THÈSE

En vue de l'obtention du

DOCTORAT DE L'UNIVERSITÉ DE TOULOUSE

Délivré par :

Université Toulouse 1 Capitole (UT1 Capitole)

Présentée et soutenue par :

Li Bao

le lundi 3 juillet 2023

Titre :

Three Essays on Green Finance

École doctorale et discipline ou spécialité :

ED SG : Finance

Unité de recherche :

TSM-R

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Three Essays on Green Finance

By

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

The Doctorate Degree in Management Science

July, 2023

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To my parents, those I love, and those love me

Acknowledgements

The star itself has not changed, but my perspective of it has evolved.

I grew up in a small village in China where my family and I would gather in the yard during the summer nights to chat. One evening, I vividly recall being asked what I wanted to be when I grew up. Without much thought, I quickly responded that I wanted to become a scientist. While I wasn't sure what being a scientist meant at that time and cannot recall the exact reason why I gave that answer, looking back, it was clear that the starry night sky above us had sparked something within me.

Everything has fallen into place according to my childhood dream. I am the first in my family to attend university, earn a master's degree, and eventually pursue a PhD. Although the journey has not always been smooth, my goal has remained steadfast. Along the way, I have received immense support, both materially and mentally, from my parents, family, friends, and professors. It is almost magical to find myself now on a different continent, one that I had only read about in textbooks as a child. The realization hit me one night as I was driving back from Andorra to Toulouse after a trip. The stars were shining just as beautifully as they did decades ago in my hometown. The stars haven't changed, but I have moved to a place that my dad had only dreamed of.

While I may never have the ability to become a scientist in the traditional sense, the journey to becoming a researcher has permanently changed the way I view the world. I learnt how to improve my approach to problem-solving from erudite professors, exchanged ideas with colleagues from diverse countries, and engaged in debates with my German friends to share our concerns about the future of our world. The skills I acquired as a researcher even helped me find a job that will allow me to contribute more to my family. Additionally, I have surprised myself by becoming a good chef, something I never expected before coming to Toulouse. I am grateful for these experiences, and the people I met that made them possible.

First and foremost, I would like to express my heartfelt gratitude to my supervisor, Sophie Moinas, for her unwavering support, encouragement, and numerous research discussions throughout my six-year study in Toulouse. Her constant availability and willingness to provide help have been invaluable to me and will be a precious memory in my life. Additionally, her support extends not only to me but also to all the PhD students in organizing our workshop, setting a great example that I will strive to follow in my future job.

Next, I would like to extend special thanks to Milo Bianchi, Ulrich Hege, Alexander Guembel and Sebastien Pouget for their invaluable suggestions during my PhD thesis and job market preparation. I am particularly grateful to Uli for our discussions on navigating difficult situations in life. I have benefited greatly from the expertise and guidance of Alex and Milo for years, which have helped me develop my research skills significantly.

I would like to extend my heartfelt thanks to William Cheung for generously hosting me during my visit to Waseda University, guiding me into the world of Finance research, and providing constant support throughout my career.

I would also like to express my gratitude to other professors who have assisted me in preparing for job interviews, including Matthieu Bouvard, Siliva Rossetto, Catherine Casamatta, and Patrick Coen. I would also like to extend special thanks to Fany Declerck for providing me with the opportunity to begin my journey in Toulouse.

To friends that support me and help me open mind to the world: Wenhao Li, Lukas Dargel, Thi Nguyen, Jonas Gathen, Oscar Fentanes, and Yaxin Li, it's my honor to have you as my friends along my PhD study.

For the remaining space, I would like to reserve it for my girlfriend, Yixin Huang. We have shared many fun experiences together, including stargazing, developing our cooking skills, traveling, mountain climbing, walking in the rain, driving jet skis, playing golf, and many other activities that I cannot begin to list. We have also supported each other through tough times, such as enduring COVID-19 quarantines, living far from home for four years, and going through the challenging job application process together. Together, we make each other better and I feel fortunate to have her by my side.

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Chapter 1

Introduction

Motivation

Environmental protection is perhaps the most significant challenge that humans have faced in recent decades and will continue to face in the future. This challenge can take the form of preventing pollution in developing countries or neutralizing carbon emissions worldwide. The public expects firms to take more responsibility in creating a better world since they cause the most damage to the environment and have the resources to bear the cost of taking green actions to reduce emissions. However, firms have different concerns that prevent them from taking action. One such concern is the standard view of their objective as maximizing shareholders' value, while pollution prevention is often perceived as a costly action and pollution itself is an externality. Additionally, firms are worried about losing their competitive advantage relative to their peers.

To promote the adoption of environmentally friendly practices, which is a common good, the state and the market are two complementary powers that we can rely on (Tirole, 2019). On the one hand, the state serves as the regulator and sets the framework and ground rules for firms to follow. It can establish environmental regulations, create carbon markets, decide on carbon quotas allocated to firms, facilitate green bond issuance, and even subsidize green projects (Gianfrate and Peri, 2019). These rules and regulations create boundaries that firms cannot easily break. On the other hand, the market shapes firms' behavior through economic forces. The main players that have influence power in the market are stock investors, bond investors, employees, and customers. Shareholders can directly influence firms through voting channels and price channel, bondholders can drive down firms' financial costs by accepting lower returns, employees are more willing to work for green firms and accept lower wages, and customers can change firms' products by consuming goods provided by green firms (Barzuza et al., 2020; Dikolli et al., 2022; Pástor et al., 2021; Krueger et al., 2021; Bolton and Kacperczyk, 2021; Kleimeier and Viehs, 2021; Gong et al., 2023). With governments' clear regulation framework, and market players' green preference, ideally firms can find a balance between profit driven business and internalize pollution extenality.

Both governments and private initiatives seem to have a significant impact on firms' behavior. Firms respond not only to laws passed within their jurisdiction but also to agreements made between governments. For instance, in response to the facilitation of green bond issuance in Mainland China, the amount of green bonds issued by Chinese listed firms grew from zero in 2013 to 43.337 billion USD in 2019. Similarly, listed firms in North America described more carbon emission abatement actions in their annual reports after the Paris Agreement was passed in 2015 (Ramadorai and Zeni, 2021). In addition, large asset management companies have started to actively promote the integration of ESG (Environmental, Social, and Governance) factors into their investment activities, which creates incentives for firms to achieve a higher ESG score (Alda, 2021; Dai et al., 2022). This shift in investment focus has led to an increased emphasis on sustainable practices and reduced carbon footprint among firms. Furthermore, customer preferences are also driving firms' behavior towards environmentally friendly practices. Without the power of demand, government subsidies cannot lead to the success of a low-carbon market (Fan and Dong, 2018). The success of Tesla and the forced production of electric cars by traditional manufacturers can potentially be attributed to consumers' shift towards electric cars.

However, despite the progress made in our society, the tensions between economic growth and environmental protection at the regulatory level, and the tensions between profit maximization and internalizing environmental protection costs at the firm level are still fundamental issues that slow down the pace of energy transition. While asset managers claim to care about ESG, they are primarily concerned with ESG issues that have a potential negative impact on investment value (Pucker and King, 2022; McCahery et al., 2022). These tensions become even tighter during adverse market scenarios. For instance, because of the COVID-19 crisis, local governments prioritized maintaining the stability of employment rates and the economy, making it challenging to implement green policies. Similarly, fund managers were less likely to focus on pushing for green practices in firms since it was challenging to maintain acceptable investment returns.[1]

Therefore, it's crucial to investigate whether it is possible for firms to achieve both environmental protection and value maximization. Without answering this question, the adoption of green practices may remain in a back-and-forth situation. Although it is clear that internalizing environmental protection costs can be expensive in the short run, one potential solution is that firms with early green actions can reap sufficient long-term benefits. Theorists also suggest that a CSR-oriented firm can coexist with a value-maximizing firm if shareholders have a preference for green firms (Baron, 2007). This thesis aims to address this question along these two dimensions empirically. Chapter 2 attempts to determine whether firms that adopt green practices early can

[1] This argument is based on an informal interview with an ESG fund manager.

achieve sufficient long-term benefits. Chapter 3 explores whether investors currently have a preference on firms' green status. Although Chapter 4 is not directly related to the research question, it investigates how the increasing presence of passive investors in the market may impact firms' governance, potentially providing insight into how firms' green decisions may be influenced in the long run.

Can firms that adopt green practices early reap enough long-term benefits?

Chapter 2 aims to answer the question of whether firms that adopt green practices early can gain sufficient benefits in the long run. In general, green practices may include investing in green technology, funding environmental-friendly projects, implementing pollution abatement measures, and reducing carbon emissions. In this study, the focus is on air pollution abatement. There is a long-standing literature showing that green transformation is costly for firms as it decreases their productivity (Gollop and Roberts, 1983; Greenstone et al., 2012; Gray et al., 2013; He et al., 2020), and a growing literature showing that green firms can benefit from a low cost of debt and equity (Bolton and Kacperczyk, 2021; Kleimeier and Viehs, 2021). However, it is unclear whether these benefits are sufficient to cover the costs, as firms would engage in green practices if this is undoubtedly. But if we take into account the time constraint to build the necessary infrastructure (Kydland and Prescott, 1982), which increase the cost significantly, the result can change. Early green actions can make the time-to-build constraints less binding, potentially allowing firms with early green actions to outperform those without. Therefore, it is worth comparing the performance of firms with early green practices with those without in the long run.

I address this question in the content that Chinese firms are facing the increasing enforcement efforts of air pollution abatement regulations. The research design is innovative and departs from previous research by considering the following facts: i) the ability of governments to enforce regulations is limited, and they will consider the costs and benefits (Shimshack, 2014), ii) the government's enforcement efforts can be influenced by GDP concerns, which depend on the production of firms (Pang et al., 2019), and iii) firms can plan ahead to mitigate the impact of increased government enforcement. Previous research typically examines the impact of introducing a new regulation, such as research on the introduction of California's cap-and-trade rule (Bartram et al., 2022). However, environmental protection issues arise not only from the lack of regulations but also from the lack of regulation enforcement. Furthermore, the time variation of enforcement provides firms with the possibility to choose to adopt green practices early or not.

In the research design, I address two empirical challenges, namely the need for a proxy of enforcement ability and the endogeneity issue of GDP concern on governments' enforcement efforts. In China, environmental law enforcement is primarily implemented at the local government level, so I need to address the endogeneity issue at the local government level. To address the first challenge, I use the distance between a firm and its nearest monitoring station as a proxy for enforcement ability. The assumption is that local governments prioritize allocating their limited resources to firms that are closer to monitoring stations. To address the second challenge, I exploit the exogenous shock of the transfer of monitoring station control rights from local governments to the central government since the end of 2016. I find that firms with a high ability to shift production to their subsidiaries are less likely to conduct air pollution abatement actions and more likely to shift production to their subsidiaries when local governments increase their enforcement efforts. This is due to the fact that these firms are less constrained by time-to-build constraints and can more easily adapt to changes in regulation enforcement.

I employ a two-stage least squares methodology to investigate the impact of increased air pollution abatement actions induced by the transfer of monitoring station control rights on the profitability of firms with and without early green actions. I divide the firms into two groups based on their level of air pollution abatement actions in 2016 and find that firms with a high level of air pollution abatement actions experience an increase in profitability, while firms with a low level do not. The increase in profitability can be attributed to the decrease in financial expenses. Interestingly, both groups of firms experience a decrease in financial costs, which is measured by financial expense divided by total liabilities. The results suggest that firms with a high level of air pollution abatement actions can use low-cost funding to restructure their debts, while firms with a low level of air pollution abatement actions can only use low-cost funding to finance their green transformation.

A valid concern is that firms with a high level of air pollution abatement actions may bear significant costs ex-ante. To address this concern, I match firms with a 2016-high level of air pollution abatement actions with firms with a 2016-low level based on their industry code, firm size, market-to-book ratio, return on assets, and distance to their nearest monitoring station in 2014. I observe a parallel trend in the return on assets from 2012 to 2016, which is the year that the transfer of monitoring station control rights occurs, and find that firms with a high level of air pollution abatement actions outperform those with a low level afterwards. This suggests that firms with early green practices successfully smooth their green transformation over time and possibly do not need to bear the costs that come with time-to-build constraints.

The results are encouraging as they suggest that early adoption of green practices can provide firms with a long-term competitive advantage. With this finding in mind, it is optimal for local governments and investors to encourage firms to plan for green transformation in the long run.

Do investors have a preference firms' green status?

Chapters 3 and 4 aim to shed light on whether investors are willing to support the green transformation. This question will be divided into two parts: (i) How do investors currently perceive green companies? (ii) Will the increasing trend of passive investors impact the answer to the first question in the future?

In Chapter 3, I examine how stock and bond investors perceive firms' green status. This is joint work with Sophie Moinas and was inspired by a research project initiated by the Hong Kong Monetary Authority (HKMA). Identifying a firm as a green firm is not an easy task, as it depends on the standard we choose, such as a firm running a green business or a firm with zero carbon emissions. As a simplified approach, we label firms that have issued green bonds as green firms, since green bonds are specifically designed to fund green projects. For those that haven't, we label them as brown firms. Previous literature has examined both the stock market and bond market reactions to green bond issuance and has found encouraging results. For stock investors, studies have found a positive announcement return of green bond issuance(Flammer, 2021; Tang and Zhang, 2020; Wang et al., 2020). The stock market's positive reaction to green bond issuance is a combined reaction to both the change in firms' green status and green bond issuance. However, it is unclear whether the positive market reaction is due to the change in green status or the green bond issuance. For bond investors, studies have found a small but negative green bond premium for bonds issued with clear standards and in transparent markets (Östlund, 2014; Ehlers and Packer, 2017; Zerbib, 2019; Bachelet et al., 2019; Hyun et al., 2020; Kapraun et al., 2021). The greenium is typically calculated by comparing the green bond yield and the yield of synthetic conventional bonds constructed with conventional bonds issued before and after the green bond issuance. However, it fails to consider the impact of firms' green status on conventional bonds issued after the first green bond issuance. Departing from existing literature, We aim to understand the separate effects of firms' green status and green bond issuance.

Our analysis begins with an examination of how stock investors perceive a company's green status and green bond issuance. Climate Bonds Initiative's (CBI) three-tier system, which certifies green bond issuance, provides us a unique perspective to explore a company's green status before the first green bond issuance. The three-tier system includes green bond framework verification, use of proceeds verification, and CBI certification. Using an event study, we construct a cumulative abnormal return (CAR) around the bond issuance announcement date by green firms. We find that when firms lack green bond framework verification, the announcement of their first green bond issuance leads to a positive reaction from stock investors, while there is no impact when firms have green bond framework verification. This suggests that stock investors value a company's green status more than the issuance of green bonds itself. The lack of reaction to subsequent green bond issuance confirms this hypothesis. Therefore, we can argue that stock investors have a preference on companies that make an effort to be environmentally friendly.

Next, we investigate how bond investors perceive a company's green status and the issuance of green bonds. To conduct the analysis, we use a double-matching method. First, we match green firms with brown firms based on firm size, market-to-book ratio, previous year liquidity, and industry code. For each green firm, we keep four brown firms. Second, we match each green and conventional bond issued by green firms with a conventional bond issued by brown firms based on bond size, time to maturity, callable type, and bond seniority. After this matching process, we conduct a difference-in-differences (dif-in-dif) analysis to examine the green bond premium with and without CBI certification, as well as the conventional bond premium issued by green firms. Our findings show that only bonds with CBI certification are traded with a negative premium, while neither other green bonds nor conventional bonds issued by green firms are traded with a negative premium. This suggests that bond investors only value green bonds with certification, but do not have a preference on a company's green status.

Overall, our findings in Chapter 3 indicate that stock investors view green companies more positively than bond investors. As stock investors have more influence over a company's governance, a preference for green companies by investors can incentivize more firms to adopt environmentally friendly practices.

Chapter 4 aims to investigate the effect of changes in the investor base, specifically the rise of passive investors, on firms' governance. This is crucial because it potentially affects our understanding of the pressure that investors may exert on firms' green practices in the future. Passive funds, including index funds and exchange-traded funds, have become popular investment vehicles for individual investors as they offer a way to avoid information asymmetry issues typically experienced when investing in single stocks through institutional investors. Furthermore, individual investors tend to hold passive funds for the long run (Da Dalt et al., 2019). For instance, the percentage of stocks owned by passive funds increased from 0% to 8.21% of the total U.S. stock market capitalization between 2000 and 2016. However, passive funds' lack of exposure to individual firms' performance means they lack internal incentives to intervene in firms' governance, making their impact on firms' governance less predictable. The literature has shown that passive funds are active voters, but their impact on firms' governance has been found to be mixed (Appel et al., 2016; Schmidt and Fahlenbrach, 2017; Heath et al., 2020). Given that the trend of more passive investors is likely to continue, it is important to rationalize passive funds' voting and make their impact more predictable.

Based on the argument that passive funds lack internal incentives, it is reasonable to explore their external incentives. The analysis begins with the observation that 86.44% of U.S. passive funds' positions are voted in situations where the same fund family's active funds also vote in the voting meeting. This suggests that influence coming from the same fund family's active funds is potentially the most significant external incentive. Building on this observation, the analysis explores two questions: i) how do the same fund family's active funds adjust their holdings based on the holdings of passive funds, and ii) how do the voting pattern of the same fund family's active funds and passive funds are affected by their holdings. This approach can shed light on the potential impact of external incentives on the voting behavior of passive funds.

To investigate how the same fund family's active funds adjust their holdings, I first construct an average individual client's fund inflow within the same fund family for both active funds and passive funds. Next, I examine the relationship between this constructed measure and the stocks held by active funds and passive funds. The findings indicate that passive funds' fund inflow increases the composition of portfolios of both passive and active funds, while active funds' fund inflow does not affect active funds' composition of portfolios. This suggests that active funds do not adjust their portfolios based on their individual clients' trading activities, but rather based on the holdings of the same fund family's passive funds. These results are robust to using the Russell index reconstitution as an exogenous shock.

To understand the effect of holdings on the voting pattern of the same fund family's active and passive funds, I apply a two-stage-least-square method and examine the voting pattern when the ISS company has different recommendations than the management team. First, I use the average passive funds' fund inflow from individual clients to predict the product of passive funds' ownership and active funds' ownership from the same fund family, which I show to be a measure of active funds' incentive to align passive funds' voting. The results show that average passive funds' fund inflow increased active funds' incentive. Next, I examine how passive and active funds vote when the ISS company had different recommendations than the management team, which require both active and passive funds to make their own judgment. The findings suggest that the increased incentive made active and passive funds more likely to vote in the same direction. Overall, this study provides a standpoint to consider the potential impact of growing passive fund ownership on firms' green decisions, where active funds influence votes of passive funds in the same family.

In summary, the thesis suggests that there are benefits of adopting environmentally friendly practices early. First, firms with early green actions can smooth their costs over time. Second, they can outperform firms without early actions in the long run, if the environmental law enforcement becomes more stringent. Furthermore, stock investors currently value firms' green status. The impact of increase trend of passive investors on firms' green actions will be affected by the same fund family's active funds' green preference. If the active funds of the same fund family value firms' green status, they can encourage more firms to become green together with passive funds' stakes.

Chapter 2

Why do firms go green?

2.1 Introduction

The public is calling for government environmental policies that require firms to internalize pollution externalities. Since pollutant emissions are externalities and green transformation is expensive, profit-maximizing firms are unlikely to internalize their environmental impact on their own (Biais and Landier, 2022). Although Friedman (1970) argues that shareholders can use their wealth to promote social responsibility and that firms should prioritize profit maximization, this argument may not hold for environmental impacts that are difficult to reverse (Baron, 2007; Benabou and Tirole, 2010; Shive and Forster, 2020). Therefore, government intervention is necessary to ensure that firms internalize these externalities. Governments can establish pollution caps or taxes on excessive emission, and mandate that firms meet these requirements. Once these policies are implemented, firms will be forced to adopt environmentally friendly practices.

Despite a clear regulatory framework provided by governments, many firms choose not to take action to reduce their pollution levels. Violations of environmental laws are common worldwide, even among firms subject to Environmental Protection Agency enforcement orders. For example, the U.S. National Environmental Law Center has documented cases of firms remaining out of compliance with pollution permit limits.[1] Similar issues occur in developing countries. Although the Chinese government has been promoting air pollution abatement since 2012, the 2018 Blue Sky Defense Action in Shandong province, a major province with severe air pollution in China, resulted in the closure of 44,661 firms and required 40,559 firms to upgrade their pollution abatement facilities.[2] This paper aims to examine the reasons why some firms choose to ignore regulations, while others choose to adopt environmentally friendly practices.

I address this question by examining the benefits and costs of complying with regulations in the context of the Chinese government's efforts to force listed firms to adopt

[1] https://www.nelc.org/cases/environment-michigan-sierra-club-v-ak-steel/

[2] https://www.mee.gov.cn/xxgk2018/xxgk/xxgk15/201904/W020190428315574710732.pdf

air pollution abatement measures. My findings indicate that the enforcement efforts made by governments and monitoring instruments play a key role in determining firms' behavior, and that firms' ability to shift production away from the monitoring system also affects their response to such regulations. The underlying mechanism is that the ability to shift production is a mitigating factor that helps alleviate time-to-build constraints imposed by increased government enforcement efforts. Furthermore, I show that taking early actions can also help firms alleviate the time-to-build constraints and, importantly, outperform firms without early actions. Although both types of firms can benefit from the decrease in financing costs as they take more green actions to comply with government regulations, firms with early green actions have more flexibility. They can reduce their financial expenses by replacing existing debts with low-cost debt. In contrast, firms without early green actions can only use low-cost debts to fund their green transformation. Additionally, I find that the better performance of firms with early actions remains even after taking the cost of early actions into account. These results are encouraging, as they suggest that value-maximization and internalizing environmental impacts are not necessarily in conflict with each other. They complement the view that CSR firms can co-exist with value-maximization firms if shareholders have a preference for firms' green actions (Baron, 2007).

The first empirical challenge in this paper is to develop an environmental score that accurately captures firms' efforts to abate air pollution. However, there are several issues with existing environmental scores. Firstly, existing scores have a backward-looking nature and cannot predict a firm's future emission reductions (van Binsbergen and Brøgger, 2022). Secondly, they are relative indicators that compare a firm's environmental performance with that of firms from the same industry worldwide. As a result, the relationship between environmental scores and local environmental quality is unclear since foreign firms' environmental performance serves as the benchmark. Thirdly, they capture multiple dimensions of environmental performance, which reduces their representativeness on a specific environmental quality dimension. Lastly, they cover a limited number of firms across the years, which further complicates the analysis.

To address the issues associated with existing environmental scores, I develop a green commitment score based on textual analysis of annual reports from Chinese-listed companies between 2014 and 2020. The China Securities Regulatory Commission (CSRC) requires Chinese-listed companies to release standardized green commitment information in the corporate social responsibility section of their annual reports. Thus, pollution abatement information in Chinese companies' annual reports is less likely to suffer from the cheap talk issue, which has been criticized in many studies using 10-K files and annual reports of U.S.-listed firms (Ilhan et al., 2021). The green commitment score measures the number of sentences describing air pollution abatement actions, green risk management plans, and general abatement willingness information, standardized by the total number of characters in each annual report. Including information on air pollution abatement actions makes the score forward-looking, as it reports the comparison between actual emissions and future emission permits each year. Additionally, it is the only score that can cover all Chinese-listed firms across the years. To assess the score's reliability, I compare it with the Refinitiv Emission score and find a strong positive correlation between them. Furthermore, firms with higher green commitment scores report lower average self-reported pollutant emissions across entities within listed firms. Industrial firms with higher green commitment scores also contribute to improved air quality, as indicated by a decrease in the nearest monitoring station's air quality index. Consequently, I restrict my primary analysis to industrial firms.

Using the green commitment score that I develop, I proceed to analyze firms' decisions to abate air pollution. Firms' responses to stringent government policies on air pollution abatement depend on a trade-off between the expected costs of non-compliance and the compliance costs. However, directly observing a firm's expected costs of non-compliance is challenging. Therefore, I examine the factors that influence them. Local governments' enforcement of environmental laws affects firms' expected costs of non-compliance and is influenced by various factors, including the relationship between local and central governments, cost-benefit analysis conducted by local governments, and monitoring instruments (Shimshack, 2014). Monitoring instruments can be used to gauge the pressure faced by firms, as they provide measures directly. For air pollution monitoring instruments, we use the fact that firms' distances to their nearest air quality monitoring stations differ. Firms located closer to a monitoring station are more likely to be fined by local governments if they do not comply. However, one could argue that the locations of air quality monitoring stations can be endogenous to firms' pollution levels. To address this concern, I exploit the control right transfer of air quality monitoring stations from local governments to the central government, which served as an exogenous shock to local governments' policy enforcement efforts at the end of 2016. This transfer resulted in local governments being less lenient. I expect that the increase in policy enforcement effort, which interacts with firms' distance to their nearest monitoring stations, will increase firms' expected costs of non-compliance. I find that after the transfer, being 1 km closer to the monitoring station increases the firms' green commitment score by 0.084. Overall, my analysis shows that firms update their beliefs and take more pollution abatement activities in response to policy enforcement efforts and the intensity of monitoring instruments. This complements the findings of Ramadorai and Zeni (2021), who show that firms update their expected costs of non-compliance based on anticipations about future climate regulation.

To assess the flip side of the trade-off and capture compliance costs, I focus on analyzing firms' ability to shift production. Previous literature has shown that green transformation can have costly effects on firms' productivity (Gollop and Roberts, 1983;

Gray et al., 2013; Greenstone et al., 2012; He et al., 2020). However, rather than focusing on the productivity effects, I emphasize firms' ability to shift production, which can make the time-to-build constraint imposed by policy enforcement less binding. When firms choose to comply with regulations, they have two options: conduct air pollution abatement actions or shift production to other facilities. Inspired by Cao et al. (2021), I measure firms' ability to shift production by using the fixed asset ratio. Firms with a high fixed asset ratio are considered to have a low ability to shift production. For firms with low production shift ability, delaying compliance until government enforcement efforts increase may result in costly pollution abatement due to time-to-build constraints (Kydland and Prescott, 1982). As a result, they are incentivized to take pollution abatement actions early to smooth their compliance costs. This can involve gradually installing green facilities, deploying facilities that easily upgraded in the future, choosing production processes with less pollution, and divesting in environmentally unfriendly projects (Bauer et al., 2018). I find that before the control right transfer of air quality monitoring stations, firms with fixed asset ratios above the industry median in 2014 have a green commitment score of 0.215 higher than those with fixed asset ratios below the industry median. After the transfer, the score gap widen further by 0.509. The ability to shift production gives firms the flexibility to take less air pollution abatement actions.

Another way of handling time-to-build constraints is to abate air pollution early. I examine whether the early action can benefit firms' performance when facing increased government enforcement efforts. To do so, I separate industrial firms into two groups based on their green commitment score in 2016, comparing it to the industry median score. My findings show that for 2016-high-green-commitment-score firms, a 1 km decrease in distance to their closest monitoring station can increase their ROA by 0.3255%, while the ROA of 2016-low-green-commitment-score firms remains unaffected. Further evidence indicates that the increase in ROA can be attributed to a decrease in financial expenses by 6.795 million CNY. Interestingly, both 2016-high-green-commitment-score and 2016-low-green-commitment-score firms can benefit from a decrease in financial costs by 0.15% and 0.14%, respectively. These results suggest that firms with early air pollution abatement actions can outperform firms without, as they can use low-cost debts to replace their existing debts, while firms without early actions can only use low-cost debts to finance green transformation.

A valid concern is that the increased ROA of firms with early green actions may be due to the green transformation costs they paid earlier. To address this concern, I conducted a propensity score matching process to match firms with a 2016-high-green-commitment-score with firms with a 2016-low-green-commitment-score in 2014, based on firm size (ln(Mktcap)), market-to-book ratio, ROA, distance to the nearest monitoring station, and industry code. I observed a parallel trend of ROA from 2012 to 2016 for the two matched groups of firms. However, starting in 2017, the 2016-

high-green-commitment-score industrial firms began to outperform the 2016-low-green-commitment-score industrial firms. This suggests that abating air pollution early on provides long-term benefits to firms when facing increased regulation enforcement.

To validate the findings in this paper, another concern to address is whether the fixed asset ratio accurately captures the production shift channel or simply reflects the fact that firms with more fixed assets need to invest more in green transformation. To address this concern, I first confirm that firms with a high fixed asset ratio in 2014 are more likely to be assigned to the group of 2016-high-green-commitment-score industrial firms. Next, I examine the different impacts of an increase in local government policy enforcement efforts on the production processes of firms with 2016-high(low)-green-commitment-score. I find that after the control right transfer of monitoring stations, being 1 km closer to the monitoring station increases the operating cost, revenue, and employee salaries of subsidiaries of 2016-low-green-commitment-score industrial firms by 0.171 billion CNY, 0.207 billion CNY, and 9.249 million CNY, respectively. However, there is no impact on 2016-high-green-commitment-score industrial firms. This production shift effect is similar to the outcome of California's cap-and-trade rule's impact on financially constrained firms (Bartram et al., 2022), but the mechanism is different, as the final analysis shows that the firms shifting production are those with fixed asset ratios below the industry median instead of financially constrained firms. Overall, the results confirm the conjecture that the fixed asset ratio is a good proxy for firms' ability to shift production.

This paper contributes to the literature in several ways. Firstly, this paper contributes to the long-standing literature on the costs and benefits of adopting environmentally friendly practices. Previous literature has shown that green transformation has costly effects on firms' productivity (Gollop and Roberts, 1983; Gray et al., 2013; Greenstone et al., 2012; He et al., 2020), but also benefits from a low cost of debt and equity (Bolton and Kacperczyk, 2021; Kleimeier and Viehs, 2021). Complementing these studies, this paper shows that firms can smooth green transformation cost and decrease their financial expenses by decreasing their environment impact early.

Secondly, this paper contributes to the growing literature on understanding firms' timing choices of environmentally friendly actions. The follower advantage can affect firms' timing choices. For example, researchers have shown that investments in green technologies have positive spillover effects, which can benefit firms that adopt environmentally friendly practices late (Acemoglu et al., 2012, 2016; Aghion et al., 2016). Another explanation for firms' timing choices is the interaction between their environmental actions and their beliefs about regulations. Ramadorai and Zeni (2021) provide evidence that firms' abatement behavior is strongly influenced by their beliefs about climate regulation. Biais and Landier (2022) analyze that regulations can be endogenous; if firms believe that there will be no regulation and do not take environmentally friendly actions early, governments will find it too costly to implement green policy, thus imposing no regulation. Different from the existing literature, this paper highlights that the ability to shift production deters firms from abating air pollution early.

Thirdly, this paper also contributes to the literature on emission leakage effects of locally implemented policies. The emission leakage effects arise from the fact that local governments' environmentally friendly policies are designed locally without coordination (Shaked and Sutton, 1982; Bushnell et al., 2017; Fowlie et al., 2016). This paper shows that a policy designed at the national level can also have an emission leakage effect. As monitoring pollution is costly, firms can shift production to plants with less monitoring. Bartram et al. (2022) point out that, driven by financial constraints, firms internally reallocate plant-level emissions, causing an emission leakage. This paper's results suggest that financially unconstrained firms also internally reallocate plant-level emissions if their production shift ability is high.

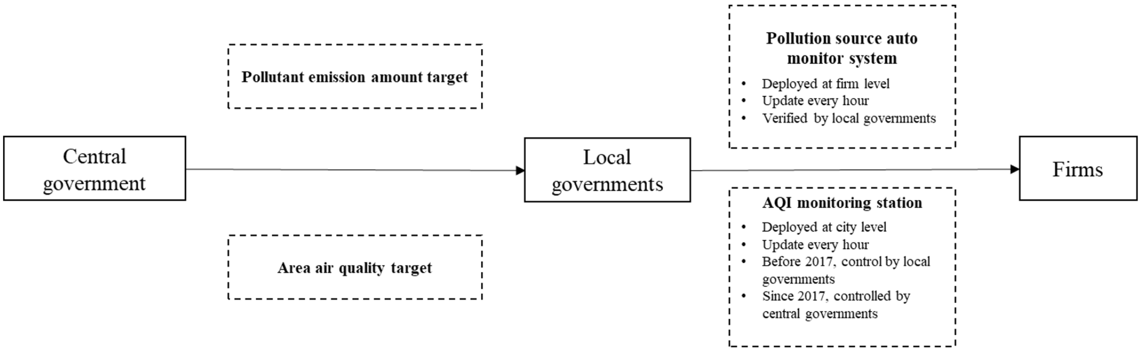


Figure 2.1: China's air pollution control system

2.2 Research background and hypothesis development

2.2.1 China air pollution control system and AQI monitoring station control right transfer

China's air pollution control system is central-government-oriented and implemented by local governments. The central government sets both the pollutant emission amount target and the area air quality target, with which the local governments monitor firms' pollutant emissions. For example, in the twelfth Five-year plan for air pollution control of key provinces, the central government set the SO2 emission amount target and the SO2 air concentrations target. Specifically, in key provinces, compared with 2010, the total SO2 emission amount should decrease by 12% per year and the SO2 air concentrations should drop by 10% per year until 2015.[3] To reach the target, the central government and local governments set up two monitoring systems: the auto-monitoring system for pollution sources and the air quality index (AQI) monitoring station system. The pollution source auto-monitoring system is deployed at the firm level and sends detailed pollutant emission information to each local government to verify every hour. The AQI monitoring station system is deployed at the city level and the AQI is released to the public every hour. Local governments control the AQI monitoring stations at the time they are constructed. By design, local governments have the ability to manipulate information in both systems. In Figure 2.1, I draw the framework of China's air pollution control system.

Local governments face an agency problem with the central government, which incentivizes them to manipulate information in the air pollution control system. This conflict arises from the tension between economic growth and environmental protection, with local government officials responsible for maintaining local economic growth, while pollution reduction can directly reduce GDP. According to a report by the Ministry of Ecology and Environment (MEE), eliminating over-polluted firms, which are considered backward production capacity by the MEE, resulted in a decrease in GDP of 114.8 bil-

[3] https://www.mee.gov.cn/gkml/hbb/bwj/201212/W020121205566730379412.pdf

lion CNY after implementing the "Air Pollution Prevention and Control Action Plan".[4] As GDP growth is crucial for evaluating local government officials, they may compromise their air quality improvement targets. Additionally, local entrepreneurs may make efforts to lobby local government officials to lower pollution control enforcement, exacerbating the problem. In April 2015, Wu Xiaoqin, former deputy minister of MEE, confirmed that some local governments had manipulated the AQI.[5]

On December 31, 2015, MEE announced its plan to transfer the responsibility of AQI monitoring stations from local governments to the central government to mitigate the agency problem.[6] The transfer process began in September 2016 and, by October 24th, 1324 monitoring stations had been transferred to operating companies assigned by the central government. On November 3, 2016, the China National Environmental Monitoring Centre (CNEMC), a department of MEE, issued a regulation stating that no entities could enter the monitoring station without permission from CNEMC.[7]

The transfer of AQI monitoring stations from local governments to the central government is expected to increase pressure on firms located closer to monitoring stations to reduce emissions. This is because the central government relies on AQI monitoring stations to evaluate the performance of local governments, and the ability of local governments to manipulate information is reduced after the transfer. As a result, local governments are likely to make genuine efforts to improve air quality around monitoring stations, leading to increased pressure on nearby firms to go green.

2.2.2 Environmental information reporting quality in annual reports

In China, listed companies follow standardized guidelines to form their annual reports' formats and contents. The standardized guideline, "Standards for the Contents and Formats of Information Disclosure by Companies Offering Securities to the Public No. 2" is released by the Chinese Securities Regulatory Commission (CSRC). CSRC actively revises this guideline to improve firms' transparency, which includes environmental information transparency. Between 2012 and 2021, it has been amended six times.

The environmental information disclosure standard has undergone significant improvements during the disclosure guideline amendment process. Since 2012, listed companies and their subsidiaries within heavy-polluting industries have been required to disclose environmental information in the annual report's corporate social responsibility section. These firms are obligated to report overall pollution emission information, environment facility information, and pollution accident emergency plans. In 2016, the coverage requirement was expanded from firms within heavy-polluting industries to heavy-

[4] http://www.xinhuanet.com/politics/2015-09/09/c_1116513933.htm.

[5] http://news.sohu.com/20150408/n410927208.shtml

[6] http://www.mee.gov.cn/gkml/hbb/bgg/201612/W020161205323170196405.pdf

[7] https://www.h2o-china.com/news/249305.html

polluting firms. Simultaneously, detailed pollution information disclosure standards were established, including major pollutants, discharge methods, number and distribution of discharge outlets, discharge concentration and total amount, excessive discharge, implemented pollutant discharge standards, and approved total discharge amount. In 2017, the disclosure requirements were further expanded to include environmental impact evaluations of projects, pollution approval information, and self-monitoring plans.

Another factor affecting the quality of environmental information disclosure in annual reports is CSRC's ability to enforce compliance. To strengthen its enforcement ability, CSRC signed an agreement with MEE on June 12, 2017.[8] The agreement aims to share information between these two government departments, allowing CSRC to check listed firms' disclosure based on the list provided by MEE. This improvement in enforcement ability has led to increased environmental information transparency among firms. During the annual report collection process, I find several versions of the 2017 annual reports for some firms, and the more recent versions contain more environmental information.

2.2.3 Hypothesis development

When the government intervenes, profit-maximizing firms are forced to internalize pollution emission costs. These firms must make a comparison between the expected costs of non-compliance and the costs of compliance. As a result, firms are more likely to engage in green activities when they expect government policies to have a significant impact, and are less likely to do so when the costs of compliance are high.

Different from what has been shown by Ramadorai and Zeni (2021), who demonstrate that firms conduct more green activities in response to the expectation of future environmental policies, this study focuses on the situation where a clear policy framework is already in place, but policy enforcement changes firms' expected costs of non-compliance. Specifically, the expected costs of non-compliance are affected by local governments' policy enforcement efforts, the intensity of monitoring instruments, and the fine. To capture the intensity of monitoring instruments, this study uses the distance between each firm and its nearest air quality monitoring station as a proxy variable. The hypothesis is that firms closer to the monitoring station will face more intensive monitoring, leading them to take more pollution abatement activities. However, the distance between a firm and the monitoring station is endogenous to firms' pollution levels and pollution abatement activities at the time the monitoring station is constructed, which raises a reverse causality issue. To address this issue, this study employs the control right transfer of air quality monitoring stations from local governments to the central government in China at the end of 2016 as an exogenous shock to local governments' policy enforcement efforts. The increase of policy enforcement efforts will increase firms'

[8] http://www.gov.cn/xinwen/2017-06/12/content_5201853.htm

expected costs of non-compliance. As the outcome of local governments' policy enforcement efforts relies on the change in air quality index from monitoring stations, the effect of the intensity of monitoring stations and local governments' policy enforcement efforts is expected to interact. After the transfer, firms closer to the monitoring stations are expected to take more green actions. Based on this analysis, this study proposes its first hypothesis.

H1: The increase in local government policy enforcement efforts, coupled with the intensity of monitoring instruments, will result in an increase in firms' pollution abatement activities. Specifically, following the transfer of control rights of air quality monitoring stations from local to central government in China, firms located closer to monitoring stations will take more green actions.

Firms' compliance costs will be affected by their ability to shift production. Government policy enforcement puts time-to-build constraints on firms' compliance. This constraint will be weakened if firms have abilities to shift their production to other places. Thus, I expect that firms with a low ability to shift production will take more green actions. I use firms' fixed asset ratios to proxy for firms' abilities to shift production, which is inspired by Cao et al. (2021). Firms with high fixed asset ratios have less ability to shift production, and thus will take more green activities.

