistics of all variables in a regression model. For upgrading recommendation revisions, statistics show positive actual returns on the day of recommendations issued and positive CAR for all the event windows. On the other hand, downgrading recommendation changes provide negative actual returns and negative CAR for all event windows. These figures indicate that stock price movement follows the same direction as analysts' recommendation revisions, implying the influence of analysts' recommendations on investors' investment decisions.

I include firm characteristics which also influence the value of analysts' recommendation revisions in my regression framework. Existing literature suggests that the value of analysts' recommendations depends on the information environment of the firm. Loh and Stulz (2011) note that analysts' influential recommendations are related to the size of firms. Analysts' recommendations covering smaller firms are more influential to the market than larger firms which have a number of information sources, e.g., more analyst coverage. Loh and Stulz (2011) suggest the value of recommendation changes can be driven by *BM_ratio*, which refers to firms' future growth opportunities, e.g., unrecorded intangible assets. However, this signal can also push investors to acquire more private information. Many studies find inconsistent evidence regarding *BM_ratio* and the value of analysts' reports (Frankel et al., 2006, Bradley et al., 2014 and Wu, 2022).

Moreover, *Volatility* and *Beta* reflect stock price risks that should affect the value of recommendations. While Loh and Stulz (2011) find that analysts' revisions are more influential in low-volatility stocks, Bradley et al. (2014) suggest that higher stock price volatility enhances the influences of analysts' recommendations in relaying firm-specific information to investors.

Furthermore, Altınkılıç and Hansen (2009) document that the value of analysts' recommendation revisions can be predicted by the firms' prior return trends, such as *MOM*. They indicate that market reaction to analysts' recommendation revisions could reflect changes in expected future returns related to information announcements of corporate earnings, investment opportunities, and other long-term drift factors.

4.4.6 Do Analysts' Recommendation Revisions Relevant to TGI Information Generate More Value?

4.4.6.1 Univariate Analysis

This section provides a univariate analysis to examine the stock price movements in response to the changes in analysts' recommendations (i.e., upgrading and downgrading) following hypothesis H4a that "*The stock price impact of TGI-relevant revisions in analysts' recommendations is greater than the impact of TGI-irrelevant revisions*". For hypothesis H4a to hold, a positive differential CAR between TGI-relevant and TGI-irrelevant upgrading revisions and a negative differential CAR for downgrading revisions must be observed. The results of analysts' upgrading and downgrading recommendation revisions are presented in Tables 4.10 and 4.11, respectively.

Table 4.10 reports the CARs of three event windows on analysts' upgrading recommendation revisions. The results from 2003-2012 show that analysts' upgrading revisions, i.e., TGI-relevant and TGI-irrelevant revisions, positively affect the stock price movement. From the results reported in Columns (1) – (3) Panel D, i.e., the comparison of the CARs of TGI-relevant and TGI-irrelevant revisions during 2003–2012 shows no significant difference in the stock price impacts of TGI-relevant and TGI-irrelevant revisions.

Table 4.11 shows the CAR of analysts' downgrading revisions. Contrary to upgrading revisions, the table reports that analysts' downgrading revisions, i.e., TGI-relevant and TGI-irrelevant revisions, negatively affect the stock price movement. From the 2003–2012 data (Columns (1) – (3)), I discover that the CARs of TGI-relevant revisions are less negative than those of TGI-irrelevant revisions[69]. Next, I compare the CARs of TGI-relevant revisions and TGI-irrelevant revisions in Panel D. The results of all event windows show that the CARs of TGI-relevant revisions are lower compared to TGI-irrelevant revisions (see Panel D Columns (1) – (3)). These findings signify that the stock price impact of TGI-relevant revisions is less than the impact of TGI-irrelevant revisions.

Based on these results, I reject the hypothesis H4a that "*The stock price impact of TGI-relevant revisions in analysts' recommendations is greater than the impact of TGI-irrelevant revisions*". The univariate analysis presents mixed results of analysts' upgrading and downgrading recommendation revisions. For analysts' upgrading revisions, the stock price movement in response to TGI-relevant revisions is slightly greater than that of TGI-irrelevant revisions. This is possibly because the market has already responded negatively to TGI information. If analysts revise recommendations against the market's expectation by upgrading after TGI information disclosure, the recommendations can impact stock price movement more than the recommendations that are irrelevant to TGI information. This finding is consistent with Bradley et al. (2014) who suggest that investors may respond more if analysts upgrade recommendations after stock price reductions, implying that analysts compare the market value with the predicted value obtained from private information.

For downgrading revisions, the results suggest that investors are less responsive to TGI-relevant revisions compared to TGI-irrelevant revisions. This could be because investors may have already responded negatively to TGI information disclosed before the

[69] See Columns (1) – (3) of Panel B and C, respectively.

analysts were able to revise their recommendations. If analysts downgrade their recommendations following the disclosed information affecting market price reductions, the value of analysts' downgrading revisions will be less (Conrad et al., 2006). To reexamine these results after accounting for possible effects of the factors that could affect the value of analysts' informativeness (e.g., firm, analyst, and analyst's report characteristics), I use a multivariate framework.

4.4.6.2 Multivariate Analysis

To investigate hypothesis H4a: "*The stock price impact of TGI-relevant revisions in analysts' recommendations is higher than the impact of TGI-irrelevant revisions*", I construct the following regression model (equation (6)) by controlling influential factors of the value of analysts' recommendation revisions.

$$CAR_{i,t} = \alpha + \beta_1 TGI\_revision_{i,d,t} + \delta_i \boldsymbol{X}_{i,t} + \varphi_i \boldsymbol{D}_{d,t} + \gamma_i + \lambda_d + \tau_t + \varepsilon_{idt} \quad (6)$$

In equation (6), i, d, and t denote firm, analyst and time, respectively. $CAR_{i,t}$ is the DGTW cumulative abnormal return on the revision date following the event windows. $TGI\_revision_{i,d,t}$ is a dummy indicator equal to one if the revision occurs within 21 trading days after the firm applied for a TGI patent application; zero is for revisions not issued in this period. $\boldsymbol{X}_{i,t}$ is a vector of firm characteristics (i.e. *Size, Bm_ratio, Volatility, MOM, Beta*) as described in sub-section 4.3.3. I include *Analyst_cov*, the natural logarithm of analyst numbers covering the firm. $\boldsymbol{D}_{d,t}$ is a vector of brokerage-analyst indicators influencing the value of analysts' recommendation revisions as described in sub-section 4.3.2.2, i.e., *Away_from_concensus, Pre_earnings, Post_earnings, Broker_size, Portfolio,* *Experience*. γ_i, λ_d, and τ_t refer to firm, analyst's broker, and time-fixed effects, respectively. All variables are defined in Appendix Table A4.1.

I also divide the estimates following equation (6) of upgrading and downgrading recommendation revisions. In the estimates of upgrading (downgrading) revision samples, a positive (negative) β_1 coefficient will support H4a. This would suggest that the stock price impact of TGI-relevant revisions is higher than that of TGI-irrelevant revisions. The results are reported in Table 4.12.

Table 4.12 reports the estimates of the stock price movement of TGI-relevant revisions compared to TGI-irrelevant revisions for both analysts' upgrading and downgrading revisions. The estimates for analysts' upgrading revisions (Columns (1) – (3) of Table 4.12) show that the market responds more favourably to TGI-relevant revisions than to TGI-irrelevant revisions. In the two-day window, the CAR of TGI-relevant revisions is significantly higher (by 0.38%) compared to that of the TGI-irrelevant revisions (Column (1)). I also find similar results for other event windows as well (see Columns (2) and (3)). These findings indicate that the stock price impact of TGI-relevant revisions is significantly higher compared to the impact of TGI-irrelevant revisions.

On the other hand, the results of the downgrading revisions show no significant difference in the impacts of TGI-relevant revisions and TGI-irrelevant revisions on stock price movements (see Columns (4) – (6)) [70].

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[70] We reduce the period of TGI-relevant revision to during 5-15 trading days. For upgrades, results show that TGI-relevant revisions affect larger stock prices at 15-day revision at statistical significances, then the stock price impact drops and is insignificant at 5-day revision period. Whereas downgrading revisions find the consistent results with the main revision window at all revision periods. We interpret that investors delay to incorporate information of analysts' recommendations (see Hirst et al., 1995).

I only find the stock price impact of TGI-relevant revisions higher than the impact of TGI-irrelevant revisions in analysts' upgrading revisions. There is no significant difference in the stock price impact of analysts' downgrading revisions between TGI-relevant and TGI-irrelevant revisions. I therefore reject hypothesis H4a that "*The stock price impact of TGI-relevant revisions in analysts' recommendations is higher than the impact of TGI-irrelevant revisions*".

The evidence indicates that analysts' recommendation revisions affect stock price movement when issuing recommendations against investors' expectations corresponding to disclosed information.

My findings suggest that analysts' downgrading recommendations following the market's expectation insignificantly affect the stock price movement because investors have already responded adversely to TGI information before the revisions. On the other hand, investors have a strong positive reaction to analysts' upgrading revisions, which can be seen as unexpected news contrasting the market's anticipated TGI information. This reaction stems from the perception that analysts are credible and informative sources given their access to superior information and close connections with firm management. These findings are consistent with the suggestions made by Conrad et al. (2006) and Bradley et al. (2014) that stock price changes to firms' disclosed information affect the value of analysts' recommendation revisions.

4.4.7 Does the 1st Kyoto Protocol Commitment Impact the Value of Analysts' Recommendation Revisions Relevant to TGI Information?

4.4.7.1 Univariate Analysis

Next, I use a univariate analysis to examine hypothesis H4b: "*In the post-Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of the TGI-irrelevant revisions*". I compare the CAR between TGI-relevant revisions and TGI-irrelevant revisions during the pre-commitment period (2003–2007) and the post-commitment period (2008–2012) as reported in Tables 4.10 and 4.11.

Considering TGI-relevant revisions of analysts' upgrading recommendations in Panel B of Table 4.10 (Columns (10) – (12)), the mean comparison of CARs between pre- and post-commitment periods indicates that the stock price impact of TGI-relevant revisions decreased during the post-commitment period.[71]

Furthermore, Panel D of Table 4.10 reports the differences in the CAR between TGI-relevant and TGI-irrelevant revisions during the pre- and post-commitment periods. The results suggest that during the pre-commitment period, the CAR of TGI-relevant revisions was higher than that of TGI-irrelevant revisions (Columns (4) – (6)). In contrast, during the post-commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of TGI-irrelevant revisions (Columns (7) – (9)). These findings indicate that during the 1st Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of TGI-irrelevant revisions.

[71] We find some mixed results in investigating the CAR comparison of TGI-irrelevant revisions between pre- and post-commitment periods (see Columns (10) – (12) in Panel C of Table 4.10)

For downgrading revisions, I compare the CAR of TGI-relevant and TGI-irrelevant revisions during the pre- and post-commitment periods (Panel D, Table 4.11). The results indicate that during the pre-commitment period, there was no significant impact between TGI-relevant and TGI-irrelevant revisions (Columns (4) – (6)). Conversely, I find that in the post-commitment period, the CAR of TGI-relevant revisions was less negative compared to that of TGI-irrelevant revisions (Columns (7) – (9)). These results imply that during the 1st Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower compared to the impact of TGI-irrelevant revisions.

Based on these findings, I find a significant difference in the stock impact of TGI-relevant revisions compared to the impact of TGI-irrelevant revisions (both upgrading and downgrading) after the 1st Kyoto Protocol commitment. The results suggest that during the post-commitment period, TGI-relevant revisions had less impact on stock price compared to TGI-irrelevant revisions. These findings support hypothesis H4b. that "*In the post-Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower than the impact pf the TGI-irrelevant revisions*".

Shane and Spicer (1983) suggest that investors' perception of regulatory risk impacts can lead them to react appropriately to those firms adhering to environmental standards. My findings indicate that the commitment to the 1st Kyoto Protocol can cause investors to incorporate and react more quickly to firms' information related to environmental engagement activities, i.e., TGI activities. This can reduce the stock price impact of analysts' recommendations corresponding to TGI information. My evidence is consistent with the argument of Bolton and Kacperczyk (2021a), who suggest that during environmental regulation enforcement, higher demand for firms engaged in environmental practices can reduce misvaluing stock prices.

Moreover, Krueger et al. (2023) note that the enforcement of environmental regulations can reduce firms' information asymmetry related to sustainable activities. Therefore, it is plausible that during the 1st Kyoto Protocol commitment, the reduction of firms' information asymmetry could potentially reduce investors' misvaluing of TGI information, which in turn adversely affects the stock price movement of analysts' recommendation revisions relevant to TGI information.

4.4.7.2 Multivariate Analysis

In this section, I discuss the results of a multivariate analysis aimed at testing hypothesis H4b that "*In the post-Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of the TGI-irrelevant revisions*". Equation (6) has been modified to include a dummy variable representing the pre- and post- Kyoto Protocol commitment periods (2003 - 2007 and 2008 – 2012, respectively):

$$CAR_{i,t} = \alpha + \beta_1(TGI\_revision_{i,d,t} \times Post_t) + \beta_2 TGI\_revision_{i,d,t} + \delta_i \boldsymbol{X}_{i,t} + \varphi_i \boldsymbol{D}_{d,t} + \gamma_i + \lambda_d + \tau_t + \varepsilon_{idt} \quad (7)$$

In equation (7), $Post_t$ is an indicator variable equal to one if the analyst issued a recommendation revision in 2008-2012 and zero for 2003-2007. All other variables in the equation are described in sub-section 4.4.6.2. I investigate the effect of the 1st Kyoto Protocol commitment on the market reaction to TGI-relevant revisions through the key coefficient (β_1) of the difference-in-differences interaction $(TGI\_revision_{i,d,t} \times Post_t)$. A negative (positive) value of (β_1) for analysts' upgrading (downgrading) recommendation revisions will support hypothesis H4b. The results are reported in Table 4.13.

The results of analysts' upgrading recommendation revisions are in Columns (1) – (3) of Table 4.13. They show that during the post-commitment period, the stock price movement in response to TGI-relevant revisions was lower than that of TGI-irrelevant revisions. The estimate for the two-day event window indicates that during the post-commitment period, the stock price impact of TGI-relevant revisions was lower (by -0.64%) than the impact of TGI-irrelevant revisions (Column (1)). I also find similar results for other event windows (see Columns (2) and (3)).

Furthermore, the results of analysts' downgrading recommendation revisions in Columns (4) – (6) of Table 4.13 suggest that during the post-commitment period, the stock price impact of TGI-relevant revisions was lower compared to that of TGI-irrelevant revisions. The results of the eleven-day window suggest that the market was significantly less responsive to TGI-relevant revisions (by 1.40%) compared to TGI-irrelevant revisions.

The results, consistent with the evidence reported in the univariate analysis in 4.4.7.1, show that the 1st Kyoto Protocol commitment reduced the stock price impact of TGI-relevant revisions compared to the impact of TGI-irrelevant revisions. Therefore, my findings support hypothesis H4b that "*In the post-Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of the TGI-irrelevant revisions*".

According to these findings, the effect of environmental regulation, i.e., the 1st Kyoto Protocol commitment, can promote investors' perception regarding the value of TGI activities and reduce misinterpretation of TGI information (see Shane and Spicer, 1983).

As a result, this reduces the stock price impact of TGI-relevant revisions in analysts' recommendations.

Moreover, the 1st Kyoto Protocol commitment can reduce information asymmetry toward TGI information, thereby aiding investors in promptly integrating TGI information and identifying its intrinsic value (Krueger et al., 2023). This effect potentially decreases the stock price impact of analysts recommendation revisions relevant to TGI information. The argument is related to the evidence of Loh and Stulz (2018) and Bradley et al. (2014), finding that stock price movement of analysts' recommendation revisions is associated with the level of market information asymmetry. Therefore, the reduction of information asymmetry due to the 1st Kyoto Protocol commitment adversely affects the stock price impact of analysts' recommendation revisions relevant to TGI information.

Further, I provide the time-varying CARs between TGI-relevant and TGI-irrelevant upgrading revisions in Figure 4.4. The figure shows that the CAR on the two-day event window of TGI-relevant revisions was higher than that of TGI-irrelevant revisions during 2003–2007. However, I see a substantial divergence of the CAR between TGI-relevant revisions and TGI-irrelevant revisions after the year 2007. The CAR of TGI-relevant revisions decreased in 2008 and fell below the CAR of TGI-irrelevant revisions preceding the 1st Kyoto Protocol commitment period.

Figure 4.5 depicts the time-varying CAR on the event window (-5, +5) between TGI-relevant and TGI-irrelevant downgrading revisions. The figure shows that the CAR of TGI-relevant revisions was higher than the CAR of TGI-irrelevant revisions over the post-commitment period (2008-2012). Both figures emphasise that during the post-commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of the TGI-irrelevant revisions.

4.4.8 Robustness Tests

4.4.8.1 Market Reaction to TGI and Non-TGI Information

I start robustness tests by employing alternative CAR measures, i.e., the market-adjusted model and the value-weighted industry-adjusted model following 48 Fama-French industry classifications (Fama and French, 1997). I use the alternative CARs in equation (2) to investigate the stock price movement between TGI and non-TGI information following hypothesis H1. The results are presented in Table 4.14.

Panel A and B of Table 4.14 report the estimates of equation (2) using alternative CARs, i.e., the market-adjusted model and the value-weighted industry-adjusted model, respectively. The findings of both alternative CAR measurements show that TGI information has no different impact on stock returns compared to non-TGI information. These findings are consistent with my primary evidence and reject hypothesis H1. The evidence suggests that investors do not distinguish between the value of TGI and non-TGI information.

4.4.8.2 The Market Reaction to TGI and Non-TGI Information After the 1st Kyoto Protocol Commitment

In this part, I investigate the impact of the 1st Kyoto Protocol commitment on the market reaction to TGI and non-TGI information. I modify equation (3) by using the alternative CARs of the market-adjusted model and the value-weighted industry-adjusted model to reexamine hypothesis H2 that "*In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information than to non-TGI information*". The results are reported in Table 4.15.

Columns (1) - (4) of Table 4.15 show the estimates of equation (3), testing the impact of the 1st Kyoto Protocol commitment on the market reaction to TGI and non-TGI information. I investigate the effect of the 1st Kyoto Protocol commitment with the coefficient (β_1) of the interaction ($TGI\_revision_{i,d,t} \times Post_t$) term. The coefficients (β_1) are positive for both alternative CAR measurements. The findings suggest that during the post-commitment period, investors responded more favourably to TGI information than to non-TGI information. I also see the negative coefficient of *TGI_patent* (β_2), meaning that without the effect of the 1st Kyoto Protocol commitment, the market adversely responds to TGI information compared to non-TGI information. Hence, these results are consistent with my earlier evidence and support hypothesis H2[72]. These findings emphasise the impact of the 1st Kyoto Protocol commitment on investors' perceptions towards the differences in value of TGI and non-TGI information.

4.4.8.3 Industrial Heterogeneity and the Market Reaction to TGI Information

To test H3, I reexamine equation (5) by using an alternative dummy variable of $Industry_i$, which represents the highly polluting industries in the top 10 sectors (using GICS 6 digits) based on different types of carbon emission scopes, i.e., scopes 1, 2, and 3 referring to the

[72] We provide the alternative CARs in the subsample analysis testing the effect of the 1st Kyoto Protocol commitment on the market reaction to TGI (non-TGI) information in Appendix Table A4.3. The results of the alternative CARs are consistent with our primary evidence.

intensity of direct, indirect, and supply chain carbon emissions, respectively (see Appendix Table A4.2). I present the results in Table 4.16.

Panels A – C of Table 4.16 report the estimates of equation (5) using the alternative dummy variable of $Industry_i$ based on carbon emission scopes 1–3, respectively. Generally, the results indicate that during the post-commitment period, the market reaction of TGI information in high-polluting industries was no different compared to that of low-polluting industries. I find that only the results of the eleven-day window in scopes 1 and 2 report that, during the post-commitment period, TGI information in the high-polluting industries significantly increased market reaction compared to that of low-polluting industries. Hence, these findings confirm my main evidence and reject hypothesis H3 that "*In the post-Kyoto Protocol commitment period, investors reacted more favourably to TGI information of the firms in the high-pollution industry than that of the firms in the low-pollution industry*".

4.4.8.4 The Stock Price Impacts of Analysts' TGI-relevant and TGI-irrelevant Revisions

In this part, I use the alternative CARs of the market-adjusted model and the value-weighted industry-adjusted model in equation (6) to reexamine the stock price impacts of TGI-relevant and TGI-irrelevant revisions (hypothesis H4a). The results are shown in Table 4.17.

The results of analysts' upgrading revisions (reported in Panel A of Table 4.17) show that TGI-relevant revisions have a greater impact on stock price compared to TGI-irrelevant revisions for both alternative CAR calculations (see Columns (1) – (6)). These findings confirm my main evidence that the stock price impact of TGI-relevant revisions is greater than the impact of TGI-irrelevant revisions. However, the estimates of analysts' downgrading revisions in Panel B show that there is no difference in the stock price movement in response to TGI-relevant and TGI-irrelevant revisions.

These findings are consistent with my view that investors' pessimism about TGI information significantly enhances the stock price impact of the analysts' upgrading recommendations for TGI-relevant revisions. However, investors' responses to TGI news do not support the stock price impact of TGI-relevant downgrading revisions; in contrast, they dilute the value of the revisions. Hence, I reject the hypothesis that "*The stock price impact of TGI-relevant revisions in analysts' recommendations is higher than the impact of TGI-irrelevant revisions*".

Next, I employ the alternative CARs in equation (7) to investigate the stock price impacts between TGI-relevant revisions and TGI-irrelevant revisions during the period of the 1st Kyoto Protocol commitment (hypothesis H4b). The results are presented in Table 4.18.

Panels A and B of Table 4.18 report the results of equation (7). The results of analysts' upgrading revisions in Panel A indicate that during the post-Kyoto protocol commitment period, the stock price impact of analysts' TGI-relevant revisions was lower compared to the impact of TGI-irrelevant revisions.

Similarly, the results of analysts' downgrading revisions (Panel B) suggest that during the post-commitment period, the CAR of TGI-relevant revisions was smaller compared to that of TGI-irrelevant revisions.

Therefore, these findings are consistent with my evidence in sub-section 4.4.7.2 and the argument that the implications of the 1st Kyoto Protocol commitment, i.e., increasing investors' perceptions to value of TGI activities and reducing information asymmetry, adversely affect the stock price impact of analysts' recommendations relevant to TGI-information. Hence, these findings support hypothesis H4b that "*In the post-Kyoto Protocol commitment period, the stock price impact of TGI-relevant revisions was lower than the impact of the TGI-irrelevant revisions*".

4.5 Conclusions

A growing body of research on sustainable investment draws my attention to the possible implications of firms' investments in green technology. Furthermore, the literature provides a reasonable set of evidence on the long-term effects of technological development. However, there is a lack of evidence for how stock market participants (i.e., investors and analysts) respond to the news of firms' technological innovations. Thus, this chapter aims to fill that gap. More specifically, I analyse the short-run changes in stock prices to examine if the market participants respond positively to the news of TGI in the short run.

This study uses 14,472 TGI and 223,121 non-TGI patent application filing events between 2003-2012 by Japanese firms. The results show an adverse reaction from market participants in response to TGI (non-TGI) news. Investors hold a pessimistic view of both TGI and non-TGI information. There is no significant difference in market reaction to TGI and non-TGI information. However, when the influence of the 1st Kyoto Protocol commitment is considered, a substantial variation in stock prices in response to both types of innovations is uncovered. The results suggest that during the 1st Kyoto Protocol commitment period, the market reacted more favourably to TGI information compared to non-TGI information. This evidence supports the importance of environmental regulation in influencing investors' perceptions and differentiating between the consequences of TGI and non-TGI information.

While investors underestimate the value of TGI information, analysts' recommendation revisions in response to TGI information significantly influence stock price movement. I find that the stock price movement in response to analysts' TGI-relevant revisions is greater than that of TGI-irrelevant revisions. Specifically, analysts revising their recommendations against market expectations in response to firms' disclosed information (i.e., upgrading recommendations issued after disclosed TGI information) are highly influential on the stock price movement. In addition, the evidence indicates that the impacts of the 1st Kyoto Protocol commitment, i.e., increasing investors' perception of the value of TGI information and reducing information asymmetry, can decrease the influence of analysts' TGI-relevant revisions.

Investor awareness of environmental issues is the key element which shifts investors' attention towards TGI information. Shifting investors' investment conditions from non-TGI to TGI activities pushes corporate managers to focus more on the green transition strategy through TGI activities. My evidence points out the necessity of environment regulations in promoting firms which are engaged in TGI activities in the capital markets and maximise the value of TGI.

Table 4.1 Descriptive Statistics

This table reports the summary statistics of time-varying variables between firms engaged in TGI and non-TGI for the entire sample period 2003 -2012. *Size* is firm market value at the end of the year, *Bm_ratio* is the ratio of book value per share to the market value per share of firm at the end of the year, *Volatility* is standard deviation of daily stock returns over the month, *MOM* is the buy and hold return over between -12 month and -2 month, *Beta* is a systematic risk indicator of the firm. All variables are defined in Appendix Table A4.1.