H2: Production shift ability mitigates time-to-build constraints imposed by policy enforcement, and firms with high fixed asset ratios will take more green actions.

While the ability to shift production is an initial endowment that helps mitigate time-to-build constraints, another way to handle these constraints is to take green actions early. By taking early green actions, firms can have more flexibility to handle the increased government pressure. Therefore, we can expect that firms with early green actions will perform better than firms without early green actions.

H3: Firms with early green actions will perform better under increased local government enforcement efforts.

2.3 Data construction

2.3.1 Data Sources

Annual report

As part of this study, I collect annual reports for all Chinese listed firms with trading activities between 2014 and 2020. The firm list includes all firms listed on both the Shanghai and Shenzhen stock exchanges, resulting in a total of 4144 firms. To obtain the annual reports, I develop a python program to download them from the Sina finance website, which features a structured annual report archive.[9] In total, I obtain 23,183 annual reports for all the firms analyzed in this study.[10]

Air quality index and monitoring station location

The air quality index (AQI) is provided by China National Environmental Monitoring Centre (CNEMC) and is released every hour for each monitoring station. The exact longitude and latitude of each monitoring station is also provided by CNEMC. The AQI data used in this study is downloaded from an open source database.[11]

Firm location

I obtain the geographic coordinates for each firm's headquarters location from CSMAR.

Financial data

I download the financial data of the firms from CSMAR from 2012 to 2020. The data includes revenue, operating costs, net profit, financial expenses, marketing expenses, total assets, total liabilities, and total loans.

SO2/NOX/Dust emission

I manually collect data on SO2/NOX/Dust emissions from annual reports spanning from 2017 to 2020. While some firms report detailed emission data for their related entities, the data I collect is incomplete. Nevertheless, this data can be used to test the robustness of my green commitment score.

2.3.2 Measure construction

Continuous sample SO2/NOX/Dust emission production intensity

I calculate the emission production intensity by standardizing the emission amount with the total revenue.

[9] For instance, annual reports for firm 600031 can be found at http://vip.stock.finance.sina.com.cn/corp/go.php/vCB_Bulletin/stockid/600031/page_type/ndbg.phtml. By replacing the stock code, annual reports for other firms can be accessed.

[10] The number of annual reports obtained for each year is presented in Table 2.A1.

[11] https://quotsoft.net/air/

Firm-monitoring station distance

With the firm locations and monitoring station locations, I calculate the distance of each firm to its closest monitoring station with the Haversine formula, which is specified in equation 2.1. The monitoring stations are restricted to the monitoring station that was constructed before 2017.

$$Distance = 2 \times \arcsin\left(\sqrt{\sin^2 \frac{(Long_f - Long_m)}{2} + \cos\left(Lat_f\right) \times \cos\left(Lat_m\right) \times \frac{\sin^2\left(Lat_f - Lat_m\right)}{2}}\right) \times 6371 \tag{2.1}$$

Where $Long_f$ and $Long_m$ are the firm's longitude and the nearest monitoring station's longitude. Lat_f and Lat_m are the firm's Latitude and the nearest monitoring station's Latitude. All the longitude and latitude are in radians.

Table 2.1 presents the number of firms in each distance group between the firms and their nearest monitoring stations from 2014 to 2020. The distance groups are categorized as 0-5km, 5-10km, and above 10km. The table provides information for both the all-firm sample and the industrial-firm-only sample.

Table 2.1: Number of firms by distance groups

Table 2.1 reports the number of firms by distance groups from 2014 to 2020. The distance is calculated as the Haversine distance between each firm and its closest monitoring station. Firms are separated into three groups based on their distance to the monitoring station: 0-5km, 5-10km, and above 10km.

	All firms			Industrial firms		
	0-5km	5-10km	≥10km	0-5km	5-10km	≥10km
2014	1,477	495	577	710	330	469
2015	1,591	539	640	777	362	522
2016	1,692	589	718	828	395	586
2017	1,867	696	870	930	479	729
2018	1,915	722	904	954	495	761
2019	2,006	785	956	999	543	805
2020	2,156	882	1,106	1,083	624	935

Green measure construction

Step 1. Identify the CSR part and the non-CSR part from annual reports

The first step in constructing a green measure is to separate the annual reports into the CSR and non-CSR parts. As specified in section 2.2.2, CSRC requires firms in heavy-polluting industries (before 2016) or firms classified as key pollutant discharging entities (including and after 2016) to disclose environmental information in the corporate social responsibility (CSR) part of their annual reports. Identifying standardized information can help improve the quality of the green commitment score measure.

Using the pdfplumber package in Python, I extract texts and tables from annual reports in PDF format. In the non-CSR part, I extract all the available text. For the CSR part, which is where firms are required to disclose environmental information, I extract both text and tables. Tables are the preferred format for reporting structured information and contain the standardized information necessary for constructing the green commitment score measure.

In this step, I obtain a total of 23,166 separated texts for both parts, after deleting 17 cases due to encoding errors or images that could not be identified. In the CSR part, I extract a total of 60,027 tables.

Step 2. Identify and classify environmental information

Annual reports usually include both CSRC-required environmental information and firms' self-reported environmental information. The CSRC requires pollution information, information on pollution prevention facility operation and construction, government permit information, an emergency plan for environmental emergencies, and an environmental self-monitor plan. Self-reported information varies, but two types of information can be standardized: green investment and environmental management system (ISO 14000) deployment status.

To structure key information, the environmental information in annual reports is classified into three categories: risk management, detailed action, and general green. Risk management includes information on the emergency plan for environmental emergencies, the environment self-monitor plan, and environmental management system deployment status. Detailed action includes air pollution-related pollution information, pollution prevention facility operating and construction information, government permits related to air pollution, and green investment related to air pollution reduction. Lastly, general green includes information on environmental protection and abating emissions, but not specifically related to specific actions of reducing pollution.

Before starting the analysis, a dictionary needs to be designed that includes all the items in the above three categories and keywords related to air pollution reduction. The keywords are developed based on the components of the air quality index used in China after 2014, which consist of PM2.5, SO2, NOX, and O3. For each component, a list of pollutants that could physically affect the pollution level is set up. Additionally, typical facilities that firms use to reduce pollutant emissions are also included in the dictionary. Detailed information on the pollutants and facilities can be found in Appendix Table 2.A2.

All the classification is performed at the sentence level or the table row level. The dictionary is used to determine whether each sentence or table row contains environmental information. If it does, it is assigned to one of the three categories.

Step 3. Calculate green commitment score

After categorizing each sentence and table row into one of three categories, I count the total number of sentences and table rows in each category. I then calculate the green commitment score using Equation (2.2), where $N_{total\ words}$ is the total number of Chinese characters in each annual report. Since I have separated each annual report into the CSR and non-CSR parts, I have calculated both the CSR and non-CSR green commitment scores, as well as the scores for each category.

$$Green\ commitment\ score^{CSR/non-CSR} = \frac{N_{general\ green} + N_{risk\ management} + N_{detailed\ action}}{N_{total\ words}} \times 10,000 \tag{2.2}$$

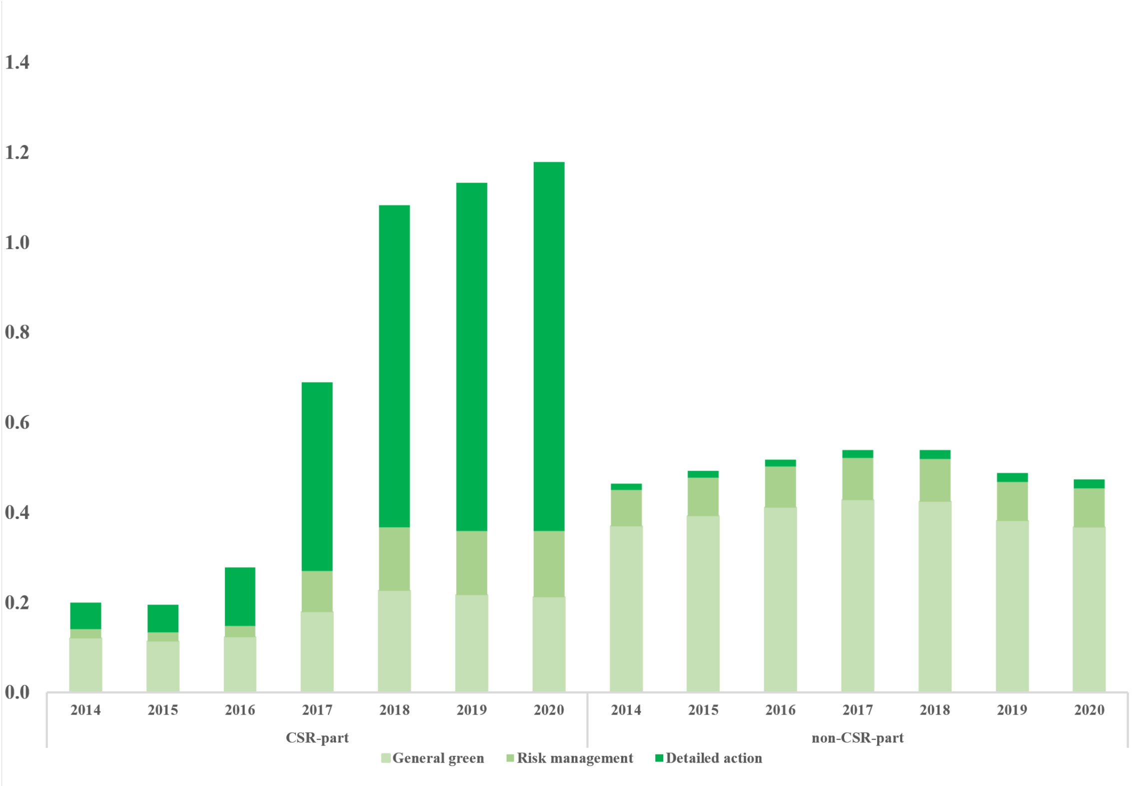


Figure 2.2: Listed firm green commitment score from 2014 to 2020

2.4 Green commitment score validity and reliability

2.4.1 Green commitment score distribution

Figure 2.2 plots the listed firms' green commitment scores from 2014 to 2020 for both the CSR and non-CSR parts. The green commitment score for the CSR-part shows a significant increase in 2017 after the transfer of air quality monitoring stations from local governments to the central government, whereas the non-CSR-part green commitment score remains relatively stable. The detailed action sub-score contributes the most to the increase within the CSR-part green commitment score. Given detailed actions are the standardized information required by CSRC, I expect that firms are conducting more green actions to reduce their environmental footprint.

2.4.2 Green commitment score validity

The green commitment score is designed to capture firms' actual green efforts, which require standardized reporting instead of mere cheap talk and greenwashing. In general, without standardized reporting requirements, firms may easily engage in cheap talk or selectively report only favorable information, as has been criticized in the analysis of U.S. 10k files and annual reports (Ilhan et al., 2021). Fortunately, Chinese listed firms' annual reports follow the CSRC's guidelines and release standardized environmental information. This standardized environmental information forms the foundation of the green commitment score. Moreover, the CSRC strengthens its ability to check firms' compliance with the guidelines by sharing information with the MEE, thereby increasing the trustworthiness of environmental information in annual reports. Hence, I can use the green commitment score as a credible measure of firms' green efforts.

2.4.3 Green commitment score reliability

Whenever available, I evaluate the reliability of my green commitment score by comparing it with the Refinitiv ESG score, examining its relationship with firms' self-reported pollutant emissions, and verifying its association with the air quality index from the nearest monitoring station. The results indicate that my green commitment score has a positive correlation with the Refinitiv ESG score and performs well with the Refinitiv emission score. Furthermore, it is negatively correlated with the average pollutant emission across entities within listed firms. Most importantly, I find that higher weighted green commitment scores of industrial firms around the monitoring station can lead to a decrease in the air quality index reported from the monitoring station.

Green commitment score and ESG score

The Refinitiv ESG score covers Chinese listed firms, but its coverage is limited. Since 2008, Chinese listed firms that belong to the MSCI Emerging Markets Index have had an ESG score from Refinitiv. The list was expanded in 2018 and 2020, but the coverage is still limited.[12] Given the wide use of the Refinitiv ESG score, I compare it with my green commitment score to begin evaluating the reliability of my score.

Table 2.2 compares the green commitment score with the Refinitiv ESG score for Chinese listed firms. Three levels of Refinitiv ESG score, namely the emission score, environment score, and ESG score, are analyzed. The regression analysis is conducted separately for the CSR part and non-CSR part of the annual reports. Results for the sub-score from three categories, namely risk management, detailed actions, and general green, are reported in columns (1)-(3), (5)-(7), and (9)-(12), respectively. Columns (4), (8), and (10) report results for the green commitment score, which is the sum of the three sub-scores. In both Panel A and Panel B, it is observed that the green commitment score positively correlates with the emission score, environment score, and ESG score. The results are more stable for the emission score in the case of sub-scores. It suggests that the green commitment score captures firms' emission reduction efforts well.

[12] According to Refinitiv's customer service response, the Refinitiv ESG score is calculated using data from annual reports.

Table 2.2: Compare the green commitment score with Refinitiv ESG score

Table 2.2 compares the green commitment score with the Refinitiv ESG score. The regression analysis examines the association between three levels of Refinitiv ESG score (emission score, environment score, and ESG score) and the green commitment score, which is separated into sub-scores from three categories: risk management, detailed actions, and general green. Panel A presents the results for the CSR part of the annual reports, while Panel B reports results for the non-CSR part. Year fixed effects and industry fixed effects are included in the analysis. The significance levels are 1%, 5%, and 10%, respectively.

Panel A: CSR-part												
	Emission score				Environment score				ESG score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Detailed action	1.635***				1.005***				0.386***			
	(0.255)				(0.212)				(0.148)			
Risk management		9.372***				3.714*				-1.217		
		(2.225)				(1.996)				(1.407)		
General green			7.745***				4.843***				1.680*	
			(2.147)				(1.451)				(0.873)	
Green commitment score^{CSR}				1.540***				0.928***				0.327**
				(0.231)				(0.190)				(0.132)
Year Fixed effect	Yes											
Industry Fixed effect	Yes											
N	2034	2034	2034	2034	2034	2034	2034	2034	2034	2034	2034	2034
adj. R-sq	0.208	0.198	0.202	0.211	0.196	0.188	0.193	0.196	0.186	0.183	0.184	0.185
Panel B: non-CSR-part												
	Emission score				Environment score				ESG score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Detailed action	8.456***				4.961**				2.584			
	(2.891)				(2.331)				(1.853)			
Risk management		30.237**				19.975*				9.230		
		(14.637)				(11.540)				(8.067)		
General green			6.079***				6.711***				3.459***	
			(1.390)				(1.226)				(0.929)	
Green commitment score$^{non-CSR}$				5.396***				5.192***				2.673***
				(1.108)				(0.978)				(0.739)
Year Fixed effect	Yes											
Industry Fixed effect	Yes											
N	2034	2034	2034	2034	2034	2034	2034	2034	2034	2034	2034	2034
adj. R-sq	0.194	0.193	0.198	0.199	0.188	0.188	0.198	0.197	0.184	0.183	0.189	0.188

2.4.4 Green commitment score and firms' emission

Before comparing the green commitment score with firms' emission data, a summary of listed firms' pollutant emission levels and emission intensity is provided to better understand the emission data and firms' green efforts. To make the emission level comparable across years, only firms with continuous records are included.[13] Table 2.3 Panel A reports the emission level, and Panel B reports the emission production intensity, which is the number of pollutants divided by total revenue.

In Panel A, the summary statistics of the emission level show that if we compare pollution emission data between 2017 and 2020, the median, mean, and maximum of all indicators decrease. For example, in terms of mean, NOX decreases by 17.43%, SO2 decreases by 42.52%, and dust decreases by 13.02%. Pollution levels are highly correlated with the exact products produced. The decreased pollutant number could be attributed to the decreased number of produced products, new production technology, and pollution reduction equipment installation. However, the decreased number of produced products could simply be due to bad market conditions, which is not necessarily linked to green efforts.

The summary statistics in Panel B of Table 2.3 show that the emission production intensity decreased between 2017 and 2020. On average, NOX emission production intensity decreased by 24.96%, SO2 emission production intensity decreased by 46.70%, and dust emission production intensity decreased by 17.84%. This indicates that firms may have improved their production technology or deployed pollution reduction equipment to reduce their pollutant emissions per unit of revenue.

While the emission data is incomplete, it can still serve as a benchmark for the green commitment score. The data is incomplete in two ways. Firstly, many firms only report the emission rate, not the total pollutant emission amount, despite the CSRC reporting standard requiring both. Secondly, even when firms do report total emission amounts, they often only report some of their related entities' emissions instead of all of them, making it challenging to use the data at the firm level. To address this, I trimmed the risk management index, the detailed action index, the general green commitment score, and the green commitment score at the 1% and 99% levels. [14]

Table 2.4 presents the relationship between the green commitment score and the average pollutant emission across reported subsidiaries within listed firms. The CSR-part green commitment score and the non-CSR-part green commitment score results are

[13] One outlier has been removed. Firm (600882)'s emission dropped more than six hundred times from 2017 to 2018, while its revenue was stable. So it had a high possibility of writing errors.

[14] Alternatively, I removed firms that had more than 150 records of detailed actions and less than 10 subsidiaries reporting pollutant emission amounts. The result has the same pattern.

Table 2.3: Emission level and emission intensity for firms with continuous records

Table 2.3 reports the emission level and emission production intensity for firms with continuous records across from 2017 to 2020. Panel A reports the emission level and Panel B reports the emission production intensity. Emission production intensity is the number of pollutants divided by total revenue.

Panel A: Emission level (ton)									
Pollutant	Year	Min	P25	Median	P75	Max	Mean	STD	N
NOX	2017	0.000	13.080	117.220	699.800	54900.000	1586.131	5222.404	345
	2018	0.000	16.098	123.920	771.560	41605.200	1500.076	4353.579	345
	2019	0.000	15.840	107.600	677.640	44486.490	1567.375	4776.661	345
	2020	0.000	13.721	106.260	739.662	40965.119	1309.680	3938.338	345
SO2	2017	0.000	11.523	106.260	517.133	38000.000	923.113	3284.452	332
	2018	0.000	9.811	95.475	447.610	30349.080	739.680	2332.571	332
	2019	0.000	6.360	81.355	407.545	23908.950	710.474	2208.979	332
	2020	0.000	3.925	55.575	350.482	12449.015	530.603	1469.723	332
Dust	2017	0.000	4.808	33.135	145.324	34321.250	610.310	2720.075	276
	2018	0.000	4.841	28.713	158.080	19979.464	534.427	2181.272	276
	2019	0.000	4.484	26.895	123.717	23247.812	516.987	2086.281	276
	2020	0.000	3.289	21.244	107.127	24820.772	530.853	2209.124	276
Panel B: Emission production intensity (g/CNY)									
Pollutant	Year	Min	P25	Median	P75	Max	Mean	STD	N
NOX	2017	0.000	0.005	0.027	0.152	2.118	0.136	0.281	345
	2018	0.000	0.004	0.026	0.118	1.889	0.117	0.232	345
	2019	0.000	0.004	0.026	0.113	2.009	0.104	0.209	345
	2020	0.000	0.003	0.022	0.094	3.459	0.102	0.264	345
SO2	2017	0.000	0.004	0.021	0.089	1.258	0.075	0.148	332
	2018	0.000	0.002	0.015	0.067	0.837	0.055	0.099	332
	2019	0.000	0.002	0.014	0.059	0.588	0.049	0.084	332
	2020	0.000	0.001	0.009	0.048	0.696	0.040	0.077	332
Dust	2017	0.000	0.001	0.007	0.032	1.211	0.033	0.100	276
	2018	0.000	0.001	0.005	0.026	0.414	0.025	0.055	276
	2019	0.000	0.001	0.005	0.020	0.326	0.022	0.047	276
	2020	0.000	0.001	0.004	0.017	1.255	0.027	0.107	276

reported in panels A and B, respectively. Columns (1) – (4) cover the results for SO2 emissions, columns (5) – (8) cover the results for NOX emissions, and column (9) – (12) cover the results for dust emissions.

In panel A of Table 2.4, the relationship between the CSR-part green commitment score and average pollutant emission is reported. The key coefficients of the CSR-part green commitment score are -85.117, -114.708, and -46.120 for SO2 emission, NOx emission, and Dust emission, respectively, in columns (4), (8), and (12). The significance of the CSR-part green commitment score comes from the detailed action index, where the coefficients in columns (2), (6), and (10) are negatively significant.

In Panel B of Table 2.4, the relationship between the non-CSR-part green commitment score and average pollutant emission is presented. The coefficients for all pollutants are found to be insignificant, suggesting that there is no significant relationship between the non-CSR-part green commitment score and average pollutant emission.

In additional analyses in appendix (Table 2.A4), I examine the relationship between Refinitiv ESG score and average pollutant emission within listed firms. The results reveal a positive correlation between Refinitiv's emission score and average pollutant emission within listed firms. Specifically, the overall ESG score is positively and significantly correlated with the average SO2 emission and average NOX emission, while it is insignificant with the average Dust emission.

Table 2.4: Green commitment score with average pollutant emission across entities within listed firms

Table 2.4 reports the comparison of the green commitment score with the average pollutant emission across entities within listed firms. I run a regression for SO2 emission, NOX emission, and Dust emission respectively. All three pollutant emissions are manually collected from firms' annual reports. Panel A reports results for the green commitment score from the CSR part of annual reports. Panel B reports results for the green commitment score from the non-CSR part of annual reports. Columns (1)-(3), columns (5)-(7), columns (9)-(12) report results for the sub-score from three categories. Columns (4), (8), and (10) report results for the green commitment score, which is the sum of the three sub-scores. Year fixed effect and industry fixed effect are included. The significant levels are 1%, 5%, and 10% respectively.

Panel A: CSR-part green commitment score												
	SO2				NOX				Dust			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Risk management	-228.794*				-316.541				-321.662***			
	(125.586)				(218.281)				(123.867)			
Detailed action		-113.742***				-153.873***				-65.355***		
		(31.069)				(42.698)				(18.026)		
General green			96.935				127.149				-0.666	
			(82.116)				(138.909)				(89.543)	
Green commitment score^{CSR}				-85.117***				-114.708***				-46.120***
				(23.102)				(33.706)				(16.763)
Year FE							Yes					
Industry FE							Yes					
N	2155	2145	2172	2145	2255	2249	2276	2248	1996	1991	2018	1992
adj. R-sq	0.066	0.059	0.062	0.057	0.172	0.160	0.166	0.157	0.303	0.288	0.298	0.284
Panel B: non-CSR-part green commitment score												
	SO2				NOX				Dust			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Risk management	-826.662				-979.234				-388.784			
	(894.771)				(1088.834)				(671.362)			
Detailed action		240.555*				341.936*				97.610		
		(183.191)				(227.939)				(132.850)		
General green			61.284				114.994				-7.573	
			(77.079)				(95.822)				(59.005)	
Green commitment score$^{Non-CSR}$				67.469				114.763				22.603
				(60.937)				(75.777)				(46.131)
Year FE							Yes					
Industry FE							Yes					
N	2225	2210	2215	2210	2327	2314	2322	2317	2069	2057	2058	2058
adj. R-sq	0.063	0.057	0.064	0.064	0.167	0.160	0.168	0.168	0.294	0.281	0.294	0.294

2.4.5 Green commitment score and monitoring station air quality index

Firms' green efforts are expected to have a measurable impact on air quality, as indicated by the monitoring station air quality index (AQI). A high air quality index corresponds to poor air quality. Decreasing air pollution directly improves air quality near the firms, making it reasonable to assume that reducing pollution will decrease the air quality index. The proposed green commitment score serves as a proxy for green efforts, and it is thus expected that a negative relationship exists between firms' green commitment scores and the nearby monitoring station air quality index.

To account for the impact of distance on the air quality index, it is important to give more weight to firms that are located closer to the monitoring stations. The distance between a firm and the closest monitoring station can be a significant factor in determining the firm's impact on the air quality index. Firms that are located closer to the monitoring station are likely to have a larger impact on the air quality index than those located further away. Therefore, it is important to include only those firms that are within a certain distance from the monitoring station in the analysis, such as within 10 km. By doing so, we can ensure that the analysis captures the most relevant firms that have a significant impact on the air quality index.

I test the impact of firms' green efforts on nearby air quality, as proxied by the monitoring station air quality index. In equation (2.3), the regression is conducted at the monitoring station level, with the green commitment scores of firms within 10 km of the monitoring station averaged.[15] To account for the impact of distance, a weighted average is used in the calculation, with the weight being ten minus the distance between the listed firm and its nearest monitoring station. The coefficient of β_1 in the regression is expected to be negative, indicating a negative relationship between the green commitment score and the nearby monitoring station air quality index.

$$AQI_{i,t} = \alpha + \beta_1 Weighted\ Green\ Index_{i,t} + \ Monitor_i + Year + \epsilon_{i,t} \tag{2.3}$$

Industrial firms, which belong to the manufacturing industry and the electricity, heat, gas, water production, and supply industry, are expected to have a greater impact on the air quality of nearby monitoring stations due to their production processes. These industries produce more pollutants, which may result in a more significant impact on the surrounding environment. Therefore, we may expect to observe a more pronounced effect within the industrial firm sub-sample. This sub-sample includes firms with the

[15] As a robustness check, similar tests are conducted at distances of 3 km and 5 km, with similar results observed. This is expected, as the green commitment score is weighted by distance in the calculation of the weighted average.

first industry classification code of C and D in the 2012 CSRC industry classification code.

Table 2.5 presents the results of the relationship between the monitoring station air quality index and the green commitment score of firms within 10 km. The independent variables include both the weighted sub-indexes and the weighted green commitment score. The sub-indexes include the weighted risk management, weighted detailed action, and weighted general green. Panel A and panel B report the results for the CSR-part index and the non-CSR-part index, respectively. Columns (1) – (4) present the sample of all firms, while columns (5) – (8) present the sample of all industrial firms.

In Panel A of the CSR-part result, among the three sub-indexes, the weighted detailed action is negatively significant with the nearby monitoring station air quality index in columns (2) and (6). For the sample of all firms, the result is weakly significant with a coefficient of -0.197. For the sample of industrial firms, the result is significant with a coefficient of -0.342. This suggests that the detailed actions taken by more firms can lead to an improvement in air quality, with a stronger effect observed in the industrial firm sub-sample. The magnitude of the correlation in the industrial firm sub-sample is larger than that in the sample of all firms, indicating that the impact of detailed actions on air quality is more significant for industrial firms.

In Panel B, the non-CSR-part result shows that for the sample of all firms, the weighted general green sub-index is positively associated with the air quality index. This suggests that firms are more likely to prioritize becoming green when the air quality is low. However, for the sample of industrial firms in columns (5) - (7), the coefficients of the three sub-indexes are all negative. The coefficients for the weighted risk management and weighted detailed action sub-indexes are -8.881 and -1.020, respectively, and both are weakly significant. The coefficient for the weighted general green sub-index is -0.532 and insignificant.

The results from the analysis of the relationship between firms' green commitment score and nearby monitoring station air quality index suggest that the CSR-part green commitment score is a good indicator of firms' efforts to decrease pollution and improve air quality. Specifically, the analysis shows a negative relationship between the weighted detailed action sub-index and the air quality index for both the sample of all firms and the sample of industrial firms, indicating that firms' specific actions towards environmental responsibility have a significant impact on nearby air quality. Overall, the findings support the use of the CSR-part green commitment score as a reliable proxy for firms' green efforts in relation to air quality improvement.

Table 2.5: Monitoring station AQI and green commitment score of firms within 10 km

Table 2.5 reports the relationship between the monitoring station air quality index and the green commitment score of firms within 10 km. I run the following regression. $AQI_{i,t} = \alpha + \beta_1 Weighted\, Green\, Index_{i,t} + Monitor_i + Year + \epsilon_{i,t}$. The regression is at the monitoring station level. For each monitoring station, I calculate the weighted average green index of all the listed firms within 10 km. The weight is ten minus the distance between the listed firm and its nearest monitoring station. Panel A reports results for the green commitment score from the CSR part of annual reports. Panel B reports results for the green commitment score from the non-CSR part of annual reports. Columns (1)-(4) reports results for all listed firms. Columns (5)-(8) report results for industrial firms only. Year fixed effect and industry fixed effect are included. The significant levels are 1%, 5%, and 10% respectively.

Panel A: CSR-part								
	$AQI_{i,t}$							
	All firms				Industrial firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted Risk management	-0.499				-0.828			
	(1.101)				(1.129)			
Weighted Detailed action		-0.197*				-0.342***		
		(0.114)				(0.127)		
Weighted General green			0.895				0.666	
			(0.754)				(0.821)	
$Weighted\ Green\ commitment\ score^{CSR}$				-0.146				-0.275**
				(0.102)				(0.115)
Year FE	Yes							
Monitoring station FE	Yes							
N	3827	3827	3827	3827	3249	3249	3249	3249
adj. R-sq	0.891	0.891	0.891	0.891	0.885	0.885	0.885	0.885

Panel B: Non-CSR part								
	$AQI_{i,t}$							
	All firms				Industrial firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted Risk management	-3.641				-8.881			
	(4.575)				(4.581)			
Weighted Detailed action		-0.063				-1.020**		
		(0.505)				(0.559)		
Weighted General green			0.836				-0.532	
			(0.503)				(0.514)	
$Weighted\ Green\ commitment\ score^{Non-CSR}$				0.290				-0.661**
				(0.317)				(0.340)
Year FE	Yes							
Monitoring station FE	Yes							
N	3827	3827	3827	3827	3362	3362	3362	3362
adj. R-sq	0.891	0.891	0.891	0.891	0.888	0.889	0.888	0.888

2.5 Empirical methodology: Two-stage-least-square regression

2.5.1 Instrument variable

A firm's green level is endogenous to the firm's performance. Firms' green level is bounded by their resources to invest in green projects. The resources could be affected by its profitability, funding ability, investment in other projects, and so on. Thus, to find out the impact of firms' green status on firms' performance, solving the reverse causality is needed.

To address the potential endogeneity issue, a suitable instrument variable is required that affects a firm's green level but not its performance. One potential candidate is the distance between the firm and its nearest air pollution monitoring station. Firms located closer to monitoring stations are likely to have a greater impact on air quality and may face more pressure from local governments to improve their green efforts. This pressure could lead to an increase in the firm's green level. This satisfies the relevance condition for the distance variable as an instrumental variable. However, the relevance condition may not hold if local governments manipulate the air quality index directly, rather than focusing on improving air quality.

There are also concerns regarding exclusion restrictions in this study. The selection of monitoring station locations may be endogenous to firms' pollution levels and performance. The technical regulation for selection of ambient air quality monitoring stations requires stations to be located in areas with high concentrations of pollution that may affect human health, and areas with fixed pollution sources that have a significant impact on air quality.[16] This means that monitoring station locations are determined by firms' pollution levels, which may make the distance between firms and monitoring stations endogenous to their performance. Additionally, local government officials may have an incentive to hide pollution to maintain GDP growth, making the monitoring station location endogenous to firm pollution levels and performance as well.

One possible solution to address the endogeneity issues is to identify an exogenous event that impacts local governments' pressure but does not directly affect firms' performance. The transfer of monitoring stations' control rights from local governments to central governments could serve as such an event. This is because it is beyond the control of local governments or listed firms, making it unrelated to firms' performance. Additionally, it could shed light on the relative importance of air quality to local versus central governments. If the central government places greater emphasis on air quality, monitoring stations are less likely to be manipulated, and the air quality index can

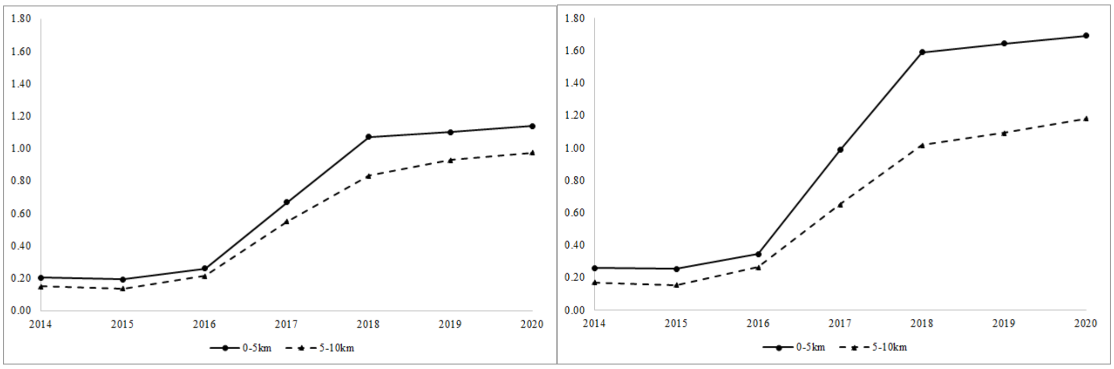
[16] https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201309/W020131105548727856307.pdf

serve as an indicator for the central government to verify local governments' efforts to improve air quality. This would increase the pressure on local governments to monitor firms closer to the monitoring stations. Conversely, if the central government places less emphasis on air quality, the monitoring station air quality index may be distorted. In this case, local governments would lack a benchmark index to monitor listed firms, and the distance between the firm and the monitoring station would have no impact on the firm's green level.

The proposed instrument variable is the product of the After dummy and the distance between the listed firm and its closest air pollution monitoring station. The After dummy equals 1 after the monitoring stations transfer to the central government. By using this instrument variable, the endogeneity issue caused by the distance between the listed firm and its closest air pollution monitoring station can be addressed. The transfer of monitoring stations control rights from local governments to the central government is an exogenous event that shocks the local government's pressure, while not affecting firms' performance directly. As a result, the IV regression can provide more reliable estimates of the causal impact of the firms' green level on their performance.

Figure 2.3a shows a comparison of the CSR-part green commitment score between listed firms located within 5 km and those located between 5 and 10 km from the nearest monitoring station. Prior to 2017, the green commitment scores of both groups of firms followed a similar trend. However, starting in 2017, the gap between the two groups increased, suggesting that firms located closer to monitoring stations are facing greater pressure to improve their green efforts.

For industrial firms, as shown in Figure 2.3b, the gap between the two distance groups is even more pronounced. Given that industrial firms tend to produce more pollutants, it is reasonable to expect that those located in close proximity to monitoring stations would face more pressure and would need to invest more in green initiatives.



(a) all listed firms (b) industrial firms

Figure 2.3: CSR-part green commitment score within 10 km

2.5.2 Two-stage-least-square regression

In the first stage, I employ the instrument variable $After \times Distance_{i,j}$ to predict the firm's green level, as specified in equation (2.4). The expected result is a negative coefficient for the key variable β_2. This is because after the transfer of monitoring stations from local governments to the central government, firms located closer to monitoring stations are likely to face more pressure from local governments to improve their green efforts. The analysis will focus on firms within a 10 km distance from the monitoring stations.

$$Green_{i,t} = \alpha + \beta_1 Distance_{i,j} + \beta_2 After \times Distance_{i,j} + X_{i,t} + Ind_i + Year + Monitor_j + \epsilon_{i,t} \tag{2.4}$$

The control variables ($X_{i,t}$) include a state-owned dummy $State_{i,t}$, market capitalization $ln(Mktcap)_{i,t}$, and tax contribution $Tax\ contribution_{i,t}$. State-owned dummy $State_{i,t}$ equals 1 if the firm is a state-owned firm. State-owned firms' behavior is a signal of Chinese policy, and it is expected that they are more likely to be green if the central government is truly committed to improving air quality. Large firms may have more resources to invest in green projects, so it is expected that they are more likely to be green. Tax contribution $Tax\ contribution_{i,t}$ is defined as the amount of tax paid by firm i divided by the total tax paid by all listed firms located in the same city as firm i at year t. It is included to control for the relationship between firms and local governments. The aim of this specification is to test hypothesis H1, and it is expected that the coefficient β_2 is negative, indicating that firms closer to monitoring stations experienced more pressure from local governments and are more likely to have a higher green commitment score.

Based on this regression, I will test hypothesis H2 by adding $High\ fixed\ asset\ ratio_{i,2014}$ and its interactions with other variables. The fixed asset ratio is a proxy for firms' ability to shift production. I will separate firms into two groups by comparing their fixed asset ratio with the industry median fixed asset ratio in 2014. $High\ fixed\ asset\ ratio_{i,2014}$ will equal to 1 if firm i's fixed asset ratio is above the 2014-industry-median fixed asset ratio. The detailed specification will be given in equation (2.5). With this specification, hypothesis H2 can be tested. It is expected that β_2 and β_5 are positive.

$$\begin{aligned} Green_{i,t} = \alpha &+ \beta_1 Distance_{i,j} + \beta_2 High\ fixed\ asset\ ratio_{i,2014} \\ &+ \beta_3 Distance_{i,j} \times High\ fixed\ asset\ ratio_{i,2014} + \beta_4 After \times Distance_{i,j} \\ &+ \beta_5 After \times High\ fixed\ asset\ ratio_{i,2014} \\ &+ \beta_6 After \times Distance_{i,j} \times High\ fixed\ asset\ ratio_{i,2014} + X_{i,t} + Ind_i \\ &+ Year + Monitor_j + \epsilon_{i,t} \end{aligned} \tag{2.5}$$

In the second stage, the predicted green commitment score ($Green_{i,t}$) is used to examine the impact of increased government enforcement efforts on firms' performance. The model specification is presented in equation (2.6). To test hypothesis H3, firms are divided into two groups based on their green commitment score in 2016. The difference in the impact of increased government enforcement efforts on the performance of firms with and without early green actions can then be compared. The dependent variable ($Dep\ Var_{i,t}$) can be return on assets, return on equity, or earnings per share. It is expected that the coefficient β_1 for firms with early green actions is larger than that for firms without green actions.

$$Dep\ Var_{i,t} = \alpha + \beta_1 Gr\hat{e}en_{i,t} + \beta_2 Distance_{i,j} + X_{i,t} + Ind_i + Year + Monitor_i + \epsilon_{i,t} \quad (2.6)$$

2.6 Main results

2.6.1 Government enforcement efforts and air pollution abatement actions

In this section, the focus is on testing the reasons why industrial firms choose to adopt green practices, based on the two hypotheses H1 and H2 presented earlier. The results are summarized in Table 2.6, where year, industry, and monitoring station fixed effects are controlled for. Summary statistics of key variables can be found in Table 2.A3.

In Table 2.6 columns (1) – (3), I test the relationship between local government policy enforcement efforts and firms' green commitment scores after the transfer of air quality monitoring station control rights. Column (1) has no fixed effects or firm-level controls, column (2) includes year, industry, and monitoring station fixed effects, and column (3) includes both fixed effects and firm-level controls. The key coefficient is on the interaction term $After \times Distance$, which captures the effect of policy enforcement efforts and monitoring instrument intensity after the transfer of control rights. The coefficient is similar across columns (1), (2), and (3), with a significant negative coefficient of -0.084 in column (3). This supports my first hypothesis that firms will increase pollution abatement activities in response to local government enforcement efforts and monitoring instrument intensity.