Variable		Total patent samples	TGI patent samples	Non-TGI patent samples	Mean difference (TGI – non-TGI)	t-statistics
(1)		(2)	(3)	(4)	(5)	(6)
Firm-year observations						
Size (billion USD)	Mean	2.097	2.874	2.094	0.780***	6.73
	Std.	(5.398)	(5.656)	(5.234)		
Bm_ratio	Mean	0.906	1.153	1.249	-0.096***	-5.52
	Std.	(0.719)	(0.544)	(0.551)		
Number of observations		8,384	2,881	8,175		
Firm-event observations						
Volatility (%)	Mean	2.279	2.275	2.273	0.001	0.15
	Std.	(1.172)	(1.063)	(1.066)		
MOM (%)	Mean	1.728	3.266	1.869	1.396***	5.11
	Std.	(32.671)	(32.045)	(31.645)		
Beta	Mean	1.047	1.057	1.032	0.024***	9.50
	Std.	(0.297)	(0.308)	(0.304)		
Number of observations		272,823	14,356	223,574		
Number of firms		1,267	647	1,242		

Table 4.2 Univariate Analysis of Cumulative Abnormal Returns on TGI and Non-TGI Patent Applications

This table reports the univariate summary statistics of cumulative abnormal returns (CARs) for four different event windows. The statistics reported the CARs for the entire sample period of 2003-2012 and compared the CARs between the pre-commitment period (2003 – 2007) and post-commitment period (2008 -2012) of the 1st Kyoto Protocol. Panel A reports the CARs of TGI patent application filing dates, excluding the common dates of filing non-TGI patent applications. Panel B reports the CARs of non-TGI patent application filing dates, excluding the common dates of filing TGI patent applications. Panel C reports the mean comparison of the CARs between TGI and non-TGI patent application filing dates. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

			DGTW returns				**Market adjusted returns**				**Industry-adjusted returns**			
			(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Period	**Observations**	**Event-window**	**(0,+1)**	**(0,+5)**	**(-2,+2)**	**(-5,+5)**	**(0,+1)**	**(0,+5)**	**(-2,+2)**	**(-5,+5)**	**(0,+1)**	**(0,+5)**	**(-2,+2)**	**(-5,+5)**
Panel A: TGI patent application filling dates														
2003-2012	14,356	Mean	-0.01	-0.06*	-0.04	-0.12***	-0.02	-0.10***	-0.07*	-0.19***	-0.01	-0.10***	-0.08**	-0.17***
		Std.	2.77	4.58	4.19	6.05	3.00	4.92	4.52	6.51	2.83	4.61	4.27	6.10
		t-statistic	-0.59	-1.69	-1.15	-2.46	-0.82	-2.35	-1.73	-3.48	-0.67	-2.60	-2.30	-3.44
2003-2007	5,877	Mean	-0.03	-0.06	-0.04	-0.09	-0.03	-0.11*	-0.06	-0.18**	-0.04	-0.13***	-0.11**	-0.23***
		Std.	2.52	4.21	3.71	5.57	2.69	4.54	4.00	5.85	2.55	4.29	3.78	5.54
		t-statistic	-0.85	-1.05	-0.85	-1.23	-1.02	-1.93	-1.16	-2.86	-1.32	-2.97	-2.35	-3.19
2008-2012	8,479	Mean	-0.00	-0.07	-0.04	-0.15**	-0.01	-0.08	-0.07	-0.19***	0.01	-0.05	-0.06	-0.13*
		Std.	2.93	4.83	4.49	6.45	3.19	5.18	4.84	6.93	3.01	4.83	4.58	6.46
		t-statistic	-0.11	-1.33	-0.81	-2.15	-0.36	-1.51	-1.30	-2.73	0.10	-1.04	-1.18	-1.95
Mean comparison between		Mean	0.02	-0.01	0.00	-0.06	0.02	0.03	-0.01	-0.01	0.04	0.08	0.05	0.07
2008 - 2012 and 2003 - 2007		t-statistic	0.52	-0.15	0.02	-0.60	0.39	0.35	-0.09	-0.36	0.79	1.09	0.73	0.71
Panel B: Non-TGI patent application filling dates														
2003-2012	223,574	Mean	-0.03***	-0.12***	-0.11***	-0.22***	-0.03***	-0.13***	-0.13***	-0.24***	-0.03***	-0.11***	-0.08***	-0.19***
		Std.	2.73	4.58	4.08	6.00	2.90	4.88	4.47	6.38	2.75	4.60	4.21	6.09
		t-statistic	-6.03	-12.66	-13.34	-17.59	-5.76	-12.82	-14.14	-18.20	-4.64	-11.59	-9.16	-15.06
2003-2007	97,633	Mean	-0.02***	-0.05***	-0.04***	-0.08***	-0.02**	-0.05***	-0.05***	-0.09***	-0.02***	-0.09***	-0.08***	-0.16***
		Std.	2.38	4.02	3.65	5.36	2.51	4.27	3.87	5.66	2.41	4.05	3.69	5.41
		t-statistic	-2.23	-4.22	-3.75	-4.78	-2.13	-3.46	-3.94	-5.07	-3.43	-6.80	-6.45	-9.38
2008-2012	125,941	Mean	-0.05***	-0.18***	-0.17***	-0.33***	-0.05***	-0.20***	-0.19***	-0.35***	-0.03***	-0.13***	-0.09***	-0.22***
		Std.	2.96	4.98	4.38	6.44	3.17	5.33	4.66	6.88	2.99	4.99	4.57	6.58
		t-statistic	-5.80	-12.54	-13.80	-18.31	-5.53	-13.37	-14.59	-18.26	-3.26	-9.39	-6.66	-11.81
Mean comparison between		Mean	-0.03***	-0.13***	-0.12***	-0.25***	-0.03***	-0.15***	-0.14***	-0.27***	-0.01	-0.04**	-0.01	-0.06**
2008 - 2012 and 2003 - 2007		t-statistic	-2.70	-6.22	7.28	-9.80	2.60	7.33	-7.71	-10.02	-0.07	-2.21	-0.50	-2.14

Table 4.2 continued

			DGTW returns				Market adjusted returns				Industry-adjusted returns			
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Period	**Observations**	**Event-window**	**(0,+1)**	**(0,+5)**	**(-2,+2)**	**(-5,+5)**	**(0,+1)**	**(0,+5)**	**(-2,+2)**	**(-5,+5)**	**(0,+1)**	**(0,+5)**	**(-2,+2)**	**(-5,+5)**
Panel C: Mean comparison between TGI and non-TGI patent application filling dates														
2003-2012	237,930	Mean	0.02	0.06	0.07**	0.09*	0.01	0.02	0.06*	0.05	0.02	0.01	-0.00	0.02
		t-statistic	0.89	1.46	2.12	1.90	0.50	0.65	1.70	0.99	0.47	0.32	-0.01	0.37
2003-2007	103,510	Mean	-0.01	-0.01	-0.00	-0.01	-0.01	-0.06	-0.03	-0.08	-0.02	-0.04	-0.03	-0.07
		t-statistic	-0.34	-0.06	-0.04	-0.07	-0.53	-1.50	-0.20	-1.12	-0.54	-1.43	-0.80	0.93
2008-2012	134,420	Mean	0.04	0.10*	0.13***	0.18***	0.04	0.12*	0.12**	0.16**	0.04	0.08	0.03	0.09
		t-statistic	1.34	1.90	2.65	2.52	1.00	1.91	2.34	2.14	0.92	1.40	0.53	1.13

Table 4.3 The Market Reaction to TGI and Non-TGI Information

The table below reports the results of a regression model as in the following equation (2):

$$CAR_{i,t} = \alpha + \beta_1 TGI\_patent_i + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{i,t}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm *i* at on day *t*. $TGI\_patent_{i,t}$ is a dummy variable that equals one if firm *i* applied a TGI patent application on day *t*, zero firm *i* applied a non-TGI patent application on day *t*. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta*). All variables are defined in Appendix A4.1. γ_i and τ_t are *i* firm and year fixed effects, respectively. ε_{it} is the error term for firm *i* and day *t*. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for double clustering at the firm level and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)
	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)
TGI_patent	**-0.0107**	**-0.0237**	**-0.0179**	**-0.0903**
	(-0.37)	**(-0.64)**	**(-0.46)**	**(-1.78)**
Size	-0.3526**	-1.0582***	-0.8224***	-1.7015***
	(-4.65)	(-6.69)	(-5.73)	(-6.31)
Bm_ratio	0.1585**	0.5021**	0.3201*	0.8030**
	(3.19)	(2.75)	(2.36)	(2.66)
Volatility	-0.0164	-0.0421	-0.0553	-0.0677
	(-0.73)	(-0.74)	(-1.08)	(-0.66)
MOM	0.1312*	0.4078*	0.2441	0.5180
	(2.19)	(2.09)	(1.62)	(1.56)
Beta	0.0017	0.0933	0.0759	0.1001
	(0.02)	(0.41)	(0.41)	(0.25)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	236,894	236,894	236,894	236,894
Adjusted R^2	0.005	0.005	0.012	0.012

Table 4.4 The Market Reaction to TGI and Non-TGI Information After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (3):

$$CAR_{i,t} = \alpha + \beta_1(TGI\_patent_i \times Post_t) + \beta_2 TGI\_patent_i + \beta_3 Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm i at on day t. $TGI\_patent_{i,t}$ is a dummy variable that equals one if firm i applied a TGI patent application on day t, zero firm i applied a TGI patent application on day t. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta*). All variables are defined in Appendix A4.1. γ_i and τ_t are i firm and year fixed effects, respectively. ε_{it} is the error term for firm i and day t. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for double clustering at the firm level and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)
TGI_patent× Post	**0.0890****	**0.1830*****	**0.1815****	**0.3174*****	**0.0888****	**0.1835*****	**0.1789****	**0.3118****
	(3.09)	**(4.56)**	**(2.77)**	**(3.44)**	**(3.18)**	**(4.46)**	**(2.58)**	**(3.08)**
TGI_patent	-0.0677*	-0.1455***	-0.1354**	-0.2998***	-0.0633*	-0.1323**	-0.1238**	-0.2748**
	(-2.13)	(-3.71)	(-2.59)	(-3.61)	(-2.10)	(-3.22)	(-2.38)	(-3.17)
Post	-0.1270**	-0.4182**	-0.3442**	-0.7751**	-	-	-	-
	(-2.51)	(-3.05)	(-2.78)	(-3.06)				
Size	-0.2205**	-0.6520***	-0.5058**	-1.0197**	-0.3537**	-1.0604***	-0.8246***	-1.7052***
	(-2.85)	(-3.31)	(-3.10)	(-3.06)	(-4.67)	(-6.71)	(-5.74)	(-6.32)
Bm_ratio	0.2095***	0.6518***	0.4717**	1.1163***	0.1583**	0.5017**	0.3197*	0.8023**
	(3.90)	(3.34)	(3.12)	(3.28)	(3.20)	(2.76)	(2.37)	(2.66)
Volatility	-0.0176	-0.0461	-0.0662	-0.0948	-0.0165	-0.0422	-0.0554	-0.0679
	(-0.82)	(-0.94)	(-1.24)	(-0.92)	(-0.73)	(-0.74)	(-1.08)	(-0.66)
MOM	0.1074	0.3265*	0.1926	0.4148	0.1316*	0.4087*	0.2450	0.5196
	(1.76)	(1.81)	(1.46)	(1.43)	(2.21)	(2.09)	(1.63)	(1.56)
Beta	0.0207	0.1315	0.1389	0.2328	0.0015	0.0929	0.0754	0.0993
	(0.29)	(0.68)	(0.81)	(0.64)	(0.02)	(0.41)	(0.41)	(0.25)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	236,894	236,894	236,894	236,894	236,894	236,894	236,894	236,894
Adjusted R^2	0.005	0.010	0.008	0.016	0.005	0.012	0.010	0.020

Table 4.5 The Market Reaction to TGI Information in Comparison Before and After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (4):

$$CAR_{i,t} = \alpha + \beta_1\, Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm i at on day t. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta*). All variables are defined in Appendix A4.1. γ_i is i firm fixed effect. ε_{it} is the error term for firm i and day t. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm level, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	(1) (0,+1)	(2) (0,+5)	(3) (-2,+2)	(4) (-5,+5)
Post	**-0.0594**	**-0.1212**	**-0.1354**	**-0.3880***
	(-0.92)	**(-0.99)**	**(-1.05)**	**(-1.67)**
Size	-0.1867	-0.7112***	-0.4677**	-0.9273**
	(-1.62)	(-3.87)	(-2.64)	(-3.07)
Bm_ratio	0.2419	0.4098	0.3924	1.0939**
	(1.66)	(1.77)	(1.69)	(2.71)
Volatility	-0.0610	-0.0667	-0.0734	-0.1433
	(-1.69)	(-1.05)	(-1.21)	(-1.45)
MOM	-0.0417	0.1491	-0.0900	0.1286
	(-0.46)	(0.90)	(-0.56)	(0.52)
Beta	0.1068	-0.1492	-0.0784	-0.3414
	(0.72)	(-0.65)	(-0.38)	(-1.05)
Firm FE	Yes	Yes	Yes	Yes
Observations	14,158	14,158	14,158	14,158
Adjusted R^2	0.017	0.016	0.017	0.028