In Table 2.6 column (5), I test the relationship between firms' ability to shift production and firms' green commitment score. I separate firms into two groups by comparing their fixed asset ratio with the industry median fixed asset ratio in 2014. $High\ fixed\ asset\ ratio_{i,2014}$ equals to 1 if firm i's fixed asset ratio is above the 2014-industry-median fixed asset ratio. The coefficient of the key variable, $High\ fixed\ asset\ ratio_{i,2014}$, is positive and significant (0.215). This suggests that firms with high fixed asset ratios are more likely to engage in pollution abatement activities. The coefficient on the interaction term $After \times High\ fixed\ asset\ ratio_{i,2014}$ is also positive and significant (0.509), indicating that after the transfer of monitoring stations, firms with high fixed asset ratios are more likely to increase their green commitment score.[17] The coefficients of $Distance_i \times High\ fixed\ asset\ ratio_{i,2014}$ and $After \times Distance_i \times High\ fixed\ asset\ ratio_{i,2014}$ are negative but insignificant, indicating that the ability to shift production effect is weakly affected by policy enforcement efforts.[18] Overall, the result confirms my second hypothesis that firms with low ability to shift production will take more green actions.

[17] Results are similar for regression without samples in 2014.

[18] The overall effects of these two variables are significant in the unreported test.

Table 2.6: Industrial firms' reasons to go green

Table 2.6 reports the regression analysis for industrial firms' reasons to go green. I run the following regression. $Green_{i,t} = \alpha + \beta_1 Distance_{i,j} + \beta_2 \times High\ fixed\ asset\ ratio_{i,2014} + \beta_3 Distance_{i,j} \times High\ fixed\ asset\ ratio_{i,2014} + \beta_4 After \times Distance_{i,j} + \beta_5 After \times High\ fixed\ asset\ ratio_{i,2014} + \beta_6 After \times Distance_{i,j} \times High\ fixed\ asset\ ratio_{i,2014} + X_{i,t} + Ind_i + Year + Monitor_j + \epsilon_{i,t}$. $Distance_{i,j}$ is the distance between firm i and its nearest monitoring station j. After is a dummy variable that takes 1 if year is larger than or equals 2017. $High\ fixed\ asset\ ratio_{i,2014}$ is a dummy variable that takes 1 if its fixed asset ratio is larger than its industry median fixed asset ratio. $X_{i,t}$ includes state owned dummy $State_{i,t}$, firm size $ln(Mktcap)_{i,t}$ and tax contribution to the city $Tax\ contribution_{i,t}$. The difference between column (3) and column (4) is that I restrict the sample that $High\ fixed\ asset\ ratio_{i,2014}$ is not missing. Year fixed effect, industry fixed effect, and monitoring station fixed effect are included. Robust standard errors are reported. The significant levels are 1%, 5%, and 10% respectively.

	(1)	(2)	(3)	(4)	(5)
	$Green_{i,t}$	$Green_{i,t}$	$Green_{i,t}$	$Green_{i,t}$	$Green_{i,t}$
$Distance_i$	-0.017***	0.023***	0.037***	0.021**	0.035***
	(0.003)	(0.008)	(0.008)	(0.010)	(0.013)
$After \times Distance_i$	-0.078***	-0.084***	-0.084***	-0.083***	-0.068***
	(0.010)	(0.009)	(0.009)	(0.011)	(0.015)
$High\ fixed\ asset\ ratio_{i,2014}$					0.215***
					(0.083)
$Distance_i \times High\ fixed\ asset\ ratio_{i,2014}$					-0.023
					(0.015)
$After \times High\ fixed\ asset\ ratio_{i,2014}$					0.509***
					(0.123)
$After \times Distance_i \times High\ fixed\ asset\ ratio_{i,2014}$					-0.024
					(0.022)
$State_{i,t}$			0.369***	0.244***	0.242***
			(0.048)	(0.055)	(0.056)
$ln(Mktcap)_{i,t}$			0.306***	0.343***	0.338***
			(0.025)	(0.031)	(0.031)
$Tax\ contribution_{i,t}$			0.021	0.002	0.020
			(0.124)	(0.124)	(0.124)
Year FE	Yes	Yes	Yes	Yes	Yes
Ind FE	No	Yes	Yes	Yes	Yes
Monitoring station FE	No	Yes	Yes	Yes	Yes
N	10206	10206	10202	7902	7902
adj. R-sq	0.098	0.316	0.340	0.373	0.381

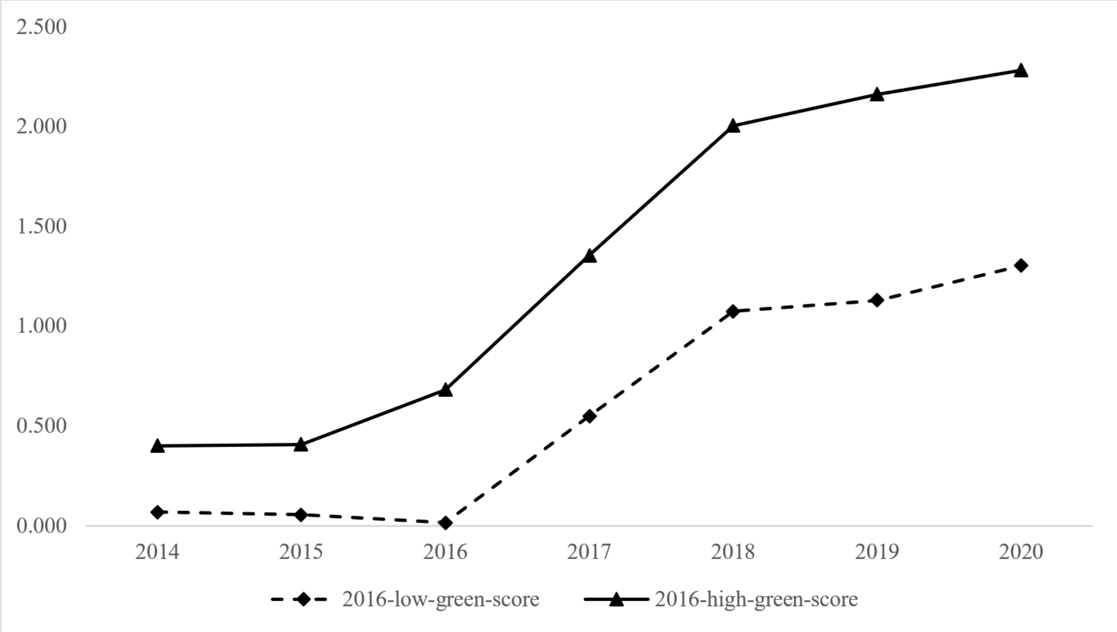


Figure 2.4: Green commitment score of 2016-high-green-commitment-score and 2016-high-green-commitment-score industrial firms from 2014 to 2020

2.6.2 Benefits of being green early

In this section, I test the long-term benefits of being green early with 2SLS regression based on hypothesis H3. First, I classify industrial firms into two groups: those with high green commitment scores in 2016 and those with low green commitment scores in 2016. I then conduct a two-stage least squares regression to analyze the impact of increased local government enforcement efforts on the performance of these two groups of firms. Next, I examine the sources of the observed performance differences. Finally, I confirm the benefits of being green early, even after considering the costs of early green actions, using the propensity score matching method.

Classify firms into high and low green commitment score groups

In this step, I divide firms within each industry into two groups based on their green commitment score in 2016. Firms with a green commitment score above the industry median are assigned to the 2016-high-green-commitment-score group, while those with a score below the median are assigned to the 2016-low-green-commitment-score group. The average green commitment score for these two groups is plotted in Figure 2.4. The figure reveals that until 2016, the average score of the 2016-low-green-commitment-score industrial firms is not significantly different from zero.

Policy enforcement effort and benefits of being green early

In this step, I test the long-term benefits of being green early. The results are presented in Table 2.7. Columns (1)-(4) and (5)-(8) report the results for 2016-high-green-commitment-score industrial firms and 2016-low-green-commitment-score industrial firms separately. In column (1) and column (5), the impact of policy enforcement efforts on the industrial firms' green commitment score is reported for the two groups of firms. The key coefficients of $After \times Distance$ are -0.093 and -0.071 for 2016-high-green-commitment-score industrial firms and 2016-low-green-commitment-score industrial firms, respectively. This suggests that, for each group, a firm being located 1 km closer to the monitoring station within 10 km results in an increase in the green commitment score by 0.093 and 0.071, respectively.

In columns (2)-(4), I report the results for the return on assets (ROA), return on equity (ROE), and earnings per share (EPS) of 2016-high-green-commitment-score industrial firms. The key coefficient of $\widehat{Green}$ is positively significant. In column (2), the coefficient of $\widehat{Green}$ is 0.035, suggesting that an increase of one point in the predicted green commitment score leads to a 3.5% increase in the ROA of 2016-high-green-commitment-score industrial firms. Combining this with the first-stage results in column (1), we can argue that being 1 km closer to the nearest monitoring station increases the ROA of 2016-high-green-commitment-score industrial firms by 0.3255%. These results are robust when using ROE and EPS as the performance measures. In columns (6)-(8), I report the results for the ROA, ROE, and EPS of 2016-low-green-commitment-score industrial firms. The key coefficients of $\widehat{Green}$ are insignificant for ROA and ROE and weakly significant for EPS.

Overall, the results suggest that firms with early green actions perform better than firms without early green actions in terms of dealing with increased government enforcement efforts. The result support my third hypothesis that firms can get long-term benefit by being green early.

Policy enforcement effort and financial costs

In this step, I aim to explore the mechanism behind why firms with early green actions can outperform firms without early green actions. As firms are likely to utilize debts to fund their green transformation, I examine the debt channel by analyzing the overall financial cost, which is measured by the ratio of financial expense to total liability, the financial expense paid, and the total loans from financial institutions. The results of this analysis are reported in Table 2.8.

In columns (1) and (4), I report the results for the ratio of financial expense to total

Table 2.7: Policy enforcement effort and industrial firms' profitability

Table 2.7 reports the 2SLS regression analysis for policy enforcement effort and industrial firms' profitability. Column (1) reports the first-stage regression result. Columns (2)-(4) report results for 2016-high-green-commitment-score industrial firms. Column (6)-(8) reports results for 2016-low-green-commitment-score industrial firms. The first-stage regression is $Green_{i,t} = \alpha+\beta_1 Distance_{i,j}+\beta_2 After\times Distance_{i,j}+X_{i,t}+Ind_i+Year+Monitor_j+\epsilon_{i,t}$. The second-stage regression is $Dep\ Var_{i,t} = \alpha+\beta_1 \widehat{Green}_{i,t}+\beta_2 Distance_{i,j}+X_{i,t}+Ind_i+Year+Monitor_j+\epsilon_{i,t}$. $Dep\ Var_{i,t}$ can be Return on assets $ROA_{i,t}$, Return on equity $ROE_{i,t}$, and Earnings per share $EPS_{i,t}$. Control variable $X_{i,t}$ includes state owned dummy $State_{i,t}$, firm size $ln(Mktcap)_{i,t}$ and tax contribution to the city $Tax\ contribution_{i,t}$. Year fixed effect, industry fixed effect, and monitoring station fixed effect are included. Robust standard errors are reported. The significant levels are 1%, 5%, and 10% respectively.

	2016-high-green-commitment-score				2016-low-green-commitment-score			
	$Green_{i,t}$	$ROA_{i,t}$	$ROE_{i,t}$	$EPS_{i,t}$	$Green_{i,t}$	$ROA_{i,t}$	$ROE_{i,t}$	$EPS_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$After \times Distance_{i,t}$	-0.093***				-0.071***			
	(0.016)				(0.013)			
$\widehat{Green}_{i,t}$		0.035***	0.070***	0.262***		0.013	0.007	0.137*
		(0.010)	(0.021)	(0.069)		(0.010)	(0.020)	(0.074)
$Distance_{i,t}$	0.016	0.002**	0.002	0.013*	-0.005	0.001*	0.004**	0.012**
	(0.019)	(0.001)	(0.002)	(0.007)	(0.013)	(0.001)	(0.002)	(0.006)
$State_{i,t}$	0.194*	-0.021***	-0.025**	-0.094**	0.266***	-0.002	-0.001	-0.059*
	(0.101)	(0.005)	(0.010)	(0.036)	(0.068)	(0.004)	(0.009)	(0.032)
$ln(Mktcap)_{i,t}$	0.368***	0.012***	0.029***	0.167***	0.237***	0.021***	0.054***	0.216***
	(0.047)	(0.004)	(0.009)	(0.031)	(0.035)	(0.003)	(0.006)	(0.020)
$Tax\ contribution_{i,t}$	-0.229	0.049***	0.101***	0.457***	0.011	0.048***	0.074***	0.316***
	(0.176)	(0.009)	(0.026)	(0.076)	(0.216)	(0.012)	(0.027)	(0.067)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitor Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4341	4254	4254	4270	4597	4486	4490	4516

liability for 2016-high-green-commitment-score and 2016-low-green-commitment-score industrial firms, respectively. The coefficient of $\widehat{Green}$ is -0.016 and -0.020, indicating that a 1-point increase in the green commitment score decreases the financial cost of these firms by 1.6% and 2%, respectively.[19] However, this result does not provide evidence about the interest rate comparison of newly added loans, as financing cost measures the aggregate cost for all liabilities. We can only argue that firms could get access to lower-interest-rate loans compared with their previous loans. Empirical literature documents that firms with higher green levels receive a lower interest rate, which suggests that the larger decrease in financial cost for 2016-low-green-commitment-score firms is due to larger loan engagements.

In columns (2) and (5), I report the results for financial expenses. For 2016-high-green-commitment-score industrial firms, the coefficient of $\widehat{Green}$ is -0.075, indicating that a 1-point increase in the green commitment score decreases financial expenses by 0.075 billion CNY and 1 km closer to the nearest monitoring station decreases its financial expense by 6.975 million CNY.[20] For 2016-low-green-commitment-score industrial firms, $\widehat{Green}$ is insignificant, suggesting that the decrease in financial cost does not decrease financial expenses. This could be because 2016-low-green-commitment-score industrial firms take on more loans to support their green transformation, while 2016-high-green-commitment-score industrial firms replace their existing debts with lower interest rate debts.

In columns (3) and (6), I examine the impact of green pressure on firms' total loans from financial institutions. For 2016-high-green-commitment-score industrial firms, $\widehat{Green}$ is insignificant, consistent with my conjecture that they do not engage in more loans to support green transformations. In contrast, for 2016-low-green-commitment-score industrial firms, the coefficient of $\widehat{Green}$ is 0.886, suggesting that a 1-point increase in the green commitment score increases their total loan by 0.886 billion CNY and 1 km closer to the nearest monitoring station would increase their total loan by 0.0629 billion CNY.

In summary, the results suggest that early green actions can help firms handle government enforcement efforts more flexibly. Firms with early green actions can decrease both their financial cost and financial expenses, while firms without early green actions can only decrease their financial costs.

[19]It means that 1 km closer to the nearest monitoring station would decrease their financial cost by 0.15% and 0.14% respectively

[20]In Appendix Table 2.A7, firms that can decrease financial expenses are those with high fixed asset ratio in 2014.

Table 2.8: Policy enforcement effort and industrial firms' financial cost

Table 2.8 reports the 2SLS regression analysis for policy enforcement effort and industrial firms' profitability. Columns (1)-(3) report results for 2016-high-green-commitment-score industrial firms. Column (4)-(6) reports results for 2016-low-green-commitment-score industrial firms. Only second-stage regression results are reported. The second-stage regression is $Dep\ Var_{i,t} = \alpha + \beta_1 \widehat{Green}_{i,t} + \beta_2 Distance_{i,j} + X_{i,t} + Ind_i + Year + Monitor_j + \epsilon_{i,t}$. $Dep\ Var_{i,t}$ can be financial cost $Financial\ cost_{i,t}$, financial expense $Financial\ expense_{i,t}$, and total loan $Totalloan_{i,t}$. $Financial\ cost_{i,t}$ is measured by financial expense divided by total liabilities. Control variable $X_{i,t}$ includes state owned dummy $State_{i,t}$, firm size $ln(Mktcap)_{i,t}$ and tax contribution to the city $Tax\ contribution_{i,t}$. Year fixed effect, industry fixed effect, and monitoring station fixed effect are included. Robust standard errors are reported. The significant levels are 1%, 5%, and 10% respectively.

	2016-high-green-commitment-score			2016-low-green-commitment-score		
	$Financial\ cost_{i,t}$	$Financial\ expense_{i,t}$	$Total\ loan_{i,t}$	$Financial\ loan_{i,t}$	$Financial\ expense_{i,t}$	$Total\ cost_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Green}_{i,t}$	-0.016***	-0.075***	0.500	-0.020***	-0.003	0.886*
	(0.004)	(0.026)	(0.435)	(0.005)	(0.027)	(0.479)
$Distance_{i,t}$	-0.001***	-0.001	0.069	-0.001	0.004*	0.081**
	(0.000)	(0.003)	(0.052)	(0.000)	(0.002)	(0.037)
$State_{i,t}$	0.006**	0.062***	1.442***	0.005**	-0.008	-0.215
	(0.002)	(0.017)	(0.296)	(0.002)	(0.013)	(0.164)
$ln(Mktcap)_{i,t}$	0.005***	0.137***	2.390***	0.005***	0.080***	1.997***
	(0.002)	(0.014)	(0.243)	(0.001)	(0.009)	(0.203)
$Tax\ contribution_{i,t}$	-0.002	0.032	1.142**	-0.002	-0.049**	0.082
	(0.004)	(0.036)	(0.572)	(0.005)	(0.021)	(0.505)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4271	4206	4001	4475	4536	4091

Long-term performance track with propensity score matching

While I demonstrate that firms with early green actions can outperform those without when facing increased government enforcement efforts, it remains unclear whether the benefits of going green early still exist when taking into account the transformation costs borne by these firms for early green actions. To solve this concern, in this step, I explore the performance evolution of firms with high and low green commitment scores over time while controlling for industry classification, firm size, and growth potential using the propensity score method.

First, I conduct a propensity score matching process to match 2016-high-green-commitment-score industrial firms with 2016-low-green-commitment-score industrial firms in 2014 based on firm size (ln(Mktcap)), market-to-book ratio, return on assets, distance to the nearest monitoring station, and industry code. Before matching, there are 546 firms in the 2016-low-green-commitment-score firm group and 560 firms in the 2016-high-green-commitment-score firm group. After matching, I obtain 308 paired firms. Table 2.9 reports the comparison of size, market-to-book ratio, ROA, and distance before and after matching. After matching, all variables are insignificantly different from each other.

Table 2.9: Propensity score matching results

Table 2.9 reports propensity score matching results for 2016-high-green-commitment-score industrial firms and 2016-low-green-commitment-score industrial firms in 2014. I match the firm size (ln(Mktcap)), market-to-book ratio, return on asset, distance to the nearest monitoring station, and industry code in 2014. Panel A reports t-test results for each variable before matching. Panel B reports t-test results for each variable after matching.

Panel A: Before matching			
	2016-high-green-commitment score	2016-low-green-commitment-score	Difference
Size	22.592	22.498	0.094*
market to book	3.573	4.826	-1.254***
ROA	0.038	0.033	0.005*
distance	3.967	4.081	-0.115
Panel B: After matching			
	2016-high-green commitment score	2016-low-green-commitment-score	Difference
Size	22.505	22.526	-0.021
market to book	3.408	3.599	-0.192
ROA	0.039	0.038	0.001
distance	4.326	4.092	0.235

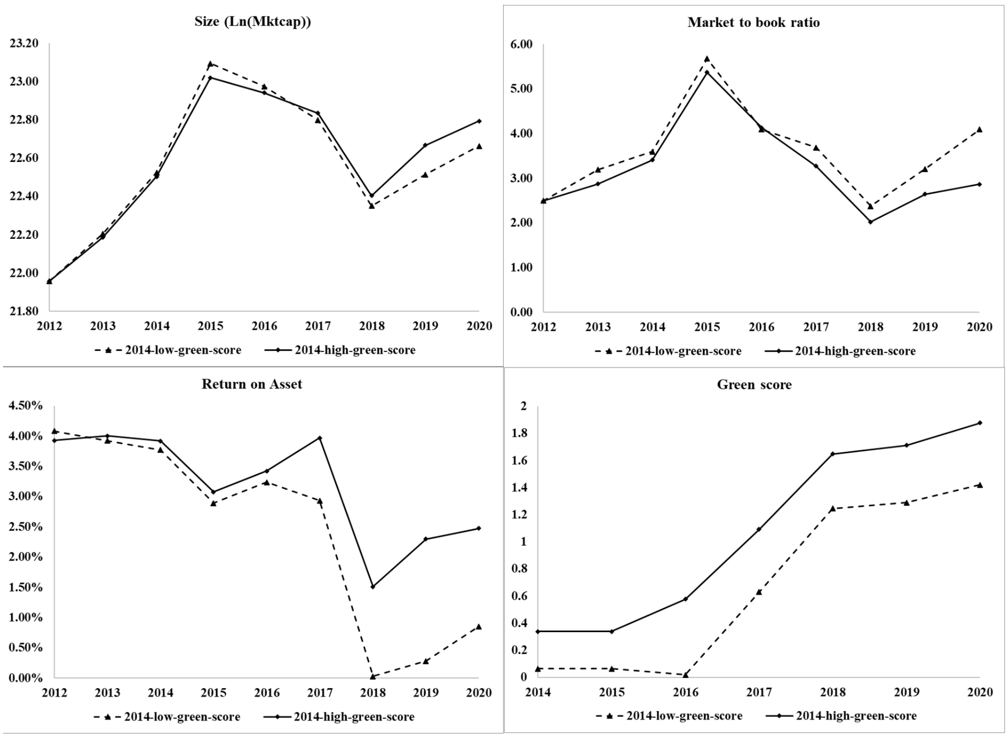


Figure 2.5: Parallel trend

In Figure 2.5, the evolution of size, market-to-book ratio, return on asset, and green commitment score from 2012 to 2020 is plotted. The plot starts from 2012 to verify parallel trends before 2014, as the green commitment score is calculated starting from 2014. From 2012 to 2016, both 2016-low-green-commitment-score and 2016-high-green-commitment-score industrial firms show a similar trend in size, market-to-book ratio, and return on asset. However, starting in 2017, the return on asset of the two groups of firms diverges, with 2016-high-green-commitment-score industrial firms having larger return on asset than 2016-low-green-commitment-score industrial firms. One possible argument for this difference is that 2016-low-green-commitment-score firms put more effort into increasing their green level and thereby had a greater impact on their return on asset. But the trend of green commitment scores does not support this argument, as both groups of firms show a similar trend in green commitment score except in 2016, when the green commitment score of 2016-high-green-commitment-score industrial firms started to increase earlier. The figure suggests that industrial firms' green commitment scores in 2014 are associated with their return on asset in the future. Overall, these results confirm that early green actions can help firms build flexibility to handle green pressure from governments.

2.7 Further evidence: Policy enforcement efforts and production shift

In this section, I aim to provide further evidence that the fixed asset ratio captures firms' ability to shift production. One potential counterargument is that the fixed asset ratio merely reflects the need to invest more in air pollution abatement facilities, rather than a lack of ability to shift production. If the fixed asset ratio indeed serves as a proxy for the ability to shift production, I can draw the following inference: if firms with low fixed asset ratios take fewer green actions because they have a higher ability to shift production, I would expect them to shift production when local government policy enforcement efforts increase.

In order to support this inference, I first verify that the fixed asset ratio can predict lower levels of early green actions. Then, I show that only firms with less early green actions have their production process affected by increased local government enforcement efforts. Thirdly, I demonstrate that the change in production is due to the shifting of production. Finally, I provide evidence to show that within the group of firms with less early green actions, it is specifically those with low fixed asset ratios that are more likely to shift production.

2.7.1 Fixed asset ratio and green actions

In this step, I analyze the predictability of the fixed asset ratio on firms' green actions. I run a logit regression to analyze the probability that firms are assigned to the high green commitment score group in equation (2.7). The group classification is the same as section 2.6.2. The main variables are the fixed-asset ratio, R&D expenses, and the kz index. Control variables (X) include state-owned dummy, market capitalization, and tax contribution. The fixed-asset ratio is a proxy for firms' difficulty level of shifting production, R&D expenses measure firms' ability to conduct green technology innovation, and the kz index measures firms' ability to get external financing.

$$\begin{aligned} Pr(High\ green\ score\ group_{i,2016}) = f(\alpha + \beta_1 Fixed\ asset\ ratio_{i,2016-j} + \beta_2 R\&D_{i,2016-j} \\ + \beta_3 KZ_{i,2016-j} + X_{i,2016-j} + Ind_i + \epsilon_{i,2016}), j = 0, 1, 2 \end{aligned} \tag{2.7}$$

Table 2.10 reports the logit regression result. Columns (1) and (2) report the result for 2014, columns (3) and (4) report the result for 2015, and columns (5) and (6) report the result for 2016. The coefficient of $Fixed\ asset\ ratio_{i,2016-j}$ is positive across all specifications. Firms with a high fixed-asset ratio are more likely to take green actions early. It suggests that the production shift ability can affect firms' decision of taking green action early. The coefficient of $R\&D_{i,2016-j}$ is insignificant across all specifications. The coefficient of firms $KZ_{i,2016-j}$ is positive across all specifications. Firms with a high kz index are less likely to take green actions early. It suggests that firms' external financing ability will limit their ability to take early green actions.

Table 2.10: Logit regression of high and low green commitment score groups

Table 2.10 reports the logit regression analysis for high and low green commitment score groups. The regression models the probability that the firm is in the high-green-commitment-score group in 2016. The logit model is $Pr(High\ green\ score\ group_{i,2016}) = f(\alpha + \beta_1 Fixed\ asset\ ratio_{i,2016-j} + \beta_2 R\&D_{i,2016-j} + \beta_3 KZ_{i,2016-j} + X_{i,2016-j} + Ind_i + \epsilon_{i,2016}), j = 0, 1, 2$. Control variable X includes state owned dummy $State$, firm size $ln(Mktcap)$ and tax contribution to the city $Tax\ contribution$. Industry fixed effect is included. The significant levels are 1%, 5%, and 10% respectively.

	$Pr(High\ green\ score\ group_{i,2016})$					
	(1)	(2)	(3)	(4)	(5)	(6)
	j=2		j=1		j=0	
$Fixed\ asset\ ratio_{i,2016-j}$	1.645***	1.441***	1.821***	1.722***	1.896***	2.009***
	(0.266)	(0.323)	(0.268)	(0.335)	(0.254)	(0.315)
$R\&D_{i,2016-j}$	-0.097	-0.091	-0.056	-0.052	-0.113	-0.128
	(0.091)	(0.099)	(0.073)	(0.077)	(0.077)	(0.086)
$KZ_{i,2016-j}$	-0.051***	-0.054***	-0.056***	-0.057***	-0.051***	-0.041**
	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)	(0.021)
$State_{i,2016-j}$	0.145	0.169*	0.156*	0.189**	0.120	0.161*
	(0.089)	(0.096)	(0.086)	(0.093)	(0.083)	(0.089)
$ln(Mktcap)_{i,2016-j}$	0.060	0.060	0.040	0.050	0.131**	0.153**
	(0.056)	(0.060)	(0.061)	(0.065)	(0.061)	(0.066)
$Tax\ contribution_{i,2016-j}$	0.019	-0.080	-0.053	-0.096	-0.006	-0.063
	(0.163)	(0.175)	(0.175)	(0.184)	(0.179)	(0.190)
Ind FE	No	Yes	No	Yes	No	Yes
N	1016	1000	1034	1025	1167	1154

2.7.2 Policy enforcement effort and production process

In this step, I aim to explore whether the production process for firms with different early green actions will be affected differently by increased green actions. To do so, I analyze firms' operating revenue, operating costs, assets under construction, and employee salaries. Table 2.11 presents two-stage-least-square regression results between policy enforcement efforts and firms' production process variables. Panel A and Panel B report results for 2016-high-green-commitment-score industrial firms and 2016-low-green-commitment-score industrial firms, respectively.

In Table 2.11, Panel A (columns 1-4) and Panel B (columns 1-4), the relationship between predicted green commitment score ($\widehat{Green}$) and firms' production process variables is presented. For Panel A, the key coefficients of $\widehat{Green}$ are insignificant for all variables, indicating that government policy enforcement effort does not have an impact on the production processes of 2016-high-green-commitment-score industrial firms. In contrast, for Panel B, the key coefficients of $\widehat{Green}$ are significant for 2016-low-green-commitment-score industrial firms. In column (1) for operating revenue, the coefficient is positively significant at 3.298, together with the first-stage results from Table 2.7, suggesting that a decrease of 1 km to the nearest monitoring station results in an increase in operating revenue by 234.158 million CNY. For operating costs in column (2), the coefficient is also positively significant at 2.644, indicating that a decrease of 1 km to the nearest monitoring station leads to an increase in operating costs by 187.724 million CNY. While the results for assets under construction and employee salaries are weakly significant, it is notable that a decrease of 1 km to the nearest monitoring station increases assets under construction and employees' salaries by 18.247 million CNY and 11.644 million CNY, respectively. Overall, these results suggest that increased policy enforcement efforts result in 2016-low-green-commitment-score industrial firms producing more, while doesn't affect the production of 2016-high-green-commitmment-score industrial firms.

2.7.3 Policy enforcement effort and production shift

In this step, I aim to investigate how the production process of firms with low green commitment scores in 2016 is affected, specifically whether it's due to production shifting. To achieve this, I leverage the availability of both consolidated and parent-firm financial reports for firms and examine changes in the production processes at both parent firm level and subsidiary level for 2016-low-green-commitment-score firms. I estimate the accounting indicators of listed firms' subsidiaries by subtracting their parent-firm accounting indicators from their consolidated accounting indicators. The results are presented in Table 2.12, where Panel A shows the results for the entire sample, and Panel B shows the results for firms with a kz index lower than the industry median in 2014, representing firms with high financing ability. Exploring firms with different kz index is an extension of the study by Bartram et al. (2022), which shows that firms with low financing ability will shift production. Columns (1)-(4) report the results for parent firms, while columns (5)-(8) report the results for subsidiaries.

In Panel A, the coefficients for $\widehat{Green}$ are insignificant for parent firms, while they are significant for estimated subsidiaries, with magnitudes similar to those at the overall firm level. A 1 km proximity to a monitoring station leads to an increase in new assets under construction of subsidiaries by 16.432 million CNY. The increased production occurs at the subsidiary level, leading to an increase in their operating costs, revenue, and employees' salaries by 0.171 billion CNY, 0.207 billion CNY, and 9.249 million CNY.

Table 2.11: Policy enforcement effort and industrial firms' production process

Table 2.11 reports the 2SLS regression analysis for policy enforcement effort and industrial firms' production process. Panel A reports the result for 2016-high-green-commitment-score industrial firms. Panel B reports the result for 2016-low-green-commitment-score industrial firms. Firms will be assigned to the 2016-high-green-commitment-score group if it has a green commitment score, which is larger than the industry median green commitment score in 2016. Otherwise, it will be assigned to the 2016-low-green-commitment-score. Column (2)-(5) report second-stage regression results. The second-stage regression is $Dep\ Var_{i,t} = \alpha + \beta_1 \widehat{Green}_{i,t} + \beta_2 Distance_{i,j} + X_{i,t} + Ind_i + Year + Monitor_i + \epsilon_{i,t}$. $Dep\ Var_{i,t}$ can be operating revenue $Revenue_{i,t}$, operating cost $Cost_{i,t}$, assets under construction $Construction_{i,t}$, and employee's salary $Salary_{i,t}$. Control variable $X_{i,t}$ includes state owned dummy $State_{i,t}$, firm size $ln(Mktcap)_{i,t}$ and tax contribution to the city $Tax\ contribution_{i,t}$. Year fixed effect, industry fixed effect, and monitoring station fixed effect are included. Robust standard errors are reported. The significant levels are 1%, 5%, and 10% respectively.

Panel A: 2016-high-green-commitment-score industrial firms				
	$Revenue_{i,j}$	$Cost_{i,j}$	$Construction_{i,j}$	$Salary_{i,j}$
	(1)	(2)	(3)	(4)
$\widehat{Green}_{i,t}$	1.085	0.853	-0.082	0.060
	(0.97)	(0.838)	(0.115)	(0.100)
$Distance_{i,j}$	-0.517***	-0.426***	0.005	-0.059***
	(0.134)	(0.113)	(0.015)	(0.012)
$State_{i,t}$	3.872***	3.720***	0.447***	0.441***
	(0.591)	(0.501)	(0.087)	(0.054)
$ln(Mktcap)_{i,t}$	7.591***	5.822***	0.716***	0.704***
	(0.512)	(0.441)	(0.062)	(0.051)
$Tax\ contribution_{i,t}$	6.939***	5.339***	0.122	-0.054
	(1.795)	(1.459)	(0.167)	(0.094)
Year FE	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes
N	4297	4306	4099	4322
Panel B: 2016-low-green-commitment-score industrial firms				
	$Revenue_{i,j}$	$Cost_{i,j}$	$Construction_{i,j}$	$Salary_{i,j}$
	(1)	(2)	(3)	(4)
$\widehat{Green}_{i,t}$	3.298***	2.644***	0.257**	0.164*
	(1.111)	(0.932)	(0.111)	(0.091)
$Distance_{i,j}$	0.061	0.039	0.012	0.010
	(0.092)	(0.075)	(0.011)	(0.008)
$State_{i,t}$	1.378**	1.463***	-0.129**	0.259***
	(0.548)	(0.462)	(0.062)	(0.046)
$ln(Mktcap)_{i,t}$	6.264***	4.464***	0.380***	0.552***
	(0.434)	(0.337)	(0.039)	(0.045)
$Tax\ contribution_{i,t}$	11.475***	10.288***	0.167	0.794***
	(2.144)	(1.867)	(0.148)	(0.18)
Year FE	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes
N	4502	4519	4206	4501

Table 2.12: Policy enforcement effort and 2016-low-green-commitment-score industrial firms' production shift

Table 2.12 reports the 2SLS regression analysis for policy enforcement effort and 2016-low-green-commitment-score industrial firms' production in parent and subsidiaries. Panel A reports the result for all 2016-low-green-commitment-score industrial firms. Panel B reports the result for 2016-low-green-commitment-score industrial firms with a low kz index, which equals to or below the industry median kz index in 2014. Columns (1)-(4) report results with accounting data for parent firms. Columns (5)-(8) report results with accounting data for estimated subsidiaries. I estimate listed firms' subsidiaries' accounting indicators by deducting parent-firm accounting indicators from consolidated accounting indicators. Only second-stage regression results are reported. The second-stage regression is $Dep\ Var_{i,t} = \alpha + \beta_1 \widehat{Green}_{i,t} + \beta_2 Distance_{i,j} + X_{i,t} + Ind_i + Year + Monitor_j + \epsilon_{i,t}$. $Dep\ Var_{i,t}$ can be operating revenue $Revenue_{i,t}$, operating cost $Cost_{i,t}$, assets under construction $Construction_{i,t}$, and employee's salary $Salary_{i,t}$. Control variable $X_{i,t}$ includes state owned dummy $State_{i,t}$, firm size $ln(Mktcap\_i,t)$ and tax contribution to the city $Tax\ contribution_{i,t}$. Year fixed effect, industry fixed effect, and monitoring station fixed effect are included. Robust standard errors are reported. The significant levels are 1%, 5%, and 10% respectively

Panel A: 2016-low-green-commitment-score industrial firms

	Parent firm				Estimated subsidiaries			
	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Green}_{i,t}$	-0.036	-0.156	0.027	-0.027	3.100***	2.226***	0.183*	0.132**
	(0.336)	(0.278)	(0.034)	(0.026)	(0.957)	(0.657)	(0.108)	(0.061)
$Distance_{i,t}$	0.080***	0.046*	0.005	-0.000	0.035	0.006	0.005	0.000
	(0.030)	(0.025)	(0.003)	(0.002)	(0.077)	(0.062)	(0.011)	(0.006)
$State_{i,t}$	0.480***	0.545***	0.039**	0.028**	1.530***	1.681***	-0.001	0.269***
	(0.154)	(0.136)	(0.016)	(0.013)	(0.486)	(0.409)	(0.055)	(0.033)
$ln(Mktcap)_{i,t}$	1.600***	1.296***	0.062***	0.131***	3.491***	2.390***	0.328***	0.343***
	(0.143)	(0.109)	(0.009)	(0.013)	(0.311)	(0.249)	(0.040)	(0.026)
$Tax\ contribution_{i,t}$	1.817***	1.674***	0.296***	0.276***	4.371***	4.289***	0.045	0.222***
	(0.576)	(0.519)	(0.108)	(0.069)	(1.226)	(1.118)	(0.113)	(0.071)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4206	4090	3249	4434	4208	4094	3230	4434

Panel B: 2016-low-green-commitment-score industrial firms with low kz index

	Parent firm				Estimated subsidiaries			
	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Green}_{i,t}$	-0.559**	-0.616***	0.011	-0.026	1.864***	1.213***	0.110	0.113***
	(0.269)	(0.206)	(0.032)	(0.020)	(0.558)	(0.383)	(0.097)	(0.035)
$Distance_{i,t}$	0.129**	0.081*	0.013***	0.011***	-0.380***	-0.332***	-0.092***	-0.014*
	(0.053)	(0.044)	(0.004)	(0.003)	(0.105)	(0.086)	(0.027)	(0.007)
$State_{i,t}$	-1.056***	-0.655**	0.049**	-0.064**	-0.183	-0.157	0.033	0.157***
	(0.363)	(0.305)	(0.025)	(0.028)	(0.570)	(0.501)	(0.071)	(0.044)
$ln(Mktcap)_{i,t}$	2.403***	1.768***	0.072***	0.148***	2.577***	1.845***	0.478***	0.195***
	(0.219)	(0.164)	(0.016)	(0.016)	(0.275)	(0.226)	(0.063)	(0.020)
$Tax\ contribution_{i,t}$	0.398	0.323	0.021	0.017	-1.233**	-0.824	0.137	-0.051
	(0.438)	(0.344)	(0.085)	(0.030)	(0.592)	(0.511)	(0.164)	(0.043)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1889	1842	1502	1998	1866	1816	1495	1980

In Panel B, I exclude firms with a kz index above the industry median, which corresponds to less ability to conduct green transformation. As shown, the key coefficient of $\widehat{Green}$ for predicting revenue and cost is negatively significant for parent firms, while it is positively significant for estimated firms in predicting revenue, cost, and salary. Different from Bartram et al. (2022), I show that firms that shift production are those with high financing ability.

Overall, these findings support my hypothesis that 2016-low-green-commitment-score industrial firms shift their production from parent firms to subsidiaries in response to increased local government enforcement efforts. Notably, this shift in production does not necessarily conflict with the central government's air quality improvement targets. On one hand, if the increased production is closely monitored by another local government and does not violate local environmental policies, it can reflect the market's ability to adjust to climate transition risk. On the other hand, the emission of SO2, NOX, and dust is different from CO2 emissions, as they are not treated at the global aggregate level.

2.7.4 Fixed asset ratio and production shift

In the final step, I aim to demonstrate that among the 2016-low-green-commitment-score industrial firms, those that shift their production are the ones with a low fixed asset ratio in 2014. This suggests that fixed asset ratio can capture firms' ability to shift production. To provide evidence for this claim, I divide the 2016-low-green-commitment-score industrial firms into two groups based on their fixed asset ratio relative to the industry median in 2014. Specifically, if a firm's fixed asset ratio was higher than the industry-median fixed asset ratio in 2014, it is assigned to the high fixed asset ratio group, otherwise, it is assigned to the low fixed asset ratio group, within each industry.