Table 4.6 The Market Reaction to Non-TGI Information in Comparison Before and After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (4):

$$CAR_{i,t} = \alpha + \beta_1 Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm *i* at on day *t*. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta*). All variables are defined in Appendix A4.1. γ_i is *i* firm fixed effect. ε_{it} is the error term for firm *i* and day *t*. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm level, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	(1) (0,+1)	(2) (0,+5)	(3) (-2,+2)	(4) (-5,+5)
Post	**-0.1253********	**-0.4243*****	**-0.3444*****	**-0.7762*****
	(-5.80)	**(-8.31)**	**(-8.11)**	**(-9.51)**
Size	-0.2287***	-0.6551***	-0.5167***	-1.0363***
	(-6.69)	(-7.25)	(-7.12)	(-7.29)
Bm_ratio	0.2070***	0.6641***	0.4749***	1.1089***
	(4.68)	(6.31)	(5.64)	(6.80)
Volatility	-0.0154	-0.0444*	-0.0662***	-0.0914*
	(-1.66)	(-2.03)	(-3.36)	(-2.46)
MOM	0.1188***	0.3351***	0.2101***	0.4315***
	(3.99)	(4.71)	(3.41)	(3.42)
Beta	0.0128	0.1506	0.1493*	0.2737
	(0.37)	(1.79)	(2.04)	(1.92)
Firm FE	Yes	Yes	Yes	Yes
Observations	222,583	222,583	222,583	222,583
Adjusted R^2	0.004	0.010	0.008	0.016

Table 4.7 The Market Reaction to TGI Information Between High- and Low-polluting Industries After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (5):

$$CAR_{i,t} = \alpha + \beta_1(Post_t \times Industry_i) + \beta_2\, Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm i at on day t. $Post_t$ is a dummy variable that equals one if the firm applied a patent application in 2008 to 2012, zero if otherwise. $Industry_i$ is a dummy variable that equals one if firm i is in the high-polluting industry, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size*, *Bm_ratio*, *Volatility*, *MOM*, *Beta*). All variables are defined in Appendix A4.1. γ_i is i firm fixed effect. ε_{it} is the error term for firm i and day t. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm level, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)
	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)
Post× Industry	**0.0292**	**0.0567**	**0.0566**	**0.2784****
	(0.52)	**(0.59)**	**(0.65)**	**(2.17)**
Post	-0.0936	-0.2186**	-0.2182**	-0.6186***
	(-1.54)	(-2.11)	(-2.32)	(-4.48)
Size	-0.0001	0.0509	0.0342	0.1136***
	(-0.01)	(1.88)	(1.39)	(3.15)
Bm_ratio	0.2356***	0.5719***	0.4814***	1.1772***
	(4.72)	(6.74)	(6.22)	(10.39)
Volatility	-0.0327	-0.0750**	-0.0593	-0.1238***
	(-1.59)	(-2.14)	(-1.86)	(-2.65)
MOM	-0.0546	0.0434	-0.1062	0.0045
	(-0.78)	(0.36)	(-0.98)	(0.03)
Beta	0.0694	-0.1346	-0.0687	-0.1683
	(0.96)	(-1.09)	(-0.61)	(-1.02)
Firm FE	Yes	Yes	Yes	Yes
Observations	14,305	14,305	14,305	14,305
Adjusted R^2	0.002	0.004	0.004	0.009

Table 4.8 The Number of Analysts' Recommendation Revisions

This table reports number of analysts' recommendation revisions by levels of recommendation changes. Panel A provides the number of upgrading recommendations between TGI-relevant and TGI-irrelevant revisions. Panel B provides the number of downgrading recommendations between TGI-relevant and TGI-irrelevant revisions.

Panel A: Upgrading recommendation revisions (325 firms)

Recommendation change	TGI-relevant revisions			TGI-irrelevant revisions		
	Number of revisions	Number of analysts	Number of brokerages	Number of revisions	Number of analysts	Number of brokerages
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	1,625	229	21	1,680	333	22
2	144	62	18	159	82	18
3	5	3	3	10	8	6
4	2	2	2	2	2	2
Total	1,776	296	44	1,851	425	48

Panel B: Downgrading recommendation revisions (337 firms)

Recommendation change	TGI-relevant revisions			TGI-irrelevant revisions		
	Number of revisions	Number of analysts	Number of brokerages	Number of revisions	Number of analysts	Number of brokerages
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-1	1,863	263	23	1,698	318	23
-2	160	70	16	174	87	17
-3	9	3	3	20	11	5
-4	2	1	1	3	3	2
Total	2,034	337	43	1,895	419	47

Table 4.9 Descriptive Statistics

This table reported for summary statistics of all time-variant and time-invariant variables compose of *Actual_ret* is the actual returns on the revision dates. *CAR* is the DGTW cumulative abnormal return on the recommendation revision dates. *TGI_revision* is a dummy variable that equals one if the analyst d change the recommendation for firm i within 21 trading days after the TGI patent application filling date, zero is otherwise. *Size* is firm market value at the end of the year, *Bm_ratio* is the ratio of book value per share to the market value per share of firm at the end of the year, *Volatility* is standard deviation of daily stcok returns over the month, *MOM* is the buy and hold return over between -12 month and -2 month, *Beta* is a systematic risk indicator of the firm, *Analyst_cov* is the number of analysts covering the firm, *Away_from_concensus* is a dummy variable that takes the value of one if the absolute deviation of the new recommendation is higher than the absolute deviation of the prior recommendation from the consensus, and zero is otherwise, *Pre-earnings* is a dummy variable that takes value of one if the recommendation revision is issued in the two weeks (10 trading days) prior to a quarterly earnings announcement date, and zero is otherwise, *Post-earnings* is a dummy variable equal one if the recommendation revision is issued in the two weeks (10 trading days) after to a quarterly earnings announcement date, zero is otherwise, (*Broker_size*), the number of analysts employed by the brokerage house, analyst's portfolio (*Portfolio*), the number of firms followed by an individual analyst, analyst's experience (*Experience*) is the period (year) the analyst has covered the firm. All variables are defined in Appendix Table A4.1.

	Upgrading revision			Downgrading revision		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Observation	Mean	Std.	Observation	Mean	Std.
Actual_ret	2,812	0.805	2.895	3,057	-0.869	3.338
CAR (0,+1)	2,812	1.144	3.075	3,057	-1.461	3.639
CAR (0,+5)	2,812	1.123	4.557	3,057	-1.944	5.169
CAR (-5,+5)	2,812	2.575	6.934	3,057	-3.775	7.886
TGI_revision	2,812	0.367	0.482	3,057	0.385	0.487
Firm controls						
Size (billion USD)	2,812	7.572	10.093	3,057	6.698	9.599
Bm_ratio	2,812	0.768	0.392	3,057	0.849	0.462
Volatility (%)	2,812	2.420	0.935	3,057	2.623	1.380
MOM (%)	2,812	2.055	34.099	3,057	-1.887	33.845
Beta	2,812	1.106	0.285	3,057	1.097	0.287
Analyst_cov	2,812	11.954	5.501	3,057	11.521	5.718
Analyst controls						
Awa_from_concensus	2,812	0.417	0.493	3,057	0.421	0.494
Pre_earnings	2,812	0.303	0.459	3,057	0.306	0.461
Post_earnings	2,812	0.047	0.211	3,057	0.049	0.216
Broker_size	2,812	50.376	67.459	3,057	50.727	66.975
Portfolio	2,812	21.242	12.788	3,057	21.401	13.037
Experience (year)	2,812	3.553	2.178	3,057	3.553	2.219

Table 4.10 Univariate Analysis of Cumulative Abnormal Returns on Analysts' Upgrading Recommendation Revisions

This table reports the univariate summary statistics of DGTW cumulative abnormal returns (CARs) for three different event windows. The statistics reported for the entire sample period of 2003-2012 and compared the CARs between pre- (2003 – 2007) and post-commitment period (2008 – 2012) of the 1st Kyoto Protocol. Panel A reports the CARs of all analysts' upgrading recommendation revisions. Panel B reports the CARs of analysts' TGI-relevant upgrading recommendation revisions. Panel C reports the CARs of analysts' TGI-irrelevant upgrading recommendation revisions. Panel D reports mean comparison of CARs between TGI-relevant and TGI-irrelevant upgrading recommendation revisions. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Panel A: All upgrades												
	2003-2012 (2,812 Obs.)			Pre-period (1,306 Obs.)			Post-period (1,506 Obs.)			Mean comparison of CAR between pre-and post-period		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Event-window	(0,+1)	(0,+5)	(-5,+5)	(0,+1)	(0,+5)	(-5,+5)	(0,+1)	(0,+5)	(-5,+5)	(0,+1)	(0,+5)	(-5,+5)
Mean	1.14^{***}	1.12^{***}	2.57^{***}	1.11^{***}	1.22^{***}	2.81^{***}	1.17^{***}	1.03^{***}	2.37^{***}	0.06	-0.19	-0.44^{*}
std.	3.07	4.55	6.93	3.01	4.41	6.97	3.12	4.68	6.89	-	-	-
t-statistics	19.72	13.06	19.69	13.29	10.07	14.56	14.57	8.54	13.34	0.56	-1.15	1.68
Panel B: TGI-relevant upgrades												
	2003-2012 (1,033 Obs.)			Pre-period (429 Obs.)			Post-period (604 Obs.)					
Mean	1.19^{***}	1.29^{***}	2.77^{***}	1.39^{***}	1.75^{***}	3.39^{***}	1.04^{***}	098^{***}	2.33^{***}	-0.34^{*}	-0.77^{***}	-1.06^{**}
std.	3.07	4.48	6.75	3.05	4.37	7.30	3.08	4.53	6.29	-	-	-
t-statistics	12.42	9.30	13.19	8.33	8.28	9.62	9.41	5.29	9.08	1.77	-2.73	-2.51
Panel C: TGI-irrelevant upgrades												
	2003-2012 (1,779 Obs.)			Pre-period (877 Obs.)			Post-period (902 Obs.)					
Mean	1.11^{***}	1.02^{***}	2.46^{***}	0.97^{***}	0.97^{***}	2.52^{***}	1.26^{***}	1.06^{***}	2.40^{***}	0.29^{**}	0.09	-0.12
std.	3.07	4.59	7.03	2.98	4.41	6.79	3.15	4.77	7.26	-	-	-
t-statistics	15.33	9.36	14.75	9.63	6.54	11.01	11.99	6.70	9.91	1.99	0.42	-0.38
Panel D: Mean comparison of CAR between TGI-relevant and TGI-irrelevant upgrades												
	2003-2012			Pre-period			Post-period					
Mean-diff	0.08	0.27	0.31	0.42^{**}	0.77^{***}	0.87^{**}	-0.22	-0.08	-0.07^{*}	-0.64	-0.85	-0.94
t-statistics	0.60	1.55	1.14	2.37	2.99	2.12	-1.30	-0.36	-0.19	-	-	-

Table 4.11 Univariate Analysis of Cumulative Abnormal Returns on Analysts' Downgrading Recommendation Revisions

This table reports the univariate summary statistics of DGTW cumulative abnormal returns (CARs) for three different event windows. The statistics reported for the entire sample period of 2003-2012 and compared the CARs between pre- (2003 – 2007) and post-commitment period (2008 – 2012) of the 1st Kyoto Protocol. Panel A reports the CARs of all analysts' downgrading recommendation revisions. Panel B reports the CARs of analysts' TGI-relevant downgrading recommendation revisions. Panel C reports the CARs of analysts' TGI-irrelevant downgrading recommendation revisions. Panel D reports mean comparison of CARs between TGI-relevant and TGI-irrelevant downgrading recommendation revisions. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

	2003-2012 (3,057 Obs.)			Pre-period (1,385 Obs.)			Post-period (1,672 Obs.)			Mean comparison of CAR between pre-and post-period		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Event-window	(0,+1)	(0,+5)	(-5,+5)	(0,+1)	(0,+5)	(-5,+5)	(0,+1)	(0,+5)	(-5,+5)	(0,+1)	(0,+5)	(-5,+5)
Panel A: All downgrades												
Mean	-1.46***	-1.94***	-3.77***	-1.39***	-1.85***	-4.15***	-1.51***	-2.01***	-3.45***	-0.13	-0.15	0.70**
std.	3.63	5.17	7.88	3.22	4.62	7.76	3.94	5.58	7.97	-	-	-
t-statistics	-22.19	-20.79	-26.47	-16.04	-14.95	-19.92	-15.73	-14.76	-17.73	-0.96	-0.85	2.45
Panel B: TGI-relevant downgrades												
	2003-2012 (1,177 Obs.)			Pre-period (462 Obs.)			Post-period (715 Obs.)					
Mean	-1.39***	-1.67***	-3.45***	-1.34***	-1.62***	-4.54***	-1.43***	-1.71***	-2.74***	-0.09	-0.08	1.80***
std.	3.54	5.01	7.78	3.14	4.57	8.28	3.79	5.27	7.35	-	-	-
t-statistics	-17.71	-11.47	-15.23	-9.19	-7.64	-11.80	-10.11	-8.66	-9.98	-0.41	-0.28	3.90
Panel C: TGI-irrelevant downgrades												
	2003-2012 (1,880 Obs.)			Pre-period (923 Obs.)			Post-period (957 Obs.)					
Mean	-1.50***	-2.11***	-3.98***	-1.41***	-1.97***	-3.96***	-1.58***	-2.24***	-3.99***	-0.17	-0.27	-0.02
std.	3.69	5.26	7.94	3.26	4.64	7.49	4.06	5.79	8.36	-	-	-
t-statistics	-17.60	-17.40	-21.69	-13.14	-12.90	-16.07	-12.05	-11.99	-14.75	-0.99	-1.12	-0.06
Panel D: Mean comparison of CAR between TGI-relevant and TGI-irrelevant downgrades												
	2003-2012			Pre-period			Post-period					
Mean-diff	0.10	0.43**	0.52*	0.07	0.34	-0.58	0.15	0.53*	1.24***	0.08	0.19	1.82
t-statistics	0.76	2.26	1.79	0.38	1.32	1.31	0.77	1.94	3.16	-	-	-

Table 4.12 Stock Price Impacts of TGI-relevant and TGI-irrelevant Recommendation Revisions

The table below reports the results of a regression model as in the following equation (6):

$$CAR_{i,t} = \alpha + \beta_1 TGI\_revision_{i,d,t} + \delta_i \boldsymbol{X}_{i,t} + \varphi_i \boldsymbol{D}_{d,t} + \gamma_i + \lambda_d + \tau_t + \varepsilon_{idt}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm i at on day t. $TGI\_revision_{i,t}$ is a dummy variable that equals one if the analyst d change the recommendation for firm i within 21 trading days after the TGI patent application filling date, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size*, *Bm_ratio*, *Volatility*, *MOM*, *Beta*, *Analyst_cov*). $\boldsymbol{D}_{d,t}$ is a vector of analyst characteristic controls (*Away_from_concensus*, *Pre_earnings*, *Post_earnings*, *Broker_size*, *Portfolio*, *Experience*). All variables are defined in Appendix A4.1. γ_i, λ_d, and τ_t are i firm, d analyst and the year of day t fixed effects, respectively. ε_{idt} is the error term for firm, analyst, and day. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm, analyst and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Variable	Upgrade			Downgrade		
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)
TGI_revision	**0.3867*****	**0.5998****	**0.9582*****	**-0.2579**	**0.3393**	**0.2571**
	(3.33)	**(2.94)**	**(3.63)**	**(-0.89)**	**(1.18)**	**(0.52)**
Size	-0.5485	-0.9734*	-2.1993**	0.1135	0.2960	-0.7653
	(-1.36)	(-2.05)	(-2.30)	(0.26)	(0.39)	(-1.03)
Bm_ratio	0.7077	0.8778	1.2518	1.0604***	1.9224***	2.7060**
	(1.85)	(1.05)	(1.05)	(5.53)	(3.61)	(2.53)
Volatility	0.0792	-0.0386	0.1004	0.0333	-0.2138	-0.3894*
	(0.84)	(-0.23)	(0.42)	(0.60)	(-1.36)	(-2.13)
MOM	0.2556	0.0528	0.0221	-0.0313	0.2721	0.5864
	(1.16)	(0.09)	(0.04)	(-0.11)	(0.59)	(0.83)
Beta	0.2749	0.7547	0.7050	-0.2852	-0.9881	-1.4815
	(0.56)	(1.20)	(0.85)	(-0.69)	(-1.50)	(-1.17)
Analyst_cov	-0.2188	-0.7698	-1.3265	0.6516*	0.7548	0.6787
	(-0.75)	(-1.76)	(-1.69)	(1.93)	(1.35)	(1.00)
Away_from_concensus	0.3057**	0.3311**	0.3704*	-0.5758***	-0.6412*	-0.4830
	(3.18)	(3.16)	(2.02)	(-3.42)	(-2.25)	(-1.35)
Pre_earnings	0.2577	-0.1278	-0.1923	-0.3446	-0.9002	-1.3255
	(1.03)	(-0.34)	(-0.31)	(-1.16)	(-1.50)	(-1.16)
Post_earnings	-0.0481	0.1945	1.1795***	0.3168*	0.4850**	-0.8773
	(-0.32)	(0.75)	(4.46)	(2.00)	(2.34)	(-1.52)
Broker_size	0.1338	0.2134	0.7459***	0.2282	0.3220	-1.0833
	(1.71)	(1.66)	(6.50)	(0.93)	(0.82)	(-1.45)
Portfolio	-0.0202***	-0.0213**	-0.0157	0.0032	0.0133*	0.0290**
	(-3.63)	(-2.61)	(-1.17)	(0.41)	(1.99)	(2.64)
Experience	0.2377	0.2266	0.2776	0.0024	-0.0977	-0.0338
	(1.58)	(1.34)	(1.11)	(0.01)	(-0.51)	(-0.14)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,760	2,760	2,760	3,017	3,017	3,017
Adjusted R^2	0.085	0.076	0.105	0.060	0.077	0.144

Table 4.13 Stock Price Impacts of TGI-relevant and TGI-irrelevant Recommendation Revisions After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (7):

$$CAR_{i,t} = \alpha + \beta_1(TGI\_revision_{i,d,t} \times Post_t) + \beta_2 TGI\_revision_{i,d,t} + \delta_i \boldsymbol{X}_{i,t} + \varphi_i \boldsymbol{D}_{d,t} + \gamma_i + \lambda_d + \tau_t + \varepsilon_{idt}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm *i* at on day *t*. $TGI\_revision_{i,t}$ is a dummy variable that equals one if the analyst *d* change the recommendation for firm i within 21 trading days after the TGI patent application filling date, zero is otherwise. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta, Analyst_cov*). $\boldsymbol{D}_{d,t}$ is a vector of analyst characteristic controls (*Pre_earnings, Post_earnings, Broker_size, Portfolio, Experience*). All variables are defined in Appendix A4.1. γ_i, λ_d, and τ_t are *i* firm, *d* analyst and the year of day *t* fixed effects, respectively. ε_{idt} is the error term for firm, analyst, and day. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm, analyst and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Variable	Upgrade			Downgrade		
	(1) CAR(0,+1)	(2) CAR(0,+5)	(3) CAR(-5,+5)	(4) CAR(0,+1)	(5) CAR(0,+5)	(6) CAR(-5,+5)
TGI_revision×Post	**-0.6436*****	**-0.9436****	**-0.8421***	**0.0485**	**0.1302**	**1.4037****
	(-3.27)	**(-2.56)**	**(-1.90)**	**(0.12)**	**(0.28)**	**(3.11)**
TGI_revision	0.7523***	1.1358***	1.4366**	-0.2855	0.2652	-0.5416
	(4.11)	(3.92)	(3.16)	(-0.88)	(0.65)	(-0.96)
Size	-0.5573	-0.9863*	-2.2108**	0.1148	0.2993	-0.7287
	(-1.44)	(-2.19)	(-2.38)	(0.26)	(0.40)	(-0.96)
Bm_ratio	0.7506*	0.9406	1.3079	1.0560***	1.9106**	2.5781**
	(1.94)	(1.15)	(1.10)	(5.40)	(3.70)	(2.35)
Volatility	0.0793	-0.0384	0.1005	0.0334	-0.2137	-0.3888*
	(0.85)	(-0.24)	(0.42)	(0.60)	(-1.38)	(-2.17)
MOM	0.2498	0.0444	0.0146	-0.0332	0.2671	0.5320
	(1.13)	(0.07)	(0.02)	(-0.11)	(0.59)	(0.77)
Beta	0.3182	0.8182	0.7617	-0.2892	-0.9987	-1.5957
	(0.65)	(1.29)	(0.90)	(-0.70)	(-1.56)	(-1.26)
Analyst_cov	-0.2258	-0.7801	-1.3357	0.6477*	0.7443	0.5658
	(-0.77)	(-1.81)	(-1.72)	(2.01)	(1.36)	(0.83)
Away_from_concensus	0.2929**	0.3124**	0.3537*	-0.5762***	-0.6425*	-0.4962
	(3.04)	(2.94)	(1.92)	(-3.39)	(-2.26)	(-1.42)
Pre_earnings	0.2805	-0.0943	-0.1624	-0.3435	-0.8972	-1.2930
	(1.09)	(-0.24)	(-0.25)	(-1.16)	(-1.50)	(-1.13)
Post_earnings	-0.0492	0.1930	1.1781***	0.3171*	0.4859**	-0.8679
	(-0.32)	(0.74)	(4.45)	(2.03)	(2.34)	(-1.50)

Table 4.13 continued

Variable	Upgrade			Downgrade		
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)
Broker_size	0.1372	0.2185	0.7504***	0.2273	0.3196	-1.1087
	(1.79)	(1.71)	(6.31)	(0.92)	(0.82)	(-1.50)
Portfolio	-0.0197**	-0.0205**	-0.0150	0.0031	0.0133*	0.0285**
	(-3.50)	(-2.47)	(-1.11)	(0.40)	(1.95)	(2.44)
Experience	0.2331	0.2198	0.2716	0.0019	-0.0991	-0.0490
	(1.55)	(1.31)	(1.08)	(0.01)	(-0.50)	(-0.21)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,760	2,760	2,760	3,017	3,017	3,017
Adjusted R^2	0.087	0.078	0.105	0.060	0.077	0.145

Table 4.14 The Market Reaction to TGI and Non-TGI Information

The table below reports the results of a regression model as in the following equation (2):

$$CAR_{i,t} = \alpha + \beta_1 TGI\_patent_i + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the cumulative abnormal return for firm *i* at on day *t*. $TGI\_patent_{i,t}$ is a dummy variable that equals one if firm *i* applied a TGI patent application on day *t*, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta*). All variables are defined in Appendix A4.1. γ_i and τ_t are *i* firm and year fixed effects, respectively. ε_{it} is the error term for firm *i* and day *t*. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for double clustering at the firm level and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Panel A: Cumulative abnormal returns on the market adjusted model				
	(1)	(2)	(3)	(4)
	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)
TGI _patent	-0.0044	-0.0067	0.0061	-0.0530
	(-0.16)	(-0.15)	(0.13)	(-0.88)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	237,480	237,480	237,,480	237,480
Adjusted R^2	0.005	0.010	0.009	0.020
Panel B: Cumulative abnormal returns on the value-weight industry-adjusted model				
	(1)	(2)	(3)	(4)
	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)
TGI _patent	0.0051	-0.0148	-0.0084	-0.0768
	(0.21)	(-0.38)	(-0.22)	(-1.34)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	237,480	237,480	237,480	237,480
Adjusted R^2	0.004	0.010	0.008	0.017

Table 4.15 The Market Reaction to TGI and Non-TGI Information After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (3):

$$CAR_{i,t} = \alpha + \beta_1(TGI\_patent_i \times Post_t) + \beta_2 TGI\_patent_i + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the cumulative abnormal return for firm *i* at on day *t*. $TGI\_patent_{i,t}$ is a dummy variable that equals one if firm *i* applied a TGI patent application on day *t*, zero is otherwise. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size*, *Bm_ratio*, *Volatility*, *MOM*, *Beta*). All variables are defined in Appendix A4.1. γ_i and τ_t are *i* firm and year fixed effects, respectively. ε_{it} is the error term for firm *i* and day *t*. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for double clustering at the firm level and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Panel A: Cumulative abnormal returns on the market adjusted model				
	(1) (0,+1)	(2) (0,+5)	(3) (-2,+2)	(4) (-5,+5)
TGI _patent× Post	0.0907**	0.1995**	0.2664***	0.3779***
	(3.02)	(2.30)	(5.68)	(3.24)
TGI _patent	-0.0583*	-0.1125**	-0.1651***	-0.2778***
	(-1.97)	(-2.32)	(-4.83)	(-3.16)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	237,480	237,480	237,,480	237,480
Adjusted R^2	0.005	0.009	0.009	0.017

Panel B: Cumulative abnormal returns on the value-weight industry-adjusted model				
	(1) (0,+1)	(2) (0,+5)	(3) (-2,+2)	(4) (-5,+5)
TGI _patent× Post	0.1143***	0.2026**	0.2803***	0.4294**
	(5.75)	(2.18)	(5.17)	(3.01)
TGI _patent	-0.0868***	-0.1289**	-0.1918***	-0.3322***
	(-3.62)	(-2.38)	(-4.51)	(-3.33)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	237,480	237,480	237,480	237,480
Adjusted R^2	0.008	0.008	0.010	0.017