The results of the production shift analysis for the low and high fixed-asset ratio groups are presented in Table 2.13. In Panel A, columns (5) and (6), the coefficients for revenue and cost are significant for subsidiaries. However, in Panel B, the coefficients for revenue and cost are insignificant. These results suggest that, when faced with increased local government enforcement efforts, firms with a low fixed asset ratio are more likely to shift production.

In summary, my study provides evidence that firms with low fixed asset ratios in 2014 are less inclined to take early green actions compared to those with high fixed asset ratios, as the former have a higher ability to shift production. Moreover, in response to increased local government enforcement efforts after 2016, these firms are more likely to shift production. These findings suggest that fixed asset ratio is a reliable indicator of a firm's production-shifting ability.

Table 2.13: fixed asset ratio and production shift for 2016-low-green-commitment-score firms

Table 2.13 reports the 2SLS regression analysis for production shift ability and production shift for 2016-low-green-commitment-score firms. Panel A reports the result for 2016-low-green-commitment-score industrial firms with 2014-low-fixed-asset ratio. Panel B reports the result for 2016-low-green-commitment-score industrial firms with 2014-high-fixed-asset ratio. Columns (1)-(4) report results with accounting data for parent firms. Columns (5)-(8) report results with accounting data for estimated subsidiaries. I estimate listed firms' subsidiaries' accounting indicators by deducting parent-firm accounting indicators from consolidated accounting indicators. Only second-stage regression results are reported. The second-stage regression is $Dep\ Var_{i,t} = \alpha + \beta_1 \widehat{Green}_{i,t} + \beta_2 Distance_{i,j} + X_{i,t} + Ind_i + Year + Monitor_j + \epsilon_{i,t}$. $Dep\ Var_{i,t}$ can be operating revenue $Revenue_{i,t}$, operating cost $Cost_{i,t}$, assets under construction $Construction_{i,t}$, and employee's salary $Salary_{i,t}$. Control variable $X_{i,t}$ includes state owned dummy $State_{i,t}$, firm size $ln(Mktcap)_{i,t}$ and tax contribution to the city $Tax\ contribution_{i,t}$. Year fixed effect, industry fixed effect, and monitoring station fixed effect are included. Robust standard errors are reported. The significant levels are 1%, 5%, and 10% respectively

Panel A: Low fixed-asset ratio (equal to or below the industry median in 2014)

	Parent firm				Estimated subsidiaries			
	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Green}_{i,t}$	-0.424	-0.474	0.049	-0.004	3.266***	2.424***	0.161	0.124
	(0.454)	(0.368)	(0.144)	(0.072)	(1.137)	(0.831)	(0.127)	(0.088)
$Distance_{i,t}$	0.075	0.070	0.034	-0.035**	0.064	-0.024	-0.004	0.004
	(0.083)	(0.075)	(0.029)	(0.016)	(0.205)	(0.164)	(0.030)	(0.016)
$State_{i,t}$	0.607*	0.858***	0.368***	0.158**	2.709***	2.404***	-0.253**	0.366***
	(0.318)	(0.299)	(0.137)	(0.062)	(0.930)	(0.854)	(0.101)	(0.060)
$ln(Mktcap)_{i,t}$	1.714***	1.486***	0.627***	0.470***	3.814***	3.052***	0.374***	0.392***
	(0.194)	(0.169)	(0.076)	(0.039)	(0.439)	(0.372)	(0.057)	(0.040)
$Tax\ contribution_{i,t}$	3.422***	2.819***	0.060	-0.117	4.439**	4.103**	-0.087	0.241*
	(0.973)	(0.877)	(0.178)	(0.098)	(1.861)	(1.656)	(0.170)	(0.124)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2075	1999	1965	2011	2055	1990	2064	2181

Panel B: High fixed-asset ratio (above the industry median in 2014)

	Parent firm				Estimated subsidiaries			
	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$	$Revenue_{i,t}$	$Cost_{i,t}$	$Construction_{i,t}$	$Salary_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Green}_{i,t}$	-0.316	-0.323	-0.066	-0.039	1.503	0.831	0.025	0.034
	(0.416)	(0.269)	(0.054)	(0.027)	(1.150)	(0.645)	(0.099)	(0.065)
$Distance_{i,t}$	0.154***	0.086***	-0.064***	0.015***	0.018	0.210***	-0.036**	0.003
	(0.047)	(0.032)	(0.023)	(0.003)	(0.099)	(0.065)	(0.016)	(0.006)
$State_{i,t}$	1.138***	1.109***	0.001	0.049***	0.871	1.125*	0.018	0.110***
	(0.239)	(0.199)	(0.036)	(0.015)	(0.638)	(0.588)	(0.039)	(0.037)
$ln(Mktcap)_{i,t}$	1.630***	0.923***	0.067***	0.093***	2.750***	1.831***	0.351***	0.239***
	(0.242)	(0.114)	(0.024)	(0.012)	(0.361)	(0.272)	(0.054)	(0.028)
$Tax\ contribution_{i,t}$	0.028	0.140	0.012	0.005	3.243**	2.715*	-0.093	0.160**
	(0.325)	(0.246)	(0.084)	(0.023)	(1.648)	(1.493)	(0.092)	(0.079)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1475	1435	1645	1579	1498	1448	1518	1599

2.8 Conclusion

To explore the reasons for firms going green, I develop a green commitment score by analyzing standardized green information from Chinese listed firms' annual reports. The score is robust to Thomson Reuters Refinitiv green score and reflects the improvement of air quality around firms. With the same methodology, the score can be extended to capture other types of pollution abatement commitments.

Using the green commitment score, I investigate the factors driving firms to go green. I find that local government policy enforcement intensity, distance to monitoring stations, and firms' low ability to shift production are positively associated with a firm's green commitment score. Furthermore, I find that firms with low green commitment scores and high ability to shift production will shift production when local governments increase policy enforcement.

Additionally, my study explores the benefits of early green actions. Firms with high green commitment scores can decrease their financial expenses and increase their performance when local governments increase policy enforcement. However, firms with low green commitment scores cannot reap the same benefits. I further demonstrate that this result remains even when considering the early green transformation cost.

Future research can explore the role of market competition in firms' decisions to go green. Firms may hesitate to go green if they believe it will result in a competitive disadvantage. However, in the long run, firms will be forced to go green due to increasing policy enforcement. Thus, early green actions may provide firms with a competitive advantage. It would also be interesting to analyze whether it is efficient for firms to remain "brown" to maintain a competitive advantage.

My study makes a significant contribution to understanding the reasons why firms decide to adopt green practices. While previous literature has explored the instant costs and benefits of taking green actions, the incentives for firms to take early green actions have been underexplored. My study highlights that firms' early green actions can be attributed to their ability to shift production. Additionally, the findings suggest that firms with early green actions can reap long-term benefits if the government increases its enforcement efforts.

Finally, my study contributes to the understanding of climate policy and firm behavior. As firms can shift production across their subsidiaries, more attention should be given to those firms with high production shift ability to design more effective and targeted climate policies.

2.9 Appendix

Table 2.A1: Number of firms from 2014 to 2020

Year	Number of firms
2014	2549
2015	2770
2016	2999
2017	3433
2018	3541
2019	3747
2020	4144

Table 2.A2: Dictionary for air pollution information

AQI	PM2.5	SO2	NO2	O3
Pollutant	particulate matter Soot Dust Ammonia	SO2 Sulfuric acid mis	NO2 NOX	O3 VOCs Methane (CH4) Benzene Toluene Xylene
Facility	Environmental smoke collection Exhaust gas collection (recovery) Dust collection (suppression/filter) Low-temperature plasma Cyclone separator Activated carbon adsorption Waste gas tower Ultra-clean emission renovation	Desulfurization Acid mist purification Waste acid tower Acid production system Sulfuric acid mist collection	Denitrification low nitrogen burner	Plasma Photocatalysis VOC Treatment System RTO

Table 2.A3: Summary statistics for firms within 10 km (in billions)

Table 2.A3 reports summary statistics for financial variables and control variables used in regressions for firms within a distance of 10 km. Panel A and panel B report the whole sample and industrial firms respectively. Industrial firms include firms that belong to the manufacturing industry, and the electricity, heat, gas, water production, and supply industry. All the financial variables, including revenue, cost, fixed asset ratio, assets under construction, financial expenses, and financial cost, are trimmed at 1% and 99% levels annually. Similar result can be got with winsorize.

Panel A: All firms									
	N	Min	P10	Median	P75	P90	Max	Mean	STD
Revenue	16553	0.028	0.380	1.948	5.507	14.840	157.200	6.540	14.040
Cost	16551	0.015	0.210	1.319	4.088	11.900	128.600	5.153	11.800
Fixed asset ratio	17408	0.000	0.013	0.144	0.274	0.427	0.954	0.188	0.166
Construction	14950	0.000	0.001	0.081	0.325	1.126	16.090	0.491	1.322
Financial expense	16645	-0.156	-0.010	0.018	0.089	0.295	2.997	0.110	0.275
Financial cost	16690	-0.218	-0.018	0.012	0.026	0.038	0.091	0.010	0.026
State	17412	0.000	0.000	0.000	1.000	1.000	1.000	0.369	0.483
Size	17409	11.140	14.700	15.700	16.420	17.210	21.280	15.860	1.040
Tax contribution	17412	0.000	0.000	0.003	0.027	0.160	1.000	0.069	0.190
Distance	17412	0.048	1.174	3.267	5.231	7.689	9.986	3.857	2.406
Panel B: Industrial firms									
	N	Min	P10	Median	P75	P90	Max	Mean	STD
Revenue	10065	0.028	0.392	1.851	5.003	13.830	157.200	6.209	13.700
Cost	10083	0.017	0.222	1.260	3.707	10.870	124.100	4.864	11.470
Fixed asset ratio	10213	0.000	0.062	0.190	0.305	0.450	0.954	0.226	0.155
Construction	9461	0.000	0.003	0.094	0.334	1.040	13.520	0.472	1.247
Financial expense	10001	-0.156	-0.010	0.016	0.077	0.256	2.997	0.098	0.254
Financial cost	9991	-0.218	-0.020	0.014	0.028	0.039	0.091	0.011	0.028
State	10213	0.000	0.000	0.000	1.000	1.000	1.000	0.323	0.468
Size	10210	13.090	14.670	15.620	16.300	17.040	20.850	15.760	0.948
Tax contribution	10213	0.000	0.000	0.005	0.036	0.236	1.000	0.085	0.215
Distance	10213	0.048	1.206	3.731	5.896	8.278	9.986	4.191	2.538

Table 2.A4: Compare Refinitiv ESG score with average pollutant emission across entities within the listed company

	SO2			NOX			Dust		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Emission Score	34.934***			33.247***			10.203**		
	(10.462)			(10.632)			(5.020)		
Environment score		39.726***			29.349**			7.288	
		(11.100)			(11.368)			(5.260)	
ESG score			49.117***			35.878**			9.847
			(15.155)			(15.347)			(7.141)
Year FE					Yes				
Industry FE					Yes				
N	438	438	438	461	461	461	381	381	381
adj. R-sq	0.040	0.044	0.038	0.179	0.173	0.170	0.523	0.519	0.519

Table 2.A5: The control right transfer of monitoring stations and firms' green commitment score

Panel A: CSR-part green commitment score									
	All firms			Industrial firms			Other firms		
	Green	Green	Green	Green	Green	Green	Green	Green	Green
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance	-0.008***	-0.002	0.007	-0.017***	0.023***	0.037***	-0.005*	-0.005	-0.001
	(0.002)	(0.005)	(0.005)	(0.003)	(0.008)	(0.008)	(0.003)	(0.006)	(0.006)
$After \times Distance$	-0.027***	-0.033***	-0.034***	-0.078***	-0.084***	-0.084***	-0.012	-0.013*	-0.014*
	(0.007)	(0.006)	(0.006)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
State			0.275***			0.369***			0.173***
			(0.028)			(0.048)			(0.023)
ln(Mktcap)			0.202***			0.306***			0.059***
			(0.015)			(0.025)			(0.011)
Tax Contribution			0.151			0.021			0.306
			(0.105)			(0.124)			(0.217)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Monitoring station FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N	17397	17390	17386	10206	10206	10202	7191	7184	7184
adj. R-sq	0.063	0.310	0.328	0.098	0.316	0.340	0.028	0.317	0.326

Panel B: non-CSR-part green commitment score									
	All firms			Industrial firms			Other firms		
	Green	Green	Green	Green	Green	Green	Green	Green	Green
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance	-0.001	0.002	0.005	-0.018***	0.007	0.009	0.008	-0.013**	-0.010
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
$After \times Distance$	-0.000	-0.004	-0.004	-0.002	-0.008	-0.008	0.005	0.006	0.005
	(0.005)	(0.004)	(0.004)	(0.007)	(0.005)	(0.005)	(0.008)	(0.006)	(0.006)
State			0.108***			0.068***			0.133***
			(0.016)			(0.022)			(0.025)
ln(Mktcap)			-0.015***			-0.026***			0.001
			(0.006)			(0.009)			(0.007)
Tax Contribution			0.113**			0.220***			0.043
			(0.046)			(0.057)			(0.063)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Monitoring station FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N	17397	17390	17386	10206	10206	10202	7191	7184	7184
adj. R-sq	0.000	0.408	0.410	0.005	0.385	0.387	0.000	0.510	0.514

Table 2.A6: Production shift ability and production shift for 2016-high-green-commitment score firms

Panel A: Low fixed-asset ratio (equal to or below industry median)								
	Parent firm				Estimated subsidiaries			
	Revenue	Cost	Construction	Salary	Revenue	Cost	Construction	Salary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Green}$	0.276	0.259	-0.152	0.042	2.409**	1.683*	0.215	0.051
	(0.340)	(0.295)	(0.111)	(0.046)	(1.180)	(0.905)	(0.151)	(0.095)
Distance	-0.042	0.090**	0.049***	-0.018*	-0.069	-0.194	0.076***	-0.017
	(0.054)	(0.038)	(0.015)	(0.010)	(0.175)	(0.148)	(0.029)	(0.016)
State	0.173	0.006	0.038	0.093***	5.136***	3.951***	0.437***	0.511***
	(0.330)	(0.270)	(0.047)	(0.032)	(0.964)	(0.815)	(0.111)	(0.075)
ln(Mktcap)	1.216***	0.971***	0.164***	0.099***	3.482***	2.450***	0.400***	0.383***
	(0.165)	(0.140)	(0.055)	(0.023)	(0.519)	(0.358)	(0.077)	(0.048)
Tax contribution	1.940***	1.419***	0.216*	0.327***	0.109	1.266	-0.055	0.006
	(0.634)	(0.487)	(0.119)	(0.071)	(1.351)	(1.100)	(0.202)	(0.123)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1782	1708	1412	1880	1798	1714	1796	1885
Panel B: High fixed-asset ratio (above industry median)								
	Parent firm				Estimated subsidiaries			
	Revenue	Cost	Construction	Salary	Revenue	Cost	Construction	Salary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Green}$	0.781**	0.476	-0.066	0.050	0.609	0.512	0.049	-0.004
	(0.386)	(0.376)	(0.054)	(0.037)	(1.130)	(0.992)	(0.144)	(0.072)
Distance	-0.197**	-0.313***	-0.064***	-0.021**	-1.145***	-0.841***	0.034	-0.035**
	(0.077)	(0.082)	(0.023)	(0.009)	(0.267)	(0.226)	(0.029)	(0.016)
State	-0.062	-0.664**	0.001	-0.001	-0.892	-0.945	0.368***	0.158**
	(0.309)	(0.284)	(0.036)	(0.026)	(1.198)	(1.075)	(0.137)	(0.062)
ln(Mktcap)	1.736***	1.576***	0.067***	0.133***	6.335***	4.615***	0.627***	0.470***
	(0.248)	(0.233)	(0.024)	(0.022)	(0.790)	(0.658)	(0.076)	(0.039)
Tax contribution	0.857	-0.174	0.012	0.061	2.501	1.031	0.060	-0.117
	(0.699)	(0.659)	(0.084)	(0.049)	(2.244)	(1.818)	(0.178)	(0.098)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1921	1869	1645	2006	1917	1889	1965	2011

Table 2.A7: Production shift ability and financial costs

Panel A: 2016-low-green-commitment-score industrial firms						
	Low fixed asset ratio			High fixed asset ratio		
	Financial cost	Financial expense	total loan	Financial cost	Financial expense	Total loan
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Green}$	-0.016**	-0.029	1.656**	-0.023***	-0.017	0.218
	(0.007)	(0.042)	(0.816)	(0.008)	(0.038)	(0.463)
Distance	-0.001	-0.001	0.067	0.001	0.015***	0.039
	(0.001)	(0.006)	(0.102)	(0.001)	(0.004)	(0.060)
State	0.005	-0.015	-0.837**	0.000	0.013	-0.187
	(0.003)	(0.027)	(0.335)	(0.003)	(0.013)	(0.178)
ln(Mktcap)	0.004**	0.098***	2.145***	0.004**	0.058***	1.839***
	(0.002)	(0.013)	(0.291)	(0.002)	(0.010)	(0.275)
Tax contribution	0.007	-0.056	-0.104	0.003	-0.028	-1.386***
	(0.006)	(0.041)	(0.820)	(0.007)	(0.027)	(0.453)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2204	2256	2081	1598	1595	1505
Panel B: 2016-high-green-commitment-score industrial firms						
	Low fixed asset ratio			High fixed asset ratio		
	Financial cost	Financial expense	total loan	Financial cost	Financial expense	Total loan
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Green}$	-0.019***	-0.068	0.766	-0.011***	-0.093**	-0.069
	(0.007)	(0.041)	(0.666)	(0.004)	(0.037)	(0.540)
Distance	0.002*	0.022***	0.260**	-0.001	-0.011	-0.055
	(0.001)	(0.008)	(0.114)	(0.001)	(0.008)	(0.113)
State	0.011***	0.095***	2.835***	-0.002	0.024	0.018
	(0.004)	(0.031)	(0.500)	(0.003)	(0.032)	(0.714)
ln(Mktcap)	0.008**	0.129***	2.236***	0.004**	0.166***	2.630***
	(0.004)	(0.024)	(0.367)	(0.002)	(0.021)	(0.437)
Tax contribution	0.009	0.082	0.434	-0.005	-0.019	1.470*
	(0.008)	(0.066)	(0.843)	(0.004)	(0.049)	(0.799)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Monitoring station FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1887	1842	1771	2039	2016	1926

Chapter 3

Investors' preference on green firms and green bonds - evidence from green bond certification

Joint with Sophie Moinas (TSE)

3.1 Introduction

In recent years, there has been a growing investor concern regarding environmental issues, and the impact of investment decisions on the environment. To encourage the private sector to address climate change through innovative financing and investments, institutions like the European Investment Bank and the International Finance Corporation of the World Bank began issuing "green bonds" in the late 2000s. These fixed income securities were intended to finance investments with environmental or climate-related benefits. Following their success, the financial industry began issuing corporate green bonds in 2013.

Studies suggest that stock prices react positively to the announcement of green bond issuance (Baulkaran, 2019; Tang and Zhang, 2020; Flammer, 2021), and that certain green bonds trade at a premium compared to conventional bonds (Ehlers and Packer, 2017; Zerbib, 2019; Hyun et al., 2020; Kapraun et al., 2021). Our objective is to understand what drives these results. Two different mechanisms may exist. First, the results reflect an abnormal demand from investors who are willing to pay a higher price for green assets due to their preferences. These preferences could stem from investors who are willing to accept lower returns to induce firms to shift towards cleaner assets or socially responsible funds that need to report to their investors the proportion of their investments in green assets in a verifiable manner. This channel is in line with the model prediction of Baron (2007) that CSR firms can coexist with value-maximizing firms because investors have preferences for them. Second, the results reflect that investors receive a positive signal to firms' future performance. Investors believe that brown assets will yield lower returns in the long run if regulators take actions to penalize carbon emissions or if consumers demand environmentally friendly products. Green bond issuance provides information on firms' ability to handle environmental-related risks. Both of the two mechanisms are important. The demand effect suggests that investors are ready to pay for the green transition, which supports the existence of CSR firm. The information effect provide direct evidence to convince firms to internalize environmental damage. Understanding which mechanism take effect can help us understand how investors perceive green firms, as well as the profitability of green assets.

We analyze a sample of green bonds issued by firms from the U.S., Mainland China, and Hong Kong between 2013 and 2019. Our research is divided into two parts, in which we separately analyze the perspectives of stock investors and bond investors.

For stock investors, the standard approach is to examine the announcement effect of green bond issuance. However, it is difficult to attribute the positive stock price reaction solely to shareholders' preference for firms that engage in green actions, as it also reflects shareholders' confidence in the firms' future ability to manage environmental-related risks. Therefore, we need a method that can separate firms' green status from their engagement in green actions. The Climate Bonds Initiative's (CBI) three-tier certification system, which certifies green bond issuance, offers a unique perspective to solve this issue, as a company's green status is disclosed before the first green bond issuance. The three-tier system consists of green bond framework verification, use of proceeds verification, and CBI certification. Green bond framework verification is conducted before green bond issuance and only concerns firms' green status, as it does not provide information on specific green projects, but signal the firms' green status to the market. Use of proceeds verification and CBI certification are performed together or after the green bond issuance, and they ensure the quality of greenness. Our findings indicate that the stock market reacts positively to the announcement of green issuance only when the green bond framework is not verified. This suggests that shareholders don't react to the fact that firms issue green bonds to fund green project, but they react to the fact that firms become green. Shareholders have a preference on green firms.

The analysis for bond investors is more complex, as they may have a preference for both green bonds and conventional bonds issued by green firms. The preference for green bonds issued by green firms is at the bond level, while the preference for conventional bonds issued by green firms is at the firm level. Previous studies attempting to demonstrate the existence of the "greenium" have focused on comparing green bonds with synthetic conventional bonds issued by the same entity (Zerbib, 2019; Hyun et al., 2020; Kapraun et al., 2021). This approach involves using conventional bonds issued before and after the green bond issuance to construct a synthetic conventional bond that does not actually exist. However, this approach fails to consider whether bond investors have a preference for conventional bonds issued by green firms. To determine whether bond investors have a preference for green firms and green bonds, inspired by Tang and Zhang (2020), we develop a two-step matching method to construct our sample. Firstly, we match green firms with brown firms based on firm size, market-to-book ratio, previous year liquidity, and industry code. Then, we match each conventional bond and green bond issued by green firms with conventional bonds issued by matched brown firms based on bond size, time to maturity, callable type, and bond seniority. To ensure that we have enough conventional bonds issued by brown firms to match, we keep four closest brown firms in the firm match stage. After the matching process, we conduct a difference-in-differences analysis to compare green bonds as well as conventional bonds issued by green firms with conventional bonds issued by brown firms. We find that neither green bonds nor conventional bonds issued by green firms are traded at a negative premium relative to conventional bonds issued by brown firms. However, when we include information on CBI's certification, we find that green bonds with CBI certification are traded at a premium of -108 bp. This suggests that bond investors have a preference for green bonds with CBI certification but not for green firms.

Overall, our analysis supports the demand effect of stock investors on green firms and the demand effect of bond investors on green bonds, while it does not support the channel that green assets can outperform in the future. However, the results do not necessarily imply that investors believe green assets will yield lower returns in the long run. This may be due to the limited impact of funding with green bonds on firms' future cash flow, while building green projects can still have a positive effect on firms' future cash flow.

Our paper contributes to the literature in the following ways. First, it helps us better understand the mechanism of shareholders' positive reactions to green bond issuance. Flammer (2021) first finds that green bonds yield positive announcement returns. She also documents improvements in long-term value and operating performance, which may explain the positive price reaction. Tang and Zhang (2020) compile a comprehensive international green bond dataset covering 28 countries during 2007-2017 and document that stock prices and stock liquidity positively respond to green bond issuance. Our research complement to these studies by showing that the positive reactions around announcement come from the bonds without green bond framework verification.

Second, Our paper contributes to the literature on the mechanism of greenium. A new but growing body of literature has examined the existence of a greenium for green bonds issued by green firms (Östlund, 2014; Petrova, 2016; Ehlers and Packer, 2017; Zerbib, 2019; Hyun et al., 2020; Kapraun et al., 2021; Lin and Su, 2022; Sun et al., 2022). These studies have consistently found a small but significant greenium, which is particularly pronounced for green bonds with certification or traded on exchanges with a dedicated green bond segment. Lin and Su (2022) also find that although labeled and non-labeled green bonds meet the same green certification standard, only officially certified labeled green bonds can effectively reduce the yield spread. Our results support their findings by demonstrating that the greenium only exists for green bonds with certification. Furthermore, we show that there is no greenium for conventional bonds issued by green firms.

The structure of this paper is as follows. Section 2 presents green bond certification process. Section 3 outlines hypothesis development. Section 4 presents the dataset. Section 5 shows the two-step matching method. Section 6 conducts the analysis for stock investors. Section 7 conducts the analysis for bond investors. Section 8 concludes the paper.

3.2 Green bonds and their certification

Sustainable investors may be concerned about "greenwashing," which refers to the opportunity for issuers to label a bond as green even if its proceeds are not used to directly finance environmentally friendly assets. To reduce information asymmetries, a growing need for a taxonomy and certification process has emerged, either from investors who want to screen the bonds for their "greenness" or from issuers who want to signal it.

3.2.1 How to identify a "green" bond?

While the notion of "green" bond is conceptually easy to understand, it is in practice more difficult to assess whether a bond actually falls into this category. A first indicator is whether the issuing firm self-labels its bond as "green", which suggests that the bond is intended to be environmentally beneficial. Other labels may also be eligible, as for instance "climate", "environmental", "solar", "sustainable", "eco-efficient".

Compliance of the Uses of Proceeds.

When a bond is labeled as such, investors and financial intermediaries who want to understand whether the issue actually aims at financing environmentally friendly projects screen its uses of proceeds (UoP) to understand the main goal of the emission. They analyze in particular the compliance of the uses of proceeds with the bond's label, which refers to whether the firm commits to deploying funds towards projects and activities that favor energy transition and low carbon emissions, and what percentage of the uses of proceeds fall into this category. Sometimes, specific exclusions for the use of proceeds of green bonds may additionally be imposed, such as those involving coal and nuclear, or excluding fossil fuel energy but including clean coal.

To assist investors in this screening process, there are some public and private institutions that have provided a taxonomy of eligible assets or projects. For instance, Climate Bonds Initiative (CBI) develops the Climate Bonds Taxonomy based on the latest climate science research from institutions such as the Intergovernmental Panel on Climate Change (IPCC) and the International Energy Agency (IEA). Also the People's Bank of China (PBoC) collaborated with the Green Financial Bond Directive to develop the Green Bond-Endorsed Project Catalogue.

Reporting
Second, analyzing the project descriptions at the time of issuance may not be sufficient to guarantee the "greenness" of the Uses of Proceeds over the lifespan of a bond. The proceeds from the bond could be re-used to finance new projects, which may not be compliant with the bond's label. To ensure compliance, investors and financial intermediaries investigate the management of proceeds for the bond, such as the issuer's project selection process and commitment to report on future use of the proceeds.

Green bonds standards
Because of the importance of these two elements, namely compliance and reporting of the Uses of Proceeds, some public and private institutions provide a standard to issue green bonds that includes both. A standard consists in (i) guidelines to point to specific conditions that have to be met for the bond's uses of proceeds to be assessed as compliant with climate-aligned projects and assets, as well as (ii) transparency requirements on the management of proceeds and reporting before and after the issuance. These standards are voluntary, but they help investors understand how issuers of green bonds define and select projects, use and track proceeds, and verify and disclose information. Guidelines provide both issuers and investors guidance on the key components involved in launching a green bond or evaluating the environmental impact of their Green Bond investments. Due to the lifespan of a bond, the objective of pre- and post-issuance transparency requirements is to enable investors to ensure that the green credentials are guaranteed over time. The main existing standards are comparable to each other. I put the comparision between the Green Bond Principles (GBP) developed by the International Capital Market Association (ICMA) and the policies issued by the Chinese authority in the appendix 3.9.1.

3.2.2 Certification process

Green bond certification requires two preliminary checks. First, the firm must follow the requirements of a specific standard to issue green bonds: its framework must ensure that environmental-friendly projects will be financed by the uses of proceeds and include transparent reporting procedures. The issuer may engage an "external verifier" to give assurance that this is indeed the case. Second, the issued green bond's uses of proceeds need to be clearly identified and fall into the green taxonomy. An issuer may engage the same or another intermediary to verify that the uses of proceeds of the bond are appropriately allocated to eligible green projects. In addition to these two verification processes, the issuer may initiate a certification process for a specific bond, either before issuing the bond, or during the life of the bond.

The verification/certification market

Before describing what is verified in more details, we first present the parties involved in the verification/certification process.

Who initiates the verification/certification process and why
Generally, neither verification nor certification are a formal pre-requisite for green bond issuance. Yet issuers may have incentives to initiate these processes. First, issuers may voluntarily be willing to increase their own credibility to investors. This may be all the more the case as they issue bonds in foreign markets. Second, it may also increase their credibility to regulators. For instance, Chinese firms willing to issue bonds in Mainland China need to get approved by the government. The probability of approval naturally increases if the issuers is able to document that external parties have verified that the firm's green bond issuance process is in line with a specific framework and/or the bond's proceeds aim at financing green projects, and even more if the issue is pre-certified. Finally, some bond markets impose a preliminary verification or certification as a mandatory requirement. This is for instance the case of LGX, that requires the opinion from a independent third-party before listing a green bond.[1].

Who verifies/certifies
Typically, two types of intermediaries are involved in the green verification or certification process. First, some institutions like Sustainalytics, CICERO, DNV-GL, and Vigeo EIRIS, are specialized in evaluating companies' sustainability performance and provide research, analysis and services related to environmental and sustainable growth (ESG). Second, traditional accounting/auditing organizations, like Ernst & Young (hereafter EY) or Deloitte, have transitioned from a traditional accounting/auditing business and extended their services from accounting verification to green project verification.

Three shades of green

We now describe the three shades of green, that are (i) verification of the firm's green bond framework, (ii) verification of the green bond's uses of proceeds, and (iii) certification of the green bond.

Verification on the firm's green bond framework

[1] https://www.bourse.lu/documents/brochure-LGX-GB_emerging_markets-Amundi.pdf

Before issuance, the issuer may contact an external verifier. The verifier analyzes the firm's green bond framework, which is the guideline used by a firm when it issues a green bond, and guarantees that this framework follows specific standards, that is, either the Green bond principles (GBP) or the Green Financial Bond Directive. To this end, the verifier reviews the firm's Environmental Priorities and ESG Performance, the criteria applied by the company on the uses of proceeds to filter projects that would be financed by a green bond issuance, its project selection process, and its transparency in the management of proceeds and reporting. Based on this analysis, the external verifier forms a view on whether the issuance of green bonds by the company is robust and credible, and issues a "second party opinion" report describing the elements and facts it has reviewed to form this opinion.

The guidelines followed by firms and to which external verifiers refer to in their second party opinion report depend on the country in which the company is incorporated and/or listed, as well as on the bond market in which the company is willing to issue its green bonds. External verifiers and issuers in the U.S. typically follow the GBP of the ICMA. For instance, the Sustainalytics's report on Apple Inc. green bonds written on February 16, 2016 provides an opinion on Apple's green bond framework and its alignment with the Green Bond Principles 2015. By contrast in Mainland China, the external verifiers retained by issuers usually follow the rules set in the Chinese Green Bond Directive. For example, EY issued on April 9, 2019 a certification report at the request of Bank of Jiangsu for a green bond prior to its expected issuance date on April 18, 2019. The corresponding report specifies that EY followed the rules set in by the Chinese Green Bond Directive and the eligible project list comes from the Green Bond-Endorsed Project Catalogue.

Verification of compliance of the bond's uses of proceeds

Before or after the issuance, the issuer may also request a verification that the uses of proceeds of a specific green bond issue are compliant with the eligibility criteria and appropriately allocated to eligible green projects. This verification may be done by the external verifier who has written a "second party opinion" report, or by other intermediaries such as "independent accountants". Issuers may also engage into compliance verification without having its framework being verified prior to issuance. While framework verification at the firm level follows clear guidelines that are similar across countries, the compliance verification at the bond level is much less standardized. This service may for instance be provided by local subsidiaries of an accounting/auditing firm, and practices of the same company may vary across U.S., Mainland China and Hong Kong. Finally in Hong Kong, the process may depend on whether the bond is issued in the Mainland Chinese bond market or not. For example, EY issued a certification report on February 26, 2018 at the request of Huarong Xiangjiang Bank for a green bond that was supposed to be issued on the mainland China bond market on March 13, 2018, and EY also followed the rules set by PBoC. By contrast, Deloitte issued a certification (via its Shanghai entity) at the request of CGNPC International Ltd on November 21, 2017 before CGNPC's first green bond issuance on December 11, 2017, but followed the rules set by Green bond principles (GBP) of the ICMA, instead of those set by PBoC.

The practice of verification of the compliance of the uses of proceeds differs across regions. In the U.S., we noticed that issuers often engage an independent accountant to verify the uses of proceeds of a specific bond after issuance. For example, EY issued a report of independent accountants at the request of Alexandria Real Estate Equities, Inc., a U.S. company, to certify that the net proceeds of their 4% Senior Notes due 2024 is appropriately allocated to eligible green projects.[2] The report specifies that the accountants have followed the rules set by American Institute of Certified Public Accountants. There may consequently be variations in the timing of the verification process, in practices, and in the set of rules followed by companies across markets.

Green Bond certification

Some intermediaries provide a green bond formal certification. Among those, the Climate Bonds Standard Board seems to be the market leader with its Climate Bonds Certification.

Since the launch of the first version of CBI Standards in 2011, investors have relied on the inclusion in the CBI green bonds' list as a signal of the "environmental integrity" of a green bond. The criteria followed by CBI for inclusion are indeed among the most restrictive. From their description, the CBI only includes the bonds such that (i) the label of the bond indicates that it is intended to be environmentally friendly, (ii) at least 95% use of proceeds financing or refinancing green/environmental projects in line with the GBP, (iii) the use of proceeds is aligned with the Climate Bonds Taxonomy, which identifies assets and projects deliver a low carbon economy and gives GHG emissions screening criteria consistent with the 2-degree global warming target set by the COP 21 Paris Agreement [3], (iv) the bond issue meets transparency requirements, (v) the use of proceeds is not subject to CBI's exclusion criteria, and (vi) whenever necessary, after a review by external experts (second party opinion). A bond which satisfies the standards can be awarded the "climate bond certified" stamp by CBI. Along the years, CBI has upgraded its standards to clarify the pre-issuance and post-issuance certification process and requirements, and released the third version in December 2019.

[2] https://www.are.com/cr/GreenBondReportJune2019.pdf

[3] https://www.climatebonds.net/cbi/pub/data/bonds

3.3 Hypothesis development

Our target is to understand whether the positive reaction of the announcement of green bond issuance and the greenium are attributable to information or investor preferences. For stock investors, we analyze the stock price reaction around the announcement of a green bond. There are two types of firms on the announcement date of green bond issuance: those whose green bond framework has been verified and those whose green bond framework has not been verified. They are different from each other in terms of whether their green status has been released to the market or not. For firms without a green bond framework, the announcement of green bond issuance implies that a brown firm is transitioning to a green firm and issuing bonds to fund green projects, which may impact their future cash flow. In contrast, for firms with a green bond framework, the announcement only indicates the issuance of bonds to fund green projects. Based on this difference, we can propose the following hypothesis.

H1a: If stock investors value firms' transition to green but do not consider the impact of funding green projects with green bonds on future cash flow, we would expect to see a positive market reaction only for firms without a green bond framework on the announcement date. This corresponds to a demand effect.

H1b: If stock investors believe that funding green projects with green bonds has a positive impact on future cash flow, we would expect that both firms with and without green bond framework verification experience a similar positive effect on the announcement date. This corresponds to an information effect.

H1c: If stock investors value both a firm's transition to green and the positive impact of funding green projects with green bonds on future cash flow, we would expect that on the announcement date, firms without green bond framework verification will experience a larger positive effect than firms with green bond framework verification. This corresponds to both an information effect and a demand effect.

Literature has shown that green bonds with certification will be traded at a negative premium (Hyun et al., 2020). Bond investors pay a high price for green bonds with certification issued by green firms, which can be attributed to five layers. Firstly, they have a preference for investing in green firms. Secondly, they believe that investing in green projects will decrease firms' credit risk. Thirdly, they have a preference for green bonds issued by firms with green bond framework verification. Fourthly, they have a preference for green bonds with use of proceeds verified. Finally, they have a preference for certified green bonds. The first layer is captured by the difference between the yields of conventional bonds issued by green firms and those issued by brown firms. The second layer is represented by the difference between the yields of green bonds issued by green firms and those of conventional bonds issued by green firms. Thirdly, the third layer is captured by the difference between the yields of green bonds issued by firms with green bond framework verification and those issued by firms without green bond framework verification. Fourthly, the fourth layer is captured by the difference between the yields of green bonds with use of proceeds verified and those without use of proceeds verified. Finally, the fifth layer is captured by the difference between the yields of green bonds with certification and those without certification. Based on this analysis, we propose our hypothesis.

H2a: If bond investors value firms' transition to green, the yields of conventional bonds issued by green firms are lower than those of conventional bonds issued by brown firms. This corresponds to a demand effect at firm level.

H2b: If bond investors believe investing in green projects will decrease firms' credit risk, the yields of green bonds issued by green firms are lower than those of conventional bonds issued by green firms. This corresponds to an information effect at bond level.

H2c: If bond investors have a preference for green bonds issued by firms with green bond framework verification, the yields of green bonds issued by firms with green bond framework verification are lower than those of green bonds issued by firms without green bond framework verification. This corresponds to a demand effect at firm level.

H2d: If bond investors have a preference for bonds with use of proceeds verified, the yields of green bonds with use of proceeds verified are lower than those of green bonds without use of proceeds verified. This corresponds to a demand effect at bond level.

H2e: If bond investors have a preference for certified green bonds, the yields of green bonds with certification are lower than those of green bonds without certification. This corresponds to a demand effect at bond level.

3.4 Data and summary statistics

3.4.1 Variables of interest

The existing empirical literature suggests that green bonds would trade at a premium (higher prices, lower yields) relative to traditional bonds, but only when the "greeness" of the bond is certified by a second party. To disentangle whether whether the greenium is attributable to information or investor preferences, we proceed in two steps. First, we analyze the stock price reaction around the announcement of a green bond. Our objective is to investigate the informational content of a green bond issuance by analyzing the determinants of the firm's cumulative abnormal returns. Second, we develop a two-step matching procedure to compare the bond yields of firms which have issued a green bond and engaged into green investments, relative to those which have not. This procedure enables us to evaluate the impact of green bond issuance on the yields of the firm's conventional bonds. In both parts of the analysis, we aim at understanding the impact of verification/certification on stock and bond prices.

Abnormal stock returns around the announcement date

We conduct an event study to analyze the stock price reaction to the firm's bond announcement. We calculate the issuing firm's cumulative abnormal return (CAR) around the announcement date based on the one-factor CAPM model, as shown in equation (3.1).

$$R_i - r_f = \alpha_i + \beta_i(R_m - r_f) + \epsilon, \tag{3.1}$$

where r_f is the risk-free rate, R_i is the stock return of firm i, and R_m is the return of the stock market portfolio. To estimate the beta over the period [-252,-30] trading days, we run a regression for each stock. Then, we use the estimated beta to calculate the daily abnormal return for each day from 10 days prior to the issuance day to 10 days after the issuance day, that is, over an event window of [-10,10].