Table 4.16 The Market Reaction to TGI Information Between High- and Low-polluting Industries After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (5):

$$CAR_{i,t} = \alpha + \beta_1(Post_t \times Industry_i) + \beta_2\, Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the DGTW cumulative abnormal return for firm *i* at on day *t*. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $Industry_i$ is a dummy variable that equals one if firm *i* is in the high-polluting industry, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size*, *Bm_ratio*, *Volatility*, *MOM*, *Beta*). All variables are defined in Appendix A4.1. γ_i is *i* firm fixed effect. ε_{it} is the error term for firm *i* and day t. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm level, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Panel A: Carbon emissions scope 1				
	(1) (0,+1)	(2) (0,+5)	(3) (-2,+2)	(4) (-5,+5)
Post×Industry	**0.0332**	**0.0962**	**0.0518**	**0.2513***
	(0.56)	**(0.98)**	**(0.58)**	**(1.93)**
Post	-0.1029*	-0.2253**	-0.1995**	-0.5610***
	(-1.66)	(-2.18)	(-2.11)	(-4.09)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	14,305	14,305	14,305	14,305
Adjusted R^2	0.005	0.012	0.010	0.020
Panel B: Carbon emissions scope 2				
	(1) (0,+1)	(2) (0,+5)	(3) (-2,+2)	(4) (-5,+5)
Post×Industry	**0.0325**	**0.0938**	**0.0110**	**0.3036****
	(0.53)	**(0.92)**	**(0.12)**	**(2.24)**
Post	-0.1054	-0.2324**	-0.1761*	-0.6196***
	(-1.59)	(-2.11)	(-1.75)	(-4.24)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	14,305	14,305	14,305	14,305
Adjusted R^2	0.005	0.012	0.010	0.020
Panel C: Carbon emissions scope 3				
	(1) (0,+1)	(2) (0,+5)	(3) (-2,+2)	(4) (-5,+5)
Post×Industry	**0.0269**	**0.0950**	**-0.0171**	**0.2091**
	(0.42)	**(0.90)**	**(-0.18)**	**(1.49)**
Post	-0.1021	-0.2351**	-0.1565	-0.5590***
	(-1.50)	(-2.07)	(-1.51)	(-3.72)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	14,305	14,305	14,305	14,305
Adjusted R^2	0.005	0.012	0.010	0.020

Table 4.17 Stock Price Impacts of TGI-relevant and TGI-irrelevant Recommendation Revisions

The table below reports the results of a regression model as in the following equation (6):

$$CAR_{i,t} = \alpha + \beta_1 TGI\_revision_{i,d,t} + \delta_i \boldsymbol{X}_{i,t} + \varphi_i \boldsymbol{D}_{d,t} + \gamma_i + \lambda_d + \tau_t + \varepsilon_{idt}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the cumulative abnormal return for firm *i* at on day *t*. $TGI\_revision_{i,t}$ is a dummy variable that equals one if the analyst *d* change the recommendation for firm i within 21 trading days after the TGI patent application filling date, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta, Analyst_cov*). $\boldsymbol{D}_{d,t}$ is a vector of analyst characteristic controls (*Away_from_concensus, Pre_earnings, Post_earnings, Broker_size, Portfolio, Experience*). All variables are defined in Appendix A4.1. γ_i, λ_d, and τ_t are *i* firm, *d* analyst and the year of day *t* fixed effects, respectively. ε_{idt} is the error term for firm, analyst, and day. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm, analyst and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Panel A: Upgrading revisions

Variable	Market-adjusted returns			Industry-adjusted returns		
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)
TGI_revision	0.3369**	0.6567**	0.6649**	0.3218**	0.4975**	0.4484
	(2.92)	(2.91)	(2.57)	(2.58)	(2.90)	(1.69)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,762	2,762	2,762	2,762	2,762	2,762
Adjusted R^2	0.078	0.077	0.107	0.096	0.076	0.109

Panel B: Downgrading revisions

Variable	Market-adjusted returns			Industry-adjusted returns		
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)
TGI_revision	-0.2118	0.2865	0.2798	-0.1553	0.1792	-0.0275
	(-0.71)	(0.83)	(0.53)	(-0.76)	(0.66)	(-0.05)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,017	3,017	3,017	3,017	3,017	3,017
Adjusted R^2	0.063	0.078	0.147	0.075	0.089	0.169

Table 4.18 Stock Price Impacts of TGI-relevant and TGI-irrelevant Recommendation Revisions After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (7):

$$CAR_{i,t} = \alpha + \beta_1(TGI\_revision_{i,d,t} \times Post_t) + \beta_2 TGI\_revision_{i,d,t} + \delta_i \boldsymbol{X}_{i,t} + \varphi_i \boldsymbol{D}_{d,t} + \gamma_i + \lambda_d + \tau_t + \varepsilon_{idt}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the cumulative abnormal return for firm *i* at on day *t*. $TGI\_revision_{i,t}$ is a dummy variable that equals one if the analyst *d* change the recommendation for firm i within 21 trading days after the TGI patent application filling date, zero is otherwise. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size, Bm_ratio, Volatility, MOM, Beta, Analyst_cov*). $\boldsymbol{D}_{d,t}$ is a vector of analyst characteristic controls (*Pre_earnings, Post_earnings, Broker_size, Portfolio, Experience*). All variables are defined in Appendix A4.1. γ_i, λ_d, and τ_t are *i* firm, *d* analyst and the year of day *t* fixed effects, respectively. ε_{idt} is the error term for firm, analyst, and day. I winsorise all control variables at 1% and 99% levels. The standard errors are corrected for clustering at the firm, analyst and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Panel A: Upgrading revisions						
	Market-adjusted returns			Industry-adjusted returns		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)
TGI_revision×Post	-0.5063**	-0.9425**	-0.6621	-0.4077**	-0.7589**	-0.4077**
	(-2.28)	(-2.36)	(-1.38)	(-2.33)	(-2.73)	(-2.33)
TGI_revision	0.6245**	1.1771***	1.0022*	0.5535**	0.9287***	0.5535**
	(3.10)	(3.63)	(2.00)	(2.89)	(3.49)	(2.89)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,762	2,762	2,762	2,762	2,762	2,762
Adjusted R^2	0.079	0.079	0.106	0.096	0.077	0.109
Panel B: Downgrading revisions						
	Market-adjusted returns			Industry-adjusted returns		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)	CAR(0,+1)	CAR(0,+5)	CAR(-5,+5)
TGI_revision×Post	0.0626	0.0647	1.2803**	0.0999	0.2576	1.0625**
	(0.14)	(0.14)	(2.49)	(0.42)	(1.00)	(2.88)
TGI_revision	-0.2474	0.2497	-0.4488	-0.2122	0.0327	-0.6320
	(-0.75)	(0.62)	(-0.74)	(-0.90)	(0.10)	(-1.12)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,017	3,017	3,017	3,017	3,017	3,017
Adjusted R^2	0.062	0.078	0.148	0.075	0.089	0.170

Figure 4.1 Cumulative Abnormal Returns of the Two-day Window Between TGI and Non-TGI Patent Applications

Figure 4.1 shows the trend of the DGTW cumulative abnormal returns on the event window (0,+1) between TGI and non-TGI patent application filling dates. The red line and blue line, respectively, represent the TGI patent and non-TGI patent applications. The figure covers the pre- and post-periods of the 1st Kyoto Protocol commitment (2003 – 2012).

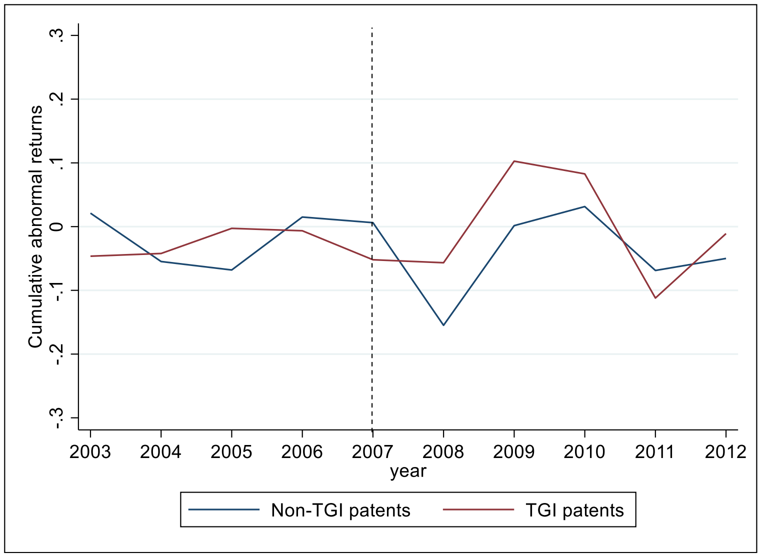


Figure 4.2 Cumulative Abnormal Returns of the Eleven-day Window Between TGI and Non-TGI Patent Applications

Figure 4.2 shows the trend of the DGTW cumulative abnormal returns on the event window (-5,+5) between TGI and non-TGI patent application filling dates. The red line and blue line, respectively, represent the TGI patent and non-TGI patent applications. The figure covers the pre- and post-periods of the 1st Kyoto Protocol commitment (2003 – 2012).

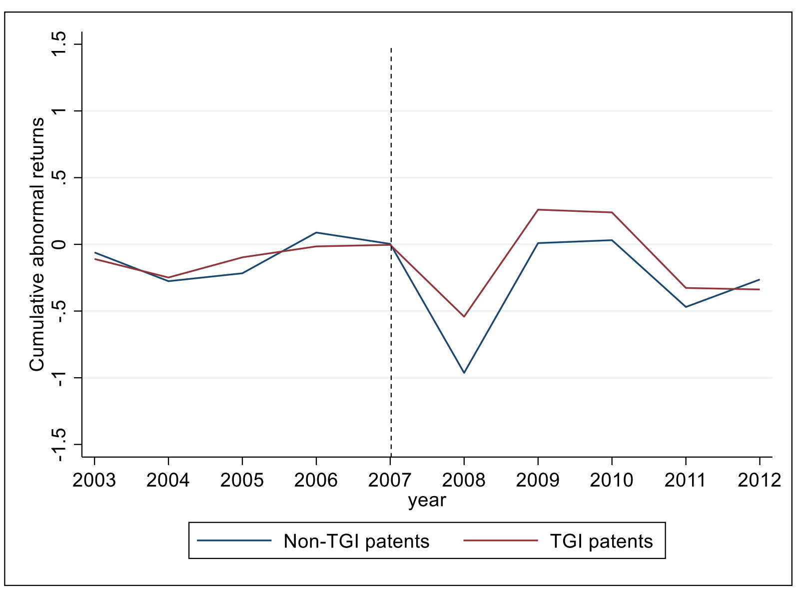


Figure 4.3 The Frequency of TGI-relevant Upgrading and Downgrading Recommendation Revisions

Figure 4.3 reports the number of TGI-relevant upgrading and downgrading revisions cover 22 trading days (day zero is the TGI patent application filling dates). The blue bar chart and red bar chart, respectively, represent upgrading revisions and downgrading revisions.

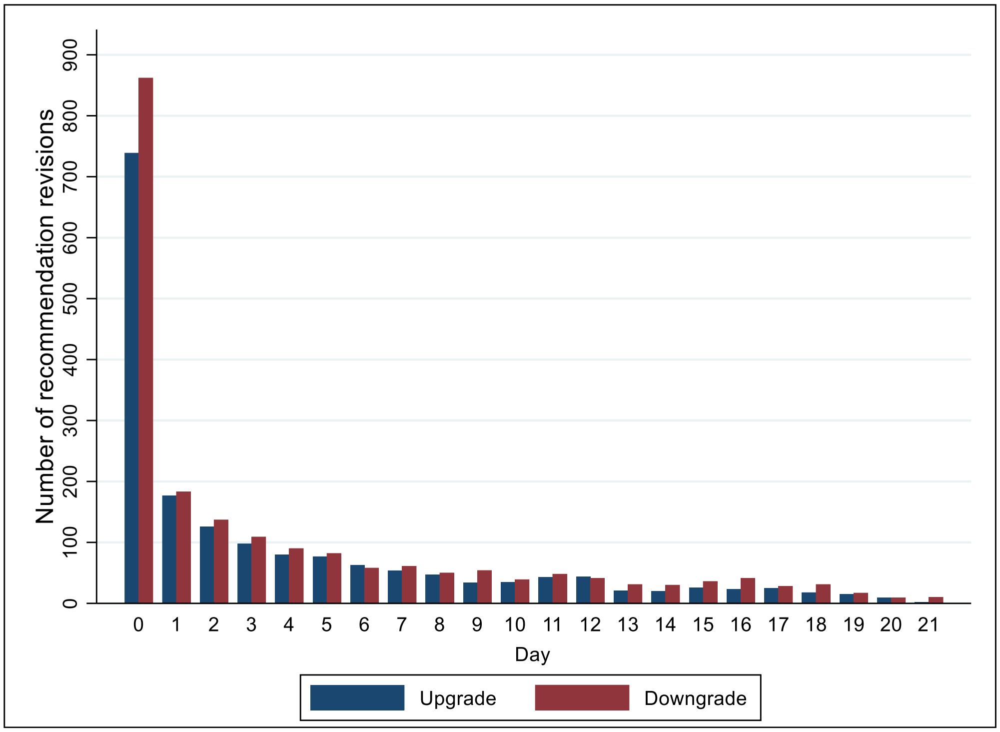


Figure 4.4 Cumulative Abnormal Returns on TGI-relevant and TGI-irrelevant revisions of Analysts' Upgrading Recommendations

Figure 4.4 shows the trend of the DGTW cumulative abnormal returns on the event window (0,+1) between TGI-relevant and TGI-irrelevant revisions of analysts' upgrading recommendations. The red and blue lines represent the stock price movements of TGI-relevant revisions and TGI-irrelevant revisions, respectively. The figure covers the pre-commitment period (2003 – 2007) and the post-commitment period (2008 – 2012) of the 1st Kyoto Protocol.