Matching bond yield

To determine whether bonds issued by green firms are traded at a premium, we utilize a diff-in-diffs approach. Specifically, we compare the bond yields received by green firms, which have issued green bonds, with those of brown firms, which have not issued green bonds. To conduct this analysis, we employ a double matching process. Firstly, we match each green firm (g) with a brown firm (b) based on several dimensions, including industry, market capitalization (as a proxy for firm size), liquidity (measured by the one-year lagged Amihud measure), and market to book ratio. Additionally, we ensure that the brown firm issued at least one bond in the same or following year as the green firm's first green bond, similar to previous research (Tang and Zhang, 2020). We retain four candidate firms for each treated firm $g \in G$, based on their propensity score being closest to the treated firms.

Next, we match each bond (j_g) issued by a green firm (g) with a conventional bond (j_b) issued by one of the four closest brown firms (b). We select the bond (b^*) with the highest propensity score, based on criteria such as bond size, time to maturity, callable type, and bond seniority. The bonds matched are conventional bonds issued before green bond issuance, green bonds and conventional bonds after each green bond issuance.[4]

Typically, literature compares the green bond premium with synthetic bonds following Zerbib (2019). This approach employs the synthetic bonds constructed from conventional bonds issued by the same issuer. It requires (1) the conventional bonds are issued a maximum of six years before or six years after the green bond issuance, (2) the conventional bonds' issue amount is less than four times the green bond's issue amount and greater than one-quarter of this amount. However, this approach does not consider the impact of the green bond issuance on conventional bonds. If the issuer's conventional bond is less (or more) in demand due to the green bond issuance, the green bond premium will be overestimated (or underestimated). Alternatively, Tang and Zhang (2020) employ another approach. They try to compare the same issuer's green bond yield with the same issuer's conventional bond yield without considering that both the conventional bonds and green bonds could be affected. Following the spirit of their approach, our approach aims to provide a better understanding of the conventional and green bond yields of green firms by matching with conventional bonds yields of matched brown firms.

Main explanatory variables: verification and certification dummies

Our study aims to understand whether stock and bond prices react differently to green bond issuances, depending on whether the firm's framework or the bond's uses of proceeds have been verified by an external party, or the bond has been certified by CBI. To capture these pieces of information and our three shades of green, we use the following dummy variables:

- a dummy $D\_framework_g$ that equals one if the green bond framework of the bond issuer g has been verified by an external verifier whose report express a second party opinion prior to the bond's issuance;
- a dummy $D\_UoP_{j_g}$ that equals one if the uses of proceeds of the bond j_g issued by firm g have been verified by an independent party prior to the bond's issuance and

[4] To minimize the impact of matched firms before and after the green bond issuance, we ensure that the brown firms matched to conventional bonds issued after the green bond issuance are the same firms matched to conventional bonds issued before the green bond issuance. Specifically, we first match the bonds issued after the green bond issuance and generate a list of matched firms. We then restrict the bonds issued by brown firms before the green bond issuance to only those issued by the firms on the generated list of matched firms.

are compliant with the green bonds' framework (which requires the firm's green bond framework to have been verified);

- a dummy $D\_CBI\_certified_{j_g}$ that equals one if the bond j_g issued by firm g is certified by CBI (which requires the firm's green bond framework and the green bond's uses of proceeds to have been verified).

3.4.2 Public data sources

Our objective is to analyze the determinants of stock markets' reaction and bond yields to the issuance of green bonds for firms in Mainland China, the U.S. and Hong Kong. The sample period starts on Nov 21, 2013 for the U.S., and on May 08, 2014 for China.[5] We collect data on firms' characteristics, stock prices and bonds' prices and characteristics until December 2019.

Bonds and issuers

We collect corporate bond data from Thomson Reuters Refinitiv, which includes the characteristics of the bonds (issuer, amount, maturity, coupon, coupon frequency, issue price, issue date, callability), as well as a green bond tag. These variables allow us to calculate the issuance yield for each bond.[6] We also obtain the announcement date of bond issuances from Bloomberg.

Matching bond issuers with listed firms

Within the universe of bonds (including bills and notes) reported in Refinitiv, we focus on those issued by listed firms. For Mainland China, we use the Thomson Reuters RSearch function to search for the names of Refinitiv's green bond issuers and identify the issuer's local listed code, while for the U.S., we match bond and stock data using the Trace-WRDS link. Our initial sample consists of 1,090 listed firms in Mainland China (and 106 in Hong Kong) who issued 41,861 (and 12,516) different debt securities, as well as 1,585 listed firms in the U.S. who issued 76,788 securities.

Data on Firms

After identifying the listed issuers of the bonds, we collect information on the firms' characteristics (balance sheet data including leverage ratio or Return on Assets (ROA), credit risk, corporate events) from Compustat for U.S. firms, CSMAR for Mainland China firms, and Datastream for Hong Kong firms. These variables will be used as controls in our analysis.

[5] For China, the starting date is the first green bond issuance date, while for U.S., it is the second green bond issuance date. The first U.S. bond issuance indeed took place on Sep 1, 1985 and is excluded from our sample.

[6] For simplicity, we do not price the option value of the callability, but we will control for it in our analysis.

Market data

We obtain daily stock returns, daily stock trading volumes, market returns, and interest rates for different regions from various data sources. For the U.S., we collect daily cum-dividend individual stock returns and daily stock trading volumes from CRSP, while the market risk premia and the risk-free rates are downloaded from Kenneth French's website. For Mainland China, we obtain daily cum-dividend returns, annual Amihud measures, and market risk premiums (for total A shares) from CSMAR.[7] The CSMAR manual indicates that these risk premia are computed using the 3-month deposit rate as the risk-free rate, and we therefore obtain the latter rate from Thomson Reuters Datastream. For Hong Kong, we collect daily cum-dividend returns of individual stocks, daily stock trading volumes, the Hang Seng index, and the 3-month government bond yield as a proxy for the risk-free rate from Thomson Reuters Datastream.

3.4.3 Sample selection

Green Bonds

We select all the bonds labeled as "green" (Green Bond) in Refinitiv for issuers (Issuer Name) listed in the U.S. or China from the universe of corporate bonds. According to Refinitiv's manual, Thomson Reuters uses the Climate Bond Initiative (CBI) database to identify green bonds.[8]

Listed firms related to green bonds' issuers

After identifying the "green bonds," we manually browse the issuer's name in the Refinitiv database to determine whether the entity issuing the bond is a listed company, a subsidiary, or an indirect subsidiary of a listed company. Refinitiv provides information on the parent company and all its subsidiaries for each name, which enables us to identify whether the issuer is (i) a single listed firm, (ii) the subsidiary of a listed firm, or (iii) the indirect subsidiary of a listed firm.[9]

We identify 25 unique listed firms for 30 entities issuing green bonds in the U.S. and 40 unique listed firms for 57 entities in China.[10] As the Mainland China and Hong Kong stock markets are partially segmented, we separate the Chinese firms into those listed in Mainland China and those listed in Hong Kong. In the Mainland China sample, we identify 19 unique listed firms for 32 entities, and in the Hong Kong sample, we identify

[7] For Mainland China, CSMAR provides us with the annual Amihud measure directly, so we do not need to download daily stock trading volume.

[8] https://www.refinitiv.com/content/dam/marketing/en_us/documents/brochures/esg-research-brochure.pdf

[9] An indirect subsidiary of a listed firm refers to the subsidiary of the subsidiary of a listed firm.

[10] A listed firm may have several (indirect) subsidiaries issuing green bonds, or both the listed firm itself and its (indirect) subsidiary issued green bonds.

21 unique listed firms for 25 entities.[11]

Green and Brown Firms

We label "green firms" (G) as the listed firms that are related to entities that have issued a green bond at least once – reported in Panel B of Table 3.A2. By contrast, we label "brown firms" (B) as all the other listed firms in our sample that do not issue green bonds.

After identifying green and brown firms, we split the sample of bonds into two subsamples: one composed of green and conventional bonds issued by green firms, and one composed of conventional bonds issued by brown firms.[12] We then filter the bond data and drop: (i) bills with less than one year of maturity, (ii) bonds with zero issuance amount, (iii) bonds for which we cannot find complete data on the coupon rate, coupon frequency, time to maturity, and issue price, and (iv) bonds related to ST firms in Mainland China.[13] Details are reported in Table 3.A3 of Appendix.

3.4.4 Collection of verification and certification data

The first step of our analysis involved collecting information on green bond verification from CBI.[14] The CBI data includes the unique identification code (ISIN) and issuer's name for each bond, which allowed us to merge the CBI dataset with the Thomson Reuters Refinitiv data.[15] The CBI database indicates whether each bond included in their dataset has undergone an external review, and in the latter case, provides a link to the report issued by the second party.

Second, we supplemented this data source by manually collecting certification information for each green bond. We searched for information related to bonds issued by financial institutions in the Mainland Chinese inter-bank market on the website of the China Central Depository & Clearing Co., Ltd. (CCDC) by searching issuer names.[16] For all firms, we also collected information from the listed firm's websites and checked

[11] Details are reported in Table 3.A2 of Appendix.

[12] Within our sample, 127 green bonds are issued by a single name, namely Tesla, whose business model is environmentally friendly. We excluded this outlier from our analysis.

[13] ST firms are firms that have profitability issues and risk being delisted. The ST information is downloaded from CSMAR.

[14] We would like to acknowledge Miguel and Aneil from the Climate Bond Initiative for providing us with the CBI green bond and certification data.

[15] We matched the issuers by ISIN code, and for the bonds without an ISIN, we manually cross-checked the two files using the issuer names.

[16] The website of CCDC is https://www.chinabond.com.cn/. For example, documents related to issuance following a search on the name "ABC Financial Leasing Co Ltd" (a subsidiary of Agriculture Bank of China) can be found at the following address: https://www.chinabond.com.cn/cb/eng/sy/qtfxfs/20190529/151681512.shtml.

for the availability of any other public information on the internet.[17] When CBI provides a second party opinion, we also searched for the external reviewer's report.[18]

The complete list of our hand-collected verification data, including the report or letter reference, issuer, and issuance date, is available upon request. This data allows us to determine the values of our three verification dummies. The first dummy, $D\_framework_g$, equals one when we find a second-party opinion report confirming that the issuer's green bond issuance framework complies with a standard prior to the green bond issuance.The second dummy, $D\_UoP_{j_g}$, equals one when we find an Independent Accountants' report or letter confirming that the bond's use of proceeds complies with the standard prior to issuance. Finally, the third dummy, $D\_CBI\_certified_{j_g}$, takes a value of one if the green bond is certified by CBI prior to issuance.

3.4.5 Summary statistics

Evolution of green bond issues

Since 2013, the issuance of green bonds has gained popularity in the U.S., Mainland China, and Hong Kong. Table 3.1 presents the growth in the number of green bonds issued by listed firms, their parents, or subsidiaries in our sample, along with the corresponding outstanding amount.[19] We categorize these statistics: i. by stock market (U.S., Mainland China, or Hong Kong), and ii. based on whether the bond's issuer has initiated a verification or certification process with an independent verifier.

The last column (Total) shows that between 2013 and 2019, the number of green bonds issued by listed firms increased from 1 to 43 per year, and the outstanding amount rose from USD 500 million to more than USD 24,318.09 million.

When comparing green bond issuances by region, we note that U.S. firms began issuing green bonds two years earlier than firms in Mainland China and Hong Kong. However, in recent years, firms in Mainland China and Hong Kong have issued more

[17] Some firms have a section on their website dedicated to green bond relevant information. For example, the Hong Kong and China Gas CO,. Ltd,. (HKCG) has all the green financing information on its website: https://www.towngas.com/en/Social-Responsibility/Health,-Safety-and-Environmental-Management/Green-Financing

[18] Some websites collect these reports. For example, you can find all the certification reports from China bond rating here: https://www.chinaratings.com.cn/CreditRating/RatingInfo/GreenBond/. Some external reviewers also directly provide their certification reports on their website. For example, the certification report that Sustainalytics provides to Verizon Communications Inc. is available here: https://www.sustainalytics.com/wp-content/uploads/2019/02/Verizon-Green-Bond-Second-Party-Opinion.pdf.

[19] The sample of the Table 3.1 sample reports here is the same as we used in event study part. The sample in the DID part is slightly different, but almost the same, as they have slightly different filter procedures.

Table 3.1: Summary of green bond issuances

Table 3.1 reports the summary of green bond issuances for three areas. Panel A reports the number of green bonds issued, and panel B reports the size of green bonds issued. "Ind_verif" means that the bond process or the bond uses of proceeds have been verified or certified prior to bond's issuance.

Panel A: number of green bonds issued

	US		Mainland China		Hong Kong		Total
	No Ind_verif	Ind_verif	No Ind_verif	Ind_verif	No Ind_verif	Ind_verif	
2013	1	0	0	0	0	0	1
2014	4	0	0	0	0	0	4
2015	11	0	1	3	0	0	15
2016	6	1	0	10	1	8	26
2017	2	2	0	13	0	14	31
2018	10	1	2	16	3	11	43
2019	14	4	1	17	0	7	43
Total	48	8	4	59	4	40	163

Panel B: Amount of green bonds issued (in millions USD)

	US		Mainland China		Hong Kong		Total
	No Ind_verif	Ind_verif	No Ind_verif	Ind_verif	No Ind_verif	Ind_verif	
2013	500.00	0.00	0.00	0.00	0.00	0.00	500.00
2014	1,700.00	0.00	0.00	0.00	0.00	0.00	1,700.00
2015	5,750.00	0.00	300.00	985.25	0.00	0.00	7,035.25
2016	2,801.39	1,500.00	0.00	8,014.32	142.92	2,643.35	15,101.98
2017	850.00	1,600.00	0.00	8,687.91	0.00	1,762.47	12,900.38
2018	6,353.47	400.00	200.09	14,090.60	914.39	2,894.99	24,853.54
2019	8,050.00	3,562.65	71.46	10,987.40	0.00	1,646.58	24,318.09
Total	26,004.86	7,062.65	571.56	42,765.47	1,057.31	8,947.39	86,409.25

green bonds, both in terms of the number of bonds and the outstanding amount.

The breakdown of green bond issuances by whether the bond's framework and uses of proceeds have been verified or certified by an independent party suggests that issuers' willingness to engage in the certification process varies across regions and over time. U.S. firms have issued most of their green bonds without verification (85.71%). In contrast, most firms from Mainland China and Hong Kong have issued their green bonds after an independent verification (93.65% and 90.91% respectively). This is consistent with the fact that any green bond issuance in the Mainland Chinese bond market needs government approval, which may be easier to obtain if the firm's green bond framework or the bond's uses of proceeds have been verified by an independent party. Furthermore, the size of the verified bonds is on average larger than that of the unverified ones across the three areas, suggesting that larger green bonds may need second-party assurance to attract investors.

Verified and certified bonds

To gain a better understanding of the role and significance of the verification process, we have provided a breakdown in Table 3.2 of the number of green bonds issued by region based on the characteristics of the verification process. Specifically, we analyze whether the issuer's green bond framework has been verified, whether the green bond's uses of proceeds' compliance have been verified in addition to the framework, and whether the bond has been certified by CBI. Additionally, when there is an independent verifier, we indicate whether the verifier is approved by CBI or not. The last category, labeled "unverified," includes all cases for which we could not find any verification report.

Table 3.2 indicates that firms often request both verification of their green bond framework and uses of proceeds when engaged in a verification process, and typically choose a verifier certified by CBI. Additionally, out of the 163 bonds in our sample, 21 are certified by CBI.

Table 3.2: Green bond issuance details by verification types

Table 3.2 reports the statistics of green bond details by verification types. An Independent verification consists in either the verification of the green firm's green bond framework, or both the verification of the green firm's green bond framework and the green bond's uses of proceeds, or a CBI certification. We detail observations depending on whether the verifier is certified by CBI or not. Issuances for which we could not find any verification report are labelled as "unverified". Panel A reports the verification status for the first green bond issuance, while Panel B reports the verification status for later green bond issuances.

Panel A: First Issuance

	U.S.	Mainland China	Hong Kong
Independent verification			
Framework verified by:			
CBI verifiers	2	2	9
non-CBI verifiers	0	1	2
Framework & Compliance verified by:			
CBI verifiers	1	19	7
non-CBI verifiers	0	0	0
CBI_Certification	1	5	0
Unverified	27	3	4

Panel B: Later Issuance

	U.S.	Mainland China	Hong Kong
Independent verification			
Framework verified by:			
CBI verifiers	4	0	10
non-CBI verifiers	0	8	3
Framework & Compliance verified by:			
CBI verifiers	0	7	9
non-CBI verifiers	0	2	0
CBI_Certification	0	15	0
Unverified	21	1	0

3.5 Two-step matching for bonds issued by green firms

3.5.1 First step: firm matching process

Following the identification of green and brown firms in Table 3.A3 of section 3.4.3, we first match each green firm with the four closest brown firms, as explained in section 3.4.1.

Propensity score matching

We perform a propensity score matching between green firms and brown firms using firm size, market to book ratio, previous year liquidity, and industry sector as matching variables. For each green firm, we compute its propensity score, compare it with the propensity score of all brown firms, and keep the four brown firms with the closest score (with replacement). The first-step's propensity score matching results are reported in Table 3.3. For the U.S. (resp. Mainland China and Hong Kong), 39 (resp. 34 and 31) observations in the treated group have matched observations. The matched group has 148 (resp. 136 and 63) firm-year observations.[20] The p-value of a Student test of the propensity score difference between the control group and the treated group is 0.7921 (resp. 1.0000 and 0.3462), indicating that the treated and control groups are not significantly different from each other.

Table 3.3: First step propensity score matching of green and brown firms

Table 3.3 reports the propensity score comparison of the treated group of green firms and in the control group of brown firms after the first-step firm matching process for three areas. The p-value of the Student test is reported in the last column.

Location	Treated group			Control group			Mean Difference	P-value
	N	Mean	STD	N	Mean	STD		
U.S.	39	0.8014	0.3905	148	0.7825	0.3987	0.0189	0.7921
Mainland China	34	1.0000	0.0000	136	1.0000	0.0000	0.0000	1.0000
Hong Kong	31	0.1564	0.0545	63	0.1457	0.0497	0.0107	0.3462

Parallel trends

Figure 3.1 displays the parallel trends of the one-to-many matching of firms after the first step of the matching process.

[20] For the U.S. (resp. Mainland China and Hong Kong), we expect to have 156 (resp. 136 and 124) matched observations, while not all the firms in the control group can find four matched firms in the same industry.

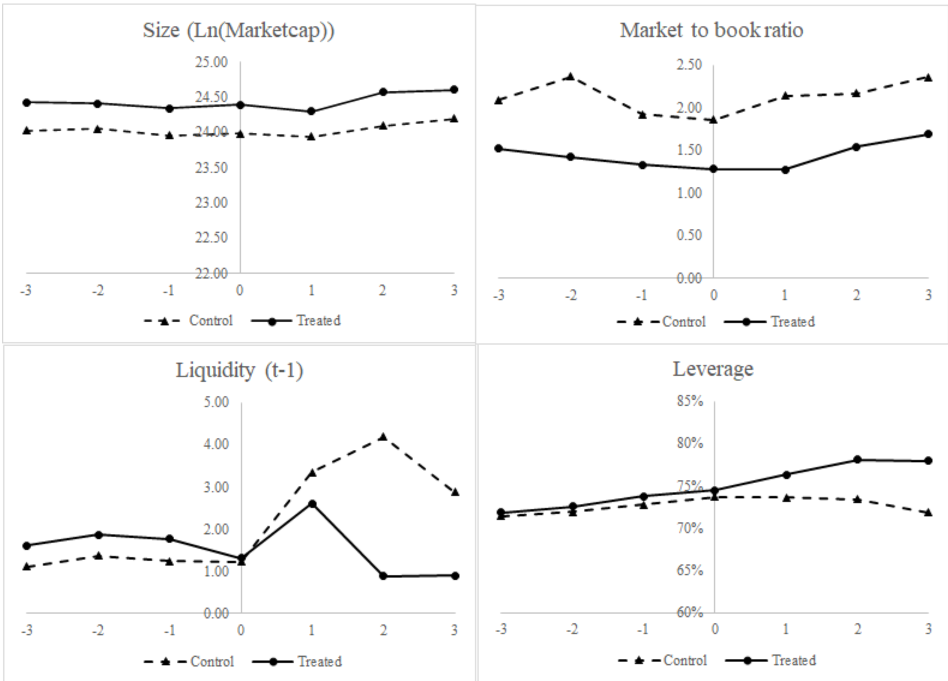


Figure 3.1: Parallel trend of control firms and treated firms after the first step firm matching

Figure 3.1 reports the parallel trend of control firms and treated firms after the first step firm matching. The trends are shown along the dimensions of firm size (ln(Marketcap)), Market to book ratio, Lag one period liquidity (Amihud), and Leverage.

3.5.2 Second step: bond matching process

For each green firm successfully matched with a brown firm, we identify the first two conventional bonds issued after their green bond issuance and three conventional bonds issued prior to the first green bond issuance. Table 3.4 describes the sample of bonds issued by matched firms before the bond matching process. For the U.S. (resp. Mainland China and Hong Kong), our sample consists of 56 (resp. 65 and 42) green bonds, 46 (resp. 48 and 22) conventional bonds issued before the firms became green, and 57 (resp. 43 and 16) conventional bonds issued after the firms became green. The bonds issued after the green bond issuance are matched first. The bonds issued by green firms after the green bond issuance will be matched with 16,126 (resp. 333 and 188) conventional bonds issued by matched brown firms.

Table 3.4: Bond sample before the second step bond matching process

Table 3.4 reports the number of observations in the bond sample used for the second stage bond matching process for three areas. The green bonds and conventional bonds issued by green firms are reported separately.

Location	U.S.			Mainland China			Hong Kong		
	Green	Conventional		Green	Conventional		Green	Conventional	
		Before	After		Before	After		Before	After
Bonds issued by green firms	56	46	57	65	48	43	42	22	16
Bonds issued by brown firms	-	11,380	16,122	-	223	333	-	159	188

The second step of our double-matching process consists of a one-to-one propensity score matching of bonds issued by green firms with bonds issued by brown firms in the same year or in the following year, based on bond size, time to maturity, callable type, and bond seniority.[21] Table 3.5 Panel A reports the second-step's propensity score matching results for matching after green bond issuance. For the U.S. (resp. Mainland China and Hong Kong), 46 (resp. 57 and 32) green bonds and 49 (resp. 27 and 11) conventional bonds issued by green firms are matched with 95 (resp. 84 and 43) conventional bonds issued by brown firms. The p-value of a Student test on the propensity score difference between the control group and the treated group is 1.0000 (resp. 0.5402 and 0.7190), which means they are insignificantly different from each other.

We then restrict the bonds issued by brown firms before the green bond issuance, with the constraint that these bonds are issued by brown firms matched after the green bond issuance, as shown in Table 3.4. For the U.S. (resp. Mainland China and Hong Kong), there are 11,380 (resp. 223 and 188) conventional bonds issued by the limited matched brown firms. Table 3.5 Panel B reports the propensity score matching result

[21] For perpetuity-type bonds, we assign 100 years as their time to maturity.

for matching before the green bond issuance. For the U.S. (resp. Mainland China and Hong Kong), 30 (resp. 31 and 15) conventional bonds issued by green firms are matched with conventional bonds issued by brown firms. The p-value of a Student test on the propensity score difference between the control group and the treated group is 0.8768 (resp. 0.7989 and 0.5717), indicating that they are insignificantly different from each other.

Table 3.5: Second step propensity score matching of bonds issued by green and brown firms

Table 3.5 reports the propensity score comparison of the treated group of bonds issued by green firms and the control group of conventional bonds issued by brown firms after the second-step bond matching for three areas. The p-value of the Student test is reported in the last column.

Location	Treated group			Control group			Mean Difference	P-value
	N	Mean	STD	N	Mean	STD		
Panel A. Propensity score of bonds matched *after* the green firm's first green bond issuance								
U.S.	95	0.9789	0.1443	95	0.9789	0.1443	0.0000	1.0000
Mainland China	84	0.0673	0.0265	84	0.0648	0.0249	0.0024	0.5402
Hong Kong	43	0.1221	0.0110	43	0.1229	0.00907	-0.0008	0.7190
Panel B. Propensity score of bonds matched *before* the green firm's first green bond issuance								
U.S.	30	0.0646	0.0279	30	0.0657	0.0274	-0.0011	0.8768
Mainland China	31	0.0417	0.0072	31	0.0413	0.0061	0.0004	0.7989
Hong Kong	15	0.1309	0.0828	15	0.1479	0.0796	-0.0170	0.5717

3.5.3 Matched sample exploration

Firm similarity

The second-step matching of bonds reduces the sample of brown firms with which treated green firms are matched. We reproduce the analysis of the propensity scores in Table 3.3 and the parallel trends of Figure 3.1 using the matched brown firms of the final sample in Table 3.6 and Figure 3.2, respectively.

The differences in propensity scores after the one-to-one final matching of firms are not significantly different. Additionally, the trends of market capitalization, market to book ratio, liquidity, and leverage are parallel before the issuance of bonds.

Table 3.6: Final propensity score of green firms and brown firms issuing matched conventional bonds

Table 3.6 reports the firm propensity score comparison of the treated group of green firms and the control group of brown firms issuing conventional bonds that have been matched with green firms' bonds in the bond matching process for three areas. The p-value of the Student test is reported in the last column.

Location	Treated group			Control group			Mean Difference	P-value
	N	Mean	STD	N	Mean	STD		
Panel A. Propensity score of firms matched *after* the green firm's first green bond issuance								
U.S.	95	0.7680	0.4134	95	0.7619	0.4201	0.00605	0.9204
Mainland China	84	1.0000	0.0000	84	1.0000	0.0000	0.0000	1.0000
Hong Kong	43	0.1554	0.0500	43	0.1465	0.0476	0.00898	0.396
Panel B. Propensity score of firms matched *before* the green firm's first green bond issuance								
U.S.	30	0.8907	0.2980	30	0.8812	0.3012	0.0095	0.9023
Mainland China	31	1.0000	0.0000	31	1.0000	0.0000	0.0000	1.0000
Hong Kong	15	0.1553	0.0396	15	0.1412	0.0310	0.0141	0.2881

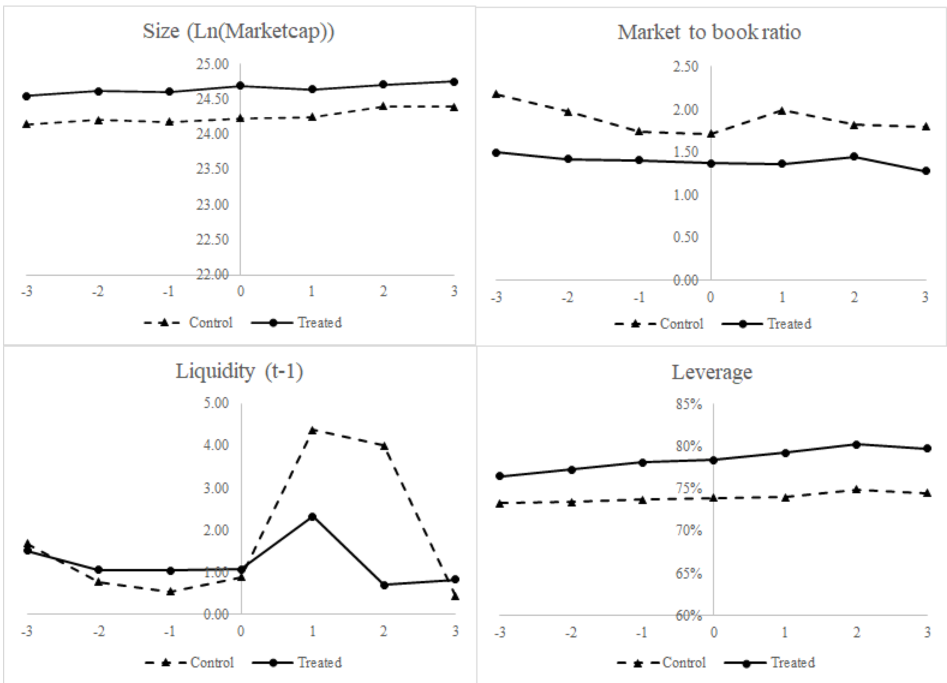


Figure 3.2: Parallel trend of control firms and treated firms after the second step bond matching

Figure 3.2 reports the parallel trend of control firms and treated firms after the second step bond matching. The trends are shown along the dimensions of firm size (ln(Marketcap)), Market to book ratio, Lag one period Liquidity (Amihud), and Leverage.

Bond similarity

We calculate the yield to maturity at the issuance date for each bond by using the coupon rate, coupon frequency, time to maturity, and issue price. (For simplicity, we do not price the option value of callable bonds, but as callable type is our matching criteria, this will not affect our analysis. We also include a control in our regressions.) Table 3.7 compares the yields at the issuance date of green and conventional bonds issued by green firms with the yields of their matched conventional bonds issued by brown firms.

Table 3.7: Descriptive statistics on the yields of matched bonds at the issuance

Table 3.7 reports the bond issue yields on green bonds and conventional bonds issued by green firms and matched conventional bonds issued by brown firms for three areas and the overall samples. The p-value of the Student test is reported in the last column.

Location		Treated group			Control group			Mean Difference	P-value
		N	Mean	Standard	N	Mean	Standard		
U.S.									
Green bonds		46	0.0358	0.0162	46	0.0407	0.0190	-0.0049	0.1850
Conventional bonds	Before	30	0.0301	0.0140	30	0.0316	0.0153	-0.0015	0.6895
	After	49	0.0338	0.0138	49	0.0333	0.0172	0.0006	0.8554
Mainland China									
Green bonds		57	0.0309	0.0162	57	0.0446	0.0113	-0.0136	< .0001
Conventional bonds	Before	31	0.0457	0.0107	31	0.0478	0.0139	-0.0021	0.5093
	After	27	0.0461	0.0115	27	0.0501	0.0120	-0.0040	0.2168
HK									
Green bonds		32	0.0462	0.0167	32	0.0495	0.0131	-0.0033	0.3849
Conventional bonds	Before	15	0.0436	0.0169	15	0.0510	0.0173	-0.0074	0.2465
	After	11	0.0537	0.0137	11	0.0493	0.0164	0.0043	0.5084
Total									
Green bonds		135	0.0362	0.0173	135	0.0444	0.0150	-0.0082	< .0001
Conventional bonds	Before	76	0.0391	0.0151	76	0.0420	0.0173	-0.0029	0.2700
	After	87	0.0402	0.0150	87	0.0405	0.0176	-0.0004	0.8829

In this univariate analysis, we do not find any significant premium on conventional bonds issued by green firms listed in the U.S., Mainland China, and Hong Kong relative to conventional bonds issued by brown firms. We also do not find any significant premium on green bonds issued by green firms listed in the U.S. and Hong Kong relative to conventional bonds issued by brown firms. However, green bonds issued by Mainland Chinese listed green firms are found to be issued at a discount (i.e., have a lower yield to maturity) relative to matched conventional bonds issued by matched brown firms. The premium is as large as 136 bp. This indicates that the Mainland China market is unique, which may be due to i) the general practice of verifying green bonds before the green bond issuance, or ii) Mainland China firms issuing green bonds in the Eurobond market.

3.6 Stock investors and green bond issuance

As previously described, there are two types of verification protocols for green bonds. Firstly, external verifiers provide a second-party opinion on the firm's green bond issuance process. Secondly, independent accountants or verifiers may analyze the uses of proceeds of a given bond issue and verify that they comply with the standard. Additionally, issuers may request certification. In the following analysis, we investigate whether the type of verification or certification affects the stock market reaction around the bond announcement.

3.6.1 Event cleaning

For our event study on the stock price reaction around the green bond issue date, we focus on the issuance of green bonds, which includes 57 observations in the U.S., 82 in Mainland China, and 53 in Hong Kong (see Table 3.A3). We then apply a standard process to prepare our event study by dropping 11 bonds where the stock listing date is after the bond issuance date and 18 bonds where other events potentially impact the listed firms' stock price around the bond issuance date.[22]

3.6.2 Univariate analysis

Prior studies by Flammer (2021) and Tang and Zhang (2020) find a positive stock price reaction to the announcement of green bonds. As a preliminary step to our analysis, we conducted an event study as described in section 3.4.1 to check whether we find consistent results in our sample. We analyzed the cumulative abnormal stock returns around the firm's green bond announcement.

Figure 3.3 shows the evolution of the CAR over the $[-10, 10]$ period, depending on whether the bond is verified by an independent reviewer or not. We observe that at day 3 after the announcement, the CAR for the first unverified green bond is 2.66%, while for subsequent unverified green bonds it is -0.67%. In contrast, the CAR for the first verified green bond is -0.39%, while for subsequent verified green bonds it is only slightly positive at 0.01%. These results suggest that the stock market reaction is associated with the status of the independent reviewer and the timing of the issuance.[23]

3.6.3 Multivariate analysis

In this section, we build on prior literature and investigate the determinants of stock market reaction in a panel regression. Our independent variable is the CAR around

[22] We checked for corporate events in Refinitiv for U.S. firms, in Shanghai and Shenzhen Stock (resp. Hong Kong) exchange databases for Mainland China (resp. Hong Kong) firms. We excluded financial report events, earnings announcement events, preferred stock issuance events, other bond issuance events, and top management team events. Details are reported in Table 3.A4 of Appendix.

[23] The evolution of the CAR by area can be found in Figure 3.A1 of Appendix.

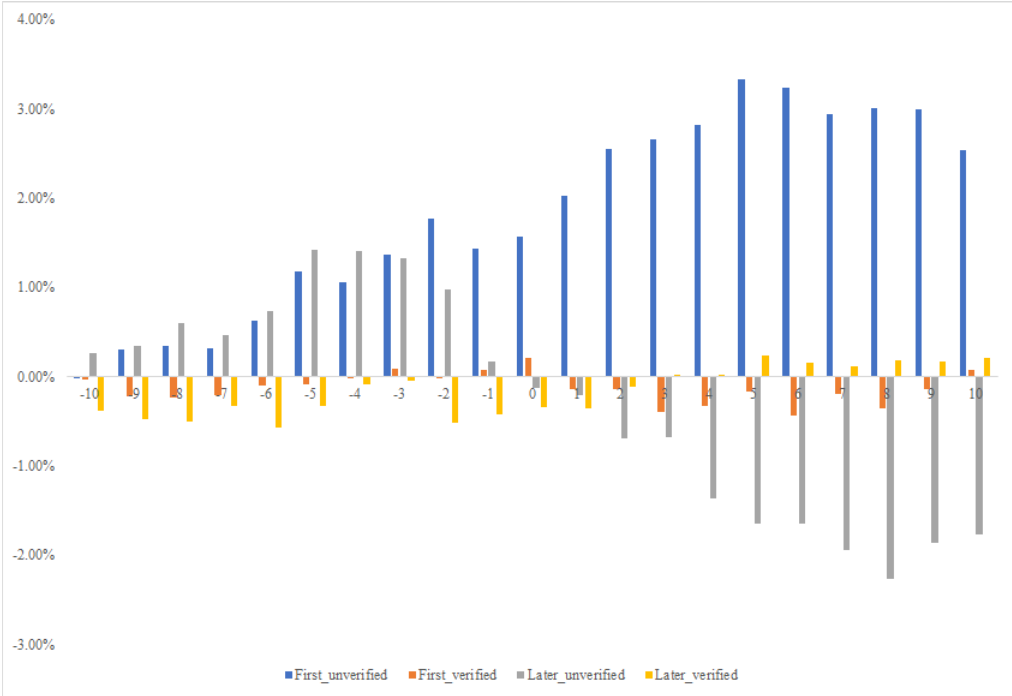


Figure 3.3: CAR around the green bond announcement date depending on the verification status

Figure 3.3 reports the CAR around the green bond announcement date depending on the verification process by first issuance and later issuance. The estimation is based on (one factor) CAPM model. The estimation window is [-252,30] and the reported event window is [-10,10].

the announcement of a bond issued by a green company in the time window of [-10,3], which captures the stock market reaction. Apart from estimating green bonds, we also estimate the conventional bonds issued before the first green bond issuance and the first conventional bonds issued after the first green bond issuance.[24] Table 3.8 reports the CAR around the bond announcement day. The first green bonds have a significant 0.86% CAR, while the later green group's CAR is insignificant at -0.17%. The conventional bonds issued before the first green bond issuance experience an average CAR of -0.31%, which is also insignificant. Surprisingly, the first conventional bonds issued after the first green bond issuance have a significant 2.9% CAR.[25]

We run the following regression model on the sample of bonds j_f for which the issuer is related to firm f:

$$CAR[-10,3]_{j_f,t} = \beta_0 + \beta_1 Post_{j_f} + \beta_2 D\_Green\_bond_{j_f} + \beta_3 D\_First\_Green_{j_f} + X + \epsilon_{j_f,t} \tag{3.2}$$

We include several control variables at both the bond and firm levels in our panel re-

[24] It's possible that there are several conventional bonds issued after the first green bond issuance on the same issuance date.

[25] Even if we only count once for the days that have several bonds issued, the CAR is significant and has the same level of significance.

Table 3.8: Cumulative abnormal return [-10, 3] around bond announcement day

Table 3.8 reports the stock cumulative abnormal return around the bond announcement day with the time window [-10,3]. Green bonds are separated into two groups, first green bond issuance group and later green bond issuance group. Conventional bonds are separated into two groups, before first green bond issuance group, and first conventional bond issuance after first green bond issuance group.

		N	Mean	STD	P-value
Green bonds	First	83	0.0086	0.0414	0.0618
	Later	80	-0.0017	0.0393	0.6923
Conventional bonds	Before	63	-0.0031	0.0403	0.5486
	After	93	0.0290	0.0400	0.0000

gression analysis. The binary variable $D\_Eurobond_{j_f}$ accounts for the fact that some Chinese firms issue green bonds in the Eurobond market, which may lead to lower cost of debt but also require CBI certification. $ln(Bond\_Size_{j_f})$ controls for differences in bond size. The variable $Issuance\_date - Green\_date$ tests whether the CAR for green firms decays over time. Firm-level controls include $ln(Firm\_size_f)$, $Market\_to\_book\_ratio_f$, $Amihud_f$, $Leverage_f$, and $Profitability_f$. We also include area fixed effects to account for potential heterogeneity in investor preferences across regions, industry fixed effects, and year fixed effects.[26]

Our explanatory variables of interest are as follows. To test whether the market reacts differently for conventional bonds issued before a firm becomes green, we include the dummy variable $Post_{j_f}$, which equals 0 if the bond is issued before the first green bond issuance, otherwise 1. The variable $D\_Green\_bond_{j_f}$ is used to test whether the market reacts differently for conventional bonds and green bonds issued after the firms become green. The literature suggests that the first issuance of green bonds yields a stronger stock market price reaction. Therefore, we include a dummy variable D_First_Green that equals one for the first time a listed firm or its related subsidiary issues a green bond.