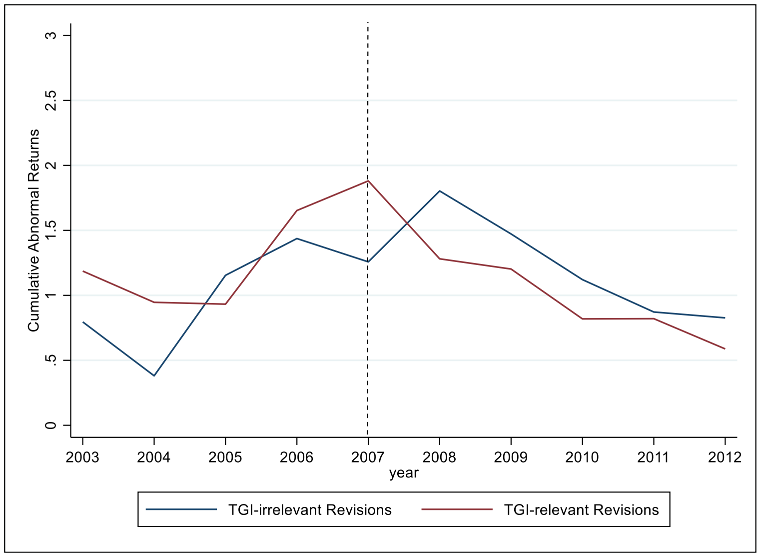
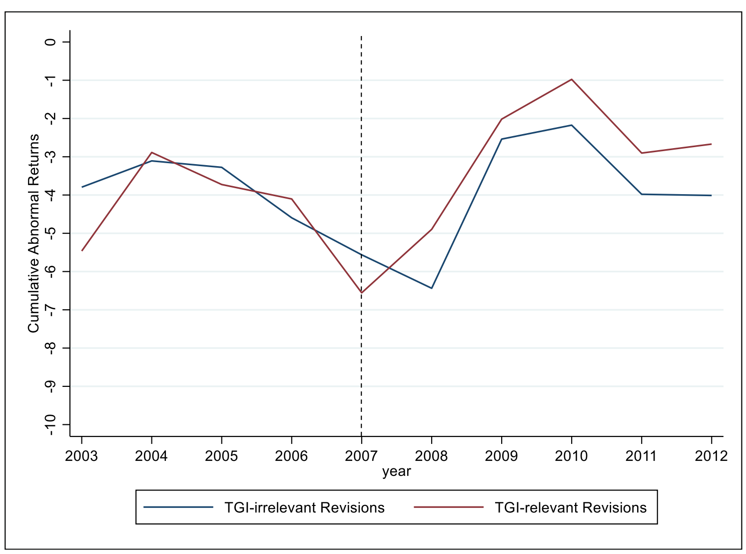


Figure 4.5 Cumulative Abnormal Returns on TGI-relevant and TGI-irrelevant revisions of Analysts' Downgrading Recommendations

Figure 4.5 shows the trend of the DGTW cumulative abnormal returns on the event window (-5,+5) between TGI-relevant and TGI-irrelevant revisions of analysts' downgrading recommendations. The red and blue lines represent the stock price movements of TGI-relevant revisions and TGI-irrelevant revisions, respectively. The figure covers the pre-commitment period (2003 – 2007) and the post-commitment period (2008 – 2012) of the 1st Kyoto Protocol.



Appendix

Table A4.1 Variable Descriptions

Variable	Description	Source
TGI_patent	A dummy variable that equals one if the firm applied a TGI patent application, zero if the firm applied a non-TGI patent application.	PATSTAT
TGI_revision	A dummy variable that equals one if the analyst changes the recommendation for the covered firm within 21 trading days after TGI patent application filling date, zero is otherwise.	I/B/E/S
Post	A dummy variable that equals one for the year 2008 to 2012, zero is otherwise	
Industry	A dummy variable that equals one if the firm is in highly carbon emission industry, zero is otherwise.	TRUCOST
Size	The natural logarithm of firm market value at the end of the year prior to the day t	COMPUSTAT
Bm_ratio	The ratio of book value per share to the market value per share of firm at the end of the year prior to the day t	COMPUSTAT
Volatility	Standard deviation of daily stock returns over the month prior to the day t	COMPUSTAT
MOM	The buy and hold return over between -12 month and -2 month prior to the day t	COMPUSTAT
Beta	Systematic risk indicator of the firm compared to the exchange market	COMPUSTAT
Analyst_cov	The natural logarithm of the number of analysts following the firms in the corresponding period	I/B/E/S
Away_from_concensus	A dummy variable that takes the value of one if the absolute deviation of the new recommendation is higher than the absolute deviation of the prior recommendation from the consensus, and zero is otherwise	I/B/E/S
Pre_earnings	A dummy variable equal one if the recommendation revision issued in the two weeks (10 trading days) prior to a quarterly earnings announcement date	I/B/E/S
Post_earnings	A dummy variable equal one if the recommendation revision issued in the two weeks (10 trading days) after to a quarterly earnings announcement date	I/B/E/S
Broker_size	The natural logarithm of employed analyst numbers by the brokerage house	I/B/E/S
Portfolio	The number of firms followed by an individual analyst	I/B/E/S
Experience	The period (year) the analyst has covered the firm minus the average number of years that all analysts have covered	I/B/E/S

Table A4.2 Carbon Emission Industry Classifications

Panel A: Total Cabon emission			
No.	GICS (6 digits)	Industry Name	CO2e.(Million tons)
1	101020	Oil, Gas & Consumable Fuels	4903.060
2	551010	Electric Utilities	4277.858
3	151040	Metals & Mining	2778.988
4	551050	Independent Power and Renewable Electricity Producers	1573.802
5	302020	Food Products	1354.210
6	201060	Machinery	1156.006
7	151010	Chemicals	845.691
8	203010	Air Freight & Logistics	667.090
9	201020	Building Products	619.216
10	101010	Energy Equipment & Services	600.200

Panel B: Carbon emission Scope 1			
No.	GICS (6 digits)	Industry Name	CO2e.(Million tons)
1	551010	Electric Utilities	3821.901
2	101020	Oil, Gas & Consumable Fuels	2644.045
3	151040	Metals & Mining	1718.209
4	551050	Independent Power and Renewable Electricity Producers	1467.686
5	203010	Air Freight & Logistics	541.604
6	101010	Energy Equipment & Services	397.233
7	151010	Chemicals	309.668
8	201050	Industrial Conglomerates	274.106
9	201020	Building Products	205.253
10	302020	Food Products	154.260

Panel B: Carbon emission Scope 2			
No.	GICS (6 digits)	Industry Name	CO2e.(Million tons)
1	101020	Oil, Gas & Consumable Fuels	349.598
2	151040	Metals & Mining	289.673
3	201010	Aerospace & defense	98.332
4	151010	Chemicals	96.731
5	551010	Electric Utilities	95.809
6	201060	Machinery	77.548
7	201020	Building Products	77.104
8	302020	Food Products	59.985
9	301010	Food & Staples Retailing	58.335
10	253010	Hotels, Restaurants & Leisure	46.143

Table A4.2 continued

Panel B: Carbon emission Scope 3			
No.	GICS (6 digits)	Industry Name	CO2e.(Million tons)
1	101020	Oil, Gas & Consumable Fuels	1909.417
2	302020	Food Products	1139.965
3	201060	Machinery	992.432
4	151040	Metals & Mining	771.105
5	151010	Chemicals	439.291
6	201010	Aerospace & defense	392.994
7	551010	Electric Utilities	360.148
8	201020	Building Products	336.859
9	201030	Construction & Engineering	277.354
10	301010	Food & Staples Retailing	231.848

Table A4.3 The Market Reaction on TGI and Non-TGI Information After the 1st Kyoto Protocol Commitment

The table below reports the results of a regression model as in the following equation (4):

$$CAR_{i,t} = \alpha + \beta_1 Post_t + \delta_i \boldsymbol{X}_{i,t} + \gamma_i + \tau_t + \varepsilon_{it}$$

All variables noted in the above equations are defined in Appendix A4.1. $CAR_{i,t}$ is the cumulative abnormal return for firm *i* at on day *t*. $Post_t$ is a dummy variable that equals one for the year 2008 to 2012, zero is otherwise. $\boldsymbol{X}_{it-1}$ is a vector of firm-level controls (*Size*, *Bm_ratio*, *Volatility*, *MOM*, *Beta*). All variables are defined in Appendix A4.1. γ_i and τ_t are *i* firm and year fixed effects, respectively. ε_{it} is the error term for firm *i* and day *t*. We winsorise all control variables at 1% and 99% levels. The standard errors are corrected for double clustering at the firm level and time, and the t-stats are presented in parentheses. *, **, and *** denote statistical significance at 10%, 5% and 1% significance levels, respectively.

Panel A: TGI information samples								
	Market adjusted CAR				Value-weight industry-adjusted CAR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)
Post	0.0161	0.0617	0.0667	-0.0746	-0.0296	-0.1032	-0.0434	-0.3719***
	(0.24)	(0.55)	(0.64)	(-0.50)	(-0.44)	(-0.94)	(-0.43)	(-2.60)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,472	14,472	14,,472	14,472	14,472	14,472	14,,472	14,472
Adjusted R^2	0.025	0.016	0.021	0.020	0.022	0.014	0.016	0.015

Panel B: Non-TGI information samples								
	Market adjusted CAR				Value-weight industry-adjusted CAR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)	(0,+1)	(0,+5)	(-2,+2)	(-5,+5)
Post	-0.0860***	-0.4059***	-0.2811***	-0.6692***	-0.1442***	-0.4981***	-0.3925***	-0.9380***
	(-3.73)	(-7.04)	(-6.11)	(-7.36)	(-6.44)	(-8.65)	(-8.21)	(-9.85)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	223,002	223,002	223,002	223,002	223,002	223,002	223,002	223,002
Adjusted R^2	0.004	0.009	0.007	0.014	0.003	0.007	0.005	0.011

5. CONCLUSIONS

The shifting of investment behaviour and strategy, the enthusiasm of global listed companies on sustainability transition, and existing academic literature emphasise the importance of participation in developing climate change prevention mechanisms. That growing and sustainable the finance considers/discusses financial value and values based on principles separately, exposes significant research gaps in the ambiguity of market participants' decision-making on climate-friendly engagement. While most finance literature focuses on strategic outcomes, e.g. firms' carbon emission levels and environmental performance, my study examines the market participants' responses to firms' climate-friendly strategies, particularly innovative development activities related to the environment, representing the reliability of firms' commitment to the environment.

My study addresses the gap in the literature regarding strategic management promoting innovative environmental activities. The empirical chapters discuss long-term and short-term TGI implications, e.g. economic and environmental contributions. I develop empirical frameworks that show the effects of TGI activities on the views of market participants, investors and financial analysts.

In summary, I identify that investors view the long-term and short-term effects of TGI activities differently. In the long term, TGI generates competitive advantages and sustainability. Consequently, firms' TGI activities attract more IIs' investments. In the short run, however, TGI increases uncertainty in profitability and information asymmetry. This creates pessimism in investors' views regarding the firm's future value. Similarly, uncertainty related to TGI activities reduces analysts' confidence in covering such firms. All empirical chapters offer significant evidence to support my primary predictions.

In the following paragraphs, I briefly summarise the key findings of each empirical chapter alongside their implications.

5.1 The Key Findings of the First Empirical Chapter: Does Technological Green Innovation Attract Institutional Investors?

The first empirical chapter of this thesis analyses the relationship between firms promoting TGI activities and institutional ownership (IO) following the investment mainstream of institutional investors (IIs) towards sustainability. Using a large granular dataset and covering global exchange markets, this study shows the impacts of TGI on IIs' investment. My evidence encourages firms to transform green assets by highlighting the benefits of firms using innovative strategic transitions. I conclude my findings on the following two aspects.