In a second specification, we want to test the impact of verification. When the bond has been verified or certified prior to the green bond issuance, we include the dummy $D\_Green\_bond \times Framework_{j_f}$ that equals one if the issuer or intermediaries

[26]We use the SIC code as the industry code for U.S. firms and the industry code based on the 2012 guidance from the China Securities Regulatory Commission for Mainland China firms. We assign the industry code to Hong Kong listed firms based on the 2012 guidance as well. We classify SIC code 32, 36, and 37 as manufacturing firms, SIC code 48 and 49 as utility firms, and SIC code 60, 61, 62, 63, and 67 as financial firms for all U.S. firms. For all Mainland China firms, we classify industry code C as manufacturing firms, industry code D and N as utility firms, industry code J as financial firms, and industry code K, L, and E as real estate firms. For all Hong Kong firms, we classify industry code C as manufacturing firms, industry code D, N, and G as utility firms, industry code J as financial firms, and industry code K, L, and E as real estate firms, thus unifying the industry codes for all areas.

have released any verification report or certification prior to the issue date, and zero otherwise (that is, whether no report is available or whether the report became available after the issuance). We also include the interaction of dummy D_First_Green with our main variable$D_Green_bond \times Framework_{j_f}$. Further, we break down the impact of verification into three more detailed dummy variables that capture the nature of the verification, namely, the dummy $D\_framework$ that captures whether the firm's green bond framework has be verified prior to issuance, the dummy D_UoP that captures whether the bond's uses of proceeds have additionally been verified, and the dummy $D\_CBI\_certified$ that captures whether the bond is certified by CBI.

$$\begin{aligned} CAR[-10,3]_{j_f,t} =& \beta_0 + \beta_1 Post_{j_f} + \beta_2 D\_Green\_bond_{j_f} + \beta_3 D\_Green\_bond \times Framework_{j_f} \\ &+ \beta_4 D\_First\_Green_{j_f} + \beta_5 D\_First\_Green \times Framework_{j_f} + X + \epsilon_{j_f,t} \end{aligned} \tag{3.3}$$

Table 3.9 reports the regression analysis for stock reactions CAR to green firm bond announcement. First, the dummy *Post* is significantly positive through three specifications, with a coefficient larger than 3%. It suggests that relative to the conventional bonds issued before the firms become green, conventional bonds issued after experience a positive CAR as suggested in the univariate analysis part. Second, relative to conventional bonds issued after the first green bond issuance, the dummy D_Green_bond suggests that the green bonds have smaller CAR. If we add up the impact of *Post* and D_Green_bond, we can find that later issued green bond's announcement CAR is insignificantly positive. If we add up the impact of *Post*, D_Green_bond and D_First_Green, the first issued green bonds' announcement CAR is significantly positive. It is consistent with the literature that the first green bond issuance has positively stock market reaction, while the second one doesn't. Surprisingly, we find that the market has even higher reaction to the first conventional bonds issued after the first green bond issuance.

Table 3.10 reports the regression analysis for stock reactions CAR to green firm bond announcement with verification details. First, the sum impact of *Post*, D_Green_bond and D_First_green are positive with the coefficient 0.0313 in specification (3). It suggests that relative to conventional bonds issued before the firms become green, first unverified green bonds has positive CAR around the announcement day. The market reaction to fist unverified green bonds has similar magnitude to the first conventional bonds issued after the first green bond issuance.

Second, the interaction coefficient between the two dummies, D_First_Green and $Framework$, is significantly negative. However, the sum of coefficients, *Post*, D_Green, D_First_Green, and $D\_First\_Green \times Framework$, is not significantly different from zero. This suggests that there is no reaction to the first green bond issued by a firm with green bond framework verified. It supports our hypothesis H1a that stock investors have a preference on firms that make a transition to green, while do not consider the impact of funding green projects with bonds on future cash flow.

Table 3.9: Regression analysis for the stock reactions to green firm bond announcement

Table 3.9 reports the regression analysis for the stock reactions around the green firms' bond announcement. The regression is specified in equation (3.2). CAR is the cumulative abnormal return during the time window [-10,3] around the bond announcement day. *Post* equals one if the bond issued after the firm's first green bond issuance. *D_Green_bond* equals one if the bond is a green bond. *D_First_Green* equals one if it is the green firm's first issued green bond. *D_Eurobond* equals one if the bond is issued in Eurobond market. $Issuancedate - Greendate$ is the difference between the bond issuance date and the firm's first green issuance date. Controls include Bond size defined as the amount that the bond issued in USD, Firm size defined as market capitlaization, Market to book ratio, Amihud, Leverage, and Profitability. Area, industry and Year fixed effects are included. Industry and year fixed effects. The significance levels are at 1%, 5% and 10% respectively.

	Conventional only	Conventional and first green	Whole sample
	(1)	(2)	(3)
	CAR	CAR	CAR
Post	0.0356***	0.0356***	0.0317***
	(0.0085)	(0.0089)	(0.0079)
D_Green bond		-0.0180**	-0.0269***
		(0.0076)	(0.0073)
D_First_Green			0.0087
			(0.0071)
D_Eurobond		0.0098	0.0135*
		(0.0095)	(0.0070)
Ln(Bond Size)	0.0010	0.0016	0.0012
	(0.0015)	(0.0014)	(0.0013)
Issuance date - Green date	-0.0077*	-0.0080*	-0.0051*
	(0.0044)	(0.0042)	(0.0030)
Ln(Firm Size)	0.0104***	0.0058***	0.0056***
	(0.0028)	(0.0021)	(0.0018)
Market to book ratio	0.0126***	0.0081**	0.0043
	(0.0045)	(0.0039)	(0.0032)
Amihud	0.0001	0.0001	-0.0000
	(0.0003)	(0.0002)	(0.0002)
Leverage	0.0150	0.0297	0.0285*
	(0.0327)	(0.0202)	(0.0161)
Profitability	-0.3940**	-0.3236**	-0.1879
	(0.1765)	(0.1535)	(0.1234)
Area fixed effect		Yes	
Industry fixed effect		Yes	
Year fixed effect		Yes	
N	156	239	319
adj. R-sq	0.408	0.263	0.204

Table 3.10: Regression analysis for stock reactions to green firm bond announcement with verification process

Table 3.10 reports the regression analysis for the stock reactions around the green firm's bond announcement date with verification process. The regression is specified in equation (3.3). CAR is the cumulative abnormal return during the time window [-10,3] around the bond issuance day. $D\_framework$ equals one if the firm's green bond framework has be verified prior to issuance, D_UoP equals one if the uses of proceeds have been verified, $D\_CBI\_certified$ equals one if the bond is certified by CBI. D_First_Green equals one if it is the green firm's first issued green bond. $D\_Eurobond$ equals one if the bond is issued in Eurobond market. $Issuancedate - Greendate$ is the difference between the bond issuance date and the firm's first green issuance date. Controls include Bond size defined as the amount that the bond issued in USD, Firm size defined as market capitlaization, Market to book ratio, Amihud, Leverage, and Profitability. Area, industry and Year fixed effects are included. The significance levels are at 1%, 5% and 10% respectively.

	Conventional and first green		Whole sample	
	(1)	(2)	(3)	(4)
	CAR	CAR	CAR	CAR
Post	0.0362***	0.0366***	0.0324***	0.0315***
	(0.0088)	(0.0088)	(0.0077)	(0.0079)
D_Green_bond	-0.0030	-0.0024	-0.0358***	-0.0365***
	(0.0089)	(0.0090)	(0.0101)	(0.0102)
$D\_Green\_bond \times Framework$	-0.0303***	-0.0262*	0.0096	0.0072
	(0.0099)	(0.0134)	(0.0111)	(0.0132)
$D\_Green\_bond \times UoP$		-0.0081		0.0098
		(0.0136)		(0.0138)
$D\_Green\_bond \times CBI\_certified$		0.0140		-0.0158
		(0.0171)		(0.0155)
D_First_green			0.0347***	0.0359***
			(0.0111)	(0.0112)
$D\_First\_green \times Framework$			-0.0405***	-0.0347**
			(0.0130)	(0.0163)
$D\_First\_green \times UoP$				-0.0179
				(0.0174)
$D\_First\_green \times CBI\_certified$				0.0266
				(0.0218)
D_Eurobond	0.0152	0.0125	0.0144**	0.0165**
	(0.0095)	(0.0100)	(0.0070)	(0.0079)
Ln(Bond Size)	0.0010	0.0009	0.0010	0.0009
	(0.0014)	(0.0014)	(0.0013)	(0.0013)
Issuance date - Green date	-0.0085**	-0.0085**	-0.0055*	-0.0050
	(0.0041)	(0.0042)	(0.0030)	(0.0030)
Ln(Firm Size)	0.0066***	0.0066***	0.0061***	0.0062***
	(0.0020)	(0.0021)	(0.0017)	(0.0018)
Market to book ratio	0.0078**	0.0077**	0.0038	0.0036
	(0.0038)	(0.0039)	(0.0032)	(0.0032)
Amihud	0.0000	0.0000	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Leverage	0.0266	0.0279	0.0303*	0.0308*
	(0.0198)	(0.0201)	(0.0158)	(0.0163)
Profitability	-0.2874*	-0.2830*	-0.1631	-0.1549
	(0.1511)	(0.1537)	(0.1214)	(0.1247)
Area fixed effect	Yes			
Industry fixed effect	Yes			
Year fixed effect	Yes			
N	239	239	319	319
adj. R-sq	0.290	0.286	0.231	0.226

The results of specification (4) confirms this conjecture, as investors mainly react to the verification of the firm's green bond framework instead of the use of proceeds or CBI certification. Because only green bond framework is verified before knowing the details of the green bond.

Overall, our findings suggest that there is a demand effect in investors that value firms with green bond framework verified, leading to higher stock prices for green firms. However, it remains unclear why investors also treat the first conventional bond issuance after a firm becomes green as a positive signal.

3.7 Bond investors and green bond issuance

This section investigates the impact of the "greeness" of the bond or of the firm on bond prices. Our variable of interest is the bond yield difference analysis between any bond j_g issued by the green firm g and the matched bond j_{b^*} issued by the matched brown firm b^*, as defined in equation (3.4).

Our baseline regression is as follows:

$$\begin{aligned} YTM_{j_f,t} =& \alpha_0 + \alpha_1 Post_{j_f} + \alpha_2 D\_Green\_firm_j + \alpha_3 Post \times D\_Green\_firm_j + \\ & \alpha_4 Green\_Bond_{j_f}(\times Post) + X + \epsilon_{j,t}, \end{aligned} \tag{3.4}$$

where YTM is the bond yield, $Post$ is a dummy that takes value one if firm g issues a bond after having issued a first green bond (the green bond issue included), $Greenfirm$ is a dummy takes value one if the firm is a green firm, and $GreenBond$ is a dummy that takes value one if the bond issued by the green firm is green. Our explanatory variables of interest in regression (3.4) are the following:

- α_1 captures whether matched conventional bonds issued by brown firms after the first green bond issuance trade at a different yield than matched conventional bonds issued by brown firms before green firms issue its first green bond;

- α_2 captures whether conventional bonds issued by green firms trade at a different yield than the conventional bonds issued by brown firms;

- α_3 captures whether conventional bonds issued by green firms after green firms issue its first green bond trade at a different yield than the conventional bonds issued after green firms issue its first green bond;

- α_4 captures whether green bonds issued by green firms trade at a different yield than the conventional bonds issued by green firms after green firms issue green bonds;

If α_3 is significantly negative, it supports our hypothesis H2a that there exists a demand effect at the firm level. If α_4 is significantly negative, it supports our hypothesis H2b there exists an information effect at the bond level.

Table 3.11 reports difference in difference analysis result for understanding the change of green firms' bond yield. Our results are reported in three groups, conventional bonds and matched conventional bonds group, green bonds and matched conventional bonds group, and all the green firms' bonds and matched conventional bonds group. Each group has three specifications. From the specifications that only include fixed effect, we we sequentially differences in bond size, time to maturity and whether the bonds are callable as bond controls (specification 2), and differences in firm size, (lag) Amihud liquidity ratio, market-to-book ratio, leverage and profitability as firm controls (specification 3).

Table 3.11: Differences-in-differences analysis for bond yields

Table 3.11 reports the results of the diff-in-diffs analysis on bond yields in the baseline model. The regression is specified in equation (3.4). The independent variable YTM is the yield to maturity at the issuance date of the bond. The dependent variables of interest consist in *Post*, a dummy that takes value one if the firm has issued a green bond in the past or is issuing a green bond, D_Green_firm is a dummy that takes one if the firm has or will issue a green bond, and D_Green_Bond, a dummy that equals one if the bond issued is a green bond. We introduce control variables sequentially in three different specifications for each subsample. Controls for bonds include: Callable bond, a dummy that equals one if the bond is callable, the difference in bond size, defined as the amount issued in USD (in log), the difference in time to maturity of the matched bonds, and a dummay that equals one if the bond is issued in Eurobond market. Controls for differences across matched firms include: the market capitalization in USD (in log), the lagged one period standard annual Amihud illiquidity measure, the market to book ratio defined as the market value of the equity divided by the book value of the equity, the leverage, and the profitability. All specifications include Area, Industry and year fixed effects. The significance levels are at 1%, 5% and 10% respectively.

	Conventional bonds only			**Green bonds only**			**All bonds**		
	(1) YTM	(2) YTM	(3) YTM	(4) YTM	(5) YTM	(6) YTM	(7) YTM	(8) YTM	(9) YTM
Post	0.0000	-0.0006	0.0004				0.0002	0.0003	0.0002
	(0.0021)	(0.0019)	(0.0018)				(0.0019)	(0.0017)	(0.0016)
Green firm	-0.0023	-0.0025	-0.0023				-0.0027	-0.0032	-0.0030
	(0.0021)	(0.0018)	(0.0018)				(0.0023)	(0.0020)	(0.0019)
Post*Green firm	0.0031	0.0025	0.0034				0.0021	0.0011	0.0024
	(0.0028)	(0.0025)	(0.0024)				(0.0029)	(0.0025)	(0.0024)
Green bond				-0.0081***	-0.0023	-0.0024	-0.0063***	0.0012	-0.0005
				(0.0018)	(0.0018)	(0.0018)	(0.0019)	(0.0019)	(0.0019)
ln(Bond Size)		-0.0018***	-0.0014***		-0.0040***	-0.0033***		-0.0028***	-0.0020***
		(0.0004)	(0.0004)		(0.0007)	(0.0007)		(0.0004)	(0.0004)
Callabe bond		0.0136***	0.0118***		0.0307***	0.0262***		0.0185***	0.0156***
		(0.0020)	(0.0019)		(0.0040)	(0.0041)		(0.0017)	(0.0017)
Time to maturity		0.0001**	0.0001**		-0.0003***	-0.0002***		-0.0000	-0.0000
		(0.0001)	(0.0001)		(0.0001)	(0.0001)		(0.0000)	(0.0000)
D_Eurobond					-0.0136***	-0.0122***		-0.0135***	-0.0103***
					(0.0023)	(0.0024)		(0.0022)	(0.0021)
ln(Firm Size)			-0.0022***			-0.0019***			-0.0027***
			(0.0007)			(0.0006)			(0.0004)
Lag(Amihud)			0.0002			0.0006**			0.0003*
			(0.0003)			(0.0003)			(0.0002)
Market to book ratio			0.0011**			0.0003			0.0007*
			(0.0005)			(0.0006)			(0.0004)
Leverage			-0.0094			0.0111*			0.0055
			(0.0061)			(0.0063)			(0.0043)
Profitability			-0.0531*			-0.0472			-0.0330
			(0.0319)			(0.0419)			(0.0251)
Area fixed effect					Yes				
Industry fixed effect					Yes				
Year fixed effect					Yes				
N	324	324	320	270	270	270	594	594	590
adj. R-sq	0.417	0.530	0.578	0.232	0.454	0.518	0.296	0.461	0.517

For conventional bonds and matched conventional bonds group, not surprisingly, across three specifications, the coefficients are insignificant. It suggests that our matching process works well. We have the same findings as in the descriptive statistics of Table 3.7. Being a green firm doesn't affect a firm's cost of conventional debt.

For green bonds and matched conventional bonds group, with only fixed effects, the coefficient of *D_Green_bond* is negatively significant as suggested by the descriptive statistics. But when we include bond level controls, it becomes insignificant. The variable that absorb the impact of *D_Green_bond* is *D_Eurobond*. It's true that the green bonds issued in Eurobond market has lower YTM than the matched conventional bonds in local market, as we didn't match conventional bonds issued Eurobond market by matched local market listed companies. It suggests that the green bond YTM is insignificantly different from the matched conventional bond YTM.

For both the green firms' bonds and the matched conventional bonds group, the coefficients α_3 for $Post \times Green\ Firm$ and α_4 for *Greenbond* are both insignificant. Therefore, the results do not support hypotheses H2a and H2b. This indicates that there is no demand effect at the firm level and no information effect at the bond level for bond investors.

Overall, our results suggest that green firms don't benefit from lower cost of debt on neither both conventional bonds nor green bonds. We depart from prior literature by analyzing both conventional bonds and green bonds, while existing papers have computed the greenium by matching green and conventional bond issued by the same firm independently of whether it is issued prior or after the green bond. Bond investors treat green firms' conventional bonds and green bonds indifferent from the situations that they hasn't issued any green bonds.

Next, we expand the baseline model (3.4) to analyze how the firm and bond's verification processes impact the bond yield. To this end, we break down green firms depending on whether their green bond framework has been verified or not, and green bonds depending on whether the bond's uses of proceeds are unverified, verified or certified. Table 3.12 reports the estimates of the following regression (3.5), introducing explanatory variables sequentially:

$$\begin{aligned} YTM_{j_f,t} =& \alpha_0 + \alpha_1 Post_{j_f} + \alpha_2 D\_Green\_firm_j + \alpha_3 Post \times D\_Green\_firm_j \\ & + \alpha_4 D\_Green\_Bond_{j_f}(\times Post) + \alpha_5 D\_Green\_bond * Framework_{j_f} \\ & + \alpha_6 D\_Green\_bond * UoP_{j_f} + \alpha_7 D\_Green\_bond * CBI\_certified_{j_f} + \\ & X + \epsilon_{j,t}, \end{aligned} \tag{3.5}$$

where $D\_framework_g$ is a dummy that takes value one if the green firm g's green bond framework has been verified, D_UoP is a dummy that takes value one if firm g's green bond framework and the green bond j_g's uses of proceeds have been verified, and $D\_CBI\_certified$ is a dummy that takes value one if firm g's green bond framework and the green bond j_g's uses of proceeds have been verified and if bond j_g has been certified as green by CBI.

The main coefficients we are interested in are α_5, α_6, and α_7. If α_5 is negatively significant, it suggests a demand effect at firm level that bond investors prefer green bonds issued by firms with green bond framework verification. It corresponds to our hypothesis H2c. If α_6 or α_7 is negatively significant, it suggests a demand effect at bond level that bond investors prefer green bonds with use of proceeds verified or CBI certification. It corresponds to our hypotheses H2d and H2e.

Table 3.12 reports the difference in difference analysis results with verification process. The first two specifications are with green bonds and matched conventional bonds only. The third two specification are with all the bonds issued by green firms and matched conventional bonds.

Our key result is as follows. Green firms' conventional and green bonds generally trade at the same yield as brown firms' conventional bonds, with the notable difference of certified green bonds: coefficients α_1 to α_6 are not significantly different from zero, while the coefficient α_7 is significantly negative. While green bonds do not benefit from a lower yield relative to issued conventional bonds issued by a green firm, bonds that have been certified by CBI benefit from a lower yield: the certification of a given bond decreases its yield. This supports our hypothesis H2e that there exists a demand effect at the bond level.[27]

It is worth noting that some of the CBI certification is taken by Mainland China firms that issue bonds in Eurobond market. It could be the fact that they want to get more credit in a non-local market. It is the reason that the coefficient of *D_Eurobond* decreases from -0.0116 (-0.0096) in specification 1 (3) to -0.0086 (-0.0067). But even we control for the impact of *D_Eurobond*, Bond with CBI certification is still significantly negative.

[27] Baker et al. (2018) indeed report that green bonds are disproportionately held by socially-oriented investors: for the average green bond in their subsample, 13.5% of par outstanding can be associated with a socially-responsible fund through the fund's name, while the proportion drops to 0.6% for an average ordinary bond. Also it is consistent with the fact that asset managers are motivated to integrate ESG factors into their investment strategies in response to increased client demand for sustainable products (McCahery et al., 2022).

Table 3.12: Differences-in-differences analysis for bond yields with verification process

Table 3.12 reports the results of the diff-in-diffs analysis on bond yields for the extended model specified in equation (4). The independent variable YTM is the yield to maturity at the issuance date of the bond. The dependent variables of interest consist in $Post$, a dummy that takes value one if the firm has issued a green bond in the past or is issuing a green bond, D_Green_firm is a dummy that takes one if the firm has or will issue a green bond, and D_Green_Bond, a dummy that equals one if the bond issued is a green bond.$D\_framework$ equals one if the firm's green bond framework has be verified prior to issuance, D_UoP equals one if the uses of proceeds have been verified, $D\_CBI\_certified$ equals one if the bond is certified by CBI. Controls for bonds include: Callable bond, a dummy that equals one if the bond is callable, the difference in bond size, defined as the amount issued in USD (in log), the difference in time to maturity of the matched bonds, and a dummay that equals one if the bond is issued in Eurobond market. Controls for differences across matched firms include: the market capitalization in USD (in log), the lagged one period standard annual Amihud illiquidity measure, the market to book ratio defined as the market value of the equity divided by the book value of the equity, the leverage, and the profitability. All specifications include Area, Industry and year fixed effects. The significance levels are at 1%, 5% and 10% respectively.

	Green bonds only		**All bonds**	
	(1) YTM	(2) YTM	(3) YTM	(4) YTM
Post			0.0002	0.0001
			(0.0016)	(0.0016)
Green_firm			-0.0029	-0.0029
			(0.0019)	(0.0019)
Post*Green_firm			0.0024	0.0023
			(0.0024)	(0.0024)
Green bond	0.0000	-0.0004	0.0014	0.0009
	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Green_bond*Framework	-0.0043	-0.0023	-0.0035	-0.0024
	(0.0027)	(0.0033)	(0.0024)	(0.0031)
Green_bond*UoP		-0.0006		0.0006
		(0.0030)		(0.0029)
Green_bond*CBI_certified		-0.0127***		-0.0108***
		(0.0034)		(0.0032)
ln(Bond Size)	-0.0033***	-0.0034***	-0.0020***	-0.0020***
	(0.0007)	(0.0007)	(0.0004)	(0.0004)
Callabe bond	0.0267***	0.0253***	0.0154***	0.0151***
	(0.0041)	(0.0040)	(0.0017)	(0.0017)
Time to maturity	-0.0002***	-0.0002***	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
D_Eurobond	-0.0116***	-0.0086***	-0.0096***	-0.0067***
	(0.0024)	(0.0026)	(0.0022)	(0.0025)
ln(Firm Size)	-0.0017**	-0.0018***	-0.0026***	-0.0026***
	(0.0007)	(0.0006)	(0.0004)	(0.0004)
Lag(Amihud)	0.0007**	0.0006**	0.0003*	0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Market to book ratio	0.0002	0.0000	0.0007*	0.0007
	(0.0006)	(0.0006)	(0.0004)	(0.0004)
Leverage	0.0114*	0.0151**	0.0052	0.0065
	(0.0062)	(0.0062)	(0.0043)	(0.0043)
Profitability	-0.0420	-0.0272	-0.0320	-0.0255
	(0.0419)	(0.0411)	(0.0251)	(0.0250)
Area fixed effect		Yes		
Industry fixed effect		Yes		
Year fixed effect		Yes		
N	270	270	590	590
adj. R-sq	0.521	0.544	0.518	0.526

3.8 Conclusion

We conduct a deep analysis to understand the drivers of positive stock market reaction to green bond issuance and the greenium for certain green bonds. We utilize the fact that CBI's three-tier verification system for green bond can isolate firms' green status from their engagement in green actions to separate the information effect and the demand effect.

We find that, on the announcement date of the first green bond issuance, stock investors react positively only to green bonds issued by firms that have not yet undergone green bond framework verification. This suggests that stock investors value firms' green status, which can be conveyed to the market when a firm's green bond framework is verified, or when the first green bond is issued if the firm has not verified its green bond framework. Our results suggest the presence of a demand effect among stock investors, indicating that they value firms' green status. However, we do not find any evidence of an information effect among stock investors.

For bond investors, we develop an innovative method that compares the yields of green bonds, with or without CBI certification, and conventional bonds issued by green firms with the yields of conventional bonds issued by brown firms. We find no evidence supporting the existence of a greenium for other green bonds, except for those with CBI certification. We also do not find any cost of debt benefit for conventional bonds issued by green firms. The results suggest that for bond investors, there is no demand effect at the firm level, while a demand effect does exist at the bond level. Also, we don't find evidence of an information effect among bond investors.

Our research is important as we confirm the existence of stock investors' preference on green firms and bond investors' preference on certain type of green bonds. Investors' preference can contribute the existence of CSR firms, and push more firms to adopt green actions.

3.9 Appendix

3.9.1 Comparision between GBP and China policies

Let us first compare the principle related to the use of proceeds. In its GBP, the ICMA proposed ten supporting green categories, which are renewable energy, energy efficiency, pollution prevention and control, environmentally sustainable management of living natural resources and land use, terrestrial and aquatic biodiversity, clean transportation, sustainable water and wastewater management, climate change adaptation, eco-efficient and/or circular economy adapted products, production technologies and processes, and green buildings.[28] China policies employ six categories and thirty-one sub-categories proposed by the Green Finance Committee (GFC), China Society for Finance & Banking. The six categories include energy saving, pollution prevention, resource saving and recycling, clean transportation, clean energy, ecological protection and climate change adaptation.[29] Cross-checking the description of categories and sub-categories of China policies, those could actually easily be mapped with the ten GBP categories. The main difference is that the China policy rules' categories take into account the Chinese industry classification which enables Chinese firms to more easily fit into a category.

Second, regarding the process for project evaluation and selection, the two standards are similar. The China policy rules additionally require the issuer to declare these pieces of information in the prospectus, and to commit to invest the proceeds in green projects.

Third, regarding the management of proceeds, the GBP standard requires the firm to trace the use of proceeds, for instance by setting up a sub-account. Temporary placement of unallocated proceeds should be released to the public. China policy rules include various principles depending on the issuer's regulator. For instance, firms issuing green bonds in the interbank market are requested to set up a special account or a special ledger to track the use of proceeds, and are allowed to invest unallocated proceeds in green bonds issued by non-financial business or money market instrument with good credit rating and liquidity.[30] Firms issuing bonds in other financial markets must set up a specific account, and the trustee of the account is responsible for monitoring the uses of proceeds.[31]

Fourth, regarding reporting standards, the GBP standard requires to release information annually. When significant developments happen, the information should be released on a timely basis. By contrast, the China policy rules require a more fre-

[28] https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/June-2018/Green-Bond-Principles—June-2018-140618-WEB.pdf

[29] http://www.gov.cn/xinwen/2015-12/22/5026636/files/d400bce25c9f42b3a2707dd4cb57d4bd.doc

[30] https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/PBOC-Announcement-No-39-2015.pdf

[31] http://www.csrc.gov.cn/pub/newsite/flb/flfg/bmgf/fx/gszj/201805/P020180515572638143453.pdf

quent information release. In the interbank market, financial institutions are required to release information quarterly and to submit an annual report and a special auditor report to PBoC, while non-financial institutions are required to release information semi-annually.[32] But outside of the interbank market, rules only require the trustee of the account to disclose information in the annual entrusted affair report and do not state clearly the frequency of reporting.

Finally, both standards encourage the issuers to engage a second party service and get a certification, but those services are not mandatory.

[32]http://www.nafmii.org.cn/ggtz/gg/201703/P020170322639776098176.pdf

Table 3.A1: Comparison between GBP and China policies

Table 3.A1 compares the green bond principle (GBP) proposed by ICMA and the green bond issuance rules proposed by Chinese government. The comparison is taken based on the four core principles of GBP, which are the use of proceeds, the process for project evaluation and selection, the management of proceeds, and the reporting on the uses of proceeds. In addition, we report the attitudes of the two rules towards second party opinion.

Green principles	Use of proceeds	Process for project evaluation and selection	Management of proceeds		Reporting		second party opinion
ICMA Green bond principles	10 categories	1.The environmental sustainability objectives 2. The process by which the issuer determines how the projects fit within the eligible Green Projects categories identified above 3. The related eligibility criteria, including, if applicable, exclusion criteria or any other process applied to identify and manage potentially material environmental and social risks associated with the projects.	1. Sub-account or other trackable method 2. Temporary placement for unallocated proceeds should be released		1. Annually update 2. In case of material developments, update on a timely basis		Encourage
China four policy rules	6 categories and 31 sub-categories	1. The prospectus shall include project categories, project selection criteria, decision-making procedures, environmental benefits, use and management of green financial bond proceeds	Interbank market	1. Used within given time frame	Interbank market	For financial green bonds, quarterly release and submit the annual report and special auditor report to PBoC	Encourage
				2.Special account or ledger			
				3. Unallocated procceds is investable		For non-financial green bonds, disclose semi-annually	
			Public market	1. Procceds could be used to finance the constrution, operatoin or acquisition of green projects or pay back the bank loan of green projects	Public market	1. The issuer should disclose the use of the proceeds, the progress of the green projects and environmental benefits following relevant regulations or the commitment	
		2. Commitment of investing proceeds in green projects		2. Specific account and monitor of the account trustee		2. The green bond trustee should disclose the same above information in the annual entrusted affair report	

3.9.2 Other tables and figures

Table 3.A2: Green bonds' issuers and relations to listed firms

Table 3.A2 reports the statistics of linkages between green bond issuers and listed firms in three areas. The issuer could be (i) a single listed firm, (ii) the subsidiary of a listed firm, (iii) the indirect subsidiaries of a listed firm. Panel A reports the statistics of entities linked to listed firms issuing green bonds. Panel B reports the statistics of the corresponding listed firms to which the entities issuing green bonds are linked.

	U.S.	Mainland China	Hong Kong
Panel A: entities issuing green bonds			
- Issuers that are related to listed firms	30	32	25
- Issuers that are listed firms	13	14	14
- Issuers that are not listed but whose direct parent is a listed firm	17	18	9
- Issuers that are not listed but whose indirect parent is a listed firm	0	0	2
Panel B: listed firms related to entities issuing green bonds			
- Listed firms related to green bond's issuer	25	19	21
- Listed firms that directly issued green bonds	13	14	14
- Listed firms whose subsidiaries issued green bonds	16	8	9
- Listed firms whose indirect subsidiaries issued green bonds	0	0	1

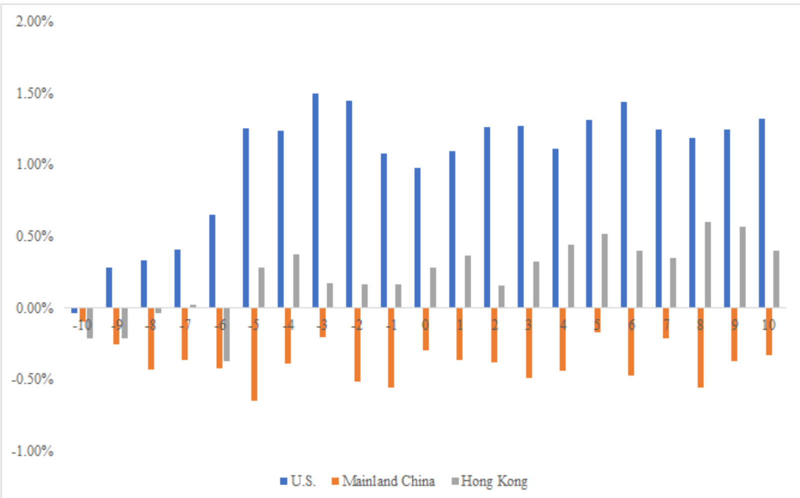


Figure 3.A1: CAR around the green bond announcement date for three areas

Figure 3.A1 reports the Cumulative Abnormal Returns (CAR) around the green bond announcement date for the U.S., Mainland China and Hong Kong. The estimation is based on (one factor) CAPM model. The estimation window is [-252,30] and the reported event window here is [-10,10].

Table 3.A3: Green and brown firms

Table 3.A3 reports the number of bills/notes/bonds related to "green" or "brown" firms in our sample by area, and the corresponding number of firms and firm-year observations. The filter process consists of dropping: (i) bills with less than one year of maturity, (ii) bonds with zero issuance amount, (iii) bonds for which we cannot find complete data on the coupon rate, coupon frequency, time to maturity, and issue price, and (iv) bonds related to ST firms in Mainland China.

	U.S.	Mainland China	Hong Kong
Panel A: green firms			
# Firms	25	19	21
# Firm-year observations	39	30	31
# Green bonds issued by the firm or a subsidiary	58	84	53
- **After filtering**	**57**	**82**	**53**
# Conventional bonds/notes/bills issued by green firms	9,936	17,877	3,963
- **After filtering**	**7,752**	**341**	**86**
Panel B: brown firms			
# Firms	1,558	963	90
# Firm-year observations	3,728	2,404	255
- After filtering	3,407	2,049	207
# Conventional bonds/notes/bills issued by brown firms	66,818	23,948	8,529
- **After filtering**	**39,802**	**3,128**	**481**
Total # of bonds/notes/bills	76,788	41,861	12,516
- **After filtering**	**47,611**	**3,570**	**626**

Table 3.A4: Number of green bonds in the event study

Table 3.A4 reports the number of bonds employed in the event study. The filter process consists of dropping: i. bonds issued before stock listing date, ii. bonds issued when other events happened, which potentially impact the stock price

	U.S.	Mainland China	Hong Kong	Total
# green corporate bonds in Refinitiv	57	82	53	192
- issue before listing	0	8	3	11
- other event taking place	1	11	6	18
# green corporate bonds in the event study	56	63	44	163

Chapter 4

Interplay between passive funds and active funds

4.1 Introduction

In recent decades, passive funds have grown substantially, leading to a division of the equity mutual fund industry into two groups: passive and active. Passive funds seek to track an index and deliver market returns, and can be in the form of exchange-traded funds (ETFs) or index funds. Conversely, active funds strive to beat the index and generate higher returns. Between 2000 and 2016, active funds increased from 8.19% to 11.38% of the total U.S. stock market capitalization, while passive funds' ownership of stocks grew from almost 0% to 8.21%. The Investment Company Institute's annual report reveals that ETFs have witnessed rapid growth, with an annual growth rate of more than 22% between 2008 and 2017.[1] Passive funds have become increasingly popular among individual investors as they provide a means to avoid the information asymmetry issues faced by institutional investors when investing in single stocks. Furthermore, individual investors tend to hold passive funds for the long run (Da Dalt et al., 2019).

The rapidly growing prevalence of passive ownership is fundamentally altering the ownership structure and monitoring practices of firms. Unlike active funds, passive funds can only intervene in corporate governance through the voice channel. Mutual funds have two channels through which they can intervene in corporate governance as shareholders: the exit channel, where mutual funds may follow the "Wall Street walk" or employ the threat of exit (Admati and Pfleiderer, 2009); and the voice channel, where mutual funds may directly affect corporate governance through voting. However, passive funds are required to hold shares based on index weight and cannot sell shares based on their discretion. Therefore, the only option left for passive funds is to vote in firms' voting meetings.

[1] https://www.ici.org/doc-server/pdf%3A2019_factbook.pdf

Though the literature has shown that passive funds are active voters, there are mixed results regarding their voting impacts. Firstly, the voting records of passive funds are easily accessible in their NPX files, which mutual funds are required to disclose by submitting them to the SEC. There are over 8 million passive funds' voting records available in the SEC EDGAR database, indicating that they actively exert their voting rights. Secondly, previous research has established a causal relationship between passive funds' stake and firms' voting results, but the conclusions vary. Studies by Appel et al. (2016), Schmidt and Fahlenbrach (2017), and Heath et al. (2020) have employed Russell index reconstitution as an exogenous shock to passive ownership to examine the causal relationship between passive ownership and firms' governance choices. These studies have found that passive mutual funds can improve firms' value by enhancing board independence, opposing takeover defenses, removing unequal voting rights, and avoiding excessive awards, which are all essential corporate governance issues (Appel et al., 2016). However, Heath et al. (2020) find evidence that passive funds lead to less board independence and worse pay-performance sensitivity at their portfolio companies. Furthermore, when it comes to complex voting issues, such as board appointments and mergers and acquisitions decisions, passive funds can decrease firm value (Schmidt and Fahlenbrach, 2017).

The central question to understand the impact of passive funds' voting is to determine where their voting incentives originate. Previous research has focused on passive funds' internal incentives and argued that these may not be sufficient to encourage active monitoring. One possible internal incentive for passive funds is to improve overall market performance (Appel et al., 2016). If the market performs well, passive funds' assets under management would increase, which could attract more investors to buy their shares. This may explain why passive funds have established voting protocols and use voting services from other entities, such as ISS. However, there are two potential issues with this incentive. First, it may not yield immediate profits for passive funds. Second, the funds may face a free-rider problem, as the benefits of overall market improvement would be shared by all passive funds. As a result, passive funds may be hesitant to bear the costs of active monitoring without receiving more direct and immediate benefits.

Given the lack of internal incentives for passive funds to actively monitor, I aim to address this question by examining the external incentives of passive funds. To achieve this, I analyze a sample of mutual funds' voting records in the US spanning from 2005 to 2016. Passive funds' positions in firms where they have a voting record were valued at USD 2.026 trillion in 2016, with 86.44% of these positions being voted on in situations where the same fund family's active funds also had a voting record at the meeting. I label the fact that the same fund family's passive funds and active funds have voting records at the same meeting as "co-present". Accordingly, my main objective is to investigate whether the voting behavior of passive funds is influenced by the voting decisions made by the "co-present" active funds within the same fund family. This could serve as one of the external incentives for passive funds to vote.

I explore the impact of the same fund family's active funds on the voting behavior of "co-present" passive funds in three steps. First, I develop and empirically test two proxies that capture active funds' incentives to influence the same fund family's passive funds. The first proxy is based on the value-maximization channel, which analyzes the behavior of active funds using the incentive compatibility constraint. If the alignment benefits outweigh internal communication costs, active funds may try to influence the voting of the same fund family's passive funds. I show that the alignment incentive provided by the same fund family's active funds can be proxied by the product of passive ownership and active ownership ($Ownership^{fp}_{j,t} \times Ownership^{fa}_{j,t}$). The second proxy is based on the beat-the-market channel. Active funds aim to outperform the market, so they are more likely to align passive funds' voting when active shares exceed passive shares. I show that the alignment incentive can be proxied by $\max((Ownership^{fa}_{j,t} - Ownership^{fp}_{j,t}, 0))$.

After developing these proxies, I empirically test their effectiveness. I use the probability of voting against ISS company recommendations when the ISS company and the management team have different recommendations to infer passive funds' voting attitudes. If passive funds solely rely on the ISS company's service and do not conduct their own research or make their own voting choices, they will always vote with ISS company recommendations. However, this is not the case, especially when the ISS company and the management team have different recommendations. This suggests that when ISS company and the management team have different recommendations, passive funds are more likely to conduct their own research and pay attention to different firms. I find that the product of passive ownership and active ownership ($Ownership^{fp}_{j,t} \times Ownership^{fa}_{j,t}$) can predict the behavior of passive funds, which supports the value-maximization channel.

Second, I investigate how active funds adjust their portfolios based on the holdings of the same fund family's passive funds, which ultimately affects their incentives to influence passive funds' voting decisions. To examine this, I use the average fund inflow of passive funds' individual clients in the same fund family as an exogenous shock to active funds' portfolios. I find that active funds do adjust their portfolios in response to the average fund inflow from passive funds' individual clients in the same fund family, which supports the idea that active funds are influenced by the holdings of passive funds. I also use Russell index reconstitution as an exogenous shock as a robustness check and find similar results.[2] To rule out the concern of potential effects of the correlation between passive funds' inflow and active funds' inflow, I also examine the reaction of active funds'

[2] I don't use Russell index as my main analysis, as the Russell index reconstitution method can only generate local results, while I aim to achieve generalizability across all firms.

portfolios to the same fund family's average fund inflow from active funds' individual clients, but find no significant reaction. Additionally, since passive funds' portfolio also positively react to the same fund family's average fund inflow from passive funds' individual clients, I find that the active funds' incentive proxy ($Ownership^{fp}_{j,t} \times Ownership^{fa}_{j,t}$) will also exhibit a positive reaction.

Finally, I test how passive funds' voting is affected by the same fund family's active funds' incentives. Specifically, I use the active funds' incentive predicted by the same fund family's average fund inflow from passive funds' individual clients to explain passive funds' voting behavior. The increase of predicted incentive will decrease the probability that passive and active funds vote with ISS company recommendations.

This paper provides an important contribution to the literature by shedding light on the voting incentives of passive funds, which will enable us to better understand the potential impact of the growing trend of passive ownership on corporate governance (Appel et al., 2016; Schmidt and Fahlenbrach, 2017; Heath et al., 2020; Hshieh et al., 2021). The findings provide consistent evidence of the interplay between passive and active funds within the same fund family. Specifically, the findings suggest that same fund family's active funds tend to increase their ownership in firms when passive funds have large shares, and passive funds' voting behaviors are influenced by the same fund family's active funds' voting alignment incentive. While passive funds themselves may serve as passive monitors, they can transfer control to the same fund family's active funds. This is advantageous for active funds, as they do not need to purchase additional shares and thus can lower their governance costs.

The structure of this paper is as follows. Section 2 outlines the hypothesis development. Section 3 presents the dataset. Section 4 explores the voting behavior of "co-present" passive funds. Section 5 validates the proxy of active funds' incentive on the voting of "co-present" passive funds. Section 6 examines the voting interplay between passive and active funds using two-stage least square regression. Section 7 conducts a robustness check. Finally, Section 8 concludes the paper.

4.2 Hypothesis development

Passive funds' large stakes in firms make them a valuable target for alignment by the same fund family's active funds. This is due to two primary reasons. First, active funds directly benefit from the improvement of the firm's performance, and aligning passive funds' voting is one way to achieve this goal. Second, fund managers within the same fund family compete with each other, creating a strong incentive to intervene in firms' governance (Kempf and Ruenzi, 2008). By aligning passive funds' voting with their own, active funds can exert influence on the firms' governance. Many prominent fund families, such as BlackRock and Vanguard, have both passive and active funds, and are among the top 5 shareholders of almost 70% of the largest 2,000 listed firms in the U.S. (Anton et al., 2018).

Mutual fund families are known to support the value-enhancing actions of their active funds. However, the families do not have a uniform voting attitude, and there is a significant divergence in voting within them (Angela et al., 2011). Nonetheless, they have an incentive to utilize the passive stakes to help improve the active stakes' performance. Gaspar et al. (2006) find that mutual fund families strategically transfer performance across member funds to favor those more likely to increase overall family profits. In a clinical case study, Becht et al. (2009) find that the fund family increases stakes in companies that its index tracker fund has already invested in and actively engages in the firms' operations. To measure the incentives of active funds within fund families, this paper proposes two candidate channels for verification: the value-maximization channel and the beat-the-market channel.

4.2.1 Value maximization channel

Active funds are expected to maximize their portfolio value, which can be achieved by taking value-enhancing actions. Assuming the existence of a value-enhancing proposal that could increase the firm's value by ΔV, active funds have two options: vote by themselves or align the passive funds to vote together with them. Aligning passive funds' voting could incur an internal communication cost of c. Furthermore, it is assumed that the probability of the value-enhancing proposal's passage is a linear and monotonically increasing function of the supporters' ownership. This assumption can be formally written as follows.

Assuming:

- A value-enhancing proposal would increase firm value by ΔV
- An internal communication cost of c if active funds align passive funds' voting attitude

- The probability of the proposal passing is a linear and monotonically increasing function of supporters' ownership, expressed as $Pr(Pass = 1) = \alpha \times Ownership$

To justify the behavior of active funds aligning passive funds' voting, the benefits gained from taking such actions must outweigh the benefits of not taking any action. Therefore, the incentive compatibility constraint (IC) for active funds is given by Equation (4.1):

$$Pr(Pass = 1|align) \times Ownership^{f^a}_{j,t} \times \Delta V - c \geq Pr(Pass = 1|not\ align) \times Ownership^{f^a}_{j,t} \times \Delta V \tag{4.1}$$

After rearranging equation (4.1), I obtain equation (4.2):

$$[Pr(Pass = 1|align) - Pr(Pass = 1|not\ align)] \times Ownership^{f^a}_{j,t} \geq \frac{c}{\Delta V} \tag{4.2}$$

Assuming that $Pr(Pass = 1) = \alpha \times Ownership$, the change of the probability ($Pr(Pass = 1)$) is thus $\alpha \times Ownership^{f^p}_{j,t}$. Then the IC constraint can be expressed as equation (4.3):

$$\alpha \times Ownership^{f^p}_{j,t} \times Ownership^{f^a}_{j,t} \geq \frac{c}{\Delta V} \tag{4.3}$$

Therefore, the incentive for active funds to align passive funds' voting depends on the product of their respective stakes in the firm, $Ownership^{f^p}_{j,t} \times Ownership^{f^a}_{j,t}$. If this product is less than $\frac{c}{\alpha \Delta V}$, active funds are not motivated to change the passive funds' voting behavior. If both active and passive funds hold substantial stakes in the firm, active funds will likely align passive funds' voting with theirs. However, if active funds hold a high stake and passive funds hold a low stake, active funds may not see the benefit in aligning passive funds' voting behavior due to the communication cost outweighing the potential increased benefits. If passive funds hold a large stake and active funds do not, active funds may choose to increase their stake and align passive funds' voting to increase the probability of the value-enhancing proposal passing and to obtain increased benefits. This is consistent with the observation that as passive fund stakes increase around the cutoff points of the Russell 1000 and Russell 2000 indexes, the active fund stakes increase even more.

4.2.2 Beat the market channel

In addition to maximizing their portfolio value, active funds are also motivated to beat the market and achieve a higher return. This incentive is positively correlated with the active stakes they hold in the firm, as they stand to benefit more from value-enhancing actions. However, higher passive ownership can also improve the index performance through such actions. Since the overall performance of active funds is measured by comparing with the index performance, their incentives may be compromised if passive stakes are higher in the firms. To simplify their decision-making process, active funds may base their decisions on the passive shares within their fund families, rather than considering the entire market's passive shares. Obtaining information on other passive funds may be costly, and they can estimate total passive funds' share based on their passive fund market share. As a result, the active funds' incentives are likely to depend on the relative positive ownership between active and passive shares. When active funds have higher ownership than passive funds, they are more likely to beat the market if they take value-enhancing actions.

I measure the active funds' incentive with the expression $max(Ownership^{fa}_{j,t} - Ownership^{fp}_{j,t}, 0)$. When this difference is high, active funds stand to gain significantly from aligning passive funds' voting attitudes and executing value-enhancing projects without being concerned about being outperformed by the market. When the difference is low, both passive and active funds could benefit similarly from active funds' voting alignment actions and the value-enhancing projects, which could make it more challenging for active funds to outperform the market.

4.3 Data sources

The objective of this analysis is to examine the incentive for passive funds' voting behavior. The analysis relies on mutual fund ownership data, mutual fund voting records, and passive fund identifiers. Mutual funds are required to report their voting records through NPX files for the most recent 12 months ending on June 30th of each year[3]. The sample period for this analysis covers the years 2005 to 2016.

Mutual fund ownership

The ownership data for mutual funds is obtained from Thomson Reuters S12, which provides details on the shares owned by each fund, stock prices, and common shares outstanding at the end of each quarter. Using this data, the stake of each fund in each firm can be calculated. The dataset covers the period from 2005 to 2016 and contains 35,688,244 observations.[4] To link this dataset with CRSP mutual fund source data, the MFLINKS database is used, which provides the CRSP fund number, Thomson Reuters fund number, and the WFICN that links both of them. MFLINKS focuses on a target universe of domestic equity funds, exchange traded funds, and target-date equity funds, covering around 92% of the target funds and 96% of the assets.[5] After merging the Thomson Reuters fund number and file date with the MFLINKS database, there are 24,540,208 ownership records for U.S. mutual funds.

Mutual fund information, mutual fund asset and investment return

The CRSP mutual fund database provides information such as fund name, fund ticker, index fund tag, ETF tag, open-to-investor status, and institution share dummy in the end of each quarter. From 2005 to 2016, there are 1,310,549 observations. Using the index fund and ETF tags, I can identify the passive funds. The data in the CRSP mutual fund database is at the fund share class level, and funds may have various share classes, such as A-D shares, Adv shares, Inst shares, Investor shares, M shares, N shares, No load shares, Retirement shares, S shares, T shares, and other shares.[6]. These data will be aggregated to the fund level when merged with mutual fund ownership and voting records. After merging with the MFLINKS database, there are 744,811 CRSP mutual fund share-level data with paired ticker and WFICN codes.[7] The CRSP mutual fund database also provides monthly total net assets and monthly returns of each fund share. Using this dataset, I can track monthly fund flows.

Mutual fund voting records and Fund family identification

Mutual fund voting records are collected from the Institutional Shareholder Services

[3] https://www.sec.gov/reportspubs/investor-publications/investorpubsmfproxyvotinghtm.html

[4] Records without CUSIP identifiers are removed, and if multiple files exist for the same reported dates, only the first file date is kept.

[5] https://wrds-www.wharton.upenn.edu/documents/317/Guide_for_Mutual_Fund_Links_MFLINKS.pdf

[6] https://morningstardirect.morningstar.com/clientcomm/Share_Class_Types.pdf

[7] Observations without tickers are deleted.

(ISS) database, which provides details on each voting item such as the meeting date, voting by each fund, voting recommendations from the top management team and from the ISS company, institution id, and NPX file id. These variables allow us to track the voting behavior of each fund for each specific voting item. The institution id is used as the fund family identification. From 2005 to 2016, the original dataset contains 64,925,715 voting records for U.S. listed companies.[8]

I utilize the SEC EDGAR database to obtain the ticker for each fund in the ISS database, as the ISS database does not provide a fund identifier that can be used to link funds to other datasets. By using the NPX file id, I am able to retrieve the original NPX file from the SEC official website.[9] In the NPX files, mutual fund tickers are provided. By matching the NPX file ID and fund name, a ticker is assigned to the fund in the ISS database.[10] After merging with the mutual fund information dataset by ticker, there are 30,220,318 voting records with WFICN and institution ID.[11]

By combining the mutual fund ownership data and voting records, the final sample consists of 22,865,969 observations, which contain fund ownership, portfolio weight, active fund indicator, passive fund indicator, ISS recommendation, management team recommendation, and firm market capitalization.[12]

[8] Voting records without NPX file id are removed.

[9] I have downloaded and analyzed all the NPX files with a SAS program, which can be shared upon request.

[10] The fund names in the ISS voting records come from the main part of the NPX file, while the ticker and the fund name mapping linkages are in the head part of the NPX file. Due to the fact that there are some abbreviations of the fund names in both parts, a manual mapping check between the fund name in the head part and the fund name in the main part is necessary. This check increases the final sample size significantly.

[11] There are 55,991 paired NPX file ID and ISS fund ID in the original dataset, while there are 27,809 paired NPX file ID, ISS fund ID, and WFICN in the final sample. This is mainly due to the fact that some funds do not have a ticker and that the fund name in the main part and the head part cannot be matched.

[12] Ownership exceeding 100% is deleted.

4.4 Exploring the voting behavior of "co-present" passive funds

4.4.1 Prevalence of passive funds co-presenting with active funds

Passive funds and active funds from the same fund family may both participate in the same voting meetings for listed firms. As passive funds generally cover a diverse range of companies, it is likely that active funds from the same fund family invest in some of the same firms as the passive funds. In such cases, passive and active funds from the same fund family may attend the same voting meetings and cast their votes either similarly or differently.

To capture the extent to which passive funds have co-presenters in voting meetings, I classify passive funds into three groups: "All co-present" passive funds, "All single-present" passive funds, and "Partially co-present" passive funds. For each voting meeting in which a passive fund participates, I classify it as an "All co-present" passive fund if there is at least one active fund from the same fund family present at the meeting. If there are no active funds from the same fund family present, I classify the passive fund as an "All single-present" passive fund. Otherwise, I classify the passive fund as a "Partially co-present" passive fund, meaning that it may co-present with active funds from the same fund family at some meetings but not at others.

By a symmetric definition, I can also classify active funds as "All co-present" active funds, "All single-present" active funds, and "Partially co-present" active funds.

It is common for passive funds to be "co-present" in voting meetings. Table 4.1 shows the number and total net assets of the three types of passive funds. The largest category of passive funds, in terms of both fund number and total net assets, is the "Partially co-present" category. The "All co-present" category has the smallest number of funds but the largest average total net assets.[13] In 2016, approximately 37% of passive funds are classified as "All single-present" passive funds, but this category has the smallest average total net assets among the three types. This suggests that large passive funds are typically owned by large fund families, such as "Vanguard", "Black Rock", and "State Street".

4.4.2 Pattern of passive funds co-presenting with active funds

A passive fund is more likely to co-present with active funds when it holds a higher position in the firm, which is calculated as the number of shares held by passive funds in the company that held the voting meeting multiplied by the stock price. Table 4.2 panel A shows all the positions held by passive funds in each category from 2005 to

[13] Average total net asset is calculated as the total net asset divided by the number of passive funds.

Table 4.1: Number and total net asset (in billions) of three types of passive funds

Table 4.1 reports the number and the total net asset of three types of passive funds from 2005 to 2016. N is the number of the passive funds, and TNA is the summation of the total net asset for all the passive funds in each category.

year	Partially co-present		All Co-present		All Single-present	
	N	TNA	N	TNA	N	TNA
2005	86	311.40	9	70.56	59	85.63
2006	87	213.37	11	215.22	73	115.63
2007	99	437.54	24	114.72	122	155.32
2008	159	352.01	26	278.62	122	114.91
2009	168	327.04	40	209.71	152	133.58
2010	175	517.86	33	177.12	139	90.16
2011	189	790.07	33	368.65	101	76.40
2012	204	1052.07	30	125.68	101	106.15
2013	177	1009.96	41	498.79	86	76.80
2014	189	1678.25	43	399.94	102	86.25
2015	172	1879.86	37	434.61	119	156.89
2016	177	1807.22	41	574.34	115	216.58

2016, with "co-present" passive funds accounting for 86.44% of the total positions in 2016. Moreover, the total positions are much higher when "Partially co-present" funds are "co-present" passive funds than when they are "single-present" passive funds, suggesting that when passive funds have a higher position in a firm, it is more likely that one or more active funds will also be present at the voting meeting.

In addition, passive funds are more likely to co-present with active funds when they hold a higher ownership in the firm. Table 4.2 Panel B reports the mean of the average ownership across all companies from 2005 to 2016, with "Partially co-present" funds being "co-present" passive funds having a much higher average ownership than "single-present" passive funds. Moreover, in most cases, "all co-present" passive funds have a higher average ownership in companies than "all single-present" funds.

Overall, the data suggests that active funds and passive funds are more likely to co-present in firms with larger index weights, potentially due to large fund families' active funds being attracted to these firms or trying to utilize the advantages of the large passive ownership in them. This finding provides an angle to investigate the voting incentives of passive funds.

Table 4.2: Position and average ownership by passive funds from 2005 to 2016

Table 4.2 reports the position and average ownership by passive funds from 2005 to 2016. The position is the shares of passive funds in the company, which held the voting meeting, times the stock price. Panel A reports all the positions by passive funds in each category. Average ownership is the mean of ownership across all passive funds in the company. Panel B reports the mean of the average ownership across all the companies.

Panel A: position by passive funds in each category				
Year	Partial co-present passive funds		All Co-present	All Single-present
	Co-present	Single-present	passive funds	passive funds
2005	39.44	2.91	6.78	2.36
2006	170.64	15.91	186.91	15.37
2007	351.93	13.04	77.99	130.36
2008	177.28	78.17	173.44	59.48
2009	264.13	33.96	177.60	64.77
2010	351.59	72.58	167.72	16.08
2011	335.45	108.61	166.72	48.77
2012	787.46	119.81	5.67	8.82
2013	713.48	108.33	423.24	12.01
2014	1227.49	159.48	279.73	22.99
2015	1100.06	95.41	42.71	99.53
2016	1245.13	185.05	506.38	89.80

Panel B: Average ownership by passive funds in each category				
Year	Partial co-present passive funds		All Co-present	All Single-present
	Co-present	Single-present	passive funds	passive funds
2005	0.12%	0.06%	0.10%	0.06%
2006	0.20%	0.05%	0.18%	0.09%
2007	0.23%	0.05%	0.44%	0.15%
2008	0.17%	0.04%	0.17%	0.27%
2009	0.29%	0.06%	0.17%	0.25%
2010	0.31%	0.17%	0.05%	0.06%
2011	0.18%	0.15%	0.24%	0.10%
2012	0.24%	0.18%	0.01%	0.04%
2013	0.34%	0.19%	0.78%	0.06%
2014	0.39%	0.20%	0.26%	0.08%
2015	0.40%	0.14%	0.17%	0.10%
2016	0.50%	0.22%	0.31%	0.06%

4.4.3 Voting behavior of "co-present" passive funds

Passive funds actively participate in voting meetings, regardless of whether they are "co-present" or "single-present" passive funds. Table 4.3 reports the total number of meetings attended by passive funds and the average number of firms voted on by each passive fund from 2005 to 2016. In most years, "Partially co-present" passive funds participate in over 30,000 meetings, whether they are "co-present" or "single-present" passive funds. Each fund vote on more than 200 firms. "All co-present" and "All single-present" passive funds vote on more than 100 firms, which is much smaller than the number of firms voted on by "Partially co-present" passive funds. This observation is consistent with the fact that passive funds actively participate in voting meetings, particularly for large passive funds.

The extent to which mutual funds follow the ISS company recommendation is indicative of their voting behavior. Using the ISS service is a convenient option for mutual funds to cast their votes. When the costs of conducting research are high, relying on ISS recommendations is a cost-effective way for mutual funds to vote. The voting with ISS company recommendations strategy is widely adopted by mutual funds and significantly impacts shareholder votes (Malenko and Shen, 2016). However, the ISS company has its own cost-benefit considerations. It provides standardized recommendations for many voting proposals. As "one-size-fits-all" approaches are not always optimal for corporate governance, voting against ISS recommendations can help sway shareholder votes towards value-maximizing outcomes (Iliev and Lowry, 2015).

For the most part, passive funds tend to vote with ISS company recommendations. Table 4.4, Panel A reports the percentage of cases in which passive funds voted with ISS recommendations. When "Partially co-present" passive funds act as "co-present" passive funds (resp "single-present" passive funds), they vote with ISS recommendations in 89.98% (88.01%) of cases. "All co-present" passive funds and "All single-present" passive funds vote with ISS recommendations in 90.30% and 87.94% of cases, respectively.

Passive funds' voting behavior differs depending on whether the management team and the ISS company have a consensus or not. The variable $Agree\_IM$ is a dummy variable that equals one when the management team and the ISS company have the same recommendation. When $Agree\_IM$ equals one, the percentage of passive funds voting with ISS recommendations increases to more than 94%. However, when $Agree\_IM$ equals zero, the rate decreases sharply to less than 42%. This suggests that passive funds are less likely to vote with ISS company recommendations when there are conflicts between the management team and the ISS company recommendations.

The probability of "co-present" passive funds voting in line with ISS recommendations decreases more than that of "single-present" passive funds when $Agree\_IM = 0$.

When "partial co-present" passive funds act as a "co-present" passive fund, the percentage decreases by 58.05%, which is larger than the decrease (55.22%) seen when they act as a "single-present" passive fund. "All co-present" passive funds show the largest decrease in percentage (72.88%). Similar patterns are observed in the voting behavior of active funds. When "partial co-present" active funds act as a "co-present" passive fund, the percentage decreases by 53.33%, which is larger than the decrease (41.56%) observed when "partial co-present" passive funds act as a "single-present" passive fund. "All co-present" active funds show the largest decrease in percentage (70.00%).

Overall, it is not uncommon for passive funds to vote against ISS company recommendations, especially when there is a disagreement between the management team and the ISS company. In such cases, the probability of passive funds voting against ISS recommendations increases, with "co-present" passive funds exhibiting a greater probability change compared to "single-present" passive funds.

Table 4.3: Total number of meetings and average number of firms by each passive fund

Table 4.3 reports the total number of meetings by passive funds and the average number of firms voted in by each passive fund from 2005 to 2016. The total number of Meetings is the number of meetings that passive funds attended each year. The average number of firms is the number that each fund voted in each year.

year	Partial co-present Passive funds				All co-present		All single-present	
	Co-present		Single-present		Passive funds		Passive funds	
	Meeting	Firm	Meeting	Firm	Meeting	Firm	Meeting	Firm
2005	4350	50	4878	56	264	29	756	13
2006	28743	323	25502	289	4026	355	4013	54
2007	26129	257	16878	165	2031	82	31562	250
2008	26756	165	41813	255	5190	197	16067	128
2009	35180	204	41927	242	6045	147	22028	141
2010	34867	196	41024	230	6507	194	13958	99
2011	30447	158	47942	247	2806	83	10013	97
2012	40038	194	44228	214	1078	35	10512	103
2013	42488	235	37454	206	6113	147	7467	85
2014	46409	240	36494	188	4222	96	7682	73
2015	33909	192	24929	141	2482	65	10871	89
2016	40845	225	34854	191	4830	115	15271	129

Table 4.4: Mutual funds’ voting with ISS recommendation

Table 4.4 reports the percentage of the cases that passive funds voted with ISS recommendations. *Agree_IM* equals 1 when ISS recommendation and Management team recommendation are the same, otherwise equals 0. Panel A and Panel B report the summary statistics of passive funds and active funds separately.

Panel A: Passive funds								
	Partial co-present passive funds				All co-present passive funds		All single-present passive funds	
	Co-present		Single-Present					
	With ISS%	N	With ISS%	N	With ISS%	N	With ISS%	N
All	89.98%	3,677,317	88.01%	3,276,128	90.30%	487,837	87.94%	1,435,275
Agree_IM=1	96.68%	3,253,469	95.69%	2,821,108	98.39%	433,688	94.78%	1,251,765
Agree_IM=0	38.63%	424,033	40.47%	455,264	25.51%	54,149	41.33%	183,510

Panel B: Active funds								
	Partial co-present active funds				All co-present active funds		All single-present active funds	
	Co-present		Single-Present					
	With ISS%	N	With ISS%	N	With ISS%	N	With ISS%	N
All	90.86%	4,089,137	91.80%	1,927,033	88.14%	1,028,517	90.75%	6,944,725
Agree_IM=1	96.89%	3,626,547	97.37%	1,668,717	96.24%	909,619	96.61%	6,103,843
Agree_IM=0	43.56%	462,590	55.81%	258,316	26.24%	118,898	48.28%	840,904

4.5 Validation of active funds' incentive proxy

In this section, I test the effectiveness of my two incentive proxies. I start by setting the regression framework. Then I test the two incentive proxies separately. Overall, the results demonstrate that the incentive proxy from value-maximization channel can predict passive funds' voting behavior.

4.5.1 Regression framework

As mentioned by Iliev and Lowry (2015), when the ISS company and management team have different recommendations, funds are more likely to process their voting with their own signals. I will model the behavior of passive fund voting by modelling the probability that passive funds vote with ISS company when ISS company and management team have different recommendations.

I employ three sets of variables to construct the model. The first set variable is our main focus, which is the active funds' incentive of influencing passive funds' voting in the same fund family. The second set of variables relates to the fund itself, which includes variables the fund's ownership in the firm ($Ownership_{i,j,t}$), portfolio weight ($Weight_{i,j,t}$), and total net asset ($TNA_{i,t}$). I expect that funds with a higher ownership and portfolio weight, are more likely to conduct their own research and less likely to vote with the ISS company recommendation. Also, I expect that funds with higher total net assets have a greater potential to conduct research and are more likely to vote against the ISS company recommendation. The third set of variables relates to firm characteristics, such as the firm's size ($ln(Mktcap)j, t$) and return on assets ($ROAi, t$) (Iliev and Lowry (2015)). I also include year fixed effects and industry fixed effects. Standard errors are clustered at the fund level.

$$\begin{aligned} P(With\_ISS_{i,j,n,t}|Agree\_IM_{j,n,t} = 0) = & f(\alpha + \beta_1 Incentive_{j,t} + \\ & \beta_2 Ownership_{i,j,t} + \beta_3 Weight_{i,j,t} + \\ & \beta_4 TNA_{i,t} + \beta_5 ln(Mktcap)_{j,t} + \\ & \beta_6 ROA_{j,t} + Year_j + Ind_j + \epsilon_{i,j,n,t}) \end{aligned} \tag{4.4}$$

Where $Incentive_{j,t}$ represents $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ if it works through the value maximization channel, and represents $Ownership^{fa}_{j,t} - Ownership^{fp}_{j,t}$ if works through the beat the market channel. I expect $beta_1$ to be negative, as the higher active funds' incentive to influence passive funds' voting, the more likely passive funds will vote against ISS company recommendations.

4.5.2 Voting incentive from active fund value maximization

I will start by testing the active fund value maximization channel. $Ownership^{fp}_{j,t}$ represents the increased probability that the value-enhancing proposal could be passed by aligning passive funds' voting attitude. $Ownership^{fa}_{j,t}$ represents the proportion of benefits that active funds could collect from the value-enhancing proposal. Thus, to maximize their investment, active funds would take into account $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$. When $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ becomes larger, active funds have a higher incentive to align passive funds' voting attitudes. [14]

Table 4.5 presents the results of verifying the value-maximization channel for co-present passive funds in situations where the management teams and the ISS company have different recommendations. Panel A reports the main result for passive funds, while Panel B reports the result for active funds as a comparison. The sample is divided into two groups for both passive and active funds: the "Partial co-present" group and the "All co-present" group. The "Partial co-present" passive funds represent co-present passive funds that have a uniform voting protocol and actively vote for a broader range of holding firms, while the "All co-present" passive funds represent co-present passive funds that likely do not have a uniform voting protocol and are more likely to be encouraged by active funds to vote.

Active funds' value-maximization incentive serves as a valid channel that affects co-present passive funds' voting behaviors. Panel A reports the results for passive funds. The coefficient of key variable $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ is negatively significant across all settings.[15] It suggests that active funds' alignment incentive $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ is another channel that is different from firm characteristics and fund characteristics. Specifically, $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ is significantly negative for "co-present" passive funds with the coefficient of -4.9031. Within "co-present" passive funds, the coefficient for "Partial co-present" passive funds and "All co-present" passive funds are -3.9762 and -8.2946, respectively. This is consistent with the idea that "All co-present" passive funds are more likely to be encouraged by active funds to vote.

Panel B reports the results for active funds. $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ is significantly negative for "co-present" active funds with coefficients of -16.3536. It suggests that "Co-present" active funds are more affected. Within "co-present" active funds, the coefficient for "Partial co-present" active funds and "All co-present" active funds are -14.7427 and -12.1978, respectively. The two coefficients are larger than

[14] In the regression, to make the table look nice, the $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ in the regression actually denotes $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t} \times 100$.

[15] Compared with the results in Table 4.A1 regression (1), (3), and (5), the impact of fund ownership in a firm $Ownership$, portfolio weight $Weight$, fund size $ln(TNA)$, firm size $ln(Mktcap)$, and firm profitability ROA are similar and stable.

Table 4.5: Value maximization channel verification

Table 4.5 reports the value maximization channel verification results for both passive funds and active funds. The Logit regression $P(With\_ISS_{i,j,n,t}|agree\_MI_{i,j,n,t} = 0) = f(\alpha + \beta_1 Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t} + \beta_2 Ownership_{i,j,t} + \beta_3 Weight_{i,j,t} + \beta_4 TNA_{i,t} + \beta_5 ln(Mktcap)_{j,t} + \beta_6 ROA_{j,t} + Year_j + Ind_j + \epsilon_{i,j,n,t})$ is employed. $With\_ISS_{i,j,n,t}$ is a dummy variable, which equals one when the fund vote in the same direction as the ISS company recommendation. $Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}$ measures active funds' incentive to align passive funds' voting attitude from the value maximization prospective. In the regression, to make the table looks nice, the $Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}$ in the regression actually denotes $Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t} \times 100$. $Ownership_{i,j,t}$ is the fund ownership. $Weight_{i,j,t}$ is the weight of the firm's share value in the fund portfolio. $ln(TNA)_{i,t}$ is the fund's total net asset under management. $ln(Mktcap)_{j,t}$ is market capitalization. $ROA_{j,t}$ is firm j's return on asset. $Agree\_IM_{j,n,t}$ is the dummy variable capturing the situation that the ISS company recommendation and the management team recommendation are in the same direction. Time fixed effects and industry fixed effects are included. The industry code is the first two digits of SIC code from Compustat. Coefficient and standard deviation are reported. Standard errors are Clustered standard at the fund level. The significance levels are at 1%, 5% and 10% respectively.

Panel A: Passive funds			
	$P(With\_ISS_{i,j,n,t}\|Agree\_IM_{j,n,t} = 0)$		
	All	Partial co-present	All co-present
	(1)	(2)	(3)
$Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}$	-4.9031***	-3.9762***	-8.2946***
	(1.2440)	(1.1744)	(2.7141)
$Ownership_{i,j,t}$	-33.9524	-28.6794	6.2999
	(25.7911)	(24.9892)	(47.8874)
$Weight_{i,j,t}$	-30.0972***	-28.4380***	-40.3683*
	(5.1164)	(4.5042)	(22.0521)
$ln(TNA)_{i,t}$	-0.0400	-0.0538	-0.1290
	(0.0560)	(0.0561)	(0.1499)
$ln(Mktcap)_{j,t}$	0.0296	0.0420	0.0036
	(0.0368)	(0.0351)	(0.1626)
$ROA_{j,t}$	0.3325	0.2522	1.3025
	(0.3253)	(0.3221)	(1.3543)
Year fixed effect		Yes	
Industry fixed effect		Yes	
N	391736	347404	44318

Panel B: Active funds			
	$P(With\_ISS_{i,j,n,t}\|Agree\_IM_{j,n,t} = 0)$		
	All	Partial co-present	All co-present
	(1)	(2)	(3)
$Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}$	-16.3536***	-14.7427***	-12.1978***
	(2.4169)	(2.5888)	(2.2324)
$Ownership_{i,j,t}$	6.2432	6.6814*	-0.5368
	(3.8447)	(3.9967)	(4.4343)
$Weight_{i,j,t}$	-7.5513***	-9.5057***	1.2809
	(2.4854)	(2.6381)	(2.5061)
$ln(TNA)_{i,t}$	-0.1457***	-0.1794***	0.0177
	(0.0302)	(0.0282)	(0.0437)
$ln(Mktcap)_{j,t}$	0.0614**	0.0913***	-0.0925***
	(0.0265)	(0.0272)	(0.0343)
$ROA_{j,t}$	0.2367	0.1784	0.1546
	(0.3841)	(0.4064)	(0.5014)
Year fixed effect		Yes	
Industry fixed effect		Yes	
N	485521	386599	98921

that of "All co-present" passive funds. Both "Partial co-present" active funds and "All co-present" active funds take into account passive funds' ownership from the same fund family. What is more, for "All co-present" active funds, neither fund ownership, portfolio weight, nor fund size are significant. But active funds' alignment incentive $Ownership_{j,t}^{f^a} \times Ownership_{j,t}^{f^p}$ can affect their voting behaviors. Their investment strategies could be formed based on passive funds' ownership from the same fund family. It's similar to the example discussed in Becht et al. (2009).

4.5.3 Voting incentive from active fund beat-the-market channel

Now I will examine the active fund beat the market channel. $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ represents the relative benefits of active funds versus passive funds in a specific firm. Typically, investors expect active funds to generate higher returns than passive funds. One of the objectives of active funds is to ensure that passive funds do not outperform them. Therefore, they may have a greater incentive to intervene in the firm's governance to ensure that they benefit more than passive funds. As $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ increases, active funds have a stronger motivation to align passive funds' voting behavior.

Table 4.6 presents the results of the verification of the beat-the-market channel for "co-present" passive funds when $Agree\_IM = 0$ and the active ownership of the fund family exceeds the passive ownership. Panel A reports the main result for passive funds, while Panel B reports the result for active funds as a comparison.

The results do not provide support for the beat-the-market channel. In the case of "Co-present" passive funds, $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ is insignificant for both the entire "co-present" passive fund sample and its separated samples. On the other hand, for "Co-present" active funds, $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ is negatively significant for both the entire "co-present" active fund sample and its separated samples. $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ is a factor that is relevant only for active funds and has no impact on passive funds.[16] This effect is similar to that of $Ownership_{j,t}^{f^a}$.[17] As fund family active shares increase, active funds are more likely to vote against ISS company recommendations.

[16] $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ is highly positively correlated with $Ownership_{i,j,t}$. In unreported results, I run the regression without $Ownership_{i,j,t}$, and $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ is negatively significant, albeit with a smaller impact for regression settings in Panel B. I also ran the regression without $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$, and $Ownership_{i,j,t}$ is insignificant for all regression settings.

[17] In unreported results, I replaced $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ with $Ownership_{j,t}^{f^a}$ and obtained similar results. I also ran the regression with $Ownership_{j,t}^{f^a} - Ownership_{j,t}^{f^p}$ and $Ownership_{j,t}^{f^a} \times Ownership_{j,t}^{f^p}$ together, and both of them are significant.

Table 4.6: Beat the market channel verification

Table 4.6 reports the beat-the-market channel verification results for both passive funds and active funds. The Logit regression $P(With\_ISS_{i,j,n,t}|agree\_MI_{i,j,n,t} = 0) = f(\alpha + \beta_1 Ownership^{f^a}_{j,t} - Ownership^{f^p}_{j,t} + \beta_2 Ownership_{i,j,t} + \beta_3 Weight_{i,j,t} + \beta_4 TNA_{i,t} + \beta_5 ln(Mktcap)_{j,t} + \beta_6 ROA_{j,t} + Year_j + Ind_j + \epsilon_{i,j,n,t})$ is employed. $With\_ISS_{i,j,n,t}$ is a dummy variable, which equals one when the fund vote in the same direction as the ISS company recommendation. $Ownership^{f^a}_{j,t} - Ownership^{f^p}_{j,t}$ measures the relative benefits that active funds can obtain. $Ownership_{i,j,t}$ is the fund ownership. $Weight_{i,j,t}$ is the weight of the firm's share value in the fund portfolio. $ln(TNA)_{i,t}$ is the fund's total net asset under management. $ln(Mktcap)_{j,t}$ is market capitalization. $ROA_{j,t}$ is firm j's return on asset. $Agree\_IM_{j,n,t}$ is the dummy variable capturing the situation that the ISS company recommendation and the management team recommendation are in the same direction. Time fixed effects and industry fixed effects are included. The industry code is the first two digits of SIC code from Compustat. Coefficient and standard deviation are reported. Standard errors are Clustered standard at the fund level. The significance levels are at 1%, 5% and 10% respectively.

Panel A: Passive funds			
	$P(With\_ISS_{i,j,n,t}\|Agree\_IM\&Ownership^{f^a}_{j,t} > Ownership^{f^p}_{j,t})$		
	All	Partial co-present	All co-present
	(1)	(2)	(3)
$Ownership^{f^a}_{j,t} - Ownership^{f^p}_{j,t}$	2.7460	2.6332	8.0054
	(1.9246)	(1.9397)	(12.0060)
$Ownership_{i,j,t}$	-65.4340	-64.1057	22.3975
	(58.8215)	(56.2231)	(98.5366)
$Weight_{i,j,t}$	-19.4122***	-21.6692***	-19.9892
	(6.4786)	(7.0258)	(15.2000)
$TNA_{i,t}$	-0.0190	0.0133	-0.3652**
	(0.0724)	(0.0615)	(0.1711)
$ln(Mktcap)_{j,t}$	0.0802*	0.0884*	0.1245
	(0.0473)	(0.0467)	(0.2219)
$ROA_{j,t}$	-1.6787***	-1.5910***	-0.9471
	(0.3643)	(0.3436)	(2.1308)
Year fixed effect		Yes	
Industry fixed effect		Yes	
N	131211	123326	7853

Panel B: Active funds			
	$P(With\_ISS_{i,j,n,t}\|Agree\_IM\&Ownership^{f^a}_{j,t} > Ownership^{f^p}_{j,t})$		
	All	Partial co-present	All co-present
	(1)	(2)	(3)
$Ownership^{f^a}_{j,t} - Ownership^{f^p}_{j,t}$	-12.0134***	-11.5578***	-8.4734***
	(1.1811)	(1.3304)	(1.8692)
$Ownership_{i,j,t}$	10.4973***	11.1320***	-2.1415
	(3.8176)	(4.2983)	(4.5539)
$Weight_{i,j,t}$	-7.8841***	-6.8876***	-4.3099**
	(1.9470)	(2.1657)	(2.1969)
$TNA_{i,t}$	-0.1852***	-0.2045***	-0.0340
	(0.0257)	(0.0266)	(0.0389)
$ln(Mktcap)_{j,t}$	0.0253	0.0368	-0.0618*
	(0.0266)	(0.0293)	(0.0346)
$ROA_{j,t}$	-1.8291***	-1.5824***	-2.5032***
	(0.3260)	(0.3531)	(0.6462)
Year fixed effect		Yes	
Industry fixed effect		Yes	
N	324488	276256	48226

4.6 2SLS analysis of Voting interplay between passive and active funds

In this section, I aim to establish a causal relationship between the active fund voting alignment incentive and the voting behavior of passive and active funds within a fund family. To achieve this, I use the individual client fund flow of passive funds in the fund family as an instrument. An increase in passive fund inflow leads to a higher active fund alignment incentive, which, in turn, increases the likelihood of both “co-present” active funds and “co-present” passive funds voting against ISS recommendations. I measure the voting behavior at the fund family level using the voting distance between funds and ISS recommendations, which allows us to examine the effects of active fund voting alignment incentives on passive and active funds at the same level. As a result, my analysis is conducted at the fund family level.

4.6.1 Two stage least square methodology

To explore the mechanism and address this endogeneity issue, an exogenous shock to the incentive measures is required. Therefore, I use the passive fund individual fund flow at the fund family level, which is driven by individual clients, as the exogenous shock.

First, let us define the fund flow by measuring the change in percentage of the total net asset resulting from the clients’ buying or selling activities. To capture the clients’ desired action, I only consider observations when the funds are open to investors. This measure can be found in the paper by Chen et al. (2010).

Second, to ensure that the fund flow only captures the action of individual investors, I include only the individual share classes of each fund. It is unlikely that individual investors have private information about an individual firm, as one of the main reasons they buy passive funds is to avoid information disadvantage relative to institutional investors. Additionally, passive fund ownership changes are not adaptive to firm-level information, unlike active funds, which can allocate new funding based on their willingness. Therefore, the fund flow is calculated using equation (4.5).

$$Flow_{i,t} = \frac{\sum_{j=1}^{k} TNA_{i,j,t} - \sum_{j=1}^{k}(TNA_{i,j,t-1}(1 + Ret_{i,j,t}))}{\sum_{j=1}^{k} TNA_{i,j,t-1}} \tag{4.5}$$

where, there are k levels of individual classes, $TNA_{i,j,t}$ is total net asset of individual class j under the fund i’s management. $Ret_{i,j,t}$ is the net asset return from t-1 to t.