Firstly, the results show that TGI intensity motivates IIs (domestic and foreign) to invest more in firms promoting TGI. I find that the firms engaged in TGI reveal the firms' commitment to the environment. The evidence indicates that firms using the TGI development strategy can increase long-term sustainability and competitiveness and reap the benefits of climate regulations. These benefits alter the investors' perspectives on climate risk mitigation. On the other hand, regulatory and reputational concerns, social pressures, and mechanisms pressuring IIs' disclosure (e.g. the intensity of environmentally conscious clients) induce investment allocations of IIs into firms supporting environmental causes.

Secondly, my results show that the investment intensity of IIs in TGI firms depends on their characteristics. Investors with different roles in firm monitoring (independent versus grey) express different perspectives in firms with TGI. Independent IIs, who are concerned about firms' operations and closely monitor management decisions, tend to invest more in firms promoting TGI activities than grey IIs, who are closely linked with firm management. Holding ownership in a firm that promotes TGI activities benefits independent IIs because the TGI contribution to operating efficiency can enhance their reputation and reduce their monitoring costs.

Furthermore, I find that the investment horizons of IIs also affect their decision to invest in TGI firms. I find that TGI intensity attracts more long-term IIs' investment compared to short-term IIs. This evidence reflects an individual investor's financial constraint and conditions to the investment decision in TGI. Long-term investors who follow more passive trading strategies can take the long-term maximise benefits of TGI activities rather than short-term IIs by using the frequent trading strategy on event-specific knowledge.

The empirical evidence also suggests that investors can capture and allocate portfolios based on managers' strategic decisions related to environmental development. Firms promoting TGI activities that reflect intensive environmental practices attract more investments from IIs. Further, the investment decisions of IIs in TGI firms are associated with the financial conditions and strategies of individual IIs, including social perception and policy mechanisms encouraging environmental engagement.

5.2 The Key Findings of the Second Empirical Chapter: Financial Analysts and Technological Green Innovation

The second empirical chapter of this thesis develops arguments based on the analysts' career concern hypothesis to understand the causal relationship between firms' TGI intensity and the analysts' activities. (i.e. a decision to monitor the TGI firms, recommendations issued and earning forecast ability). The career concerns hypothesis suggests that analysts tend to avoid firms with higher information complexity and uncertainty, as such a scenario can reduce their forecasting abilities. Analysts' activities reflect their perspective and bias on the expectation of TGI benefits and affect promoting (or demoting) TGI engagement in the capital markets. My systematic analysis allowed us to understand analysts' preferences, especially under the pretext of their trade-off between generating trading commissions for their employer and building their own professional reputations. My findings are summarised below.

First, I find that the level of TGI intensity of a firm and the number of analysts following the firm are inversely related. This supports the view that TGI activities create higher information complexity and uncertainty in the firm's short-term operations. TGI activities require analysts' additional efforts to evaluate the firm's future cash flow, i.e., more brokerage resources and monitoring costs need to be deployed. In the short term, TGI causes higher uncertainty in the firm's profitability and dilutes the stock's attractiveness; hence, the analysts' trading commission is adversely affected. Thus, analysts tend to avoid following such firms.

Second, firms with high TGI intensity tend to receive poor analyst recommendations. This evidence is also related to the career concerns hypothesis, which argues that analysts' optimistic (pessimistic) bias depends on analysts’ positive (negative) expectations of firms’ future performance. TGI generates cash flow uncertainty, pushes analysts to overestimate uncertain risks, and provides unfavourable recommendations. On the other hand, analysts who are concerned about their careers also use their recommendations to pressure firms’ management to increase short-term performance by reducing long-term investment related to TGI activities.

Finally, my findings suggest that the levels of TGI intensity reduce analysts’ forecasting ability. This is confirmed by the evidence of increased forecast errors and lower consistency in the analysts’ forecasts. The evidence indicates that higher cash flow uncertainty and limited public disclosure of firms’ innovative development projects can impede analysts’ ability to incorporate the value of TGI information and the firm’s future value. This lower forecasting ability of analysts, caused by increased TGI intensity, also supports the idea that analysts are concerned about their careers.

These findings point out that financial analysts consider short-term implications of TGI contributions more than long-term TGI implications. Analysts’ pessimistic bias about TGI intensity reflects concerns about short-term cash flow uncertainty and financial distress risk. Thus, I can conclude that levels of firms’ information complexity and uncertainty in future performance are key elements that impact the analysts’ reputations and their forecasts.

5.3 The Key Findings of the Third Empirical Chapter: Market Reactions and Analysts' Recommendation Revisions on Technological Green Innovation

The final empirical chapter offers systematic frameworks to investigate markets' perceptions of TGI activities. Comparing the market reactions to TGI and non-TGI information allows us to investigate investors' views on short-term TGI value relative to non-TGI value. Moreover, the market reaction to TGI information can impact the value of analysts' recommendations. The following findings emerge.

First, the evidence indicates that the market negatively reacts to TGI and non-TGI information. The negative stock returns in response to both types of innovative information suggest that investors are concerned about the uncertainty caused by technological transition and lack confidence in innovation's short-term value benefit.

Second, the findings of the empirical analyses that employ the 1st Kyoto Protocol commitment as an exogenous regulation suggest that the commitment has no bearing on the market reactions to TGI information, while non-TGI information has a negative effect. The evidence points out that investors' perceptions shift along with their concern about climate regulation risks. This benefits firms promoting TGI activities and ultimately implies the reliability of environmental engagement. On the other hand, environmental regulation can motivate investors to expect more TGI engagement from managers. Therefore, firms providing non-TGI information that is against the investors' expectations will be pressured by the market, adversely affecting their stock prices.

Finally, my findings suggest that the value of analysts' recommendations is related to the disclosure of TGI information. I find that analysts' upgraded recommendations, in response to TGI information, generate significantly positive stock returns, but downgraded recommendations do not affect the stock price movement. I also find that market reactions to analysts' upgrading (downgrading) recommendations in response to TGI information are diluted during the 1st Kyoto Protocol commitment period. This implies that enforcing environmental regulation reduces information asymmetry related to firms' environmental practices. This, in turn, reduces investors' misinterpretation regarding TGI information and motivates them to incorporate the value of TGI in stock prices.

My empirical evidence suggests that investors are pessimistic about technological transition in the short run. Firms investing in technological innovation, particularly TGI activities, are undervalued due to uncertainty in their future profitability and TGI's limitations to increasing financial benefits. The empirical analysis using the 1st Kyoto Protocol commitment as an exogenous regulation shows that investors' behaviour and perception shift following social perspective and mandatory environmental regulation. The evidence emphasises the importance of environmental regulation in enhancing technological investment related to environmental engagement in the capital markets.

5.4 General Implications of the findings

This thesis reveals the nexus between green transitions based on technological innovation related to environmental engagement and the capital markets. My findings have implications for major firm stakeholders (managers, investors, financial analysts, and policy makers). They are discussed below.

Implications for managers: The growing social perception of environmental causes motivates investors to invest in firms with a commitment to environmental innovations. The shift toward sustainable strategies has become a primary factor in corporate investment and strategic decisions. My evidence suggests that managers who decide to engage in green transition based on a TGI activity could maximise their shareholders' interests. Public disclosure of information related to innovative projects is important to manage the expectations of the market participants – investors and financial analysts. Such information can shape the stakeholders' expectations about the firms' future growth potential and competitiveness.

Implications for investors: The evidence of the market participants' underreaction to innovative activities implies that they are concerned about the uncertainty generated by TGI activities. This finding points to the importance of investors' knowledge and ability to identify the value of TGI benefits, especially the value related to cost reduction from regulation compliance. Investors who can incorporate and evaluate the value of TGI information on stock prices more swiftly than others can generate higher returns. In addition, investors considering long-term sustainability can benefit by holding the stocks of firms engaged in TGI, which have the potential for better competitiveness under environmental regulation.

Implications for analysts: Improving knowledge and experience of valuing innovation can help them to identify the intrinsic value of TGI activities more precisely. Given the growing importance of sustainable investment in the financial markets, analysts with this skill can promote their careers and generate more trading commissions. Moreover, analysts with better abilities to value TGI can build a stronger relationship with firms' managers to access superior information and provide accurate reports. Increased reliability of the analysts' forecasts concerning TGI information can attract institutional investors to invest in firms that are engaged in TGI activities.

Implications for policymakers: My evidence suggests that the efficient mechanism of environmental policies supports corporate decisions regarding environmentally-friendly investments and induces investors' awareness of climate risks and environmental engagement. Therefore, it is imperative that policymakers consider consistency in environmental regulation, including maintaining the degree of regulation stringency and correspondence between global and domestic policies, to create efficient mechanisms and long-term environmental development.

5.5 Limitations and Recommendations for Future Research

While this thesis's three empirical chapters make novel contributions to the literature, a few important limitations could be addressed in future research.

This thesis investigates financial market participants' views on TGI activities. The first empirical chapter investigates the relationship between the firms' engagement in TGI activities and institutional investors' investment. The result of this chapter is consistent with the evidence in previous literature that social pressure and climate regulatory risk influence institutional investors' investment in firms engaged in better environmental development (Krueger et al., 2020; Bolton and Kacperczyk, 2021a and Marshall et al., 2022). However, even though my findings are consistent with substantial evidence from previous research, these are limited to the specific sample period (2004 – 2012) surrounding the 1st Kyoto Protocol commitment which has been used as the exogenous factor promoting TGI. The PSM approach also limits the findings by addressing the treatment effects of the 1st Kyoto Protocol commitment (among treated and controlled groups). This method is applied in the second empirical chapter investigating the connection between financial analysts and TGI.

However, extending the sample beyond the coverage of these chapters could reveal possible implications of evolving social and institutional factors such as social norms, legal provisions and their enforcement, and the level of stakeholders' understanding of the importance of TGI. Any qualitatively differing findings would indicate that the results are sensitive to the institutional arrangements in the given market and useful for future research and policy makers.

Furthermore, this study discusses value vs values-based arguments through ownership in firms engaged in TGI activities. With regard to the natural resource-based view theory (NRBV), although most studies promote TGI activities as a primary strategy for green transition, levels of TGI intensity are diverse depending on the industry's characteristics. Investors may have different agreements about the fact that technological innovation may not maximise the benefit for all industries. Similar to the logic of the first empirical chapter, future research could focus on the aspects of the NRBV theory by investigating the connection between investors' investment and other corporate environmental strategies such as merger and acquisition and complying with environmental management system (EMS).

Another limitation is that employing policy changes to test economic theories is limited by the fact that regulatory shocks may not be truly exogenous. Like other regulations, enforcing an environmental regulation takes some time to initiate. Moreover, the degree of environmental regulation enforcement may diverge depending on the commitment of each government. These uncertain conditions of the regulation enforcement can cause financial market participants, e.g. managers and investors, to respond (more or less) to these stimuli even before or after they are enforced, consequently potentially limiting researchers from estimating the true treatment effect.

In addition, according to the findings reported in the second empirical chapter, TGI intensity significantly relates to analysts' activities, e.g., removing TGI firms from their coverage portfolios, downgrading recommendations, and their earnings forecast abilities, it is possible that analysts' behaviours are also influenced by other corporate events or news during the estimation period. However, the findings indicate substantial evidence of analysts' responses to TGI activities and are useful for future research in exploring possible short-term effects of TGI activities in financial markets.

The final empirical chapter of this thesis investigates the market reaction to TGI and non-TGI information in the Tokyo Stock Price Index (TOPIX). Although the findings indicate the market reaction to innovative information when the firms file a patent application, some patent applications might be delayed in publishing which can cause innovative firms' higher information asymmetry. This limitation of innovative information is also reflected in the patent system in other countries. However, using other disclosing periods, e.g., the granted date of the patent application, may experience information leakage or stale information which can cause an estimation bias. Moreover, accessing and incorporating innovative information is also limited by the level of information asymmetry in different countries, which can cause investors' different perceptions of technological information. The circumstances surrounding the revelation of technological data within various markets have the potential to either promote or demote investors' responses to such information over a brief period. In this context, the query of whether market circumstances impact investors' understandings and reactions to technological data could be intriguing.

Future research incorporating distinct market conditions to distinguish the varied market responses to technological information could contribute significantly to the existing body of knowledge.

Even though PATSTAT is a patent database covering 40 global intellectual property authorities, the collection process can be delayed, and some data may be missing from patent applications, especially in developing countries that manage their patent databases. For future research, using various patent databases, e.g., the United States Patent and Trademark Office (USTPO) or the databases of the country patent office, can reduce the missing information. Expanding the scope by categorising geographic regions of individual investors, institutional investors, financial analysts and investee firms can also contribute to the literature regarding the different systematic changes in market stakeholders' perceptions of TGI activities and climate risk concerns. Moreover, in addition to the PSM approach, use of alternative matching approaches such as the entropy balancing technique (Hainmueller, 2012), can help mitigate the effect of sample size reduction and check for the sensitivity of results to the choice of the methods of analysis.

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