Third, I calculate the average fund flow for all passive funds within the fund family using equation (4.6). Taking the average helps to exclude fund-specific concerns, as it could be argued that clients buy or sell shares based on the fund manager’s management characteristics, such as their voting strategies. By looking at the average cash flow at the fund family level, I can better reflect the clients' own reasons for buying or selling shares. I expect that passive fund ownership will react positively to individual clients' inflow. If active funds take advantage of passive ownership, active fund ownership will also increase. Overall, if the fund flow is positive, I would expect the incentive measure $Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}$ to increase and vice versa. It could be argued that the fund manager is eager to improve firm performance due to fund outflow. However, the voting channel being examined here has a long-term impact that the fund manager cannot wait for. Symmetrically, I can also calculate the average fund flow for all active funds ($Aflow^{f^a}_t$) desired by individual investors at the fund family level.

$$Aflow^{f^p}_t = \frac{1}{n}\sum_{i=1}^{n} Flow_{i^p,t} \tag{4.6}$$

where, fund i^p is the "co-present" passive funds in the fund family. n is number of "co-present" passive funds within the fund family.

I conduct the first-stage regression using equation (4.7). I expect the coefficient β_1 to be positive, indicating that an increase in fund flow for passive funds within a fund family will lead to an increase in active fund alignment with passive funds' voting. In addition to the incentive measure, the first-stage regression include control variables such as $ln(Mktcap)_{j,t}$, $ROA_{j,t}$, which are also included in the second stage. The regression is estimated with time and fund family fixed effects, and standard errors are clustered at the firm level.

$$\begin{aligned} Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t} =& \alpha + \beta_1 Aflow^{f^a}_t + \beta_2 ln(Mktcap)_{j,t} + \beta_3 ROA_{j,t} + \\ &+ Year + Family + \epsilon_{f,j,t} \end{aligned} \tag{4.7}$$

In the second regression with equation (4.8), the variable $Distance^{fp(a)}_{j,n,t}$ measures the voting attitude distance between passive(active) funds in a fund family and ISS recommendations for a specific issue n in firm j at time t. The variable $\widehat{Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}}$ is the predicted incentive coming from the first stage regression, which captures the incentive change induced by individual clients' actions. The firm characteristics $ln(Mktcap)j,t$ and $ROAj,t$ are controlled for in the regression. The time fixed effect, industry fixed effect, and the fund family fixed effect are included as well. The standard error is clustered at the firm level[18]. The expected result is that β_1 is negative, as our hypothesis suggests that when active funds' incentive is higher, passive funds and active funds are more likely to vote against ISS company recommendations.

[18]The 2SLS is conducted by STATA, thus the standard deviation is adjusted automatically, compared with running two separate regression.

$$
\begin{aligned}
Distance^{fp(a)}_{j,n,t} =& \alpha + \beta_1 \widehat{I_{f,j,t}} + \beta_2 ln(Mktcap)_{j,t} + \beta_3 ROA_{j,t} + \\
&+ Year + Family + \epsilon_{f,j,n,t}
\end{aligned}
\tag{4.8}
$$

4.6.2 First stage: passive funds' fund flow from individual clients and active fund's portfolio

Table 4.7 presents the results of the relationship between individual investor fund flow and fund family's passive and active ownership. The sample excludes observations where the average individual investor passive fund flow ($Alfow^{fp}_t$) exceeds (below) 99% (1%) of the distribution.[19] The analysis controls for firm size ($ln(Mktcap)_{j,t}$) and profitability ($ROA_{j,t}$) and includes year, industry, and family fixed effects. Standard errors are clustered at the firm level. Panel A regression (1) and Panel B regression (1) indicate a positive correlation between firm size ($ln(Mktcap)_{j,t}$) and fund family passive ownership ($Ownership^{fp}_{j,t}$), as passive funds tend to invest more in larger firms with higher index weight. Panel A regression (2) and panel B regression (2) show a negative correlation between firm size ($ln(Mktcap)_{j,t}$) and fund family active ownership ($Ownership^{fa}_{j,t}$) and profitability ($ROA_{j,t}$), as active funds tend to invest more in smaller and poorly performing firms.

Passive fund individual investor fund flow is a valid instrument only if it can affect $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ but not funds' voting. To ensure that the instrument does not affect funds' voting, it is important to make sure that the fund flow is not related to the fund's voting strategy or firm value information. The use of average individual investor passive fund flow ($Alfow^{fp}_t$) addresses the concern that fund flow could be related to the individual fund level voting strategy, while the inclusion of institution fixed effects helps to control for the voting strategy at the fund family level.

Passive fund individual investor fund flow is not related to individual firm value information, as shown in Table 4.7. Specifically, panel A regression (1) shows a significant positive relationship between average individual investor passive fund flow ($Aflow^{fp}_t$) and fund family's passive ownership ($Ownership^{fp}_{j,t}$) with a coefficient of 0.0032. On the other hand, panel B regression (2) indicates that average individual investor active fund flow ($Aflow^{fa}_t$) does not affect fund family "co-present" active ownership ($Ownership^{fa}_{j,t}$), suggesting that individual investor fund flow is not informative and cannot predict active funds' investment. However, panel B regression (1) shows that

[19] Firstly, our focus is on mutual funds experiencing normal cash flow, rather than extreme scenarios. Secondly, data truncation can occur if total net asset data is missing for a month, resulting in extreme fund flow fluctuations that do not reflect actual fund flows.

average individual investor active fund flow ($Aflow_t^{f^a}$) can predict fund family's passive ownership ($Ownership_{j,t}^{f^p}$) significantly with a coefficient of 0.0034. This finding suggests that there is a correlation between the investing time of individual clients of passive funds and active funds, while active funds do not adjust their portfolios based on the fund flow of individual investors.

Furthermore, fund family's active fund ownership also responds positively to passive fund individual investor fund flow. Panel A regression (2) shows that average individual investor passive fund flow ($Aflow_t^{f^p}$) has an even greater impact on fund family's active ownership ($Ownership_{j,t}^{f^a}$) with a coefficient of 0.0055. This suggests that active funds are seeking to take advantage of the change in passive funds' ownership.

Overall, passive fund individual investor fund flow is a significant predictor of $Ownership_{j,t}^{f^a} \times Ownership_{j,t}^{f^p}$. Given that it positively predicts both fund family's passive ownership and active ownership, I would expect it to positively predict $Ownership_{j,t}^{f^a} \times Ownership_{j,t}^{f^p}$. Panel A regression (3) confirms this, with average individual investor passive fund flow ($Alfow_t^{f^p}$) having a positive coefficient of 0.0029 in predicting $Ownership_{j,t}^{f^a} \times Ownership_{j,t}^{f^p}$.

Table 4.7: Individual investor fund flow and fund family's passive and active ownership

Table 4.7 reports the impact of individual investor fund flow on fund family's passive and active ownership. I run the regression of $Ownership^{fp(a)}_{j,t}$ $(Ownership^{fp}_{j,t} \times Ownership^{fa}_{j,t}) = \alpha + \beta_1 Aflow^{fa}_t + \beta_2 ln(Mktcap)_{j,t} + \beta_3 ROA_{j,t} + Year + Industry + Family + \epsilon$. $Aflow^{fa}_t$ measures the co-present fund family's average individual investor active fund flow at time t. $Aflow^{fp}_t$ measures the co-present fund family's average individual investor passive fund flow at time t.$Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$, which is employed to measure the incentive that the active funds want to affect the passive funds. $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$ is $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t} \times 100$. $ln(Mktcap)$ and ROA are included to control for firm size and firm profit. $Ownership^{fa}_{j,t}$ and $Ownershi^{fp}_{j,t}$ are the fund family f's active ownership and fund family passive ownership in a specific firm j at time t. Year fixed effect, industry fixed effect and Institution fixed effect are included. The standard errors are clustered at firm level. The significance levels are at 1%, 5% and 10% respectively.

Panel A : Passive fund individual investor flow			
	(1) $Ownership^{fp}_{j,t}$	(2) $Ownership^{fa}_{j,t}$	(3) $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$
$Aflow^{fp}_t$	0.0032***	0.0055***	0.0029***
	(0.0007)	(0.0009)	(0.0009)
$ln(Mktcap)_{j,t}$	0.0004***	-0.0013***	0.0012***
	(0.0001)	(0.0001)	(0.0001)
$ROA_{j,t}$	0.0014	-0.0083**	0.0020
	(0.0018)	(0.0041)	(0.0030)
Year fixed effect		Yes	
Industry fixed effect		Yes	
Institution fixed effect		Yes	
N	125,284	125,285	125,284
Panel B : Active fund individual investor flow			
	(4) $Ownership^{fp}_{j,t}$	(5) $Ownership^{fa}_{j,t}$	(6) $Ownership^{fa}_{j,t} \times Ownership^{fp}_{j,t}$
$Aflow^{fa}_t$	0.0034***	-0.0010	0.0003
	(0.0006)	(0.0010)	(0.0008)
$ln(Mktcap)_{j,t}$	0.0005***	-0.0009***	0.0012***
	(0.0001)	(0.0001)	(0.0001)
$ROA_{j,t}$	0.0032*	-0.0067*	0.0037
	(0.0018)	(0.0036)	(0.0027)
Year fixed effect		Yes	
Industry fixed effect		Yes	
Institution fixed effect		Yes	
N	140,589	140,589	140,589

4.6.3 Second stage: active funds' incentive and passive funds' voting

Active funds' voting alignment incentives have an impact on the voting behavior of "co-present" passive funds, as shown in Table 4.8. Regression (1), (2), and (3) report the impact on "co-present" passive funds, "co-present" active funds, and "co-present" funds. As expected, $\widehat{Ownership_{j,t}^{f^a} \times Ownership_{j,t}^{fp}}$ is negatively significant for the voting distance of "co-present" passive funds, "co-present" active funds, and "co-present" funds, with coefficients of -55.1362, -55.4522, and -51.9326, respectively. When active funds have a higher incentive to align passive funds in the same fund family to vote with them, the voting distance decreases. A voting distance measure of 1(0) means mutual funds vote 100% (0%) with ISS company recommendations. A decrease in the voting distance measure means mutual funds are more likely to vote against ISS company recommendations. Therefore, active funds' voting alignment incentives make passive funds in the same fund family more likely to vote against ISS company recommendations.

Based on the 2SLS results, a causal relationship between active funds' voting alignment incentive and the impact on passive funds' voting can be established. The first stage results reveal that active funds within the same fund family increase their stakes in the firm when the passive funds' ownership within the same fund family increases. This action increases the probability that value-enhancing actions pass and the benefits that active funds can obtain. Therefore, this increases their incentive to align the voting of passive funds significantly. The second stage results for "co-present" funds voting show that the increased incentives have a real impact on both passive funds and active funds voting. This impact leads to both passive and active funds being less likely to vote with ISS company recommendations.

Table 4.8: Second stage regression of interplay analysis

Table 4.8 reports the second stage regression of voting interplay analysis. I do the analysis of predicted incentive $\widehat{Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}}$ on voting distance $Distance_{f,j,t}$. I run the regression of $Distance_{j,n,t} = \alpha + \beta_1 \widehat{Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}} + \beta_2 ln(Mktcap)_{j,t} + \beta_3 ROA_{j,t} + Year + Industry + Family + \epsilon_{j,n,t}$. $\widehat{Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}}$ is predicted incentive coming from the first stage regression, which captures the incentive change induced by individual clients' actions on passive funds. $\widehat{Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}}$ is actually $\widehat{Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}} \times 100$. $ln(Mktcap)_{j,t}$ and $ROA_{j,t}$ are used to control for firm size and firm profitability. Year fixed effect, industry fixed effect and institution fixed effect are included. The standard errors are clustered at firm level. The significance levels are at 1%, 5% and 10% respectively.

$Distance_{j,n,t} \| \; Agree\_IM_{j,n,t} = 0$			
	(1) $Distance^{f^p}_{j,n,t}$	(2) $Distance^{f^a}_{j,n,t}$	(3) $Distance^{f}_{j,n,t}$
$\widehat{Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}}$	-55.1362***	-55.4522***	-51.9326***
	(18.2770)	(18.1417)	(17.1821)
$ln(Mktcap)_{j,t}$	0.0800***	0.0804***	0.0731***
	(0.0255)	(0.0253)	(0.0240)
$ROA_{j,t}$	0.1634	0.1856	0.1852
	(0.1765)	(0.1781)	(0.1675)
Year fixed effect		Yes	
Industry fixed effect		Yes	
Family fixed effect		Yes	
N	125,284	125,284	125,284

4.7 Robustness check

4.7.1 Co-present status and passive, active funds' voting

In this part, I analyze the voting behavior of active funds and passive funds for the co-present situation. I employ different sub-samples to examine passive fund voting behavior. Following Ai and Norton (2003) and Greene (2010), which show that interpreting interaction terms in nonlinear models is challenging, I use sub-samples for analysis. Firstly, I separate the funds into two groups: passive and active funds, to gain a general idea of the differences in their voting patterns. Secondly, within the passive/active groups, I analyze the voting behavior when the ISS company and management team have the same recommendation or not. This step allows us to understand fund voting patterns when more input is required. I expect the funds to behave differently when they cannot simply follow the recommendation. The regression model used is Equation (4.9), and I expect the difference between β_1 when $Agree\_IM = 0$ and β_1 when $Agree\_IM = 1$ to be negative.

$$\begin{aligned} P(With\_ISS_{i,j,n,t}|Agree\_IM_{j,n,t}) =& f(\alpha + \beta_1 Co-present_{i,j,n,t} + \beta_2 Ownership_{i,j,t} + \\ & \beta_3 Weight_{i,j,t} + \beta_4 TNA_{i,t} + \beta_5 ln(Mktcap)_{j,t} + \\ & \beta_6 ROA_{j,t} + Year_j + Ind_j + \epsilon_{i,j,n,t}) \end{aligned} \tag{4.9}$$

Table 4.9 presents the logistic regression results for modeling the voting behavior of passive and active funds. The samples are divided based on whether the management team recommendations and ISS company recommendations are the same or not. Regressions (1) through (4) report the results for all passive and active funds, while regressions (5) through (8) report the results for the sub-sample with "Partial co-present" passive funds and "Partial co-present" active funds.

Passive funds and active funds are similar in their consideration of firm-level characteristics (firm size and firm profitability). Firstly, when the management team and the ISS company have the same recommendation ($Agree\_IM = 1$), firm size does not affect funds' voting decision. The coefficient of market capitalization $ln(Mktcap)_{j,t}$ is insignificant for both active and passive funds. However, it becomes positively significant when the recommendations are different ($Agree\_IM = 0$). For large firms, mutual funds tend to vote with ISS recommendations when the management team and the ISS company have different opinions regarding a specific issue. Secondly, mutual funds are more likely to vote with the management team when $ROA_{j,t}$ is high and the ISS company does not contradict its recommendation ($Agree\_IM = 1$). The coefficient of $ROA_{j,t}$ is positively significant for both active and passive funds. However, when the ISS company contradicts the management team's recommendation ($Agree\_IM = 0$), $ROA_{j,t}$ does not affect mutual funds' voting decision anymore.

When the management team and ISS company have different recommendations, both passive and active funds consider fund ownership and portfolio weight similarly. Firstly, fund ownership in the firm and portfolio weight play a stable role in the active funds' decision-making process, regardless of the conflict status between the management recommendation and ISS company recommendation. Active funds are more likely to vote against ISS recommendations when they have larger ownership ($Ownership_{i,j,t}$) or when the firm's share value occupies a larger proportion in the fund's total net asset ($Weight_{i,j,t}$). Active funds have an incentive to research the firms that they can influence more and that matter more in their portfolio. When the management team and ISS company have different recommendations, active funds rely more on their own research, and the importance of firm ownership $Ownership_{i,j,t}$ and $Weight_{i,j,t}$ increases. Secondly, passive funds behave like active funds when the management team and the ISS company have different recommendations. With higher ownership ($Ownership_{i,j,t}$), passive funds are more likely to vote against ISS recommendations. Portfolio weight $Weight_{i,j,t}$ doesn't affect their decision process. However, when the recommendations are different, larger ownership ($Ownership_{i,j,t}$) in the firm and larger portfolio weight ($Weight_{i,j,t}$) decrease the probability to vote with ISS company. Besides, passive funds' total net asset TNA does not affect their voting behavior, while active funds' total net asset TNA decreases the probability that they vote with ISS recommendation for items with different recommendations. This finding supports the idea that the probability of voting with ISS recommendations decreases when active funds have more resources to do research.

The voting behavior of "co-present" funds and "single-present" funds differs depending on whether the management team and ISS company have the same recommendation or not. For passive funds, when $Agree\_IM = 1$, "co-present" passive funds are more likely to vote with ISS recommendations than "single-present" passive funds. However, when $Agree\_IM = 0$, "co-present" passive funds are less likely to vote with ISS recommendations than "single-present" passive funds. For active funds, when $Agree\_IM = 1$, "co-present" active funds are equally likely to vote with ISS recommendations as "single-present" active funds. But when $Agree\_IM = 0$, "co-present" active funds are less likely to vote with ISS recommendations than "single-present" active funds. Thus, the behavior of "co-present" passive funds and "co-present" active funds changes when $Agree\_IM = 0$ if I take $Agree\_IM = 1$ as the baseline. [20] The summary statistics show that both "co-present" and "single-present" funds are less likely to vote with ISS recommendations when $Agree\_IM = 0$, but "co-present" funds decrease more. The "co-present" status creates forces that affect the voting behavior of passive and active

[20] Mutual funds rely on the ISS company service, and when the ISS company has the same recommendation as the management team, mutual funds have their default choices. When the recommendations are different, they need to rely more on their own signals to vote.

funds when $Agree\_IM = 0$.

The results of the "Partial co-present" passive funds and the "Partial co-present" active funds restricted sample are consistent with the whole sample. By eliminating the concern of fund characteristic differences, the restricted sample can help us understand the voting behavior differences of the same fund being a "co-present" fund or a "single-present" fund. The regression results (5) - (8) are similar to the results of regression (1) - (4).

Overall, our regression analysis suggests that active funds are more likely to vote against ISS recommendations when they have a larger ownership stake in a firm or when the firm's share value has a higher portfolio weight. This is particularly true when the management team recommendation and the ISS recommendation are different. Passive funds exhibit a similar pattern for items with different recommendations. When active funds need to rely on their own research, the resources they can utilize become important. Additionally, the "co-present" funds' voting behavior is related to their "co-present" status. Thus, the condition where the management team recommendation and the ISS recommendation are different is valid for detecting mutual funds' own voting attitudes.

Table 4.9: Regression of Passive fund and active fund voting behavior

Table 4.9 reports the logistic regression results modelling the voting behavior of passive funds and active funds. Regression (1) - (4) reports the all passive funds and all active funds, while regression (5) - (8) reports the sub-sample with "Partial co-present passive" funds and "Partial co-present active" funds. The samples are separated whether management team recommendation and ISS company recommendation are the same or not. $Agree\_MI_{i,j,n,t}$ is the dummy variable that equals 1 if for a specific voting item, the management team recommendation and the ISS company commendation are the same. Otherwise, it equals 0. The Logit regression $P(With\_ISS_{i,j,n,t}|Agree\_MI_{i,j,n,t}) = f(\alpha + \beta_1 Co-present_{i,j,t} + \beta_2 Ownership_{i,j,t} + \beta_3 Weight_{i,j,t} + \beta_4 ln(TNA)_{i,t} + \beta_5 ln(Mktcap)_{j,t} + \beta_6 ROA_{j,t} + Year_j + Ind_j + \epsilon_{i,j,n,t})$ is employed. $With\_ISS_{i,j,n,t}$ is a dummy variable, which equals one when the fund vote in the same direction as the ISS company recommendation. $Ownership_{i,j,t}$ is the fund ownership. $Weight_{i,j,t}$ is the weight of the firm's share value in the fund portfolio. $TNA_{i,t}$ is the fund's total net asset under management. $ln(Mktcap)_{j,t}$ is market capitalization. $ROA_{j,t}$ is firm j's return on asset. Time fixed effects and industry fixed effects are included. The industry code is the first two digits of SIC code from Compustat. Coefficients and standard errors are reported. Standard errors are Clustered standard at the fund level. The significance levels are at 1%, 5% and 10% respectively.

	Vote with ISS recommendation							
	Passive		Active		Partial Co-present passive funds		Partial Co-present active funds	
	Agree_IM=1	Agree_IM=0	Agree_IM=1	Agree_IM=0	Agree_IM=1	Agree_IM=0	Agree_IM=1	Agree_IM=0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Co-present_{i,j,t}$	0.3536***	-0.1607**	0.0464	-0.4615***	0.2014**	-0.0758	-0.0869	-0.6735***
	(0.0879)	(0.0724)	(0.0680)	(0.0752)	(0.0933)	(0.0699)	(0.0832)	(0.1215)
$Ownership_{i,j,t}$	29.7225***	-30.9428*	-4.7983**	-17.2845***	27.6746**	-27.8683	0.5980	-6.9915**
	(9.7344)	(17.3687)	(2.0853)	(3.3242)	(11.9822)	(20.2701)	(2.8031)	(2.9418)
$Weight_{i,j,t}$	2.8538	-18.1509***	-3.5340***	-7.6746***	-2.8872	-31.8010***	-3.6053**	-10.4103***
	(4.4005)	(3.1749)	(0.7940)	(1.9958)	(3.4936)	(4.8127)	(1.4222)	(3.0201)
$ln(TNA)_{i,t}$	-0.0082	-0.0564	-0.0014	-0.0992***	-0.0238	-0.0641	-0.0471	-0.1301***
	(0.0373)	(0.0415)	(0.0180)	(0.0242)	(0.0535)	(0.0527)	(0.0297)	(0.0388)
$ln(Mktcap)_{j,t}$	0.0114	0.0587***	-0.0084	0.0374***	0.0385	0.0806***	0.0031	0.0874***
	(0.0316)	(0.0220)	(0.0161)	(0.0135)	(0.0363)	(0.0260)	(0.0209)	(0.0237)
$ROA_{j,t}$	1.0111***	-0.0737	0.7260***	0.2128	1.1256***	-0.1864	0.9505***	0.1187
	(0.1548)	(0.1223)	(0.1706)	(0.1767)	(0.1618)	(0.1317)	(0.2328)	(0.2306)
Industry fixed effect	Yes							
Year fixed effect	Yes							
N	6,505,848	887,277	10,530,015	1,365,342	5,093,948	696,185	4,505,245	585,683

4.7.2 Active funds and passive funds co-invest - Evidence from Russell index reconstitution

Passive funds are designed to track index performance, meaning that they invest in a basket of securities that mirrors the index. Thus, any changes to the index constitution due to an exogenous shock would affect passive funds' ownership. On the other hand, active funds are not directly impacted by such shocks. However, active funds may strategically use the passive funds' position, and their ownership may also react to the index constitution. To examine the co-investment of active and passive funds within the same fund family, I use the Russell index reconstitution as the exogenous shock.

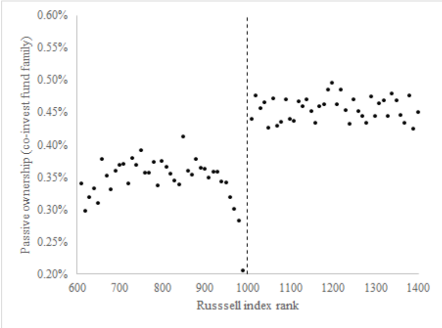
Russell index reconstitution

The Russell 3000 index is a stock market index that tracks US stocks, maintained by FTSE. It is comprised of the Russell 1000 index and the Russell 2000 index. Every year in June, the components of the two indexes are changed based on market capitalization in May. On June 23, 2017, prior to the reconstitution, there was a total of $47.1 billion and $28.9 billion traded in the closing moments of the New York Stock Exchange (NYSE) and NASDAQ exchanges, respectively.[21]

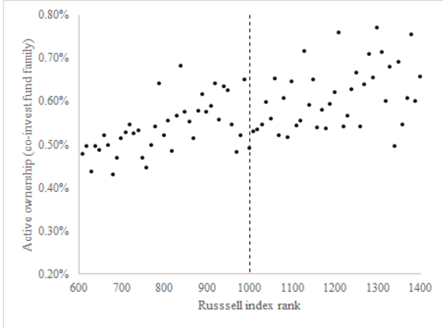
The Russell 3000 index is reconstituted annually, typically in June. Prior to 2007, firms were ranked by market capitalization and the top 1000 were assigned to the Russell 1000 index, while the firms ranked between 1001 and 3000 were assigned to the Russell 2000 index. The market capitalization used as the benchmark was determined on a single day in May. After 2007, if an existing member's market capitalization falls within 5% of the market capitalization breakpoint, it remains in its current index rather than being moved to a different index based on market capitalization. This means that the reconstitution around the breakpoint can be considered a random event, as no one can precisely control the break point or the index assignment.

Due to the weight assignment of the two indexes, the ownership structure of index funds will display a discontinuity pattern around the break point. The Russell 1000 index assigns a lower weight to firms above the break point, while the Russell 2000 index assigns a higher weight to firms below the break point. As a result, index funds that track these firms will buy more shares of firms below the break point, leading to a discontinuity in the ownership structure.

[21] http://www.ftserussell.com/research-insights/russell-reconstitution/reconstitution-frequently-asked-questions

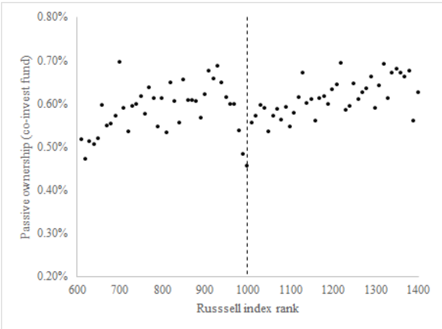


(a) Average passive ownership

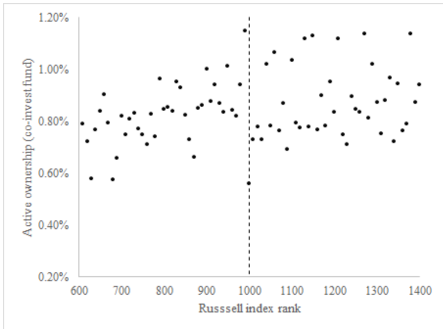


(b) Average active ownership

Figure 4.1: Average "passive and active co-invest" fund family ownership from 2005 to 2012



(a) Average passive ownership



(b) Average active ownership

Figure 4.2: Average "passive and active co-invest" fund ownership from 2005 to 2012

Passive and active co-invest ownership

It's common that fund families have both Passive and active funds. Among these fund families, I define the fund families that have passive and active funds investing in the same firm as the "passive and active co-invest" fund family. Figure 4.1 presents the "passive and active co-invest" fund family's average ownership around the Russell index cutoff point from 2005 to 2012. Figure 4.1a displays the average passive ownership for "co-invest" fund families. As expected, the figure shows a clear discontinuity pattern around the cutoff point of 1000. The passive ownership of the Russell 1000 index bottom firms is much lower than that of the Russell 2000 index top firms. Figure 4.1b depicts the average active ownership for "co-invest" fund families. Unlike passive ownership, active ownership does not exhibit a discontinuity pattern and has an upward trend. On average, active ownership is higher than passive ownership.

However, the "co-invest" passive and active funds' firm ownership is higher. I track the average "co-invest" ownership of passive and active funds from the same fund family, which excludes the firm ownership that is not co-held by passive and active funds. Figure 4.2 reports the "passive and active co-invest" fund ownership from 2005 to 2012. Figure 4.2a reports the average "co-invest" passive ownership across "co-invest" fund

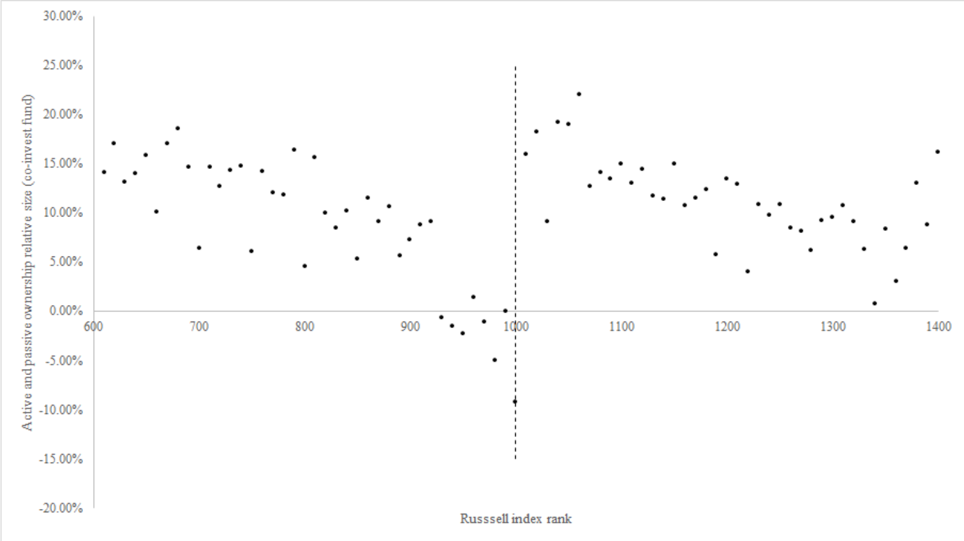


Figure 4.3: Average "co-invest" active and passive ownership relative size from 2005 to 2012

families, which is higher than that in Figure 4.1a. Figure 4.2b reports the average "co-invest" active ownership across "co-invest" fund families, which is also higher than that in Figure 4.1b. It suggests that active funds are more likely to co-invest with passive funds when passive funds have higher ownership.

Around the cutoff point, there is a decrease in active ownership relative to passive ownership. To understand the changes in active and passive ownership, I calculate the "co-invest" active and passive ownership relative size $Relative\ size^{f}_{j,t}$ for the "co-invest" fund family f in firm j at time t using equation (4.10). Figure 4.3 plots the average "co-invest" active and passive ownership relative size from 2005 to 2012. The graph shows two downward-sloping trends and a discontinuity pattern around the cutoff point. Active ownership decreases (increases) more in response to a decrease (increase) in passive ownership. This finding is consistent with the relationship between active fund ownership and individual investor passive fund flow.

$$Relative\ size^{f}_{j,t} = \frac{Ownership^{fa}_{j,t} - Ownership^{fp}_{j,t}}{Ownership^{fp}_{j,t} + Ownership^{fa}_{j,t}} \tag{4.10}$$

In summary, it's consistent with the impact of passive funds' individual client flow on active funds' ownership. active funds consider the passive ownership of the same fund family when making investments. This differs from passive ownership held by other fund families, as active funds can utilize the passive ownership within their own fund family. If passive funds lack voting incentives, active funds can encourage them to vote in alignment with their own interests.

4.8 Conclusion

Passive funds have become a significant component of equity mutual funds, with their stakes being commonplace among firms as they seek to replicate market indices. Previous research has shown that passive funds are active voters and have a real impact on firms' voting outcomes. However, it is difficult to understand the increasing influence of passive ownership if we do not understand their voting incentives.

This paper aims to shed light on passive funds' voting behavior. Passive and active funds from the same fund family could attend the same firm's voting meetings, and "co-present" passive funds hold most of the passive positions. The voting behaviors of "co-present" passive funds are influenced by "co-present" active funds. Two active fund incentive channels, the value-maximization channel and the beat-the-market channel, are examined, and the results support the value-maximization channel. Active funds have incentives to influence passive funds' voting when they want to increase the probability of passing a value-enhancing proposal.

Furthermore, this paper finds that active funds allocate their investments based on passive ownership, reacting to exogenous shocks such as changes in individual investor fund flow or the Russell index reconstitution. The results show that active funds invest more when passive ownership is higher, establishing a causal relationship between active funds' alignment incentives and passive funds' voting behavior. Specifically, an increase in active funds' alignment incentives will make passive funds less likely to vote with ISS company recommendations.

Overall, this paper argues that one source of passive funds' voting incentives is the efforts of active funds from the same fund family. This highlights the impact of passive ownership on corporate governance and gives active funds more bargaining power for firms with high passive ownership. For firms with less passive ownership, active funds are less likely to invest and intervene.

4.9 Appendix

4.9.1 Variable definition

Passive funds

I create a dummy ($Passive$), which equals one if the fund is an index fund or a Exchange-traded fund.

Total net assets

The total net assets ($TNA_{i,t}$) refer to the total net assets managed by fund i at time t.

Ownership

The ownership ($Ownership_{i,j,t}$) is defined as the number of shares owned by fund i divided by the total number of common shares outstanding in firm j at time t. Mathematically, $Ownership_{i,j,t} = \frac{Shares_{i,j,t}}{Common\ Shares\ Outstanding_{j,t}}$.

Portfolio weight

The portfolio weight ($Weight_{i,j,t}$) is defined as the value of firm j's shares owned by fund i divided by fund i's total portfolio value at time t. Mathematically, $Weight_{i,j,t} = \frac{Shares_{i,j,t} \times Price_{j,t}}{Total\ Portfolio\ Value_{i,t}}$.

Active ownership and passive ownership in "co-present" fund families

I define "co-present" fund families as fund families that have both active and passive funds attending the same firm's voting meeting. The family's passive ownership ($Ownership^{f^a}_{j,t}$) represents the "co-present" fund family's active ownership in firm j. Mathematically, $Ownership^{f^a}_{j,t} = \sum_{i^a \in f} Own_{i^a,j,t}$. Similarly, the family's passive ownership ($Ownership^{f^p}_{j,t}$) represents the "co-present" fund family's passive ownership in firm j. Mathematically, $Ownership^{f^p}_{j,t} = \sum_{i^p \in f} Own_{i^p,j,t}$.

Incentive from value maximization channel

I define incentive ($I_{f,j,t}$) as $Ownership^{f^a}_{j,t} \times Ownership^{f^p}_{j,t}$, which measures the alignment incentive for active funds to influence the voting behavior of the same fund family's passive funds in firm j.

Incentive from beat the market channel

I define incentive ($I_{f,j,t}$) as $max(Ownership^{f^a}_{j,t} - Ownership^{f^p}_{j,t}, 0)$, which measures the relative size of active shares and passive shares from the same fund family f for a specific firm j.

ISS recommendation

For each voting item, the Institutional shareholder service (ISS) company provides a voting suggestion. In the literature, the ISS recommendation is believed to have real impact on the voting outcome (Iliev and Lowry (2015)). I define ISS recommendation ($ISS_{j,n,t}$) as a binary variable that equals 1 if the ISS company recommends voting for proposal n in firm j at time t, and 0 otherwise in equation (4.11).

$$ISS_{j,n,t} = \begin{cases} 1, Vote\ Yes\ in\ item\ n \\ 0, Otherwise \end{cases} \tag{4.11}$$

Management team recommendation

For each voting item, the management team (MGT) of the company provides a voting suggestion. For firm j, I define management team recommendation ($MGT_{j,n,t}$) in equation 4.12.

$$MGT_{j,n,t} = \begin{cases} 1, Vote\ Yes\ in\ item\ n \\ 0, Otherwise \end{cases} \tag{4.12}$$

ISS company and management team co-recommendation

I create a dummy ($Agree\_IM_{j,n,t}$) to identify the items that the ISS recommendation and the management team recommendation are in the same direction.

Voting distance

Voting distance is designed to measure the voting attitude difference between passive (active) funds in a fund family and ISS company recommendations. Passive funds are defined as index funds and ETFs. Active funds are defined as other mutual funds. Voting distance is calculated as the equation (4.13). For firm j's voting item n , I calculate the percentage of passive (active) funds that vote with ISS company recommendations in the fund family f.

Voting distance is designed to measure the voting attitude difference between passive (active) in a fund family and ISS company recommendations. The percentage of passive (active) funds that vote with ISS company recommendations in the fund family f is calculated for each voting item n for firm j. The voting distance is then calculated using the equation (4.13).

$$Distance_{j,n,t}^{f^{p(a)}} = \frac{N_{vote\ with\ ISS\ recommendations}^{f^{p(a)}}}{N^{f^{p(a)}}} \tag{4.13}$$

Table 4.A1: Voting behavior of passive funds and active funds

Panel A: Passive funds						
	Vote with ISS recommendation | $Agree\_IM = 0$					
	All Passive		Partial co-present Passive		All co-present Passive	
	(1)	(2)	(3)	(4)	(5)	(6)
$Ownership^{f^a}_{j,t} + Ownership^{f^p}_{j,t}$		-4.3691*		-3.2106		-17.6946**
		(2.3412)		(2.1323)		(7.7616)
$Ownership_{i,j,t}$	-40.4568		-33.6601		-1.4952	
	(26.2426)		(24.9449)		(53.5172)	
$Weight_{i,j,t}$	-30.1466***	-31.9369***	-28.5979***	-29.9185***	-40.8867*	-35.3355*
	(5.0513)	(5.4534)	(4.4662)	(4.9019)	(21.5808)	(20.9676)
$ln(TNA)_{j,t}$	-0.0471	-0.0706*	-0.0585	-0.0822**	-0.1568	-0.0551
	(0.0573)	(0.0389)	(0.0573)	(0.0389)	(0.1482)	(0.1344)
$ln(Mktcap)_{j,t}$	0.0254	0.0300	0.0399	0.0436	0.0091	-0.0368
	(0.0360)	(0.0353)	(0.0343)	(0.0335)	(0.1601)	(0.1591)
$ROA_{j,t}$	0.2821	0.2204	0.2221	0.1648	1.2218	1.5081
	(0.3068)	(0.3427)	(0.3054)	(0.3328)	(1.3055)	(1.3509)
Year fixed effect	Yes					
Industry fixed effect	Yes					
N	391,736	391,736	347,404	347,404	44,318	44,318

Panel B: Active funds						
	Vote with ISS recommendation | $Agree\_IM = 0$					
	All Active		Partial co-present Active		All co-present Active	
	(1)	(2)	(3)	(4)	(5)	(6)
$Ownership^{f^a}_{j,t} + Ownership^{f^p}_{j,t}$		-13.7648***		-12.2294***		-11.9067***
		(1.5659)		(1.5986)		(2.4268)
$Ownership_{i,j,t}$	3.1696		4.3649		-8.0382	
	(3.1413)		(3.5790)		(5.0471)	
$Weight_{i,j,t}$	-7.6976***	-5.5297**	-9.3666***	-7.5884***	1.0145	2.6316
	(2.5217)	(2.2968)	(2.6790)	(2.4790)	(2.5153)	(2.4126)
$ln(TNA)_{j,t}$	-0.1820***	-0.1139***	-0.2077***	-0.1474***	-0.0239	0.0331
	(0.0305)	(0.0301)	(0.0284)	(0.0284)	(0.0445)	(0.0429)
$ln(Mktcap)_{j,t}$	0.0582**	0.0256	0.0906***	0.0585*	-0.0983***	-0.1228***
	(0.0259)	(0.0299)	(0.0266)	(0.0310)	(0.0356)	(0.0341)
$ROA_{j,t}$	0.1969	-0.1477	0.1586	-0.1103	0.0308	-0.5077
	(0.3231)	(0.5220)	(0.3560)	(0.5180)	(0.4567)	(0.6351)
Year fixed effect	Yes					
Industry fixed effect	Yes					
N	485,521	485,521	386,599	386,599	98,921	98,921

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